

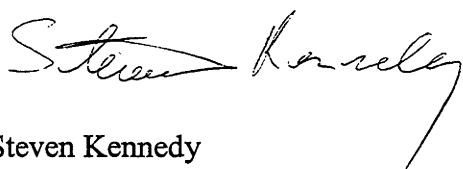
**The Production of Health:
An Examination of the Economic
Determinants of Health**

A thesis submitted for the degree of Doctor of Philosophy of The
Australian National University

Steven Kennedy, 24 October 2001

Investigations reported in Chapter Two of this thesis were carried out jointly with Thomas Crossley of McMaster University, Hamilton, Canada and Centre for Economic Policy Research, The Australian National University, Canberra. In particular, I developed the questions addressed in Chapter Two and undertook the majority of empirical analysis. Thomas Crossley was the major contributor to Section 2.6 and provided additional technical advice in regards to other Chapter Two Sections.

All other investigations are my own original work.

A handwritten signature in black ink, appearing to read 'Steven Kennedy', with a long, sweeping underline that extends to the right.

Steven Kennedy

Acknowledgments

A number of people were of enormous assistance throughout my PhD Studies. Bruce Chapman and Tom Crossley were a constant source of inspiration and I am very appreciative of their substantial efforts. I would like to thank Jeff Borland and Deborah Cobb-Clark who supported and encouraged me at every stage of my studies. I would also like to thank the Australian Bureau of Statistics for their support.

I received helpful comments on Chapter Two of my thesis from seminar participants at The Australian National University, Paul Grootendorst, Jeremiah Hurley, Michael Ornstein, Arthur Sweetman and Michael Veall. The Australian Department of Immigration and Multicultural Affairs provided the data for Chapter Three and I thank seminar participants at the Third Australian Labour Econometrics Workshop and Garry Barrett, Yvonne Dunlop, and Ranjan Ray for helpful comments. Jeremiah Hurley and Lonnie McGee provided helpful comments on Chapter Five.

All errors are my own.

To my wife Janelle and daughters Amelia and Georgia.

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Abstract

I examine whether various economic outcomes cause changes in individual health. Before examining such relationships, I evaluate the usefulness of a well-known measure of health: self assessed health status. I find that there are non-random errors in the self-reporting of health status but that self assessed health status is still a useful indicator of health.

The first relationship between an economic outcome and health that I examine is one between labour force status and the mental health of immigrants. I use the Longitudinal Survey of Immigrants to Australia to examine whether changes in labour force status cause changes in mental health rather than vice versa. I find that causality runs from unemployment to mental health and that unemployment significantly adversely affects the mental health of immigrants. I also examine the impact of the family on alleviating the stress of migration and unemployment. I find that the mental health of immigrant couples is positively correlated but that the negative effects of immigrant unemployment are not alleviated by spouse employment.

The second relationship I study is one recently popularised in the public health and medical literature: a relationship between income inequality and health. I use the 1995 Australian National Health Survey to examine the robustness of a possible relationship between income inequality and individual health status. I find that the relationship between income inequality and health is not robust. However, I did find that when particular income inequality indices are related to health they are more strongly related to mental health than measures of physical and general health. This interesting result may lead to a particular focus in future research on the income

inequality and health relationship.

The third relationship I examine is one between education and health. Here I am able to compare the features of this relationship for Australia and Canada as well as test for alternative interpretations of an education and health relationship. I attempt to distinguish between three explanations of the education and health relationship: technical efficiency, allocative efficiency and time preference explanations. I find that education is indeed related to health and to a very similar extent in Australia and Canada. I am unable to differentiate one explanation from another, finding instead evidence for all three explanations.

1. Introduction

We have next to consider the conditions on which depend health and strength, physical, mental and moral. They are the basis of industrial efficiency, on which the production of material wealth depends: while conversely the chief importance of material wealth lies in the fact that, when wisely used, it increases the health and strength, physical, mental and moral of the human race. (Alfred Marshall, 1920, Principles of Economics, 8th Edition.)

How can we measure health reliably? Why are the unemployed apparently less mentally healthy than the employed after controlling for the effect of income? Do people who reside in regions where income inequality is high have worse health than people who reside where there is less income inequality? How does education affect health? These are some of the questions addressed in this thesis. In doing so I aim to go beyond simple associations between various labour market outcomes and health. I examine whether labour market and economic outcomes cause changes in health while, at the same time, considering how changes in health might cause changes in labour market outcomes.¹ When causality is established, I am also interested in examining the question – What is the magnitude of the effect on health?

The policy imperative arising from this research is not controversial. Many economic policies, such as policies that affect the probability of employment or the

¹ There is an important role for theory to play in interpreting relationships and suggesting tests that allow us to identify causality. The major economic theoretical strand underlying most of my work is the household production model. In this model, households or individuals produce commodities subject to constraints to maximise utility.

distribution of income and educational attainment, have important health consequences. In some cases economic, social and health policies may be complementary. For example, an education policy which seeks to maximise student retention rates coupled with evidence that education has a positive and causal effect on health, will see both education and health policy objectives satisfied. On the other hand, an education policy that aims to improve the quality of tertiary education may also lead to wider differences in income. This increase in income inequality may in turn lead to poorer health overall.² If this were the case, the negative health consequences of such an education policy would clearly need to be considered.

Before we can even begin to examine labour market and health relationships we strike some substantial measurement issues. For example, how do we go about measuring health? In two of the health and labour market relationships that I examine in my thesis I use the well-accepted health indicator, self assessed health status. The use of self assessed health status as a measure of health is common in empirical research. A co-author and I analyse a unique Australian survey in which a random sub-sample of respondents answer a standard self assessed health question twice – before and after an additional set of health related questions. Twenty-eight percent of respondents change their reported health status. Response instability is found to be related to age, income and occupation. A comparison is made of the responses of these individuals to other respondents who were queried only once. The distributions of responses to both questions by the former group are statistically different from the distribution of

² This example of the possible negative health consequences of an improvement in education is due to Deaton and Paxson (1999).

responses by the latter group. In this study, we are able to provide insights into measurement error issues and the related empirical implications when using self assessed health status as a measure of health. Self assessed health status is not the only measure of health used in the thesis. The General Health Questionnaire is used to measure mental health and the SF-36 to measure general, physical and mental health. These measures are discussed in detail in Chapters 3 and 4.

Having addressed in part an important health measurement issue in Chapter 2, I then examine three aspects of the relationship between health and labour market outcomes. The first concerns the relationship between labour force status and the mental health of Australian immigrants. A more detailed knowledge of this relationship is important because of current Australian labour market policy directed at newly arrived immigrants. Under this policy, non-humanitarian Australian immigrants do not have immediate access to social security and labour market programs.

The primary objective of my analysis of immigrant mental health and unemployment is to assess whether stress associated with the transition to a new country, combined with additional stress arising from unemployment, affects not only principal immigrants but also other immigrant family members. I use the Longitudinal Survey of Immigrants to Australia (LSIA) to examine the effect of labour force status on the mental health of immigrants. By using a rich longitudinal data set it is possible to control for immigrant individual differences or fixed effects and examine whether changes in mental health cause changes in labour force status rather than changes in labour force status causing changes in mental health. I find that causality runs from unemployment to mental health, and that unemployment significantly adversely affects the mental health of immigrants. Other characteristics associated with poor mental

health include age, gender, visa category, marital status, and educational attainment. I examine the impact of the family on alleviating the stress of migration and unemployment and find that the mental health of immigrant couples is positively correlated. I also find that the negative effects of unemployment are not alleviated by spouse employment. A major contribution of Chapter 3 is that both the transition experience of immigrants and the relationships between mental health and key individual and socio-economic characteristics are examined.

The second relationship studied is one recently popularised in the public health and medical literature: a relationship between income inequality and health. A number of international studies have identified a negative relationship between income inequality and health, even after allowing for a positive relationship between income and health (for example, Kawachi *et al.*, 1997, Kennedy *et al.*, 1998, 1996, Wilkinson, 1997, and Wolfson *et al.*, 1999). I use the 1995 Australian National Health Survey to examine the relationship between income inequality and individual health status. I examine the robustness of the income inequality and health relationship by using alternative measures of health status and income inequality, measuring income inequality at two levels of geographic classification, and estimating Deaton and Paxson's (1999) theoretical model of how relative income impacts on health. I find that the relationship between income inequality and health is not robust to different measures of income inequality. The relationship is also not robust to trimming the data set and removing zero income observations, two adjustments commonly made. I find that when particular income inequality indices are related to health they are more strongly related to mental health than measures of physical and general health. This interesting result may lead to a particular focus in future research on the income inequality and health

relationship. In particular, it may help researchers identify the mechanisms through which region context variables influence individual health.

The third relationship examined is one between education and health. Here I am able to compare the features of this relationship for Australia and Canada as well as test for alternative interpretations of an education and health relationship. It is well accepted that education is positively related to health. However, there is considerably less agreement as to the explanation of this relationship. I examine the strength of the empirical relationship between education and health for Australia and Canada. I attempt to distinguish between three explanations of the education and health relationship: technical efficiency, allocative efficiency, and time preference explanations. In examining the time preference explanation, health investment profiles are derived, an approach I believe is new to the literature. I find that education is indeed related to health, and to a very similar extent in Australia and Canada. I could not rule out any of the three explanations. Instead, I find evidence to support all three.

The three labour market or economic and health relationships that are examined all point to the importance of economic conditions for individual health. Employment, income and educational attainment are all found to independently influence health. The role of income inequality is less clear though there is some evidence of a psychosocial stress effect on the mental health of individuals, due to increases in regional income inequality. Clearly more work is needed to identify more carefully the effects of economic variables on health. In particular, disentangling the influence of health on labour market outcomes from the influence of labour market outcomes on health is essential before policy makers can confidently predict the health outcomes of economic policies and conditions.

2. The Reliability of Self Assessed Health Status

2.1 Introduction

Self assessed health status is an increasingly common measure of health in empirical research (e.g., Smith, 1999; Kennedy *et al.*, 1998; Deaton and Paxson, 1998; Schofield, 1996; Ettner, 1996; Saunders, 1996). This is supported by a literature that shows that self assessed health status predicts mortality and morbidity (e.g., Idler and Kasl, 1995; McCallum *et al.*, 1994; Connelly *et al.*, 1989; Okun *et al.*, 1984). Furthermore, Gerdtham *et al.* (1999) have demonstrated that a continuous health status measure constructed from a categorical response by the method of Wagstaff and van Doorslaer (1994) is highly correlated with other continuous measures of health.¹

The 1995 Australian National Health Survey provides a unique opportunity to examine self assessed health status measures in a different way.² The following standard self assessed health status question was asked of all respondents and *twice* of a random subsample:

¹ Wagstaff and van Doorslaer (1994) constructed a continuous health measure from the categorical self assessed health status variable used in this study by assuming an underlying latent health status variable with a lognormal distribution.

² This opportunity is unique because of the size of the data set, typically test and re-test analyses are conducted using small samples and because the data set also has a randomly allocated control group.

In general, would you say that your health is:

Excellent?

Very good?

Good?

Fair?

Poor?

For the “treatment” group, this question is first asked at the beginning of a general health and well-being questionnaire.³ The question is asked again after the respondent has completed the general health and well-being questionnaire and answered some non-health related questions. The distributions of responses to these two questions are statistically different. In addition, both distributions are statistically different from the distribution of responses by the group that was asked only once.

Among respondents who were asked the self reported health status question twice, approximately 28 percent change their response, though, only 3 percent change their response by more than one category. Some socioeconomic groups are more likely than others to revise their self assessed health status on repeated questioning. For example, a higher proportion of older than younger persons change their self assessed health status.

³ Self assessed health status is often elicited using this particular question. For example, exactly the same question was asked in the 1994, 1996 and 1998 Canadian National Population Health Surveys. Kennedy *et al.* (1998) use data from the combined USA 1993-94 survey of the behavioural risk factor surveillance system where the question is “Would you say in general your health is: excellent, very good, good, fair or poor?”. In the British Household Panel Survey the question is slightly different and contains an age benchmark, “Compared to people of your own age, would you say that your health over the last 12 months has on the whole been excellent, good, fair, poor or very poor?”.

These patterns of responses and changes in responses suggest several interpretations and may have implications for research employing self assessed health measures. Before turning to those interpretations and implications, we provide further detail on the data, and its patterns.

2.2 The 1995 Australian National Health Survey

The Australian Bureau of Statistics (ABS) 1995 National Health Survey⁴ was conducted over a 12 month period from January 1995 to January 1996 and is based on a sample of private and non-private dwellings. Approximately 23,800 households were surveyed and the overall response rate for households was 91.5 percent. An important feature of the data is that they are representative of the Australian adult population which allows us to compare the reliability of self assessed health status among different groups.

In addition to the standard “face-to-face” interview, of the original sample approximately half were asked to complete a written supplement comprising the Short Form 36 health status questionnaire (SF-36). The SF-36 is a well known measure of general health and well-being; it produces scores for eight dimensions of health.⁵ Selection into this “treatment” group, the group that answered the SF-36, was based on the random assignment of blocks within census districts.

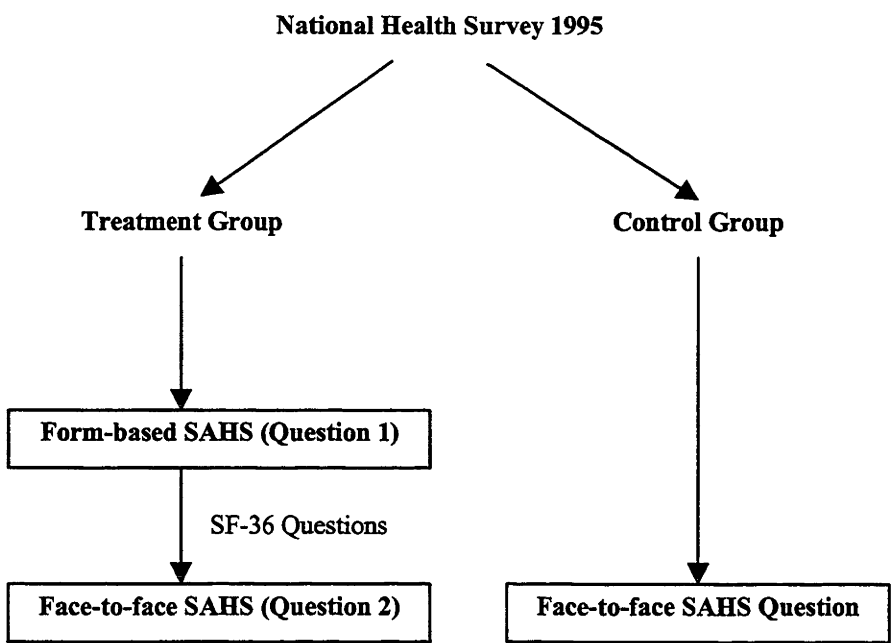
⁴ See Australian Bureau of Statistics (1995).

⁵ See Ware *et al.* (1993)

In households selected to respond to the SF-36, persons aged 18 and over were asked to complete it *prior* to the standard interview. The first question on the SF-36 is the self assessed health status question presented in the introduction. This question is asked again (but by an interviewer rather than through a self completed form) in the standard interview. In the standard interview, the self assessed health question is the first question about the respondent's health, but is preceded by questions regarding; gender, age, marital status, race, country of birth, year of arrival in Australia, language spoken at home and employment status. Thus, for the treatment group, the responses to the two self assessed health status questions are separated by the rest of the health questions on the SF-36 form and the socioeconomic questions listed above. 18436 persons responded to both self assessed health status questions.

Individuals in households that were not selected to respond to the SF-36 were only asked the self assessed health question once, in the standard (face-to-face) interview, after the socioeconomic questions listed above. We refer to these individuals as the "control" group. Figure 1 summarises the self assessed health questions asked of the treatment and control groups. Appendix 2A Table A.1 presents the distributions of socioeconomic characteristics and the results of tests for differences between the treatment and control groups. No evidence was found to suggest that randomization was inadequate.

Figure 2.1
Survey Process



Aside from the two self assessed health status variables and answers to the SF-36 questionnaire, other variables of interest include gender, age, employment status, equivalent income and occupation. The definitions of all variables are presented in Table 2.1.

Table 2.1
Variable Definitions

Variable	Definition
Age	Age is defined in 4 groups, age 18 to 24 years, age 25 to 54 years, age 55 to 69 years, and age 70 years and over.
Gender	Males and females.
Self Assessed Health Status (SAHS)	Responses to the self assessed health status questions are scored as follows (1 = excellent, 2=very good, 3=good, 4=fair, 5=poor).
Occupation	There are 3 occupation groups: managers and professionals (white collar); para-professional, clerks, salespersons and personal service workers (other white collar); and labourers and related workers, tradespersons, and plant and machine operators and drivers (blue collar).
Employment Status	Employment status was represented by 3 groups; employed, unemployed, and not in the labour force.
Equivalent Income	Equivalent income was coded according to a person's equivalent income quintile. The equivalent income measure took into account different household types by applying Henderson simplified equivalence scales at the income unit level. See Australian Bureau Statistics (1995) for a more detailed description of this variable.

2.3 The Distribution of Responses by Question and Group

To better understand revisions to self assessed health status we begin by comparing the distribution of responses. The distribution of responses to both self assessed health questions for the treatment group and to the single self assessed health question in the case of the control group are presented in Table 2.2. In Table 2.3, we present tests for differences in means and distributions across questions within the treatment group, and also across the treatment and control groups.

Table 2.2

Self Assessed Health Status Response Frequencies (percent)

	Treatment Group SAHS Question 1 Self completed, written response, asked first	Treatment Group SAHS Question 2 Personal interview, asked second	Control Group SAHS Personal Interview, asked first
Excellent	17.3	18.0	20.2
Very Good	37.2	37.5	34.5
Good	31.3	27.5	29.6
Fair	11.3	13.2	11.8
Poor	3.0	3.8	3.8

Comparing the distributions of responses to the two questions for the treatment group, we cannot reject the null hypothesis that the means are the same (at a 5 percent level of significance) but the null that the distributions are the same is strongly rejected. This is due to a fairly symmetric thickening of the tails. When respondents were questioned a second time, by face-to-face interview rather than by written questionnaire, the middle category (“Good”) was reported less frequently and *all* the other categories became more prevalent.

Table 2.3

Differences in Means and Distributions

	Difference in Means t-test (P value)	Difference in Multinomial Distributions Pearson Chi-square (P value)
SAHS Q1 vs SAHS Q2	1.58 (0.12)	93.48 (0.00)
SAHS Q1 vs SAHS Control group	0.98 (0.33)	92.41 (0.00)
SAHS Q2 vs SAHS Control group	2.53 (0.01)	77.88 (0.00)

Comparing the treatment and control groups, we find a statistically significant difference between the distribution of responses generated by the control group and that generated by either question asked of the treatment group. The differences cannot be simply characterised by either spread or location. We know from Appendix 2A Table

A.1 that the distribution of co-variates does not differ across treatment and control groups, and we have just observed that the unconditional distribution of responses does differ across the groups. Thus, it can be inferred that conditional distributions of responses differ across the treatment and control groups. This is confirmed in Table 2.4 where we see that most conditional distributions of responses do in fact vary across the treatment and control groups.

Table 2.4

Differences in Multinomial Distributions - Pearson Chi-square (P value)

Variables	SAHS Q1 vs SAHS Q2	SAHS Q1 vs SAHS Control group	SAHS Q2 vs SAHS Control group
Age			
Age 18-24	29.18 (0.00)	35.03 (0.00)	30.63 (0.00)
Age 25-54	50.27 (0.00)	55.80 (0.00)	49.18 (0.00)
Age 55-69	24.27 (0.00)	18.20 (0.00)	8.96 (0.06)
Age 70 +	6.84 (0.15)	5.20 (0.27)	2.48 (0.65)
Gender			
Female	35.02 (0.00)	47.41 (0.00)	34.56 (0.00)
Male	61.91 (0.00)	48.71 (0.00)	50.52 (0.00)
Occupation			
White collar	29.38 (0.00)	27.13 (0.00)	21.67 (0.00)
Other white collar	24.85 (0.00)	26.35 (0.00)	32.32 (0.00)
Blue collar	21.28 (0.00)	12.45 (0.01)	23.64 (0.00)
Employment Status			
Not in Labour force	72.16 (0.00)	58.89 (0.00)	71.31 (0.00)
Unemployed	17.28 (0.00)	20.60 (0.00)	14.12 (0.01)
Employed	7.85 (0.10)	18.36 (0.00)	8.94 (0.06)
Income			
Income Quintile 1	13.23 (0.01)	25.91 (0.00)	21.00 (0.00)
Income Quintile 2	13.62 (0.01)	13.89 (0.01)	9.72 (0.05)
Income Quintile 3	28.34 (0.00)	12.23 (0.02)	12.08 (0.02)
Income Quintile 4	13.23 (0.01)	11.18 (0.03)	16.21 (0.00)
Income Quintile 5	19.67 (0.00)	20.99 (0.00)	13.84 (0.01)
All	93.49 (0.00)	92.42 (0.00)	77.89 (0.00)

Table 2.5
Self Assessed Health Status Means

Variables	No	Treatment Group SAHS question 1 Self completed, written response, asked first	Treatment Group SAHS question 2 Personal interview, asked second	No	Control Group SAHS Personal interview, asked first
Age					
Age 18-24	4445	2.320	2.308	4943	2.243
Age 25-54	9321	2.316	2.347	9904	2.319
Age 55-69	2986	2.742	2.765	3185	2.793
Age 70 +	1684	3.078	3.085	1833	3.066
Gender					
Female	9583	2.451	2.474	10231	2.434
Male	8853	2.461	2.471	9634	2.458
Occupation					
White collar	3156	2.165	2.166	3244	2.101
Other white collar	4584	2.234	2.238	4880	2.177
Blue collar	3934	2.374	2.378	4227	2.359
Employment Status					
Not in Labour force	3344	2.693	2.751	3770	2.759
Unemployed	792	2.528	2.587	901	2.532
Employed	11671	2.262	2.265	12350	2.219
Income					
Income Quintile 1	2876	2.651	2.683	3182	2.659
Income Quintile 2	2920	2.827	2.850	3265	2.832
Income Quintile 3	3059	2.435	2.469	3216	2.433
Income Quintile 4	3315	2.300	2.314	3349	2.259
Income Quintile 5	3708	2.199	2.184	3857	2.165
All	18436	2.456	2.473	19865	2.445

Focusing on the treatment group, we find in Table 2.5 that for both questions, there were differences in mean self assessed health status across socioeconomic groups.⁶

⁶ Differences in mean and distribution discussed in this chapter were significant at the 5 percent level.

For example, older age groups tended to have higher self assessed health status means indicating that their reported health status was generally poorer than that of younger age groups (the categorical variable is coded numerically from 1 “excellent” to 5 “poor”).⁷

Table 2.6
Self Assessed Health Status Standard Deviations

Variables	No	Treatment Group SAHS question 1 Self completed, written response, asked first	Treatment Group SAHS question 2 Personal interview, asked second	No	Control Group SAHS Personal interview, asked first
Age					
Age 18-24	4445	0.887	0.931	4943	0.923
Age 25-54	9321	0.943	0.994	9904	1.004
Age 55-69	2986	1.061	1.131	3185	1.127
Age 70 +	1684	1.127	1.169	1833	1.174
Gender					
Female	9583	1.004	1.049	10231	1.056
Male	8853	0.996	1.051	9634	1.059
Occupation					
White collar	3156	0.866	0.919	3244	0.908
Other white collar	4584	0.867	0.915	4880	0.899
Blue collar	3934	0.905	0.942	4227	0.946
Employment Status					
Not in Labour force	3344	1.090	1.136	3770	1.150
Unemployed	792	0.944	1.021	901	1.066
Employed	11671	0.884	0.929	12350	0.923
Income					
Income Quintile 1	2876	1.077	1.130	3182	1.142
Income Quintile 2	2920	1.078	1.123	3265	1.138
Income Quintile 3	3059	0.959	1.018	3216	1.010
Income Quintile 4	3315	0.910	0.940	3349	0.942
Income Quintile 5	3708	0.872	0.917	3857	0.919
All	18436	1.000	1.050	19865	1.057

⁷ As Deaton and Paxson (1998) point out, it is not surprising to find people reporting poorer health as they age. However, this means people probably assess their health by reference not only to their own age group but also younger age groups. Older age groups also showed larger variation in health status.

The self assessed health status means and variances (Table 2.6) for persons in blue collar occupations show that their health is poorer and, as a group, more dispersed than that of persons in white collar occupations.⁸ Similarly, persons in low equivalent income quintiles seem to have poorer health and exhibit more dispersion in reported health outcomes compared to persons in high equivalent income quintiles.⁹

2.4 Who Revises their Self Assessed Health Status?

Having observed differences in means and distributions across self assessed health status questions and the treatment and control groups we now examine differences in the propensity to revise by socio-economic group. As noted in the introduction, 28 percent of the treatment group change their response between the two self assessed health status questions. 13.6 percent reported a higher level of health whilst 14.8 percent reported a lower level of health. These *gross* flows are large relative to the *net* changes discussed above. (In Table 2.2, responses in the top two categories combined went up by 1 percentage point between the first and second question, while responses to the bottom two categories increased by a combined 2.7 percentage points). There is evidently considerable “churning”. Table 2.7 shows in detail the transitions from self assessed health status question 1 categories to question 2 categories. For

⁸ Ideally, we would have examined different groups defined by educational attainment. However, persons answering the SF-36 were not asked questions about their educational attainment.

⁹ Significant differences across socio-economic characteristics also hold in a multivariate setting. For example, when socio-economic characteristics are included in probit regressions on self assessed health status all characteristics are significant.

example, of those people reporting their health as “good” in question 1, only 64.2 percent report their health as “good” in question 2.

Table 2.7
Transition Matrix (percent)

Self Assessed Health Status question 1	Self Assessed Health Status question 2					
	Excellent	Very Good	Good	Fair	Poor	Total Proportion
Excellent	77.75	17.73	3.70	0.72	0.09	17.3
Very Good	10.32	74.27	13.65	1.53	0.23	37.2
Good	2.08	20.68	64.19	12.44	0.61	31.3
Fair	0.77	3.22	14.42	71.83	9.76	11.3
Poor	0.36	0.72	1.80	16.58	80.54	3.0
Total Proportion	18.0	37.5	27.5	13.2	3.8	100

The degree of revision does seem to vary by socioeconomic group. Table 2.8 demonstrates that the proportion of persons changing their response was significantly higher for older age groups compared to younger age groups.¹⁰ Variation in revisions across age groups illustrates the importance of examining both gross and net flows. The oldest age group was the only age group in which there was no significant variation in net flows yet it had the largest gross flows of all age groups. A smaller proportion of persons in the two white collar occupation groups changed their self assessed health status than those in blue collar occupations. The proportion of persons changing their self assessed health status in the two top quintiles of equivalent income was lower than in other equivalent income quintiles. To counter the effect that age might be having on

¹⁰ These variations also held in a multivariate setting where socioeconomic characteristics were included in a logit regression on the probability of revision

occupation and family income groups, these groupings were age standardised.

Standardising for age did not qualitatively alter the patterns by occupation and family income.

Table 2.8
Proportion Changing between Self Assessed Health Status Questions

Variables	No	Proportion changing between SAHS question 1 and SAHS question 2	F and t tests*	Kappa scores	Weighted Kappa scores
Age			17.338		
Age 18-24	4445	0.272	5.409	0.60	0.69
Age 25-54	9321	0.270	6.018	0.62	0.71
Age 55-69	2986	0.312	2.113	0.58	0.71
Age 70 +	1684	0.341		0.55	0.69
Gender			11.919		
Female	9583	0.273	3.452	0.62	0.73
Male	8853	0.296		0.59	0.70
Occupation			19.908		
White collar	3156	0.243	5.841	0.65	0.72
Other white collar	4584	0.257	4.940	0.62	0.70
Blue collar	3934	0.305		0.56	0.65
Employment Status			5.484		
Not in Labour force	3344	0.292	2.380	0.61	0.73
Unemployed	792	0.308	2.570	0.57	0.68
Employed	11671	0.269		0.61	0.69
Income			13.523		
Income Quintile 1	2876	0.306	5.580	0.59	0.71
Income Quintile 2	2920	0.311	6.081	0.58	0.70
Income Quintile 3	3059	0.301	5.231	0.58	0.68
Income Quintile 4	3315	0.272	2.681	0.60	0.70
Income Quintile 5	3708	0.244		0.64	0.72
All	18436	0.284		0.61	0.72

* All t and F tests are derived from OLS regressions where change in self assessed health status is regressed on each set of variables of interest. All F tests were highly significant.

We also present weighted and unweighted Kappa scores in the final two columns of Table 2.8: these measure the agreement between the two responses by socioeconomic group and are frequently used in survey question analysis. The Kappa scores reveal the same patterns as the earlier columns.¹¹

The reliability of self assessed responses among the older population may be of particular interest for two reasons. First, there is a growing body of empirical literature on health and retirement (e.g., Bound, 1991) that often uses self reported health measures. Second, if reliability varies by age this may be indicative of non-random measurement error, (see Currie and Madrian, 1999 for a review of non-random measurement error in health measures). Table 2.9 shows the frequency of revisions by age group and initial response. Older persons exhibit higher revision propensities for every initial response except “Fair”.¹²

Even more detail can be uncovered by examining the complete transition matrices by age group. These are presented in Appendix 2A Table A.2. In younger age groups, most responses to self assessed health status were excellent, very good and good and therefore most transitions were from these categories. In older age groups, responses were more evenly spread amongst self assessed health status categories and

¹¹ Cohen (1960, 1968) developed the Kappa statistic. See Grootendorst *et al.* (1997) for an example of the use of the Kappa statistic.

¹² Older persons’ higher propensity to revise was statistically significant at a 5 percent level in Excellent and Very Good categories regardless of the method of testing. In other response categories the propensity to revise was not significant in a logit model where the propensity to revise for each category was regressed on age and sex. However, they were significantly higher in bi-variate t-test comparisons between older and younger age groups.

there tended to be slighter higher rates of transition between questions.

Table 2.9
Proportion changing between SAHS questions

	Proportion changing by response to SAHS question 1					
	Excellent	Very Good	Good	Fair	Poor	Total Proportion
Age 18-24	0.223	0.224	0.356	0.313	0.167	0.272
Age 25-54	0.211	0.248	0.346	0.264	0.180	0.270
Age 55-69	0.230	0.325	0.378	0.264	0.172	0.312
Age 70 +	0.331	0.368	0.390	0.307	0.236	0.341
Total Proportion	0.223	0.257	0.358	0.282	0.195	0.284

2.5 Interpretations

To summarise, we find that the distribution of self assessed health status responses differs between:

- (1) A form-based questionnaire and a face-to-face question asked of the same individuals in quick succession;
- (2) Form-based and face-to-face questions asked of two randomly allocated groups; and
- (3) Face-to-face questions asked of a control group and a randomly selected treatment group which was “pre-treated” with form-based questions.

We also find that for the treatment group, changes in self assessed health between the initial form-based questionnaire and the subsequent face-to-face interview

are numerous and related to age, occupation and income.¹³ How can we interpret these patterns?

Individuals in the treatment group might revise their self assessed health status for at least three reasons. First, it may be that they assess their health with some “error” and each response to a question represents a new draw from the measurement error distribution. If this were all that was happening, the frequency of revisions would seem to suggest a large degree of underlying uncertainty (or measurement error).

Second, it may be that there is an “instrument effect” as the respondents go from a written questionnaire to a face-to-face interview. There is a literature which suggests that people respond more candidly to sensitive questions when self completing a form as opposed to being personally interviewed (e.g., Tourangeau *et al.*, 1996).

Finally, and perhaps most intriguingly, it may be that respondents in the treatment group “learn” about their health status between the first and second self assessment of health. Recall that after the first summary self assessed health question they respond to a number of detailed questions about various aspects of their health status. It may be that these detailed questions stimulate a process of introspection that leads to different responses to the second question. We use the term “learn” somewhat loosely: the later responses might or might not be more accurate. There are other interpretations. The effect of preceding questions may have framing effects see for

¹³ The survey research literature suggests that single item measures are not as reliable as multiple item measures (e.g., Ornstein, 1998).

example, Tversky *et al.* (1998).¹⁴ Alternatively, when asked the same question a second time the respondent may impute motives to the survey designers and respond strategically. In what follows we use the term “learning” to refer to any effect of the intervening questions on responses to the second self assessed health status question.

It might be tempting to ask if responses to the intervening specific health questions “predict” subsequent revision. However, such a correlation could simply reflect mean reversion, and thus would be just as consistent with our first explanation (“measurement error”) as our third (“learning”). Suppose that each of the self assessed health questions and the SF-36 index represented “true” health status plus an independent draw from a measurement error distribution. Then it can be shown that the best predictor of an individual’s response to the second self assessed health status question is a (weighted) mean of their response to the first self assessed health status question and the SF-36 index.¹⁵ Thus if the SF-36 indicates better health status than the first self assessment, one would expect the second self assessment to, on average, indicate better health status as well, even though the SF-36 has no causal effect on the second assessment.

One way we might be able to distinguish between learning and mean reversion is to appeal to temporal ordering. That is, learning should proceed in only one temporal direction, so if learning is occurring, the intervening health questions should better predict responses to self assessed health status question 2 than to self assessed health

¹⁴ Framing refers to the effect that preceding questions may have on survey responses.

¹⁵ Where the weights would reflect the variances of the distributions of measurement error relative to “true” health status of the first self assessed health question and the SF-36 Index.

status question 1. By contrast, mean reversion should work equally in either direction so that the intervening questions would predict self assessed health status question 1 and question 2 equally well. With this in mind, we estimated two ordered probit regressions in which the self assessed health status questions were regressed against the 35 intervening (SF-36) health questions. For self assessed health status question 1, the pseudo R squared was 0.31; for self assessed health status question 2 it was 0.34. Thus, there is some slight evidence of learning as the intervening questions better predict responses to self assessed health status question 2 than self assessed health status question 1.

The control group may provide a more promising way of untangling the three explanations listed at the beginning of this section. If we compare the distributions of responses across the randomly selected treatment and control groups, measurement error, which should have the same structure for the two randomly selected groups, does not explain any observed differences. Thus, we can focus on other explanations.

If the *first* response of the treatment group is compared with the responses of the control group, neither group has previously responded to any other health questions. However, the treatment group are self completing a form, while the control group are responding verbally. Thus this comparison isolates (of the explanations we have considered) the instrument effect. As noted in Table 2.2, we find a statistically significant effect.

If the *second* response of the treatment group is compared with the responses of the control group, both groups are answering verbally. However, the treatment group has previously responded to the SF-36 questionnaire. Thus, this comparison isolates the

“learning” effect. Again, as noted in the discussion of Table 2.2, we find a statistically significant effect.

Thus we are forced to conclude that both the instrument (written or verbal) and the sequence of previous questions are determinants of individuals responses to a self assessed health question.

Turning now to the revision propensities of different socioeconomic groups, can we conclude, for example, that the aged are less accurate in their self assessments of health? While older persons are more likely to change categories, we know from Appendix 2A Table A.2 that the elderly have a different initial distribution of responses than younger age groups. Response unreliability will reflect both the amount of uncertainty in responses and the underlying distribution of “true” health status, so that care must be taken with cross group comparisons.

To see this simply, consider a model of responses that abstracts from the “learning” and instrument effects documented above. Suppose that the categorical self assessed health status is generated in the following way: There is an underlying continuous latent variable corresponding to “true” health. Individuals can assess the sum of this variable and make a draw from some measurement error distribution. They then generate their categorical response by comparing the sum just defined to a set of fixed “cut points”.¹⁶ Each assessment leads the individual to make a new draw from the measurement error distribution. It is possible to show that given the “cut points”, the predicted number of revisions depends not only on the variance of the measurement

¹⁶ We have in mind an ordered probit or ordered logit model.

error distribution but also on distribution of the latent health status.¹⁷ Thus, care needs to be taken in interpreting the “accuracy” of self health assessment of different socioeconomic groups. A greater propensity to revise assessments may not reflect a greater underlying uncertainty about “true” health, but rather a different distribution of health status.¹⁸

However, our results would still seem to suggest that older persons have greater difficulty in self assessing their health. Crucially, as we noted in Table 2.9, they have a higher propensity to revise for all but one category of initial response (and for that category their propensity to revise is essentially the same as younger persons). This observation would seem to argue against an interpretation that attributed their higher revision propensity entirely to a different distribution of underlying “true” health.

2.6 Implications for Empirical Research

Our results suggest that individuals’ responses to a self assessed health question depend on both the nature of the survey (particularly whether responses are written or verbal) and the sequence of preceding questions. These are important factors to keep in mind when comparing the distribution of self assessed health status across different surveys. Many health surveys contain multiple measures of health status. Our results

¹⁷ To see this in a trivial way, consider a subgroup of the population whose distribution “true” health has a single point of support far to the right of the rightmost “cut point”. This group could have a very large measurement error variance and very few revisions.

¹⁸ If we define accuracy without reference to some notion or model of underlying uncertainty, but rather in terms of revisions or response reliability, then those who revise more frequently are by definition less accurate.

suggest that it is necessary to consider the order in which health status questions are asked when comparing the results of different surveys. For example, in the Canadian National Population Health Survey the health status question is asked after a series of questions on health, whilst in the US National Interview Health Survey the question is asked prior to other health status questions.

Our results also suggest that there is considerable measurement error or underlying uncertainty in individuals' self assessment of health. This leads to response unreliability. Measurement error will lead to inconsistent estimation of models in which self assessed health appears as an explanatory variable (for example, a model of retirement). Furthermore, the degree of this uncertainty appears to be related to common observable characteristics. That is, this uncertainty is, at minimum, heteroscedastic. This means that a maximum likelihood estimate of a health status model (an ordered probit or logit for example) will be inconsistent, if such estimation assumes homoscedastic error structures (as is usually the case). It seems likely (though it cannot be shown with our data) that individuals' uncertainty about their health status is also correlated *in mean* with socioeconomic characteristics.¹⁹ This would be problematic for studies that take self assessed health status as the dependent variable even if they are estimated by OLS.

How important might such considerations be? To provide a partial answer to that question, we consider a simple linear probability model of employment status, and examine the consequences of improving the estimates by combining both our measures

¹⁹ We cannot show this because it is not possible to distinguish between alternative explanations of revisions in self assessed health status.

of self assessed health. A simple model of measurement error in an explanatory variable (such as can be found in most econometrics textbooks) leads to a prediction of attenuation bias – the coefficient is biased towards zero, and the degree of attenuation decreases as the variance of the measurement error decreases. If we average two draws from the measurement error distribution, the variance of the average is less than the variance of a single draw, and thus a strategy which uses the average of two measures as the explanatory variable should result in reduced attenuation bias.

Another possibility where two measures exist is to use one as an instrumental variable for the other. If the two measurement errors are uncorrelated, this leads to a consistent estimate. However, in our context – repeated self assessment of health – that seems unlikely to be true. Nevertheless, even if the measurement errors are correlated, under reasonable assumptions an instrumental variables (IV) estimate should lead to less attenuation bias than either a simple OLS estimate or an estimation strategy that averages the two responses. A simple model supporting this intuition is provided in Appendix 2B. The motivation behind our empirical example is that the actual attenuation bias must be at least as large as the difference between the OLS and IV estimates (if the measurement errors are uncorrelated), or even larger but in the direction indicated by that comparison (if the measurement errors are correlated).

Table 2.10
Employment Regressions

Estimation	OLS	OLS	OLS	IV
Method:				
Independent Variable:	SAHS question 1	SAHS question 2	Mean of SAHS question 1 and 2	
Instrument:				SAHS question 2
	Coefficient (t-stat)	Coefficient(t-stat)	Coefficient(t-stat)	Coefficient(t-stat)
Excellent	0.123 (1.02)	0.133 (12.87)	0.135 (12.15)	0.155 (10.66)
Very Good	0.112 (13.54)	0.116 (13.52)	0.129 (13.42)	0.170 (10.58)
Fair	-0.230 (19.43)	-0.179 (15.65)	-0.227 (17.13)	-0.241 (10.43)
Poor	-0.423 (20.57)	-0.410 (22.04)	-0.454 (21.55)	-0.513 (16.98)
The dependant variable is employment (0=not employed, 1=employed). The omitted category for the independent variables is Good. There were 18436 observations.				

In Table 2.10, we report estimates of linear probability models of employment on our treatment group, for whom the overall rate of employment is 74 percent. The explanatory variables are dummy variables indicating that the respondent reported their health as “excellent”, “very good”, “fair” or “poor” (“good” is the omitted category). This example is intended to be illustrative, and so we are abstracting from issues of reverse causation. There is a literature that attempts to estimate the effect of health on labour market outcomes (see Currie and Madrian, 1999 for a review of this literature). While some papers in this literature treat health status as exogenous but measured with error, other papers attempt to deal with the potential endogeneity of health status (the possibility that labour market outcomes affect health status, or reports of health status). To deal with this endogeneity requires exclusion restrictions, and credible exclusion

restrictions are difficult to find. Moreover, estimates seem to be sensitive to the choice of exclusion restriction.

The first two columns of Table 2.10 report OLS estimates, where the explanatory variables are derived from the first and second self assessed health questions respectively. Health status is a statistically significantly related to employment status. For example, the OLS estimates suggest that those who report their health as “fair” have an employment probability that is some twenty percentage points below those who reported “good”, and “poor” health corresponds to an employment probability more than forty percentage points below that of the group reporting “good”.

When we average the two self assessed health measures (column 3) or use the second self assessed health as an instrumental variable for the first (column 4) we find even larger differences among the groups. This is consistent with the proposition that the OLS estimates suffer from attenuation bias; that is, they are biased towards zero. Some of the differences are substantial. The OLS estimates suggest that “poor” health corresponds to an employment probability of 42 percentage points below those with “good” health, while the IV estimates suggest a differential of 51 percentage points – a 9 percentage point difference. If (as seems likely) the IV estimates also suffer from attenuation bias (because the measurement errors are correlated), the true degree of attenuation bias may be even larger. Thus, at least in some contexts the underlying uncertainty in self assessed health status can have important effects in empirical applications.

There are two other features noteworthy of this empirical illustration. First, as our simple model predicts, a strategy of averaging the two measures leads to estimates

that lie between the OLS and IV estimates. Second, the OLS estimates do not differ substantially when we derive our regressors from the second rather than first self assessed health status measure. This suggests that “learning” that occurred between the first and second response did not substantially reduce the attenuation bias.

Empirical research must always proceed with the best available measures of quantities and concepts of interest. Nevertheless, it is important to bear in mind what evidence there is on the limitations of the best available measures, and this chapter has provided some evidence on the limitations of self assessed health measures.

Appendix 2A: Auxiliary Self Assessed Health Status Tables

Table A.1
Cell Counts of Variables of Interest

Variables	Treatment Group Number	Control Group Number	Difference in Multinomial Distributions Pearson Chi-square (P value)
Age			3.516 (0.31)
Age 18-24	4445	4943	
Age 25-54	9321	9904	
Age 55-69	2986	3185	
Age 70 +	1684	1833	
Gender			0.872 (0.35)
Female	9583	10231	
Male	8853	9634	
Occupation			1.912 (0.39)
White collar	3156	3244	
Other white collar	4584	4880	
Blue collar	3934	4227	
Employment Status			6.836 (0.03)
Not in Labour force	3344	3770	
Unemployed	792	901	
Employed	11671	12350	
Income			11.76 (0.02)
Income Quintile 1	2876	3182	
Income Quintile 2	2920	3265	
Income Quintile 3	3059	3216	
Income Quintile 4	3315	3349	
Income Quintile 5	3708	3857	
All	18436	19865	

There were a number of missing observations for occupation, employment status and income variables.

Table A.2a
Transition Matrix (percent) Age 18 to 24 years

Self Assessed Health Status Question 1	Self Assessed Health Status Question 2					
	Excellent	Very Good	Good	Fair	Poor	Total Proportion
Excellent	77.69	18.55	3.26	0.50	0	17.95
Very Good	10.50	77.61	10.66	1.02	0.22	41.80
Good	2.15	21.86	64.44	11.11	0.43	31.38
Fair	1.96	5.31	19.27	68.72	4.75	8.05
Poor	0	0	5.56	11.11	83.33	0.81
Total Proportion	19.17	43.06	26.86	9.63	1.28	100

Table A.2b
Transition Matrix (percent) Age 25 to 54 years

Self Assessed Health Status Question 1	Self Assessed Health Status Question 2					
	Excellent	Very Good	Good	Fair	Poor	Total Proportion
Excellent	78.88	17.23	3.30	0.49	0.11	19.86
Very Good	9.69	75.19	13.35	1.54	0.24	40.51
Good	1.92	20.56	65.45	11.60	0.47	29.69
Fair	0.13	3.47	14.42	73.56	8.41	8.04
Poor	1.12	1.12	0.56	15.17	82.02	1.91
Total Proportion	20.19	40.29	26.66	10.36	2.50	100

Table A.2c
Transition Matrix (percent) Age 55 to 69 years

Self Assessed Health Status Question 1	Self Assessed Health Status Question 2					
	Excellent	Very Good	Good	Fair	Poor	Total Proportion
Excellent	76.98	15.87	5.03	1.85	0.26	12.66
Very Good	12.12	67.55	18.48	1.73	0.12	29.00
Good	2.00	20.15	62.17	14.73	0.95	35.23
Fair	0.95	1.90	11.76	73.62	11.76	17.65
Poor	0	0.61	0.61	15.95	82.82	5.46
Total Proportion	14.13	29.07	30.01	19.79	7.00	100

Table A.2d
Transition Matrix (percent) Age 70 years and over

Self Assessed Health Status Question 1	Self Assessed Health Status Question 2					
	Excellent	Very Good	Good	Fair	Poor	Total Proportion
Excellent	66.88	23.75	7.50	1.88	0	9.50
Very Good	11.68	63.25	20.80	3.70	0.57	20.84
Good	2.91	19.31	61.02	15.66	1.09	32.60
Fair	0.67	2.69	13.68	69.28	13.68	26.48
Poor	0	0.56	3.37	19.66	76.40	10.57
Total Proportion	9.92	22.51	28.92	26.48	12.17	100

Appendix 2B: Simple Model of Attenuation Bias

We now present a simple model to which underlies the discussion of attenuation bias in the previous section. Suppose that

$$y_i = \beta hs_i + e_i \quad (1)$$

Where y_i is an outcome of interest and hs_i is “true” health. For convenience, we express all variables as deviations from means. We have two error ridden measures of health:

$$\text{Question 1: } x_i = hs_i + u_i$$

$$\text{Question 2: } z_i = hs_i + v_i$$

We define the following:

$$\sigma_{hs}^2 = \text{plim} \frac{1}{n} \sum_1^n hs_i^2 \quad \sigma_u^2 = \text{plim} \frac{1}{n} \sum_1^n u_i^2 \quad \sigma_v^2 = \text{plim} \frac{1}{n} \sum_1^n v_i^2$$

We assume that the measurement errors are “classical” – uncorrelated with “true” health status and with the disturbance in the structural equation,

$$\text{plim} \frac{1}{n} \sum_1^n e_i v_i = \text{plim} \frac{1}{n} \sum_1^n e_i u_i = \text{plim} \frac{1}{n} \sum_1^n hs_i v_i = \text{plim} \frac{1}{n} \sum_1^n hs_i u_i = 0$$

but allow the possibility that the measurement errors can be correlated (respondents can persistently over or underestimate their health),

$$\text{plim} \frac{1}{n} \sum_1^n u_i v_i = \sigma_{uv}$$

An OLS estimate of (1) solves:

$$\sum_1^n x_i (y_i - b^{OLS} x_i) = 0.$$

With a little substitution and manipulation, it can be shown that:

$$plim b^{OLS} = \frac{\beta \sigma_{hs}^2}{\sigma_{hs}^2 + \sigma_u^2}$$

This is the usual textbook result that measurement error leads to attenuation bias, with the attenuation bias disappearing as the variance of the measurement error goes to zero.

One way to use the second question to improve such an estimate would be to use the responses of the second question as an instrumental variable for the first question.

The instrumental variable (IV) estimate of (1) solves:

$$\sum_1^n z_i (y_i - b^{IV} x_i) = 0$$

For z_i to be a valid instrument it must be uncorrelated with the measurement error in x_i , in that case the IV estimate is consistent. However, this is not the case in our example as we have allowed the measurement errors in z_i and x_i to be correlated. It can be shown that:

$$plim b^{IV} = \frac{\beta \sigma_{hs}^2}{\sigma_{hs}^2 + \sigma_{uv}}$$

The IV estimate, while not consistent, exhibits less attenuation bias than the OLS estimate as long as $\sigma_{uv} < \sigma_u^2$, or equivalently $\rho \sigma_v < \sigma_u$. (This seems quite likely both because the correlation ρ is less than one and because if respondents learn about their health via the intervening questions then $\sigma_v < \sigma_u$. That respondents learn about their

health is suggested by the results of ordered probit regressions discussed in Section 2.4. However, our model is only intended to be illustrative, as it is not necessarily the case that more information will produce less uncertainty.)

Another way to use the information might be to combine the two self assessed health responses in an attempt to “average out” the measurement error. This might lead to an estimator that solves:

$$\sum_1^n \frac{x_i + z_i}{2} (y_i - b^{avg} \frac{x_i + z_i}{2}) = 0,$$

and it can be shown that:

$$plim b^{avg} = \frac{\beta \sigma_{hs}^2}{\sigma_{hs}^2 + \frac{1}{4}(\sigma_u^2 + 2\sigma_{uv} + \sigma_v^2)}$$

This will typically lie between the OLS and IV estimates and therefore while exhibiting less attenuation bias than the OLS estimate will exhibit more attenuation bias than the IV estimate.

3. Immigrant Mental Health and Unemployment: A study of Immigrants and their Families

3.1 Introduction

It is apparent from studies in Australia and overseas that migration itself does not necessarily threaten mental health. The mental health status of immigrants and refugees becomes a concern when additional risk factors (pre-migration and post-migration factors) combine with the stresses of migration (Jayasuriya et al., 1992).

The impact of unemployment on the mental health of immigrants is an essential piece of information for policy makers who seek to improve the welfare of all citizens and reduce the potential for increased health care costs. This chapter examines the effect of labour force status in particular, unemployment, on the mental well-being of Australian immigrants. The chapter examines whether the stresses associated with the transition to a new country (or culture) combined with additional stress arising from unemployment affect not only principal immigrants but also other immigrant family members.¹

How the labour market experience of immigrants affects their health is particularly relevant to Australian policy makers. In Australia, some immigrants, usually those who have been sponsored by family members, pay a bond from which

¹ Principal immigrants (termed principal applicants in this Australian data set) being persons who applied to migrate.

monies will be deducted should they draw on the social security system in the first two years after migration. After two years, the bond or remaining portion of the bond is returned to the immigrant or the individual who put up the bond on the immigrant's behalf.² Other immigrants for example, those in the Business migrant Visa category, have no access at all to the social security system for the first two years after migration. All (permanent) immigrants to Australia have full access to the public health care system and no conditions apply. If the labour market experience of immigrants in the first two years of migration leads to health problems and there are barriers to avoiding adverse labour market experiences this may have important social as well as health care cost consequences.

There is a small literature that explores the mental health of immigrants. Studies have typically focused on the incidence of psychiatric illness amongst immigrants for example, examining the incidence of depression or schizophrenia in immigrant populations.³ A few studies have focused on the transition experience of immigrants. That is, changes in the mental health of immigrants in the period immediately following migration. In these studies, the interest is not so much in what is the incidence of a particular psychiatric disease as it is in how well do immigrants adapt to their new environment. For example, Kuo *et al.* (1986) examined the impact of social support networks on the transition experiences of immigrants and found that social networks were an important influence on mental health. This chapter focuses primarily on the

² When the LSIA was conducted the bond arrangement applied to a subset of immigrants, mostly those sponsored by family members. The policy of no access to social security for a two year period immediately following migration for Business and Independent skilled immigrants was introduced after the LSIA commenced.

³ For a review of Australian studies see Jayasuriya *et al.* (1992).

transition experience of immigrants and uses a well-known psychiatric evaluation instrument to measure mental health. A major contribution of this chapter is that both the transition experience of immigrants and the relationships between mental health and key individual and socio-economic characteristics are examined.

There is also a literature that explores the effect of unemployment on mental health or well-being (see for example, Clark and Oswald, 1994; Flatau *et al.*, 1998; Theodossiou, 1998; Warr, 1987). In general, this literature finds that the unemployed have poorer mental health compared to those whom are employed. These studies have found that the relationship between unemployment and mental health depends in part on individual characteristics and the duration of unemployment.

This chapter takes an informal theoretical approach (similar to most of the unemployment mental health literature) in identifying causal links between labour force status and mental health. An important aspect of this chapter is that the longitudinal data set upon which this analysis is based enables a more careful examination of the issue of causality than can be undertaken using a cross-section data set.

Most studies of unemployment and mental health focus on individual responses to employment status. However, many decisions such as participation in the labour market and the decision to migrate are made in a family or household setting. In addition to exploring the effect of an immigrant's labour force status on their mental health, I examine mental health responses to different labour force states in a family

context. This aspect of the chapter is an important contribution to the existing literature and, to the author's knowledge, has not been previously examined.⁴

Sections 3.2 and 3.3 of the chapter briefly examine the existing literature on unemployment, immigration and mental health. Section 3.4 discusses the data set and presents some descriptive results. In section 3.5, a number of regression models and associated results are presented and discussed. Section 3.6 concludes with a discussion of key results.

3.2 Unemployment and Mental Health

There are a number of good reviews of the unemployment and mental health literature (for example, Flatau *et al.*, 1998; Ezzy, 1993; Warr *et al.*, 1988; Jahoda, 1988). In general, this literature concludes that unemployment is associated with poor mental health compared to employment. It is not my intention to repeat this work: instead, I focus on the theoretical underpinning of this literature and relevant empirical studies.

Most studies of the effect of unemployment on mental health are in what Clark and Oswald (1994) describe as the psychologists' tradition.⁵ That is, researchers use broad descriptive models to represent the effects of different stresses on individuals. Psychologists have developed many sophisticated models of stress and there are a number of different psychological models through which behaviour can be interpreted.

⁴ For a review of related studies see Mathers and Schofield, 1998.

⁵ See Jahoda (1988) and Theodossiou (1998) for a discussion of why studies in this area have tended to be descriptive rather than directed by economic theory.

The psychological or behavioural model underlying most unemployment mental health studies appears to be a simple model of stress or perhaps more accurately chronic stress. According to Talyor *et al.* (1997), Seyle (1956) first discussed the effect of chronic stress on health in his articulation of the General Adaptation Syndrome. The General Adaptation Syndrome is a model of stimulus – resistance – exhaustion. Seyle suggested repeated cycling through these phases would lead to health problems. Models similar to that suggested by Seyle (1956) and other psychologists are starting to find their way into the economic literature (see for example, Smith, 1999).

A key aspect of all models of stress is the notion of equilibrium. Here people are always subject to some level of (healthy) stress. However, when a particularly adverse event occurs or such an event occurs over a long period (chronic stress) people become ill. As Seyle in Kutash *et al.* (1980) points out “complete freedom from stress is death”. That is, not all stress is bad: there is some healthy level of stress (or stimulation) at which people function optimally.

The theoretical focus of the unemployment mental health literature has not been on particular behavioural models of stress but rather on why unemployment stresses the individual. Flatau *et al.* (1988) notes that Jahoda (1982) and (1992) further developed the theoretical basis of her work by relating how the unemployment experience equates to the deprivation of positive influences associated with work. Positive influences of work included income, social contact and structured time. Deprivation of the positive aspects of work even in comparison to poorly paid work is also a feature of other authors’ work (for example, Theodossiou, 1998).

Warr’s (1987) ‘Vitamin model’ is a more elaborate behavioural model of why unemployment stresses individuals. This model treats different aspects of the work

environment as if they were vitamins contributing towards mental health. In this model, an excess of some aspects of work can be deleterious to mental health in the same way that too much of some vitamins can adversely affect physical health. Similarly, too little (deprivation) of some aspects of work through unemployment will also adversely affect mental health. The 'Vitamin model' carefully reflects the notion of equilibrium that is present in most behavioural models of stress. That is, people need stimulation through work but not too much and not too little.

A further illustration of how individual health states are related to the notion of equilibrium is in Warr's (1988) paper in which he discusses the adaptation of individuals to a long duration of unemployment. Warr (1988) proposes that there is an inverted U shaped response to a duration of unemployment where initially stress levels rise (mental health declines), followed by a period of higher sustained stress (further decline in mental health) followed in turn by adaptation to unemployment and an increase in mental health. However, this final (equilibrium) level of mental health is still below the pre-unemployment mental health level.

Other studies have also found evidence of mental health adaptation to labour market shocks. For example, Kasl *et al.* (1975) examined individuals' health in firms that were about to close down. In particular, he examined the effect of different social support networks on mental health. Differences in social networks were isolated through a rural/urban differentiation where it was assumed that social networks would be stronger in the rural setting. Kasl *et al.* (1975) found that stress levels were highest in the anticipatory phase of firm shutdown (prior to actual unemployment) and there was some evidence that the stress of unemployment was alleviated for individuals with stronger support networks.

An aspect of an individual's life that may alleviate stress caused by unemployment is their family. It may be the case that when one member of a family is unemployed their stress is partly offset by another member of the family being in employment. Alternatively, unemployed people may be more badly affected when members of their family are employed rather than also unemployed, an envy effect. It may also be the case that the whole family is negatively affected by having any unemployed members. Warr (1987) reviews studies of the effect of unemployment on families and finds mixed evidence, some studies suggesting adverse effects of unemployment on families other studies showing no effect.

The role of economic theory in the unemployment and mental health literature is small. Some authors have displayed a clear preference not to incorporate existing economic theory suggesting that a descriptive based approach is most appropriate (see Jahoda, 1988 and Theodossiou, 1998). Clark and Oswald (1994), whilst adopting a psychological (stress based) approach interpret their results in a utility framework. They treat a decline in mental health as an indicator of a person's utility. Thus when they observe that poorer mental health is associated with unemployment they infer that unemployment is primarily an involuntary phenomenon with an associated reduction in utility. Flatau *et al.* (1998) notes that Grossman's (1972) model of health capital is an economic model whereby unemployment might be related to mental health (or health more generally). In this model, an episode of unemployment could be treated as a negative shock to health investment or as an acceleration in the depreciation of the stock of health.

3.3 Immigrants and Mental Health

Studies of the mental health of immigrants have tended to focus on the incidence of mental illnesses such as schizophrenia and major depression in immigrant populations usually comparing this to the incidence of mental illness in native populations. Jayasuriya *et al.* (1992) reviewed Australian studies of the mental health of immigrants and found that it was difficult to draw conclusions about the relative health of immigrants compared to other Australians. Vega and Rumbaut (1991) reviewed US studies of the mental health of ethnic minorities and found mixed evidence of a higher incidence of mental illnesses.⁶ The US studies were mostly epidemiological in approach and used survey instruments to measure mental health that were similar to the instrument used in this study.

Longitudinal studies of the transition experience of immigrants have found that immigrants typically adjust to their new country in an approximate three year cycle of euphoria, disenchantment, and finally acceptance or equilibrium (see for example, Rumbaut, 1985, Portes and Rumbaut, 1989, and Ying, 1988 as cited in Vega and Rumbaut, 1991). The pace of adjustment is affected by a number of factors including: the ability to speak the adopted country's language, social support mechanisms, family issues, and the situation from which the immigrant has come. For example, immigrants leaving a stressful situation for humanitarian reasons have been found to be more anxious in their new environment than immigrants leaving a less stressful situation.

⁶Vega and Rumbaut (1991) noted that the recorded high incidence of mental illnesses in some ethnic groups could be because a large proportion of these ethnic groups are part of lower socioeconomic groups. People in low socioeconomic groups are more likely to experience mental illness.

Kuo *et al.* (1986) examined the impact of different social networks on immigrants' well being and found that ethnic support networks can play an important role in promoting immigrant mental health. The role of the family is central in most support networks, particularly where family members or relatives have sponsored an immigrant's migration.

The behavioural model underlying studies of the mental health of immigrants appears to be a model of stress (similar to the literature on unemployment and mental health) where immigration or factors associated with immigration stress the individual. Vega and Rumbaut (1991) noted that most research on whether there are inherent features of minorities (including immigrant minorities) that cause mental illness is "guided by social psychological stress theory". This theory suggests that life stresses are more significant and numerous for minority groups. The concepts of alienation and conflicts of cultural practice feature strongly in the immigrant mental health literature as sources of stress. This literature also highlights the effect of pre-migration stresses such as persecution and torture on the transition experience of refugees (see for example, Krupinski *et al.*, 1986).

Few studies have been able to compare directly the post-migration transition experience of very different immigrants. This chapter examines the impact of a variety of stressors on the mental health of Australian immigrants. Through controlling for important individual characteristics, I am able to identify the effect of important post-migration stresses in particular, the effect of unemployment. Thus, I am also able to follow the experience of a diverse groups of immigrants whilst being able to control for this diversity in my analysis. Further, as the data set used here is representative of all

Australian immigrants in a particular period the results are able to be generalised to a much larger group than is typically the case.

3.4 The Longitudinal Survey of Immigrants to Australia

The Longitudinal Survey of Immigrants to Australia (LSIA) first collected information from 5192 principal applicant immigrants and their spouses commencing in March 1994 (approximately 6 months after arrival in Australia).⁷ Of the 5192 principal applicants, 1837 had accompanying spouses as part of their migrating unit.⁸ The LSIA was designed to be representative of the principal applicant immigrant population arriving in Australia in the period September 1993 to August 1995 (approximately 75,000 people). Waves 2 and 3 of the survey were subsequently collected commencing in March 1995 (approximately 18 months after arrival) and then again in March 1997 (approximately 42 months after arrival). In wave 3, 3752 of the original 5192 principal applicants were able to be interviewed. See Appendix 3C for a discussion of attrition in this data set.

The focus of this chapter is on all (adult) immigrants and immigrant families (couples). All immigrants include the 5192 principal applicants and 1837 accompanying spouses of principal applicants. After excluding those who did not respond to all 12 mental health questions, there were 6889 immigrants in wave 1. Household income and the number of children data were only collected from principal

⁷ The survey and associated data sets are maintained and released by the Australian Department of Immigration and Multicultural Affairs (DIMA).

⁸ Some immigrants may have had a spouse already in Australia or in the country they were leaving.

applicants, with all other information being collected from principal applicants and their spouses via separate personal interviews.

All variables of interest and their definitions are presented in Table 3.1. The measure of mental health used in this study was the 12-question version of the General Health Questionnaire (GHQ). The 12 questions that comprise the GHQ are listed in Appendix 3A. The GHQ was primarily developed in the UK in the 1960 and 1970s and has been used in numerous studies mainly as an instrument for “detecting psychiatric disorders” see Goldberg (1972), (1988). The GHQ has been widely tested, used in many countries, and is considered to be an instrument largely free of cultural biases (see Bowling, 1991). Argyle (1989) as cited in Oswald and Clark (1994) suggests that the GHQ is a very good measure of psychological disadvantage. The GHQ has also been validated for Australian populations by Tennant (1977) and found to be an “efficient, reliable and valid index of non-psychotic psychological impairment”.

There are primarily two ways to code responses to the GHQ. First, using a Likert scale where the four possible responses to each question are coded 0, 1, 2 or 3. In this scale, 0 corresponds to a good outcome and 3 to a bad outcome. Second, using binary scoring where responses are scored 0, 0, 1, 1. In this case 0 scores correspond to the two better health responses and 1 scores correspond to the two feeling worse (bad) responses.⁹ Using binary scoring the minimum GHQ score a person can obtain is 0 and

⁹ Binary scoring has the advantage that “it eliminates errors due to ‘end users’ and ‘middle users’, since they will score the same irrespective of whether they prefer Columns 1 and 4 or Columns 2 and 3” (Goldberg, 1972).

In the analysis that follows, I only report the results for binary scoring. Results that were generated using a Likert scored GHQ were very similar and are not presented.

the maximum is 12. I primarily use binary scoring in this study. However, I also present in Appendix 3B mean GHQ scores based on the Likert scale.

In many studies, a benchmark GHQ score is adopted. Scores above the benchmark indicate a higher probability of psychiatric disorder or psychological disadvantage. This is known as a 'caseness' score as the benchmark score corresponds to a score typically found in psychiatric cases. The benchmark commonly used for the 12 question GHQ is 2 or more. This benchmark is designed to indicate the presence of minor or major psychological impairment and is adopted in this study.

3.4.1 Descriptive Features of the Data

In the following section I discuss differences in means and GHQ caseness score proportions primarily for comparison with other studies. Regression results presented in section 3.5 confirm in a multivariate context the reported differences in means and proportions.

GHQ mean and caseness scores (the percentage of respondents scoring 2 or more) for each wave are presented by gender, age, labour force status and visa category in Tables 3.2 and 3.3. GHQ mean and caseness scores for other variables of interest are presented in Appendix 3B Tables 3B.1a and 3B.2. GHQ mean and caseness scores were higher for all groups in wave 1 than in wave 2 and wave 3. This indicates that psychological disadvantage is on average worse for immigrants 6 months after arrival in Australia than at 18 months and 42 months. Whilst the pattern of adjustment observed in other studies of euphoria, disenchantment and acceptance is not observed in this study it is possible that the initial period of euphoria observed in other studies has passed before immigrants are surveyed in this study.

Table 3.1
Variable Definitions

Variable	Definition
General Health Questionnaire	Persons answer 12 questions related to their mental health. The questionnaire is presented in Appendix 3A.
Age	Age is defined in two ways as a continuous variable or in 10-year age groups.
Gender	The dummy variable in regressions is (Males=0, Females=1).
Labour force status	Persons are asked which category best describes their current main activity. Answers are coded into three groups: employed, unemployed or out of the labour force. People who report their main activity as wage and salary earner, conducting own business but not employing others, conducting own business and employing others, other employed are coded employed. People who report their main activity as unemployed looking for full time work or unemployed looking for part time work are coded unemployed. People who report their main activity as student, home duties, retired, aged pensioner, other pensioner or other are coded out of the labour force.
Visa categories	There are 5 visa categories: Preferential Family, Concessional Family, Business skills, Independent, and Humanitarian.
Country of birth	A person's country of birth.
Educational Qualifications	This refers to qualifications obtained prior to immigrating to Australia. It does not include qualifications since arriving in Australia.
English Speaking / Non English Speaking	This includes people who speak English and people for whom English is a second language. For those people for whom English is not their first language there are 4 self rated groups, speaks English very well, well, not well or not at all.
Number of children	This was collected only for Principal Applicants and has to be matched to Principal Applicant spouse data.
Marital status	The marital status of all persons at the time of survey.
Self assessed health status	Health status is self assessed as excellent, very good, good, fair, or poor.
Household income	Principal Applicants are asked to match to a list of categories what their before tax total household income from all sources. This information is only collected from Principal Applicants.
Hours worked	Employed persons are disaggregated according to usual hours worked in their main job.
Attitude to current job	Persons are asked how they feel about their current job.
Duration of unemployment	Currently unemployed people are disaggregated according to the duration of their unemployment.

Table 3.2
Mean General Health Questionnaire Scores

	Wave 1			Wave 2			Wave 3		
	No	Mean	SD	No	Mean	SD	No	Mean	SD
All	6889	1.35	2.26	5956	1.03	1.98	5017	1.05	2.06
Male	3274	1.22	2.09	2828	0.97	1.95	2400	0.94	1.92
Female	3615	1.47	2.39	3128	1.09	2.00	2617	1.16	2.17
AGE 15-24	803	1.13	1.98	700	0.94	1.79	567	1.12	1.96
AGE 25-34	3160	1.41	2.26	2721	1.00	1.87	2228	1.03	1.98
AGE 35-44	1781	1.45	2.39	1572	1.11	2.10	1362	1.01	2.08
AGE 45-54	630	1.32	2.45	525	1.18	2.24	471	1.20	2.36
AGE 55-64	306	1.11	2.16	259	0.90	2.02	235	0.95	1.99
AGE 65+	209	0.74	1.32	179	0.97	2.26	154	1.05	2.39
Employed	2235	1.05	1.88	2743	0.84	1.76	2787	0.77	1.64
Unemployed	1447	1.78	2.57	771	1.45	2.29	453	1.77	2.78
Out of L.F.	3207	1.36	2.32	2442	1.12	2.08	1777	1.31	2.34
Unemployed < 2mths	249	1.49	2.46	66	1.53	2.36	47	2.02	2.86
Unemployed 2-6 mths	1101	1.84	2.59	123	1.50	2.08	60	2.15	2.96
Unemployed > 6 mths	50	2.06	2.64	563	1.42	2.34	324	1.65	2.76
Unemployed unknown	47	1.57	2.59	19	1.53	2.04	22	1.95	2.38
Hours < 15	123	1.37	2.27	89	0.99	2.02	94	0.79	1.89
Hours 15-24	173	1.55	2.52	167	0.80	1.61	197	0.85	1.77
Hours 25-34	162	1.09	1.87	201	1.00	1.97	185	0.86	1.81
Hours 35+	1758	0.98	1.77	2152	0.80	1.71	2162	0.73	1.57
Hours unknown	19	0.79	1.40	134	1.08	2.07	149	1.07	2.09
Visa Pref Family	2269	1.30	2.20	1924	1.02	1.98	1614	1.15	2.12
Visa Con Family	1251	1.38	2.28	1095	0.98	1.86	986	0.85	1.85
Visa Bus Skills	897	0.97	1.90	764	0.93	1.88	659	0.76	1.70
Visa Independent	1277	1.41	2.22	1112	1.02	1.95	879	0.92	1.87
Visa Humanitarian	1195	1.62	2.57	1061	1.21	2.18	879	1.43	2.50

Table 3.3
Caseness Proportions General Health Questionnaire Scores

	Wave 1		Wave 2		Wave 3	
	Proportion	SEs	Proportion	SEs	Proportion	SEs
All	0.273	0.005	0.215	0.005	0.214	0.006
Male	0.253	0.008	0.193	0.007	0.190	0.008
Female	0.292	0.008	0.235	0.008	0.237	0.008
AGE 15-24	0.249	0.015	0.211	0.015	0.235	0.018
AGE 25-34	0.287	0.008	0.211	0.008	0.218	0.009
AGE 35-44	0.290	0.011	0.228	0.011	0.202	0.011
AGE 45-54	0.251	0.017	0.244	0.019	0.223	0.019
AGE 55-64	0.222	0.024	0.170	0.023	0.213	0.027
AGE 65+	0.158	0.025	0.173	0.028	0.175	0.031
Employed	0.224	0.009	0.177	0.007	0.165	0.007
Unemployed	0.356	0.013	0.310	0.017	0.333	0.022
Out of L.F.	0.270	0.008	0.229	0.008	0.261	0.010
Unemployed < 2 mths	0.277	0.028	0.364	0.059	0.383	0.071
Unemployed 2-6 mths	0.374	0.015	0.341	0.043	0.417	0.064
Unemployed > 6 mths	0.400	0.069	0.295	0.019	0.306	0.026
Unemployed unknown	0.298	0.067	0.368	0.111	0.409	0.105
Employed Hours < 15	0.260	0.040	0.202	0.043	0.160	0.038
Employed Hours 15-24	0.289	0.034	0.186	0.030	0.193	0.028
Employed Hours 25-34	0.247	0.034	0.199	0.028	0.195	0.029
Employed Hours 35+	0.213	0.010	0.170	0.008	0.158	0.008
Employed Hours	0.211	0.094	0.231	0.036	0.208	0.033
Visa Pref Family	0.265	0.009	0.207	0.009	0.243	0.011
Visa Con Family	0.273	0.013	0.212	0.012	0.169	0.012
Visa Bus Skills	0.211	0.014	0.202	0.015	0.155	0.014
Visa Independent	0.304	0.013	0.214	0.012	0.193	0.013
Visa Humanitarian	0.302	0.013	0.244	0.013	0.279	0.015

Female GHQ mean and caseness scores were higher than male scores in all waves. This result is commonly observed (see Vega and Rumbaut, 1991 and Goldberg, 1988). Immigrants aged 35 to 54 years tended to have higher GHQ scores in waves 1 and 2.¹⁰ However, this age effect was not present in wave 3.

¹⁰ t statistics were calculated for GHQ caseness scores for gender and age: both set of differences where significant at the 5 percent level.

Unemployed persons displayed higher levels of psychological disadvantage compared to employed persons for all waves and the relative disadvantage of the unemployed compared to the employed grew over time. In waves 2 and 3 immigrants who had been unemployed for less than 6 months tended to have higher caseness scores indicating poorer mental health relative to immigrant who have been unemployed for greater than 6 months.¹¹ This result is consistent with Warr *et al.*'s (1987) observation that unemployed persons adapt to their situation though ultimately their mental health is still worse than employed persons. There were some minor differences in caseness scores for employed persons disaggregated by the number of hours worked with higher scores (poorer mental health) for those working 15 to 34 hours. This may be indicative of some underemployment in these groups. For a discussion of immigrant underemployment issues see Wooden *et al.* (1994). Persons immigrating on humanitarian grounds had higher GHQ scores than all other immigrant groups. The difference between the humanitarian visa category and other visa categories was greatest at 42 months, possibly indicating that this group experiences greater transition difficulties.¹²

In waves 1 and 2, immigrants with higher education levels tended to have higher GHQ scores compared to less educated immigrants (see Appendix 3B Tables 3B.1 and 3B.2). However, in wave 3 there was little or no difference in GHQ scores between different education groups. Vega and Rumbaut (1991) note that other authors (Portes *et al.*, 1990 and Ying *et al.*, 1988) found that more highly educated immigrants adjust more rapidly to their new environment than less well educated immigrants. The results

¹¹ However, this difference was not significant for GHQ caseness scores at the 5 percent level.

¹² For a discussion of attrition issues and possible impacts on these descriptive statistics see Appendix 3C.

of this analysis suggest that more highly educated immigrants also have more pronounced adjustment phases compared to less educated immigrants. Immigrants who reported their marital status as separated had higher caseness scores than all other marital status groups. Differences in family size (the number of children) did not appear strongly related to differences in GHQ scores. As expected, immigrants who report poor general health also report poor mental health. Immigrants who spoke English poorly had higher GHQ scores in wave 3 than other immigrants, perhaps indicative of a relatively more difficult adjustment process for this group of immigrants.

Immigrants in households with higher household income, particularly those in households with more than 50000 AUD per annum, had lower GHQ scores than those in households with less than 35000 AUD per annum. Low income household GHQ scores remained the same or increased through time whilst higher income household caseness scores fell. Thus by wave 3 the difference in GHQ scores between high and low income households had increased.

Immigrants were also asked about how they felt about their job. Immigrants who did not like their job had higher GHQ caseness scores than those who did like their job. Perhaps more interestingly immigrants who did not like their job also had higher GHQ caseness scores (reported poorer mental health) than those who were unemployed. This is an indication that a 'bad' job can be worse than no job at all.

The GHQ mean and caseness scores from this data set were broadly consistent with those found in other studies. For example, Clark and Oswald (1994) found that 49 percent of unemployed males and 58 percent of females had GHQ caseness scores of 2 or more whilst in this study 33 percent of males and 39 percent of females had caseness scores of this order. An Australian study of teenagers by Rickwood *et al.* (1996) also

reports broadly similar GHQ caseness scores apart from scores for young females, which were much higher in Rickwood *et al.* (1996).¹³

3.5 Method and Results

In the following regression analysis I report the results of probit regressions using the GHQ caseness score. The GHQ caseness score was used for two reasons. First, this is a common and well-accepted way to model mental health using the GHQ questionnaire. Second, the results of such an analysis are more easily interpreted than results for say a 12 category ordered probit analysis. For example, a marginal effect calculated from a GHQ caseness score represents an increase in the probability of minor or major psychological impairment being present. It is more difficult to interpret the effects of independent variables when modelling the GHQ score as a 12 response ordered probit or alternatively scoring the GHQ using a Likert scale and modelling it as a continuous variable.

3.5.1 Probit Regressions on Immigrants

Probit regressions were run separately on each wave (cross-section) where the dependent variable was the GHQ caseness score.¹⁴ Independent variables were selected after considering possible stressors, individual characteristics, and the relevant literature. Independent variables included disaggregated labour force status, age and

¹³ In Rickwood *et al.* (1996) 40.8 percent of females aged 16 to 24 had GHQ scores of 2 or more whilst in this study 25.7 percent of females aged 15 to 24 scored 2 or more.

¹⁴ Ordered probit regressions were also run on each wave where the GHQ variable was ordered 0 to 12. The results from these regressions are discussed where they varied substantially from the probit regressions on GHQ caseness scores though they rarely differed.

age squared, sex, family size, household income, marital status, education, visa category and country of birth. Table 3.4 displays the marginal effects (calculated at the mean of continuous regressors and for zero/one changes in dummy variables) on aggregate and disaggregated labour force status variables from probit regressions on wave 1.¹⁵ The marginal effects can be interpreted as an increase in the probability of the GHQ caseness score equalling one (which represents minor or major psychological impairment) given an increase in the independent variable. For example, the marginal effect of unemployment in Table 3.4 is 0.079 which means that the unemployed compared to those out of the labour force (the omitted category) are 7.9 percentage points more likely to have a GHQ caseness score of 1. When discussing the GHQ caseness scores proportions in Section 3.4.1 I noted that persons out of the labour force in wave 1 had a GHQ caseness score of 0.27 and the unemployed of 0.36. Thus, the multivariate analysis in this section produces a very similar effect to that found in the bivariate analysis.

While the marginal effect of unemployment was positive and significant, employed immigrants were more likely to report higher levels of mental health. In regressions where unemployment and employment variables were disaggregated according to the duration of unemployment and hours worked respectively, the marginal effect of full-time employment was negative and significant. The effect was also relatively large compared to other labour force effects.

¹⁵ The regression results from other waves were very similar. Similar coefficients were also obtained when regressions were run separately for males and females. A Likelihood ratio test of the equality of male and female coefficient vectors did not reject the null hypothesis (LR statistic 47.88, critical value at

The marginal effects of an unemployment duration of 2 to 6 months and greater than 6 months were positive and significant indicating that these groups tended to report poorer mental health after controlling for other stressors and individual characteristics relative to those out of the labour force.

Table 3.4
Mental Health Regressions: Dependent variable General Health Questionnaire Caseness Score (Probit) – Wave 1 (1=poor mental health)

Variables	Marginal Effect	t statistic	Marginal Effect	t statistic
Employed	-0.060	3.93		
Unemployed	0.079	5.10		
Hours < 15			-0.029	0.74
Hours 15-24			0.003	0.09
Hours 25-34			-0.417	1.16
Hours 35+			-0.079	4.72
Hours unknown			0.024	0.23
Unemployed < 2 mths			-0.002	0.07
Unemployed 2-6 mths			0.096	5.63
Unemployed > 6 mths			0.123	1.85
Unemployed unknown			0.027	0.42
No of Obs	6889		6889	
Log Likelihood	-3906		-3897	
Omitted categories: Out of the labour force, Married, No Kids, Higher Degree, English Speaking or speaks English very well, Visa Humanitarian, Oceania, Income – none. Full regression results are presented in Appendix 3B, Table 3B.3.				

Full regression results for wave 1 are presented in Appendix 3B, see Table 3B.3. The marginal effects of most explanatory variables were signed similarly to those in previous studies. In particular, age was nonlinearly related to mental health, the martial status category separated had a negative and significant effect on mental health, and the

a 5 percent level 57.84). Particular male and female differences are examined in the analysis of couples in Section 3.5.4.

visa category humanitarian also had a negative and significant effect. Other studies report also that humanitarian immigrants have worse mental health compared to otherwise similar immigrants.

3.5.2 Panel Regressions on Immigrants

A second series of regressions was estimated to take advantage of the longitudinal aspect of the data. The longitudinal data set means that it is possible to control for individual differences in responses to unemployment and immigration. In examining how individuals respond to changes in their environment, there is likely to be common or average response across all individuals. However, due to individual differences in personality or learnt coping mechanisms, each individual's response will differ. When data is not available on these individual differences panel models are able to control for these effects unlike models estimated on cross-section data.

The marginal effects for disaggregated labour force status variables are presented in Table 3.5 for a pooled probit model, a balanced panel random effects probit model and an unbalanced panel random effects probit model. Full regression results, coefficients and marginal effects for the panel models are presented in Appendix 3B, see Tables 3B.4a and 3B.4b.¹⁶

A Hausman (1978) test following Nijman and Verbeek (1992) between the balanced and unbalanced panel random effects models was used to test for the effect of attrition. The test indicates that attrition was not affecting these regressions. A likelihood ratio test of whether panel level variance is an important component of

¹⁶ Marginal effects for panel regressions were calculated at the mean of explanatory variables.

overall variance is significant. Thus, the panel model is preferred to a pooled probit model.¹⁷

Table 3.5

Mental Health Regressions: Dependent variable General Health Questionnaire Caseness Score

Variables	Pooled Probit Model		Random Effects Probit Panel (Balanced)		Random Effects Probit Panel (Unbalanced)	
	Marginal Effect	t statistic	Marginal Effect	t statistic	Marginal Effect	t statistic
Hours < 15	-0.047	-1.85	-0.041	-1.43	-0.046	-1.76
Hours 15-24	-0.030	-1.53	-0.037	-1.68	-0.033	-1.66
Hours 25-34	-0.033	-1.68	-0.035	-1.58	-0.037	-1.83
Hours 35+	-0.069	-7.08	-0.069	-5.96	-0.069	-6.64
Hours unknown	-0.017	-0.67	-0.055	-1.91	-0.028	-1.07
Unemployed < 2 mths	0.038	1.73	0.033	1.32	0.035	1.59
Unemployed 2-6 mths	0.085	6.64	0.080	5.27	0.085	6.50
Unemployed > 6 mths	0.057	3.88	0.059	3.63	0.064	4.26
Unemployed unknown	0.075	1.77	0.099	2.13	0.084	1.98
				SE		SE
Sigma_u			0.724	0.027	0.733	0.025
Rho			0.343	0.017	0.349	0.015
Hausman test					38.30	(0.90)
No of Obs	17860		14268		17860	
Log Likelihood	-9464		-7136		-9214	

Omitted categories: Out of the labour force, Married, No Kids, Higher Degree, English Speaking or speaks English very well, Visa Humanitarian, Oceania, Income – none, Wave 1. Full regression results are presented in Appendix 3B, Table 3B.4a.

¹⁷ This analysis was also undertaken treating the GHQ variable as continuous and estimating a pooled model, and fixed and random effects panel models. The results of this analysis did not differ in any substantial way from the results presented in this chapter. It was also the case that for continuous models, there was no substantial difference between the random and fixed effects panel models using a Hausman test to test the equality of coefficients. This lends some support to the use of the random effects panel probit model.

In general, the marginal effects obtained from the pooled and panel regressions were similar to those obtained from the probit regression on wave 1. For the panel regressions, the marginal effect of immigrants employed full time was significant and negative indicating that this group relative to those out of the labour force has lower GHQ caseness scores (or higher levels of mental health). All marginal effects on unemployment duration variables were positive and significant except for the coefficient on unemployed for less than 2 months, which was insignificant.

The panel regression results are largely consistent with the picture provided by the descriptive results. In terms of labour force status, immigrants who are unemployed, particularly those who have been unemployed for more than 2 months, appear least mentally healthy. Adjustment to unemployment is also consistent with descriptive results with immigrants who are unemployed for greater than 6 months having poorer mental health than employed persons but better than those who have been unemployed for 2 to 6 months. Similar to the descriptive results the regression results indicate that other characteristics associated with poor mental health include: marital status - separated, the humanitarian visa category, low household income, and poor English language skills. It is also clear that the general immigrant population goes through some adjustment process after arrival in Australia with psychological disadvantage higher at 6 months after immigration than after 18 months and after 42 months.

3.5.3 Testing for Causality

Studies that use cross-section data are unable to determine whether changes in mental health are causing changes in labour force status rather than changes in labour force status (unemployment) causing changes in mental health. Bank *et al.* (1982) and

Jackson *et al.* (1983) (as cited in Warr *et al.*, 1988) have found evidence that causality runs from unemployment to mental health. Banks *et al.* (1982) examined causality in the context of school leavers where GHQ scores were taken before leaving school and at a later time when persons were in the labour force. They found that early GHQ scores (during schooling) did not predict labour force status.

The issue of causality between mental health and unemployment is complicated by a number of other factors. Studies have found that job insecurity or impending plant closures also have large mental health effects, see for example Kasl *et al.* (1975). These results suggest that it would be easy to ascribe to poor mental health a causal relationship with labour force status when in fact job insecurity is the underlying mechanism of change.

I examined reverse causality (causality running from mental health to unemployment) by testing whether underlying mental health was predicting labour force status. Multinomial logit models were estimated with wave 2 labour force status as the dependent variables and GHQ scores in wave 1 as an independent variable.¹⁸ Other independent variables were age, education, gender, English language ability and

¹⁸ The multinomial logit model relies on the assumption of the independence of irrelevant alternatives (IIA) with respect to the dependent variable. Clearly, an ordered logit or probit model is not applicable when modelling the labour force status of immigrants as there is no natural ordering in the labour force status variable. However, it is also not clear that the IIA assumption is satisfied when estimating a multinomial logit model using labour force status as the dependent variable. To ensure that the results of the multinomial logit model were robust to the possible failure of the IIA assumption, I estimated a second set of regressions. In these regressions, I conditioned on immigrant labour force status in wave 1 and estimated logit models for labour force participation. Then, conditional on labour force participation in wave 2, I estimated models on employment versus unemployment. In all these regressions, I included the GHQ variable from wave 1; the GHQ variable was insignificant in all regressions, supporting the conclusions drawn from the multinomial logit models.

visa category. Three multinomial logit models were estimated with each model conditioned on immigrant labour force status in wave 1. Models were conditioned on labour force status in wave 1 so that the effect of mental health on a change in labour force status could be estimated.¹⁹ Most coefficients on wave 1 GHQ scores were insignificant, indicating that the mental health status of immigrants did not predict labour force status and in particular, the transition from employment to unemployment, see Table 3.6.²⁰ Full regression results are presented in Appendix 3B, see Tables 3B.5a, 3B.5b and 3B.5c.

The results of this analysis are consistent with Bank *et al.* (1982) and Jackson *et al.* (1983) (as cited in Warr *et al.*, 1987) who also found that mental health in an earlier period does not predict unemployment in a later period. In this study, the time between when mental health is measured and a labour market outcome observed is one year. Thus, the analysis presented in this chapter is only likely to indicate whether ‘fairly’ long standing mental health issues predict employment or unemployment, conditional on labour market status in the earlier period. I am unable to examine short-term effects, for example, whether a decline in mental health has a less than one year impact on labour market outcomes.

¹⁹ The period between waves 1 and 2 was 1 year.

²⁰ In the regression results presented, GHQ scores in wave 1 were treated as a set of dummy variables. Results from regressions where the GHQ score is treated as a continuous variable were similar with the coefficient on the GHQ score always being insignificant. Regressions were also run where wave 2 GHQ scores were used to predict wave 3 labour force status, the results from these regressions were consistent with regressions results obtained using wave 1 and wave 2 data.

Table 3.6
Labour Force Status Regressions: Dependent variable Labour Force Status in Wave 2 - Base Case Employment Wave 2 (Multinomial Logit Regressions)

Variables	Outcome – Unemployment		Outcome – Out of LF	
	Coefficients	t statistic	Coefficients	t statistic
Wave 1 Condition - Employed				
GHQ = 0	0.01	0.02	-0.55	-2.40
GHQ = 1	0.31	0.70	-0.35	-1.24
GHQ = 2	-0.58	-0.84	-0.65	-1.80
Wave 1 Condition - Unemployed				
GHQ = 0	0.26	1.51	-0.05	-0.29
GHQ = 1	0.33	1.58	-0.01	-0.05
GHQ = 2	0.26	1.01	0.03	0.12
Wave 1 Condition – Out of L.F.				
GHQ = 0	0.25	1.32	0.12	0.96
GHQ = 1	0.30	1.30	0.10	0.66
GHQ = 2	0.62	2.23	0.26	1.38
Omitted categories: GHQ = 3 or more, Higher Degree, English Speaking or speaks English very well, Visa Humanitarian. Full regression results are presented in Appendix 3B, Tables 3B.5a, 3B.5b, and 3B.5c.				

3.5.4 Immigrant Families and Mental Health Regressions

Results discussed thus far have focused on immigrants as individuals, examining the relationship between labour force status and their mental health. There is an important emerging literature that focuses on immigrant behaviour from a family perspective (for example, Baker *et al.*, 1997). I examine the impact of labour force status on the mental health of couples. For example, if a male partner is unemployed is his psychological distress somewhat offset by his female partner working?²¹ As far as

²¹ All couples in this analysis are male female couples.

the author is aware this is the first time this particular aspect of the effect of unemployment has been examined in a longitudinal context.

GHQ caseness scores for immigrant couples for nine family labour force status groups are presented in Tables 3.7a and 3.7b. Combinations of couples' labour force status define family labour force status groups. For example, one group is both partners employed; another group is both partners unemployed, and so on. There are substantial differences in mental health for different couple labour force groups and over time. The most consistent result to emerge from Tables 3.7a and 3.7b is that male and female mental health is usually higher when they are in employment. However, there does not appear to be a clear story emerging for differences in partners' labour force status. In wave 1, males who are unemployed with partners who are employed have significantly higher GHQ caseness scores (report poorer mental health) than males who are unemployed and their partner is also unemployed. Whilst in waves 2 and 3, there is no significant difference between these two groups.²²

In Table 3.7c, the GHQ caseness scores for couples and non-couples by labour force status are presented. It is not clear from this Table whether unemployed males and females in couples are better off than those who are not in couples. Whilst in wave 1 GHQ caseness scores were higher for the unemployed not in couples compared to those in couples there is little or no difference between these groups in waves 2 and 3.²³

²² They were not significant using t tests at a 5 percent level.

²³ Only female GHQ caseness scores were significantly different at a 5 percent level.

Table 3.7a
Caseness Proportions GHQ Scores - Males in Couples

Family Labour Force Status		Wave 1		Wave 2		Wave 3	
Male	Female	Proportion	SEs	Proportion	SEs	Proportion	SEs
Employed	Employed	0.183	0.023	0.120	0.013	0.073	0.008
Employed	Unemployed	0.173	0.042	0.150	0.046	0.027	0.027
Employed	Out of LF	0.203	0.019	0.122	0.015	0.133	0.016
Unemployed	Employed	0.514	0.084	0.447	0.081	0.351	0.078
Unemployed	Unemployed	0.292	0.036	0.377	0.067	0.455	0.106
Unemployed	Out of LF	0.274	0.026	0.269	0.030	0.268	0.045
Out of LF	Employed	0.304	0.068	0.220	0.065	0.347	0.068
Out of LF	Unemployed	0.182	0.082	0.348	0.099	0.143	0.094
Out of LF	Out of LF	0.253	0.021	0.184	0.024	0.249	0.032

Table 3.7b
Caseness Proportions GHQ Scores – Females in Couples

Family Labour Force Status		Wave 1		Wave 2		Wave 3	
Male	Female	Proportion	SEs	Proportion	SEs	Proportion	SEs
Employed	Employed	0.252	0.025	0.117	0.013	0.089	0.009
Unemployed	Employed	0.257	0.074	0.132	0.055	0.243	0.071
Out of LF	Employed	0.152	0.053	0.171	0.059	0.082	0.039
Employed	Unemployed	0.395	0.054	0.333	0.061	0.297	0.075
Unemployed	Unemployed	0.317	0.037	0.302	0.063	0.364	0.103
Out of LF	Unemployed	0.227	0.089	0.174	0.079	0.214	0.110
Employed	Out of LF	0.296	0.021	0.213	0.018	0.202	0.019
Unemployed	Out of LF	0.274	0.026	0.255	0.030	0.258	0.044
Out of LF	Out of LF	0.275	0.021	0.211	0.025	0.249	0.032

Table 3.7c
Caseness Proportions GHQ Scores – Males and Females by Couples

	Labour Force Status	Wave 1		Wave 2		Wave 3	
		Proportion	SEs	Proportion	SEs	Proportion	SEs
Females in Couples	Employed	0.220	0.029	0.166	0.021	0.169	0.019
	Unemployed	0.304	0.033	0.290	0.045	0.308	0.064
	Out of LF	0.276	0.014	0.210	0.014	0.208	0.017
Females not in Couples	Employed	0.311	0.020	0.242	0.017	0.202	0.016
	Unemployed	0.429	0.026	0.328	0.035	0.377	0.043
	Out of LF	0.268	0.012	0.250	0.013	0.294	0.016
Males in Couples	Employed	0.212	0.038	0.152	0.029	0.115	0.025
	Unemployed	0.287	0.044	0.339	0.062	0.405	0.081
	Out of LF	0.172	0.035	0.228	0.047	0.333	0.064
Males not in Couples	Employed	0.191	0.011	0.155	0.009	0.155	0.009
	Unemployed	0.345	0.017	0.303	0.022	0.303	0.030
	Out of LF	0.280	0.016	0.213	0.018	0.266	0.024

Correlation coefficients were calculated for partners' GHQ scores. A significant correlation coefficient of 0.34 was estimated indicating that partners' mental health scores are positively associated. Descriptive results suggest that whilst there is a relationship between the mental health of partners: the labour force status of partners is not strongly associated with immigrant mental health. That is despite unemployment having a negative effect upon an immigrant's health and there being a positive correlation between the mental health of couples, the labour force status of partners doesn't appear to affect immigrant health.

Panel probit regression models were estimated separately on males and females (in couples) to further examine the effect of partner labour force status on mental health. Independent variables included the set of independent variables used in earlier

regressions as well as the labour force status of partners and the labour force status of partners interacted with labour force status of immigrants. Panel regression results for coefficients on labour force status variables are presented in Table 3.8. Full regression results and marginal effects are presented in Appendix 3B Tables 3B.6a and 3B.6b respectively. Following Nijman and Verbeek (1992), Hausman tests indicate that attrition was not affecting these regressions.

Table 3.8
Family Mental Health Regressions: Dependent variable General Health Questionnaire Caseness Score

Variables	Random Effects Probit Panel Model Male Partners				Random Effects Probit Panel Model Female Partners			
	Coef	t stat	Coef	t stat	Coef	t stat	Coef	t stat
Male partner employed	-0.236	2.38	-0.338	3.95	-0.047	0.51		
Male partner unemployed	0.102	1.08	0.172	2.17	0.008	0.09		
Female partner employed	0.325	2.01			-0.238	1.19	-0.199	2.85
Female partner unemployed	-0.092	0.41			-0.161	0.69	0.172	2.07
Both partners employed	-0.326	1.82			0.031	0.15		
Both partners unemployed	0.242	0.94			0.265	1.01		
Male employed Female unemployed	-0.121	0.44			0.506	1.92		
Male unemployed Female employed	0.234	1.04			0.286	1.05		
		SE				SE		
Sigma_u	0.741	0.05			0.701	0.04		
Rho	0.354	0.03			0.329	0.03		
Hausman test for attrition	46.2	(0.40)			50.96	(0.25)		
Likelihood Ratio test			16.99	(0.01)			6.96	(0.32)
No of Obs	4777				4667			
Omitted categories: Out of the labour force, Married, No Kids, Higher Degree, English Speaking or speaks English very well, Visa Humanitarian, Oceania, Income – none. Full regression results are presented in Appendix 3B, Tables 3B.6a and 3B.6b.								

In panel probit regressions for males, employment remains an important and significant predictor of good mental health. Interestingly, the coefficient on female partners' employment is significant and positive, indicating a negative effect on male mental health. The coefficient on the interaction of male unemployment and the female

partner's employment, whilst not significant in panel probit regressions, was significant in panel regressions where the GHQ variable was treated as continuous.²⁴ Using the panel probit model, a Likelihood ratio test calculated after excluding female partners' labour status and interaction terms suggests that these variables are important in explaining male GHQ caseness scores. However, their lack of individual significance in panel probit models means that the effects of partner labour force states are difficult to identify.

In the model presented in Table 3.8, columns 2 and 3 where the labour force status of males and their partners is fully interacted (the model is saturated), it is difficult to directly compare outcomes without considering some joint tests. I wanted to examine more closely the possible negative effect of female employment on unemployed males identified earlier in the descriptives. For unemployed males, the effect of female partner unemployment, employment and out of the labour force status was calculated by summing relevant coefficients. The joint coefficients and associated standard errors of these three effects were 0.25 (0.31), 0.66 (0.32), and 0.10 (0.09) respectively. Tests of whether the effects were significantly different from each other (there were three possible comparisons) indicated that none were significantly different. Thus, despite female employment having a larger (joint) coefficient it was not significantly different from the coefficients on female out of the labour force status and female unemployment.

²⁴ Similarly, when the GHQ score was treated as continuous, the coefficients on the variables both partners are unemployed and both are employed are significantly negative and positive respectively.

In panel probit regressions for females, coefficients on their male partner's labour force status are insignificant, as are coefficients on their own labour force status. Coefficients on interaction variables were also mostly insignificant. Likelihood ratio tests on the exclusion of their male partner's labour force status and interaction variables indicate that these variables were not statistically important in explaining variations in female GHQ caseness scores. When these variables are excluded the effect of female labour force status on female mental health is also better identified with a positive coefficient on employment compared to out of the labour force.²⁵

It appears from these regressions that an immigrant's employment positively impacts on their mental health compared to unemployment and out of the labour force. When a female is employed and her male partner is unemployed this may be having a negative effect on the mental health of the unemployed male. When both partners are employed this may be positively impacting on the mental health of male immigrants. Female mental health appears to be unaffected by the male partner's labour force status importantly, after controlling for income.

3.6 Conclusions

The results of this study are largely consistent with the unemployment and mental health, and the immigrant and mental health literatures. Unemployment has a significant negative effect on the mental health of immigrants. Other variables associated with immigrant mental health include age, marital status, education level,

²⁵ In regressions where the GHQ variable is treated as continuous, the results for female mental health are very similar to those described for males. For example, when females are unemployed they are negatively affected by their partners' employment.

household income, and visa category. Australian immigrants also display a pattern of adjustment to their new country similar to immigrants to other countries. In this study, immigrant psychological disadvantage was higher 6 months after migration than it was at 18 months and 42 months after migration.

Unemployed immigrants also seem to display a pattern of adjustment to unemployment similar to that found in other studies of unemployment and mental health. That is, mental health was poorest for those who had been unemployed for 2 to 6 months and slightly better for those who are unemployed for more than 6 months. However, immigrants unemployed for longer than 6 months still reported poorer mental health than employed immigrants.

I examined the issue of causality between immigrant mental health and labour force status, found that causality ran primarily from labour force status to mental health, and not vice versa.

An interesting feature of this study was the examination of the effect of labour force status on couples. Whilst the mental health of partners was strongly positively associated, the effect of labour force status on partners' mental health was less clear. A tentative conclusion drawn from bivariate comparisons of partners' labour force status is that it appears that when male partners are unemployed and their female partner is employed this has a negative effect on the mental health of men, possibly an envy effect. However, in panel regressions the effect of female employment on unemployed males was not significantly different from the effect of other female partner labour force states. In general, female partner labour force status was affecting males though the specific effects were hard to identify. Females on the other hand appear to be unaffected by their partners labour force status. These results would seem to run

counter to a model of household utility whereby each partner's utility function is essentially the same. It suggests that each partner's utility is derived independently though decisions are made in a household setting.²⁶ A more robust conclusion that can be drawn from the analyses of individuals and couples is that immigrant employment is a strong predictor of good mental health compared to both unemployment and being out of the labour force.

That unemployment has adverse mental health consequences for immigrants largely regardless of their partners' labour market outcomes is important for current Australian immigration policy. Policies that restrict immigrant access to labour market programs, assuming that these labour market programs reduce the probability of unemployment, may have counter-productive health consequences. This suggests that current Australian immigration policy, that restricts some immigrants' access to the social security system in the first two years after migration, may be mis-directed. The health consequences of this policy may not only lead to sub-optimal outcomes for immigrants it may well have health care cost implications.

²⁶ See Browning *et al.* (1998) for a discussion of intra-household allocation issues.

Appendix 3A: 12 Question General Health Questionnaire

Have you recently been able to concentrate on whatever you're doing? Better Same Less Much less	Have you recently been able to enjoy your normal day-to-day activities? More so Same Less Much less
Have you recently lost much sleep over worry? Not at all No more than usual Rather more Much more	Have you recently been able to face up to your problems? More so Same Less Much less
Have you recently felt that you are playing a useful part in things? More so Same Less Much less	Have you recently been feeling unhappy and depressed? Not at all No more than usual Rather more Much more
Have you recently felt capable of making decisions about things? More so Same Less Much less	Have you recently been losing confidence in yourself? Not at all No more than usual Rather more Much more
Have you recently felt constantly under strain? Not at all No more than usual Rather more Much more	Have you recently been thinking of yourself as a worthless person? Not at all No more than usual Rather more Much more
Have you recently felt that you couldn't overcome your difficulties? Not at all No more than usual Rather more Much more	Have you recently been feeling reasonably happy all things considered? More so Same Less Much less

Appendix 3B: Auxiliary Immigrant Mental Health Tables

Table 3B.1a

Mean General Health Questionnaire Scores – Binary Scoring

	Wave 1			Wave 2			Wave 3		
	No	Mean	SD	No	Mean	SD	No	Mean	SD
Higher Degree	659	1.44	2.32	583	1.06	2.00	473	0.90	1.87
Post Graduate Diploma	409	1.69	2.47	347	1.24	2.30	289	1.02	1.83
Bachelor Degree	1523	1.57	2.35	1304	1.15	2.08	1097	1.03	1.98
Technical / Diploma	1448	1.34	2.28	1272	1.02	1.93	1078	1.09	2.12
Trade	424	1.40	2.59	376	0.95	1.98	326	1.07	2.23
12 + Years of Schooling	1153	1.17	2.03	986	0.93	1.87	841	0.98	1.90
10-11 Years Schooling	508	1.00	2.00	422	0.84	1.67	363	1.05	2.11
7-9 Years of Schooling	394	1.10	2.11	347	1.10	2.12	281	1.20	2.39
6 - Years of Schooling	323	1.10	2.00	275	0.94	1.81	237	1.19	2.26
Other	48	1.42	2.27	44	0.98	2.10	30	2.30	3.43
Married	5295	1.33	2.23	4680	0.99	1.90	4043	0.97	1.95
Separated	79	2.30	3.40	121	2.08	3.20	156	1.95	2.75
Divorced	129	1.50	2.76	115	1.30	2.22	149	1.74	2.81
Widowed	165	1.38	2.39	145	1.30	2.46	132	1.55	2.85
Never married	1220	1.35	2.21	891	1.05	2.00	536	1.06	2.01
No KIDS	5054	1.34	2.26	4045	1.02	2.00	3124	1.05	2.10
KIDS 1	876	1.50	2.38	949	1.07	1.97	871	1.08	2.02
KIDS 2	668	1.33	2.22	681	1.09	1.96	746	1.03	1.94
KIDS 3	200	1.06	1.83	198	0.88	1.66	193	0.84	1.61
KIDS 4+	91	1.11	1.91	83	1.17	1.97	83	1.34	2.80
Health Very good	3578	0.98	1.82	2603	0.69	1.52	1990	0.63	1.48
Health Good	2717	1.51	2.35	2641	1.04	1.94	2284	0.96	1.90
Health Fair	480	2.47	3.15	563	1.90	2.65	575	1.83	2.54
Health Poor	96	4.21	3.66	126	3.35	3.38	143	4.36	3.62
Health Very Poor	14	4.50	4.33	22	4.73	4.23	24	5.33	4.08
English Speaking	1752	1.31	2.24	1589	1.01	1.95	1357	0.87	1.82
Speaks English v well	796	1.42	2.26	735	0.99	1.97	753	0.87	1.75
Speaks English well	1552	1.34	2.21	1788	1.04	2.01	1659	1.05	2.01
Speaks English not well	1998	1.30	2.21	1563	1.03	1.91	1076	1.32	2.42
Speaks English not at all	791	1.48	2.51	281	1.25	2.32	172	1.58	2.79
Income None	138	1.42	2.48	29	1.34	1.86	16	2.75	3.24
Income 1 to 8000	243	1.43	2.42	140	1.31	2.52	92	1.29	2.29
Income 8001 to 16000	682	1.51	2.53	425	1.38	2.37	316	1.73	2.80
Income 16001 to 25000	1225	1.59	2.48	1014	1.12	2.00	628	1.43	2.52
Income 25001 to 35000	799	1.35	2.27	852	1.02	2.00	719	1.14	2.09
Income 35001 to 50000	826	1.23	2.09	953	0.98	1.91	838	0.81	1.68
Income >50000	1318	1.19	2.04	1513	0.84	1.69	1780	0.84	1.77
Income NA	1658	1.27	2.15	1030	1.11	2.12	628	1.05	2.08
Job Love it	316	0.51	1.18	366	0.46	1.26	472	0.54	1.19
Job Like it	932	0.83	1.59	1152	0.67	1.42	1235	0.65	1.39
Job okay	837	1.18	1.91	1150	1.00	1.96	1116	0.92	1.88
Job Don't care	118	1.91	2.58	208	1.18	2.22	131	1.47	2.59
Job Dislike	74	3.09	3.20	62	1.68	2.41	35	3.03	3.48
Job Dislike a lot	14	2.29	3.36	16	1.69	2.47	13	2.92	3.30
Job Hate it	17	3.82	3.30	31	4.00	3.49	17	2.94	3.29
Oceania	140	0.90	1.91	120	0.58	1.56	112	0.61	1.25
Europe & USSR	2262	1.49	2.43	1981	1.10	2.10	1654	1.04	2.03
Middle East North Africa	791	1.27	2.05	689	1.12	2.08	574	1.64	2.63
Southeast Asia	1110	1.08	1.94	931	0.77	1.63	824	0.78	1.62
Northeast Asia	898	1.40	2.30	764	1.03	1.97	585	0.88	1.81
Southern Asia	630	1.28	2.13	558	1.00	1.87	497	0.98	2.02
Northern America	175	1.38	2.10	140	1.16	1.94	117	0.80	1.79
South America	388	1.43	2.39	339	1.20	2.14	276	1.30	2.28
Africa	495	1.48	2.47	434	1.13	2.02	378	1.18	2.35

Table 3B.1b
Mean General Health Questionnaire Scores – Likert Scoring

	Wave 1			Wave 2			Wave 3		
	No	Mean	SD	No	Mean	SD	No	Mean	SD
All	6889	8.81	4.96	5956	8.71	4.48	5017	8.91	4.53
Male	3274	8.42	4.74	2828	8.44	4.45	2400	8.61	4.33
Female	3615	9.16	5.13	3128	8.96	4.50	2617	9.19	4.69
AGE 15-24	803	7.95	4.56	700	7.90	4.27	567	8.32	4.57
AGE 25-34	3160	9.00	4.89	2721	8.59	4.31	2228	8.77	4.42
AGE 35-44	1781	9.08	5.15	1572	9.06	4.66	1362	9.05	4.46
AGE 45-54	630	8.66	5.46	525	9.06	4.88	471	9.47	4.91
AGE 55-64	306	8.40	4.80	259	9.19	4.44	235	9.44	4.52
AGE 65+	209	7.99	3.93	179	8.94	4.67	154	9.40	5.11
Employed	2235	8.20	4.30	2743	8.17	4.15	2787	8.28	3.91
Unemployed	1447	9.66	5.43	771	9.58	4.90	453	10.26	5.60
Out of L.F.	3207	8.85	5.11	2442	9.05	4.63	1777	9.57	4.94
Unemployed < 2mths	249	9.28	5.33	66	9.65	5.15	47	10.62	5.38
Unemployed 2-6 mths	1101	9.77	5.41	123	9.73	4.51	60	10.85	5.89
Unemployed > 6 mths	50	9.80	5.96	563	9.53	4.96	324	10.13	5.63
Unemployed unknown	47	8.83	5.97	19	10.00	4.86	22	9.82	4.91
Hours < 15	123	8.76	5.01	89	8.63	5.17	94	9.07	4.17
Hours 15-24	173	9.27	5.00	167	8.25	4.01	197	8.18	4.06
Hours 25-34	162	8.40	4.36	201	8.50	4.39	185	8.53	4.09
Hours 35+	1758	8.03	4.16	2152	8.09	4.04	2162	8.20	3.80
Hours unknown	19	8.21	3.58	134	8.56	4.84	149	8.72	4.85
Visa Pref Family	2269	8.49	4.92	1924	8.32	4.47	1614	8.84	4.70
Visa Con Family	1251	8.93	4.96	1095	8.72	4.22	986	8.58	4.19
Visa Bus Skills	897	8.20	4.38	764	8.89	4.28	659	8.76	3.80
Visa Independent	1277	9.27	4.66	1112	8.81	4.27	879	8.79	4.16
Visa Humanitarian	1195	9.25	5.63	1061	9.18	5.04	879	9.65	5.30
Higher Degree	659	9.30	4.90	583	9.28	4.11	473	9.36	3.95
Post Graduate Diploma	409	9.78	5.22	347	9.15	4.79	289	8.84	4.27
Bachelor Degree	1523	9.50	4.95	1304	9.10	4.55	1097	8.92	4.35
Technical / Diploma	1448	8.68	5.02	1272	8.65	4.44	1078	8.89	4.55
Trade	424	8.75	5.59	376	8.47	4.51	326	9.06	4.79
12 + Years of Schooling	1153	8.30	4.71	986	8.33	4.59	841	8.68	4.41
10-11 Years Schooling	508	7.83	4.62	422	8.12	4.05	363	8.56	4.90
7-9 Years of Schooling	394	8.15	4.83	347	8.30	4.83	281	8.87	5.20
6 - Years of Schooling	323	8.14	4.39	275	8.53	4.28	237	9.08	4.81
Other	48	8.71	5.64	44	8.61	4.08	30	11.23	6.91
Married	5295	8.79	4.92	4680	8.66	4.37	4043	8.80	4.37
Separated	79	10.30	6.99	121	10.50	6.38	156	10.38	5.72
Divorced	129	8.77	5.69	115	8.94	4.72	149	9.99	5.51
Widowed	165	9.11	5.46	145	9.48	5.08	132	10.26	5.84
Never married	1220	8.74	4.81	891	8.57	4.58	536	8.69	4.53
Health Very good	3578	7.80	4.40	2603	7.60	3.97	1990	7.65	3.80
Health Good	2717	9.45	4.91	2641	9.06	4.22	2284	9.02	4.16
Health Fair	480	11.44	5.92	563	10.92	5.12	575	10.86	4.79
Health Poor	96	13.99	7.60	126	12.96	6.39	143	15.36	6.93
Health Very Poor	14	14.64	10.26	22	16.59	9.47	24	17.33	8.41
English Speaking	1752	8.68	4.87	1589	8.64	4.31	1357	8.55	3.98
Speaks English v well	796	9.05	4.91	735	8.51	4.50	753	8.28	4.16
Speaks English well	1552	8.88	4.87	1788	8.69	4.51	1659	8.96	4.56
Speaks English not well	1998	8.69	4.94	1563	8.77	4.53	1076	9.57	4.99
Speaks English notat all	791	9.00	5.41	281	9.44	4.88	172	10.00	5.97
Income None	138	8.46	5.64	29	9.66	3.81	16	11.38	5.78
Income 1 to 8000	243	8.62	5.21	140	9.93	5.37	92	9.68	4.73
Income 8001 to 16000	682	9.28	5.52	425	9.50	5.28	316	10.35	5.59
Income 16001 to 25000	1225	9.34	5.14	1014	8.93	4.53	628	9.74	5.37
Income 25001 to 35000	799	8.89	5.07	852	8.57	4.52	719	8.86	4.69
Income 35001 to 50000	826	8.66	4.75	953	8.67	4.43	838	8.54	4.05
Income >50000	1318	8.58	4.50	1513	8.27	3.80	1780	8.55	4.00

Income NA	1658	8.49	4.85	1030	8.78	4.82	628	8.76	4.55
Job Love it	316	6.25	3.54	366	6.64	3.70	472	6.93	3.45
Job Like it	932	7.81	3.91	1152	7.68	3.56	1235	7.99	3.38
Job okay	837	8.74	4.32	1150	8.78	4.25	1116	8.87	4.18
Job Don't care	118	10.08	5.31	208	9.50	4.72	131	10.45	5.29
Job Dislike	74	12.09	5.84	62	10.92	5.30	35	12.74	6.33
Job Dislike a lot	14	10.71	6.71	16	10.13	5.32	13	12.38	5.58
Job Hate it	17	13.71	6.35	31	14.65	7.37	17	12.71	6.61
Oceania	140	7.05	4.82	120	6.64	4.28	112	6.81	3.79
Europe & USSR	2262	9.42	5.14	1981	9.26	4.53	1654	9.14	4.31
Middle East North Africa	791	8.12	4.71	689	8.24	4.78	574	9.55	5.58
Southeast Asia	1110	7.94	4.46	931	7.67	4.02	824	7.97	4.14
Northeast Asia	898	9.59	4.76	764	9.45	4.21	585	9.44	3.91
Southern Asia	630	8.46	4.72	558	8.47	4.25	497	8.80	4.50
Northern America	175	9.03	4.36	140	9.41	4.06	117	8.78	4.14
South America	388	8.54	5.25	339	8.51	4.83	276	8.80	4.88
Africa	495	8.70	5.56	434	8.69	4.70	378	9.07	5.04

Table 3B.2

Caseness Proportions General Health Questionnaire Scores

	Wave 1		Wave 2		Wave 3	
	Proportion	SEs	Proportion	SEs	Proportion	SEs
Higher Degree	0.303	0.018	0.226	0.017	0.188	0.018
Post Graduate Diploma	0.350	0.024	0.245	0.023	0.215	0.024
Bachelor Degree	0.321	0.012	0.236	0.012	0.210	0.012
Technical / Diploma	0.263	0.012	0.222	0.012	0.225	0.013
Trade	0.248	0.021	0.191	0.020	0.215	0.023
12 + Years of Schooling	0.252	0.013	0.198	0.013	0.209	0.014
10-11 Years Schooling	0.193	0.018	0.164	0.018	0.209	0.021
7-9 Years of Schooling	0.234	0.021	0.219	0.022	0.224	0.025
6 - Years of Schooling	0.220	0.023	0.196	0.024	0.232	0.027
Other	0.250	0.063	0.205	0.061	0.400	0.089
Married	0.272	0.006	0.207	0.006	0.203	0.006
Separated	0.342	0.053	0.364	0.044	0.365	0.039
Divorced	0.248	0.038	0.270	0.041	0.315	0.038
Widowed	0.291	0.035	0.241	0.036	0.280	0.039
Never married	0.274	0.013	0.226	0.014	0.215	0.018
No KIDS	0.269	0.006	0.210	0.006	0.207	0.007
KIDS 1	0.306	0.016	0.216	0.013	0.224	0.014
KIDS 2	0.277	0.017	0.244	0.016	0.233	0.015
KIDS 3	0.215	0.029	0.207	0.029	0.207	0.029
KIDS 4+	0.264	0.046	0.241	0.047	0.229	0.046
Health Very good	0.212	0.007	0.146	0.007	0.140	0.008
Health Good	0.312	0.009	0.226	0.008	0.200	0.008
Health Fair	0.427	0.023	0.380	0.020	0.381	0.020
Health Poor	0.646	0.049	0.595	0.044	0.713	0.038
Health Very Poor	0.571	0.132	0.636	0.103	0.792	0.083
English Speaking	0.265	0.011	0.213	0.010	0.178	0.010
Speaks English v well	0.302	0.016	0.205	0.015	0.185	0.014
Speaks English well	0.277	0.011	0.213	0.010	0.225	0.010
Speaks English not well	0.261	0.010	0.216	0.010	0.256	0.013
Speaks English not at all	0.286	0.016	0.260	0.026	0.267	0.034
Income None	0.304	0.039	0.379	0.090	0.500	0.125
Income 1 to 8000	0.276	0.029	0.236	0.036	0.272	0.046
Income 8001 to 16000	0.271	0.017	0.278	0.022	0.313	0.026
Income 16001 to 25000	0.314	0.013	0.232	0.013	0.285	0.018
Income 25001 to 35000	0.270	0.016	0.211	0.014	0.245	0.016
Income 35001 to 50000	0.268	0.015	0.198	0.013	0.177	0.013
Income >50000	0.253	0.012	0.186	0.010	0.172	0.009
Income NA	0.261	0.011	0.227	0.013	0.215	0.016
Job Love it	0.104	0.017	0.101	0.016	0.127	0.015
Job Like it	0.186	0.013	0.150	0.011	0.143	0.010
Job okay	0.260	0.015	0.210	0.012	0.192	0.012
Job Don't care	0.390	0.045	0.236	0.029	0.290	0.040
Job Dislike	0.581	0.057	0.339	0.060	0.543	0.084
Job Dislike a lot	0.429	0.132	0.375	0.121	0.462	0.138
Job Hate it	0.765	0.103	0.742	0.079	0.529	0.121
Oceania	0.186	0.033	0.117	0.029	0.125	0.031
Europe & USSR	0.291	0.010	0.226	0.009	0.212	0.010
Middle East North Africa	0.279	0.016	0.231	0.016	0.324	0.020
Southeast Asia	0.229	0.013	0.166	0.012	0.176	0.013
Northeast Asia	0.292	0.015	0.216	0.015	0.178	0.016
Southern Asia	0.252	0.017	0.220	0.018	0.201	0.018
Northern America	0.286	0.034	0.243	0.036	0.137	0.032
South America	0.278	0.023	0.230	0.023	0.264	0.027
Africa	0.291	0.020	0.247	0.021	0.230	0.022

Table 3B.3

Mental Health Regressions: Dependent variable General Health Questionnaire Caseness Score (Probit) – Wave 1

Variables	Marginal Effect	t statistic	Marginal Effect	t statistic
Employed	-0.061	-3.93		
Unemployed	0.079	5.10		
Hours < 15			-0.030	-0.74
Hours 15-24			0.003	0.09
Hours 25-34			-0.042	-1.16
Hours 35+			-0.079	-4.72
Hours unknown			0.024	0.23
Unemployed < 2 mths			-0.002	-0.07
Unemployed 2-6 mths			0.097	5.63
Unemployed > 6 mths			0.123	1.85
Unemployed unknown			0.028	0.42
Age	0.008	2.57	0.008	2.51
Age Squared	0.000	-3.36	0.000	-3.35
Separated	0.075	1.43	0.076	1.45
Divorced	-0.026	-0.64	-0.025	-0.61
Widowed	0.084	2.03	0.086	2.07
Never married	0.001	0.03	0.000	-0.02
KIDS 1	0.003	0.21	0.002	0.1
KIDS 2	0.007	0.41	0.006	0.33
KIDS 3	-0.031	-1.16	-0.034	-1.27
KIDS 4+	-0.013	-0.33	-0.015	-0.38
Post Graduate Diploma	0.025	0.92	0.026	0.95
Bachelor Degree	-0.004	-0.20	-0.006	-0.27
Technical / Diploma	-0.062	-3.03	-0.061	-3
Trade	-0.065	-2.43	-0.064	-2.38
12 + Years of Schooling	-0.081	-3.76	-0.082	-3.83
10-11 Years Schooling	-0.121	-4.86	-0.123	-4.94
7-9 Years of Schooling	-0.097	-3.51	-0.098	-3.55
6 - Years of Schooling	-0.113	-3.76	-0.113	-3.75
Speaks English well	-0.037	-2.34	-0.039	-2.45
Speaks English not well	-0.036	-2.12	-0.038	-2.28
Speaks English notat all	0.020	0.83	0.019	0.8
Visa Pref Family	-0.022	-1.20	-0.019	-1.02
Visa Con Family	-0.047	-2.36	-0.042	-2.12
Visa Bus Skills	-0.098	-4.33	-0.094	-4.15
Visa Independent	-0.035	-1.70	-0.031	-1.46
Female	0.042	3.50	0.038	3.13
Europe & USSR	0.117	2.64	0.117	2.64
Middle East North Africa	0.082	1.74	0.081	1.7
Southeast Asia	0.042	0.92	0.041	0.91
Northeast Asia	0.143	2.92	0.143	2.91
Southern Asia	0.034	0.73	0.032	0.69
Northern America	0.124	2.10	0.127	2.15
South America	0.095	1.86	0.092	1.79
Africa	0.127	2.55	0.127	2.53
Income 1 to 8000	-0.058	-1.29	-0.058	-1.3
Income 8001 to 16000	-0.069	-1.73	-0.070	-1.76
Income 16001 to 25000	-0.028	-0.69	-0.029	-0.71
Income 25001 to 35000	-0.050	-1.24	-0.049	-1.21
Income 35001 to 50000	-0.040	-0.98	-0.037	-0.91
Income >50000	-0.045	-1.15	-0.040	-1.01
Income NA	-0.049	-1.26	-0.048	-1.22

Table 3B.4a

Mental Health Regressions: Dependent variable General Health Questionnaire Caseness Score

Variables	Pooled Probit		Random Effects Probit Panel (Balanced)		Random Effects Probit Panel (Unbalanced)	
	Coefficient	t statistic	Coefficient	t statistic	Coefficient	t statistic
Hours < 15	-0.155	-1.85	-0.166	-1.43	-0.181	-1.76
Hours 15-24	-0.099	-1.53	-0.147	-1.68	-0.130	-1.66
Hours 25-34	-0.108	-1.68	-0.141	-1.58	-0.145	-1.83
Hours 35+	-0.228	-7.08	-0.276	-5.96	-0.273	-6.64
Hours unknown	-0.057	-0.67	-0.221	-1.91	-0.111	-1.07
Unemployed < 2 mths	0.126	1.73	0.133	1.32	0.139	1.59
Unemployed 2-6 mths	0.280	6.64	0.320	5.27	0.333	6.50
Unemployed > 6 mths	0.188	3.88	0.236	3.63	0.252	4.26
Unemployed unknown	0.246	1.77	0.396	2.13	0.330	1.98
Age	0.023	3.86	0.028	2.93	0.026	3.20
Age Squared	0.000	-4.75	0.000	-3.64	0.000	-3.99
Separated	0.405	5.71	0.536	5.44	0.509	5.74
Divorced	0.140	1.99	0.238	2.32	0.197	2.13
Widowed	0.206	2.82	0.248	2.09	0.287	2.82
Never married	0.073	2.05	0.109	1.94	0.091	1.90
Wave 2	-0.121	-4.56	-0.127	-3.64	-0.156	-5.21
Wave 3	-0.088	-3.09	-0.073	-2.01	-0.108	-3.30
KIDS 1	0.001	0.04	0.029	0.65	0.016	0.41
KIDS 2	0.046	1.43	0.079	1.63	0.070	1.63
KIDS 3	-0.043	-0.86	-0.048	-0.65	-0.042	-0.62
KIDS 4+	-0.026	-0.36	-0.027	-0.25	-0.033	-0.33
Post Graduate Diploma	0.038	0.71	0.053	0.59	0.036	0.47
Bachelor Degree	-0.021	-0.52	-0.042	-0.64	-0.033	-0.57
Technical / Diploma	-0.112	-2.73	-0.137	-2.02	-0.157	-2.67
Trade	-0.123	-2.22	-0.151	-1.69	-0.161	-2.05
12 + Years of Schooling	-0.230	-5.17	-0.281	-3.83	-0.295	-4.65
10-11 Years Schooling	-0.313	-5.68	-0.342	-3.79	-0.393	-5.04
7-9 Years of Schooling	-0.229	-3.89	-0.279	-2.85	-0.282	-3.38
6 - Years of Schooling	-0.297	-4.50	-0.298	-2.77	-0.345	-3.72
Speaks English well	-0.052	-1.78	-0.039	-0.90	-0.037	-0.97
Speaks English not well	-0.035	-1.05	-0.020	-0.39	-0.030	-0.67
Speaks English not at all	0.107	2.04	0.111	1.39	0.097	1.42
Visa Pref Family	0.126	5.21	0.146	3.73	0.163	4.80
Visa Con Family	-0.038	-1.11	-0.042	-0.75	-0.049	-0.99
Visa Bus Skills	-0.148	-3.81	-0.167	-2.68	-0.183	-3.31
Visa Independent	-0.212	-4.59	-0.194	-2.61	-0.273	-4.19
Female	-0.101	-2.46	-0.082	-1.23	-0.126	-2.16
Europe & USSR	0.361	4.22	0.465	3.50	0.462	3.82
Middle East North Africa	0.361	4.05	0.494	3.54	0.450	3.56
Southeast Asia	0.142	1.61	0.182	1.33	0.195	1.57
Northeast Asia	0.344	3.82	0.466	3.29	0.437	3.42
Southern Asia	0.227	2.52	0.315	2.24	0.292	2.29
Northern America	0.370	3.42	0.494	2.83	0.469	3.05
South America	0.347	3.67	0.490	3.30	0.438	3.26
Africa	0.400	4.37	0.525	3.66	0.504	3.88
Income 1 to 8000	-0.245	-2.10	-0.315	-1.79	-0.262	-1.84
Income 8001 to 16000	-0.231	-2.20	-0.269	-1.68	-0.269	-2.09
Income 16001 to 25000	-0.213	-2.08	-0.266	-1.69	-0.258	-2.05
Income 25001 to 35000	-0.243	-2.36	-0.293	-1.85	-0.280	-2.21
Income 35001 to 50000	-0.287	-2.79	-0.378	-2.39	-0.327	-2.58
Income >50000	-0.301	-2.95	-0.387	-2.46	-0.365	-2.90
Income NA	-0.255	-2.51	-0.323	-2.05	-0.293	-2.35
Intercept	-0.892	-4.84	-1.219	-4.16	-1.108	-4.41

Sigma u		0.724	0.027	0.733	0.025
Rho		0.343	0.017	0.349	0.015
Hausman test				38.30	(0.90)
No of Obs	17860	14268		17860	
Log likelihood	-9464	-7136		-9214	

Omitted categories: Out of the labour force, Married, No Kids, Higher Degree, English Speaking or speaks English very well, Visa Humanitarian, Oceania, Income – none, Wave 1.

Table 3B.4b

Mental Health Regressions: Dependent variable General Health Questionnaire Caseness Score

Variables	Pooled Probit		Random Effects Probit Panel (Balanced)		Random Effects Probit Panel (Unbalanced)	
	Marginal Effect	t statistic	Marginal Effect	t statistic	Marginal Effect	t statistic
Hours < 15	-0.047	-1.85	-0.041	-1.43	-0.046	-1.76
Hours 15-24	-0.030	-1.53	-0.037	-1.68	-0.033	-1.66
Hours 25-34	-0.033	-1.68	-0.035	-1.58	-0.037	-1.83
Hours 35+	-0.069	-7.08	-0.069	-5.96	-0.069	-6.64
Hours unknown	-0.017	-0.67	-0.055	-1.91	-0.028	-1.07
Unemployed < 2 mths	0.038	1.73	0.033	1.32	0.035	1.59
Unemployed 2-6 mths	0.085	6.64	0.080	5.27	0.085	6.50
Unemployed > 6 mths	0.057	3.88	0.059	3.63	0.064	4.26
Unemployed unknown	0.075	1.77	0.099	2.13	0.084	1.98
Age	0.007	3.86	0.007	2.93	0.007	3.20
Age Squared	0.000	-4.75	0.000	-3.64	0.000	-3.99
Separated	0.123	5.71	0.134	5.44	0.130	5.74
Divorced	0.042	1.99	0.060	2.32	0.050	2.13
Widowed	0.063	2.82	0.062	2.09	0.073	2.82
Never married	0.022	2.05	0.027	1.94	0.023	1.90
Wave 2	-0.037	-4.56	-0.032	-3.64	-0.040	-5.21
Wave 3	-0.027	-3.09	-0.018	-2.01	-0.027	-3.30
KIDS 1	0.000	0.04	0.007	0.65	0.004	0.41
KIDS 2	0.014	1.43	0.020	1.63	0.018	1.63
KIDS 3	-0.013	-0.86	-0.012	-0.65	-0.011	-0.62
KIDS 4+	-0.008	-0.36	-0.007	-0.25	-0.008	-0.33
Post Graduate Diploma	0.012	0.71	0.013	0.59	0.009	0.47
Bachelor Degree	-0.006	-0.52	-0.011	-0.64	-0.008	-0.57
Technical / Diploma	-0.034	-2.73	-0.034	-2.02	-0.040	-2.67
Trade	-0.037	-2.22	-0.038	-1.69	-0.041	-2.05
12 + Years of Schooling	-0.070	-5.17	-0.070	-3.83	-0.075	-4.65
10-11 Years Schooling	-0.095	-5.68	-0.086	-3.79	-0.100	-5.04
7-9 Years of Schooling	-0.069	-3.89	-0.070	-2.85	-0.072	-3.38
6 - Years of Schooling	-0.090	-4.50	-0.075	-2.77	-0.088	-3.72
Speaks English well	-0.016	-1.78	-0.010	-0.90	-0.010	-0.97
Speaks English not well	-0.011	-1.05	-0.005	-0.39	-0.008	-0.67
Speaks English notat all	0.032	2.04	0.028	1.39	0.025	1.42
Visa Pref Family	0.038	5.21	0.036	3.73	0.041	4.80
Visa Con Family	-0.012	-1.11	-0.011	-0.75	-0.012	-0.99
Visa Bus Skills	-0.045	-3.81	-0.042	-2.68	-0.047	-3.31
Visa Independent	-0.064	-4.59	-0.049	-2.61	-0.070	-4.19
Female	-0.031	-2.46	-0.020	-1.23	-0.032	-2.16
Europe & USSR	0.110	4.22	0.116	3.50	0.118	3.82
Middle East North Africa	0.110	4.05	0.123	3.54	0.114	3.56
Southeast Asia	0.043	1.61	0.045	1.33	0.050	1.57
Northeast Asia	0.104	3.82	0.117	3.29	0.111	3.42
Southern Asia	0.069	2.52	0.079	2.24	0.074	2.29
Northern America	0.112	3.42	0.124	2.83	0.119	3.05
South America	0.105	3.67	0.123	3.30	0.111	3.26
Africa	0.121	4.37	0.131	3.66	0.128	3.88
Income 1 to 8000	-0.074	-2.10	-0.079	-1.79	-0.067	-1.84
Income 8001 to 16000	-0.070	-2.20	-0.067	-1.68	-0.068	-2.09
Income 16001 to 25000	-0.065	-2.08	-0.067	-1.69	-0.066	-2.05
Income 25001 to 35000	-0.074	-2.36	-0.073	-1.85	-0.071	-2.21
Income 35001 to 50000	-0.087	-2.79	-0.095	-2.39	-0.083	-2.58
Income >50000	-0.091	-2.95	-0.097	-2.46	-0.093	-2.90
Income NA	-0.077	-2.51	-0.081	-2.05	-0.075	-2.35

No of Obs	17860	14268	17860
Log likelihood	-9464	-7136	-9214

Omitted categories: Out of the labour force, Married, No Kids, Higher Degree, English Speaking or speaks English very well, Visa Humanitarian, Oceania, Income – none, Wave 1.

Table 3B.5a
Labour Force Status Regressions: Dependent variable Labour Force Status in Wave 2 - Base Case Employment Wave 2 - Condition Wave1 = Employed (Multinomial Logit Regressions)

Variables	Outcome - Unemployment		Outcome – Out of LF	
	Coefficients	t statistic	Coefficients	t statistic
GHQ = 0	0.01	0.02	-0.55	-2.40
GHQ = 1	0.31	0.70	-0.35	-1.24
GHQ = 2	-0.58	-0.84	-0.65	-1.80
Age	-0.06	-0.54	-0.20	-2.90
Agesq	0.00	0.54	0.00	3.00
Bachelor Degree	0.85	1.76	0.17	0.59
Technical / Diploma	0.55	1.08	-0.15	-0.49
Trade	0.07	0.11	-0.11	-0.26
12 + Years of Schooling	0.68	1.15	0.04	0.11
10-11 Years Schooling	1.70	2.91	-0.19	-0.43
7-9 Years of Schooling	0.42	0.48	-0.15	-0.30
6 - Years of Schooling	1.98	2.76	-1.30	-1.20
Speaks English well	0.61	1.99	0.81	3.87
Speaks English not well	1.11	2.90	1.73	6.74
Speaks English notat all	0.85	0.95	-33.38	0.00
Visa Pref Family	-0.27	-0.52	0.03	0.07
Visa Con Family	-0.34	-0.60	-0.26	-0.57
Visa Bus Skilis	-0.90	-1.44	-0.58	-1.21
Visa Independent	-0.01	-0.02	-0.62	-1.31
Female	-0.19	-0.65	1.59	8.32
Constant	-3.01	-1.38	0.40	0.29
No of Obs	2235			
Log Likelihood	-753			
Omitted categories: GHQ = 3 or more, Higher Degree, English Speaking or speaks English very well, Visa Humanitarian.				

Table 3B.5b
Labour Force Status Regressions: Dependent variable Labour Force Status in Wave 2 - Base Case Employment Wave 2 - Condition Wave1 = Unemployed (Multinomial Logit Regressions)

Variables	Outcome - Unemployment		Outcome – Out of LF	
	Coefficients	t statistic	Coefficients	t statistic
GHQ = 0	0.26	1.51	-0.05	-0.29
GHQ = 1	0.33	1.58	-0.01	-0.05
GHQ = 2	0.26	1.01	0.03	0.12
Age	0.02	0.30	-0.19	-3.58
Agesq	0.00	0.21	0.00	4.11
Bachelor Degree	-0.49	-2.33	-0.23	-0.99
Technical / Diploma	-0.36	-1.53	-0.10	-0.40
Trade	-0.58	-1.81	-0.72	-1.78
12 + Years of Schooling	-0.49	-1.89	-0.35	-1.24
10-11 Years Schooling	-0.53	-1.66	-0.50	-1.45
7-9 Years of Schooling	-0.36	-1.15	-0.90	-2.39
6 - Years of Schooling	-0.15	-0.36	-0.13	-0.29
Speaks English well	1.23	7.44	1.48	8.19
Speaks English not well	1.62	8.35	1.87	8.90
Speaks English notat all	1.48	2.70	2.37	4.35
Visa Pref Family	-0.58	-2.95	-0.30	-1.49
Visa Con Family	-0.36	-1.75	-0.44	-1.96
Visa Bus Skills	-1.45	-2.19	-0.10	-0.20
Visa Independent	-0.48	-2.10	-0.62	-2.39
Female	0.03	0.17	1.27	8.18
Constant	-1.71	-1.59	1.33	1.25
No of Obs	1447			
Log Likelihood	-1308			
Omitted categories: GHQ = 3 or more, Higher Degree, English Speaking or speaks English very well, Visa Humanitarian.				

Table 3B.5c

Labour Force Status Regressions: Dependent variable Labour Force Status in Wave 2 - Base Case Employment Wave 2 - Condition Wave1 = Out of Labour Force (Multinomial Logit Regressions)

Variables	Outcome - Unemployment		Outcome – Out of LF	
	Coefficients	t statistic	Coefficients	t statistic
GHQ = 0	0.25	1.32	0.12	0.96
GHQ = 1	0.30	1.30	0.10	0.66
GHQ = 2	0.62	2.23	0.26	1.38
Age	0.09	2.33	-0.09	-4.15
Agesq	0.00	-2.57	0.00	5.12
Bachelor Degree	-0.19	-0.74	-0.17	-0.99
Technical / Diploma	-0.25	-0.97	0.04	0.21
Trade	-0.76	-2.16	-0.57	-2.28
12 + Years of Schooling	-0.44	-1.63	-0.15	-0.87
10-11 Years Schooling	-0.17	-0.52	-0.07	-0.35
7-9 Years of Schooling	0.07	0.19	-0.19	-0.80
6 - Years of Schooling	-1.06	-2.69	-0.72	-2.93
Speaks English well	2.10	10.32	1.65	14.31
Speaks English not well	2.66	12.48	2.27	17.93
Speaks English notat all	3.15	7.31	2.95	9.58
Visa Pref Family	-0.26	-1.39	-0.09	-0.66
Visa Con Family	-0.02	-0.10	-0.27	-1.67
Visa Bus Skills	-1.14	-3.50	-0.06	-0.35
Visa Independent	-0.10	-0.38	0.40	2.27
Female	-0.35	-2.42	1.20	11.25
Constant	-3.71	-4.35	0.17	0.35
No of Obs	3207			
Log Likelihood	-2399			
Omitted categories: GHQ = 3 or more, Higher Degree, English Speaking or speaks English very well, Visa Humanitarian.				

Table 3B.6a

Family Mental Health Regressions: Dependent variable General Health
Questionnaire Caseness Score (Panel Models)

Variables	Random Effects Probit Panel Model Male Partners				Random Effects Probit Panel Model Female Partners			
	Coef	t stat	Coef	t stat	Coef	t stat	Coef	t stat
Male partner employed	-0.236	2.38	-0.338	3.95	-0.047	-0.52		
Male partner unemployed	0.102	1.08	0.172	2.17	0.009	0.10		
Female partner employed	0.325	2.01			-0.239	-1.20	-0.199	2.88
Female partner unemployed	-0.092	0.41			-0.161	-0.69	0.172	2.07
Both partners employed	-0.326	1.82			0.032	0.15		
Both partners unemployed	0.242	0.94			0.266	1.02		
Male employed Female unemployed	-0.121	0.44			0.507	1.92		
Male unemployed Female employed	0.234	1.04			0.286	1.05		
Age	0.072	2.04	0.075	3.20	0.032	2.04	0.032	2.05
Age Squared	-0.000	2.08	-0.000	3.38	0.000	-2.08	0.000	-2.07
Wave 2	-0.103	3.92	-0.089	1.54	-0.219	-3.92	-0.223	-4.02
Wave 3	-0.135	3.23	-0.098	1.53	-0.202	-3.24	-0.209	-3.38
KIDS 1	-0.208	0.33	-0.210	2.58	-0.026	-0.33	-0.027	-0.34
KIDS 2	-0.102	0.18	-0.112	1.39	-0.015	-0.19	-0.019	-0.24
KIDS 3	-0.151	0.38	-0.183	1.59	-0.043	-0.39	-0.047	-0.43
KIDS 4+	-0.097	1.12	-0.131	0.78	-0.184	-1.13	-0.184	-1.13
Post Graduate Diploma	-0.213	1.95	-0.220	1.59	0.297	1.95	0.284	1.87
Bachelor Degree	-0.006	1.26	-0.012	0.12	0.150	1.27	0.141	1.19
Technical / Diploma	-0.128	0.04	-0.133	-1.29	0.005	0.04	-0.001	-0.01
Trade	-0.163	0.40	-0.161	1.32	-0.081	-0.41	-0.097	-0.48
12 + Years of Schooling	-0.271	0.49	-0.270	2.01	-0.061	-0.50	-0.068	-0.56
10-11 Years Schooling	-0.236	1.87	-0.230	1.33	-0.277	-1.88	-0.283	-1.92
7-9 Years of Schooling	-0.253	0.21	-0.278	1.42	-0.035	-0.21	-0.046	-0.28
6 - Years of Schooling	-0.534	1.50	-0.535	2.42	-0.276	-1.51	-0.285	-1.55
Speaks English well	-0.349	2.17	-0.049	0.62	-0.171	-2.17	-0.169	-2.16
Speaks English not well	0.080	0.64	0.061	0.64	-0.056	-0.64	-0.052	-0.60
Speaks English not at all	0.376	0.59	0.360	2.40	0.075	0.59	0.080	0.63
Visa Pref Family	-0.270	2.56	-0.272	1.49	-0.428	-2.57	-0.434	-2.60
Visa Con Family	-0.112	1.26	-0.082	0.81	-0.121	-1.26	-0.125	-1.32
Visa Bus Skills	-0.253	1.29	-0.214	1.74	-0.148	-1.30	-0.161	-1.45
Visa Independent	-0.014	0.20	0.043	0.38	-0.021	-0.20	-0.029	-0.28
Income 1 to 8000	0.503	2.29	0.470	2.09	0.136	0.61	0.143	0.64
Income 8001 to 16000	-0.175	0.93	-0.195	1.04	0.071	0.41	0.057	0.33
Income 16001 to 25000	0.104	0.88	0.079	0.67	-0.086	-0.73	-0.082	-0.71
Income 25001 to 35000	0.113	1.19	0.092	0.97	-0.040	-0.43	-0.039	-0.42
Income 35001 to 50000	0.031	0.31	0.038	0.37	-0.089	-0.92	-0.085	-0.89
Income >50000	-0.087	0.85	-0.077	0.75	0.006	0.07	0.004	0.04
Income NA	-0.097	0.99	-0.090	0.93	-0.069	-0.75	-0.086	-0.94
Europe & USSR	0.605	2.02	0.565	1.91	1.042	3.43	1.025	3.38
Middle East North Africa	0.775	2.49	0.712	2.31	1.002	3.16	0.994	3.14
Southeast Asia	0.215	0.70	0.180	0.59	0.642	2.07	0.629	2.02
Northeast Asia	0.407	1.31	0.374	1.21	0.765	2.44	0.748	2.39
Southern Asia	0.445	1.45	0.379	1.25	0.787	2.53	0.777	2.50
Northern America	0.657	1.84	0.622	1.76	0.613	1.66	0.588	1.60
South America	0.623	1.93	0.573	1.79	1.041	3.20	1.020	3.15
Africa	0.825	2.64	0.784	2.54	0.870	2.74	0.852	2.69
Intercept	-2.554	4.24	-2.503	4.18	-1.975	-4.21	-1.969	-4.22

Table 3B.6b

Family Mental Health Regressions: Dependent variable General Health
Questionnaire Caseness Score (Panel Models) – Marginal Effects

Variables	Random Effects Probit Panel Model Male Partners		Random Effects Probit Panel Model Female Partners	
	Marginal Effect	t stat	Marginal Effect	t stat
Male partner employed	-0.049	2.38	-0.010	-0.52
Male partner unemployed	0.021	1.08	0.002	0.10
Female partner employed	0.068	2.01	-0.050	-1.20
Female partner unemployed	-0.019	0.41	-0.033	-0.69
Both partners employed	-0.068	1.82	0.007	0.15
Both partners unemployed	0.050	0.94	0.055	1.02
Male employed Female unemployed	-0.025	0.44	0.105	1.92
Male unemployed Female employed	0.049	1.04	0.059	1.05
Age	0.015	2.04	0.007	2.04
Age Squared	0.000	2.08	0.000	-2.08
Wave 2	-0.021	3.92	-0.045	-3.92
Wave 3	-0.028	3.23	-0.042	-3.24
KIDS 1	-0.043	0.33	-0.005	-0.33
KIDS 2	-0.021	0.18	-0.003	-0.19
KIDS 3	-0.032	0.38	-0.009	-0.39
KIDS 4+	-0.020	1.12	-0.038	-1.13
Post Graduate Diploma	-0.044	1.95	0.062	1.95
Bachelor Degree	-0.001	1.26	0.031	1.27
Technical / Diploma	-0.027	0.04	0.001	0.04
Trade	-0.034	0.40	-0.017	-0.41
12 + Years of Schooling	-0.056	0.49	-0.013	-0.50
10-11 Years Schooling	-0.049	1.87	-0.057	-1.88
7-9 Years of Schooling	-0.053	0.21	-0.007	-0.21
6 - Years of Schooling	-0.111	1.50	-0.057	-1.51
Speaks English well	-0.007	2.17	-0.035	-2.17
Speaks English not well	0.017	0.64	-0.012	-0.64
Speaks English not at all	0.078	0.59	0.016	0.59
Visa Pref Family	-0.056	2.56	-0.089	-2.57
Visa Con Family	-0.023	1.26	-0.025	-1.26
Visa Bus Skills	-0.053	1.29	-0.031	-1.30
Visa Independent	0.003	0.20	-0.004	-0.20
Income 1 to 8000	0.105	2.29	0.028	0.61
Income 8001 to 16000	-0.036	0.93	0.015	0.41
Income 16001 to 25000	0.022	0.88	-0.018	-0.73
Income 25001 to 35000	0.024	1.19	-0.008	-0.43
Income 35001 to 50000	0.007	0.31	-0.018	-0.92
Income >50000	-0.018	0.85	0.001	0.07
Income NA	-0.020	0.99	-0.014	-0.75
Europe & USSR	0.126	2.02	0.216	3.43
Middle East North Africa	0.161	2.49	0.208	3.16
Southeast Asia	0.045	0.70	0.133	2.07
Northeast Asia	0.085	1.31	0.159	2.44
Southern Asia	0.092	1.45	0.163	2.53
Northern America	0.137	1.84	0.127	1.66
South America	0.130	1.93	0.216	3.20
Africa	0.172	2.64	0.181	2.74
Intercept	-0.529	4.24	-0.410	-4.21

Sigma_u	0.741	0.05	0.701	0.04
Rho	0.354	0.03	0.329	0.03
No of Obs	4777		4667	
Omitted categories: Out of the labour force, Married, No Kids, Higher Degree, English Speaking or speaks English very well, Visa Humanitarian, Oceania, Income – none.				

Appendix 3C: Attrition Statistics for the LSIA

Table 3C.1 presents mean GHQ scores for immigrants in wave 1 who could not be interviewed in wave 2 and wave 3. Mean GHQ scores were significantly higher for the attrition groups (people who could not be interviewed in all 3 waves) compared to those who could be interviewed in all 3 waves. This means that GHQ scores for wave 2 and wave 3 are likely to be biased downwards. However, a preliminary analysis of immigrants who could be interviewed in all 3 waves (of a balanced panel) indicates that the descriptive features of the data derived using all observations available (the unbalanced panel) remain.

Labour force status proportions are relatively stable between the different groups except for those who did not answer all GHQ questions in wave 1 where a large proportion of this group were employed.

Table 3C.1
Attrition Statistics

	All	Answered all GHQ questions	Didn't Answer all GHQ questions	Out in Wave 2	Out in Wave 3	In for all 3 Waves
Number of Obs	7029	6889	140	994	1920	4756
GHQ Mean (SD)	na	1.35 (2.26)	na	1.56 (2.46)	1.55 (2.44)	1.26 (2.17)
Employed (%)	33	32.4	60.7	30.3	31.3	33.1
Unemployed (%)	20.8	21	10.0	24	21.7	20.8
Out of labour Force (%)	46.2	46.6	29.3	45.7	47.2	46.2

Note, some immigrants who could not be interviewed in wave 2 were able to be interviewed in wave 3 therefore the number who could be interviewed in all 3 waves is less than wave 3 attrition subtracted from wave 1.

4. Australian Health Status and Income Inequality

4.1 Introduction

In order to frame effective economic, health and social policy, policy makers need to understand what are the main determinants of health. The objective of this chapter is to examine whether a relationship exists between income inequality and health status in Australia.

A number of important recent studies published in major health journals such as the British Medical Journal have concluded that increases in income inequality in a society affect the health of nearly all persons in that society negatively. These studies suggest that even after allowing for the effect of the level of individual income, income inequality adversely affects the health of all individuals (for example, Kawachi *et al.*, 1997, Kennedy *et al.*, 1998, 1996, Wilkinson, 1997, and Wolfson *et al.*, 1999).¹

If there is a negative relationship between income inequality and health, this has important implications for public health policy. It is well accepted that the level of individual income is causally and positively related to health: as the level of income increases so health increases. If for example, there is a asymptotic concave relationship between the level of income and health (there are declining health returns to the level of income), the average health of the population can be maximised by redistributing income from the rich to the poor. In this case, income redistribution results in the rich losing some health in order for the poor to gain relatively more health. However, if there is also a negative causal relationship between the distribution of income (income

¹ Some authors have questioned the robustness of the relationship between income inequality and health including Judge (1995), Fiscella and Franks (1997) and Milyo (1999).

inequality) and individual health then the effect on individual health outcomes of income redistribution are further complicated. In particular, the loss of health that the rich suffer because their level of income is reduced by income redistribution would be offset by the gain in health they experience because they now live in a society with less income inequality.² If the negative health effects of redistributing income were completely offset this suggests income redistribution can positively influence the health of all. The possibility of a ‘free healthy lunch’ arising from redistributing income clearly begs closer inspection.

This chapter attempts to establish the robustness of conclusions on the relationship between income inequality and health in three ways. First, I examine whether income inequality is related differently to measures of mental, physical and general health. The relationship between income inequality and different measures of health has not often been examined, particularly using the same data set. Second, income inequality at two levels of geographic classification is calculated to evaluate a possible relationship at a neighbourhood level and at a more general societal level. This is in response to a previous literature that suggests that the relationship between income inequality and health is sensitive to the level of region at which income inequality is measured. Third, alternative measures of income inequality are used to explore the impact of change in different parts of the income distribution on health.

Aside from the three approaches discussed above the paper also examines the robustness of the relationship between income inequality and health by estimating models using Deaton and Paxson’s (1999) theoretical framework. Their model of the relationship between income inequality and health is the first attempt in this literature to

² Clearly, such an argument also needs to consider the efficiency consequences of redistributing income.

formalise mathematically an explanation for why income inequality and health might be related.

In section 4.2 of the chapter, previous research and current models of the income inequality and health relationship are reviewed. Section 4.3 of the chapter discusses the data set used in this study and presents some descriptive statistics. In section 4.4 regression results and estimates of Deaton and Paxson's (1999) model are presented and discussed. Section 4.5 concludes with interpretations and comparisons to other studies and some suggestions for future research.

4.2 Models of Income Inequality and Health

Wilkinson's (1996) study of international differences in population health and income inequality is often cited as the seminal work identifying the income inequality and health relationship. Apart from questions concerning the empirical robustness of Wilkinson's findings (see for example, Judge 1995) a key methodological flaw of his aggregate cross-country approach is his inability to control for the level of individual income. That is, any asymptotic concave relationship between income and health can explain why the average health of a population declines when income dispersion (inequality) increases regardless of why the asymptotic concave relationship exists (see Rodgers, 1979 and Gravelle 1998).³ Therefore, to identify a relationship between income inequality and health we must first control for the relationship between the level of individual income and health. A relationship found at the population level that is

³ The idea that causality runs from income to health and that there are decreasing health returns to additional income fits comfortably within most aspects of economic theory. Grossman's (1972) model of health capital and associated health production function provides a theoretical basis for why health should increase (at a declining) rate with income. In this model, health production is a function of income and health related (time) behaviours.

uninformative because it simply reflects a relationship at the individual level is known as an ecological fallacy.⁴

In work that followed Wilkinson's cross-country analysis, evidence of the negative health effect of increases in income inequality is supported by a number of studies of intra-country (regional) differences in income inequality and health (for example, Kennedy *et al.*, 1998, 1996, Wolfson *et al.*, 1999). These studies usually controlled for the level of individual income using the following equation:

$$h_{ij} = \beta X_{ij} + \alpha I_{ij} + \gamma G_j + \varepsilon_{ij} \quad (1)$$

Equation (1) is the model typically employed to test whether income inequality affects individual health, where X_{ij} is a measure of individual characteristics for the i th individual in the j th region, I_{ij} a measure of income (usually non-linearly related to health by being logged or by using a set of income dummy variables), G_j is a regional Gini coefficient or some other measure of income inequality, and β, α, γ are coefficients to be estimated.

This chapter attempts to establish the robustness of the relationship between income inequality and health status for Australia by estimating equation (1). This is the first attempt of which the author is aware that estimates such a relationship for Australia. In testing the robustness of this relationship, the analysis is informed by possible explanations of a relationship between income inequality and health.

Wilkinson (1997) suggests that the income inequality pathway to poor health may be explained by psychosocial stress arising from increased distances between

⁴ In the income inequality and health literature, the ecological fallacy argument is also called a statistical artefact.

societal levels. That is, it is relative income that matters for health and not just absolute income where relative income largely defines different levels of society. Proponents of the relative income hypothesis often refer to Sapolsky (1993) in support of their hypothesis. Sapolsky's (1993) paper shows that social rank is an important element of wild baboon health. Marmot's (1997) study of British Civil Servants is also cited as evidence of the effect of social ranking on individual health. Marmot finds that an individual's grade of employment – controlling for other individual characteristics – is associated with good health. In Marmot's (1997) study, health effects are measured in a number of ways, for example, by mortality, work absences, and disease incidence.

The relative income argument is about the distance between social ranks and not just the ordering. However, the evidence called upon in support of the relative income hypothesis is largely about the ordering of ranks and is ordinal in nature rather than cardinal. One way that changes in income inequality might be capturing changes in social rank is if an increasing number of people are becoming of the lowest rank, and this in turn causes income inequality to rise. However, in the income inequality and health literature there is a rather loose and unsatisfactory discussion of how changes in rank might be related to changes in income inequality. For example, there has been little discussion about how ordinal social ranking is related to the distribution of economic resources. If there is a relationship between rank and economic resources, we cannot distinguish between the effect of rank and more standard economic explanations in explaining differences in health. For example, people of lower rank may simply have few inputs in their health production function which leads to poorer health.

A recent and promising contribution to the literature that formalises how changes in distances in social rank might be captured by measures of income inequality

is due to Deaton and Paxson (1999).⁵ Deaton and Paxson (1999) have taken the notion of relative income and developed a theoretical framework to explain a relationship between income inequality and health. They use the idea that income differences relative to a particular reference group mean income may be one way we can gain insights into social rank.⁶ They assume that relative income and health are linearly related and can be represented by:

$$E(h | y, z) = \alpha + \beta(y - z) \quad (2)$$

where h is health, y the natural log of income, and z the mean of the natural log of income in the reference group.⁷

Deaton and Paxson (1999) suggest that it is very difficult to identify the relevant reference group in which people rank themselves meaning that we cannot easily observe the appropriate mean reference group income. Given that we only observe income, equation (2) becomes

$$E(h | y) = \alpha + \beta(y - E(z | y)). \quad (3)$$

Deaton and Paxson assume z and y are joint normally distributed, that the marginal distribution of z is $N(\mu, \sigma_z^2)$ and the distribution of y conditional on z is $N(z, \sigma_\epsilon^2)$. In this framework σ_z^2 and σ_ϵ^2 can be thought of as between and within reference group inequality respectively. The distributional assumptions and the linear

⁵ There is still no clear link between the evidence often provided in favour of the relative income story that is ordinal in nature and Deaton and Paxson's model that is cardinal.

⁶ Deaton and Paxson also explain that income is just one way we might think about "ranking" in society, education is another way people might rank themselves.

⁷ The following exposition follows Deaton and Paxson (1999) closely.

relationship between relative income and health allow Deaton and Paxson to derive equation (4)

$$E(h | y) = \alpha + \beta \frac{\sigma_{\epsilon}^2}{\sigma_{\epsilon}^2 + \sigma_z^2} (y - \mu), \quad (4)$$

where income is related to health but the slope or gradient of this relationship is a function of the ratio of within and between group income inequality. Thus, by making assumptions about the relationship between income and mean reference group income Deaton and Paxson have derived a framework that predicts that when within group inequality is high relative to between group inequality the slope between income and health is greater.⁸

It should be noted that income inequality does not directly impact on health in this version of Deaton and Paxson's model: where relative income is derived by reference to group mean income. There is no measure of income inequality in equation (4) affecting health independently and separately from income. However, they have extended their model to allow income inequality to play a direct role in determining health. In this version, people rank themselves relative to the top of the reference group rather than the mean of the reference group.⁹ Thus, relative income becomes the difference between y and $z + \theta\sigma_{\epsilon}$ where the highest income person is θ standard deviations from the mean and equation (4) becomes

⁸ Deaton and Paxson suggest that an alternative way to think about this is to consider (absolute) individual income as an error ridden measure of relative income.

⁹ Note that in this discussion of distances between social ranks it must be assumed that people are ranking with respect to the top of the income distribution for an increase in income inequality to have a negative effect on health. If people were ranking with respect to the bottom of the income distribution, an increase in income inequality (or an increase in the distribution of income) would have a positive effect on health.

$$E(h | y) = \alpha + \beta \frac{\sigma_\epsilon^2}{\sigma_\epsilon^2 + \sigma_z^2} (y - \mu) - \beta\theta\sigma_\epsilon. \quad (5)$$

This model can be re-expressed to be linear in the log of income, the variance of the log of income, and the interaction of these two variables.¹⁰ Note that between reference group inequality will be constant in a cross-section data set.

Deaton and Paxson (1999) have derived a model that represents a causal relationship between relative income (defined as individual income relative to the top of the income distribution) and health. Apart from the relative income explanation, there are a number of other explanations for why income inequality might be related to health. Some authors have suggested, often in addition to social rank or relative income, that income inequality is an indirect measure of social capital and that it is differences in social capital that matter for health. Kawachi *et al.* (1997) defines social capital as ‘the features of social organisation, such as civic participation, norms of reciprocity, and trust in others that facilitate cooperation for mutual benefit’. They suggest that high income inequality will lead to disinvestment in social capital, which in turn leads to poor health. Kawachi *et al.* (1997) examined the social capital explanation using measures of the number of civic groups and associations per capita and answers to questions concerning trust. They found that these measures were statistically related to

¹⁰ Other aspects of the income inequality and health relationship that Deaton and Paxson (1999) examined were estimation of permanent income, the interaction between age and income, and education as an instrument for income. In this paper, I do not use education as an instrument for income. Instead, I estimate the independent separate effect of education on health. This means of course that since I do not have any other instruments for income I cannot control for the possibility that health is determining income. Surprisingly, Deaton and Paxson (1999) found that increased income inequality appeared to be having a positive effect on health (in their paper a reduction in cohort mortality).

health and income inequality. This led them to claim that the effect of income inequality on health is mediated by social capital.

In addition to the relative income and social capital explanations of the income inequality and health relationship Lynch *et al.* (1998) discussed two other models, the neo-material and particularists hypothesis. In the neo-material model historical under-investment in health related aspects of public infrastructure leads to poorer health outcomes and produces an associated income distribution. The neo-material hypothesis is not unlike the notion of social capital. Instead of a lack of ‘psychic’ social capital, there is a lack of ‘physical’ social capital. The particularist hypothesis appears to be one where there is no general underlying “rule”, each outcome developing because of a unique set of circumstances. This model suggests that the relationship between income inequality and health is valid only in the context of the region or country being studied and that the results of one study cannot be generalised.

None of the explanations of the income inequality and health relationship are mutually exclusive. Thus, it is difficult to identify or test for the “true” theoretical model. A serious weakness of the current set of explanations for why health might be related to income inequality is that they do not lead to testable hypotheses. This study does not attempt to distinguish among alternative hypotheses. Instead, the focus is on establishing the robustness of the empirical relationship between income inequality and health. Robustness is examined in three ways.

- (1) The two measures of health most commonly used in analysing the relationship between income inequality and health have been mortality rates and self assessed health status. This paper uses self assessed health status as well as three measures of health arising from the SF-36 questionnaire. The SF-36 questionnaire enables an examination of general health as well as

physical and mental dimensions of health. Examining different dimensions of health may provide insights into how an income inequality effect might operate. If for example, the primary impact of income inequality is on mental health and then subsequently declines in mental health affect physical health, we should observe a stronger contemporaneous relationship between income inequality and SF-36 mental health than between income inequality and SF-36 physical health. The analysis of the relationship between income inequality and health using different measures of health status is an important contribution of this chapter particularly as this has not been done before using the same data set.

- (2) Studies which examine the relationship between income inequality and health within a country typically measure income inequality using data on the distribution of income within specified geographic regions (see for example, Kennedy *et al.*, 1998, 1996, Wolfson *et al.*, 1999, and Fiscella and Franks 1997). In this study, it was possible to measure income inequality at two geographic levels, a fine neighbourhood level and a broader regional or city level. Fiscella and Franks (1997) found that income inequality measured at the USA county level of geography was not related to individual health. In response to this study, Wilkinson (1997) suggested that the geographical level at which income inequality is measured is important. Income inequality measured at a highly disaggregated level of geography may not capture differences in income across society where differences in income across society are postulated to have a negative effect on individual health. Other studies of the income inequality and health relationship have

typically not been able estimate income inequality at different levels of geography, although Wolfson *et al.* (1999) is an exception.

- (3) Whilst some authors have concluded that the relationship between income inequality and health is empirically robust (for example, Kennedy *et al.*, 1998) most have not established the strength of the relationship with respect to different measures of income inequality. A recent UK study by Weich *et al.* (2000a) found that the relationship between self assessed health status and income inequality was not robust in the face of different measures of income inequality. In this chapter, I use five income inequality indices to examine the relationship between health status and income inequality. By using different income inequality indices, I am able to examine whether changes in different parts of the income distribution are having different health effects. If a relationship between income inequality and health exists then knowing how important changes in the income distribution are to health may help identify underlying mechanisms or pathology.

In interpreting this empirical regularity, I refer to the relative income model and the estimation of Deaton and Paxson model is used is an attempt to analyse more critically a possible relationship. As noted earlier, given the general way in which the income inequality and health relationship is currently interpreted in the literature, it is difficult to distinguish between alternative hypotheses.¹¹

¹¹ If it had been possible to pool cross-sections from different time periods it might have been possible to control for fixed region effects as well as differences in regional income inequality. This might provide insights into more permanent fixed neo-material type effects as well as variation in income inequality. Unfortunately, because I am estimating this relationship on a single cross-section I am unable to control

4.3 Features of the 1995 National Health Survey

The Australian Bureau of Statistics (ABS) 1995 National Health Survey is described in Section 2.2.¹² Definitions of variables used in this Chapter are presented in Appendix 4A Table 4A.1. Measures of health were self assessed health status and SF-36 dimensions of health. Self assessed health status is becoming an increasingly common measure of health in empirical research and is discussed in detail in Chapter 2.¹³

As a number of studies of the health and income inequality relationship use mortality as the measure of health I was interested to see how closely mortality was related to self assessed health status. Mortality was used as a measure of health by Deaton and Paxson (1999) in their analysis of cohorts and by Ross *et al.* (2000) in their analysis of regional mortality rates and income inequality. The correlation coefficient of mean self assessed health status and the proportion of persons dying – both measured by single year age groups - was 0.89. Thus, at the population level self assessed health status appears to be reflecting the mortality experience of single year age groups.

for fixed regional differences. Using a single cross-section also means that I cannot clearly ascribe causality from income inequality to health.

¹² See ABS (1995) Cat no 4363.0.

¹³ There are some limitations to the self assessed health status measure. For example, in Chapter 2 a co-author and I found that measurement error associated with self assessed health status is related to individual characteristics such as age; this may create problems of bias. In this study, Huber-White sandwich estimates of the variance co-variance matrix are used to account for within group autocorrelation. The corrected standard errors arising out of this process may also in part correct for any heteroscedasticity generated by errors in self assessed health status.

The SF-36 is a well-known measure of general health and well being producing scores for eight dimensions of health.¹⁴ Other researchers have also used this measure of health to undertake the type of analysis presented in this paper for example, Hemingway *et al.* (1997). In this study, the SF-36 general health dimension and the physical and mental SF-36 summary measures of health are used.¹⁵ In households selected to respond to the SF-36, persons aged 18 and over completed the SF-36 questionnaire before being interviewed for the National Health Survey personal interview questionnaire.¹⁶ Households selected to respond to the SF-36 were not asked questions about their education, alcohol consumption, and health insurance or invited to answer supplementary women's health questions. Thus, in my analysis I cannot control for these characteristics when using SF-36 measures of health.¹⁷ SF-36 measures of health were also highly correlated with the proportion of persons dying by single year age groups.

A measure of equivalent income is constructed where each income unit's total gross personal income is equivalised using the latest OECD equivalent income scales (0.5 for each additional adult and 0.3 for each additional child aged under 15).¹⁸ Income

¹⁴ See Ware *et al.* (1993).

¹⁵ See Brazier (1993) for a discussion of the use of the SF-36 questionnaire in economic analysis.

¹⁶ There were approximately 23,800 dwelling households in the National Health Survey and of these households, around half were 'invited' to answer the Short Form 36 health status questionnaire (SF-36).

¹⁷ I examine the impact of individual education on self assessed health status to see if the effect of other explanatory variables is affected when I cannot control for education differences.

¹⁸ See Klaas De Vos *et al.* (1997) for the latest OECD equivalence scale. I also used the ABS Henderson equivalent income scales to derive equivalent income and found that the results of analyses using this scale did not vary from those obtained using the OECD scale.

inequality indices are calculated at two different levels of geography using equivalent income.

The most disaggregated level of geography in this study is the Statistical Local Area (SLA). SLAs tend to represent particular communities such as a single small town or suburb in a city and can vary dramatically in size. In 1995, there were 1286 SLAs in Australia. The 1995 National Health Survey collected data from respondents living in 762 SLAs. I only calculate income inequality for a SLA when I have information for at least 30 persons in that SLA. There were 333 SLAs for which I could calculate income inequality indices for analysis with self assessed health status and 185 SLAs when analysing SF-36 measures of health.

I also calculate income inequality indices at the Statistical Division (SD) level of geography for which there are 57 in the data set. SDs typically represent much larger rural and or urban areas. After excluding SDs for which fewer than 30 persons were observed there were 54 SDs when analysing self assessed health status and 49 when using SF-36 measures of health. In 1995, there were 66 Statistical Divisions in Australia.

I calculate five different income inequality indices: the Gini coefficient and four indices from the single parameter Generalised Entropy class $GE(\alpha)$ for α equal to -1 , 0 , 1 and 2 . For the GE class as α becomes more positive, the GE index becomes more sensitive to income differences at the top of the income distribution. Similarly as α becomes more negative, the GE index becomes more sensitive to income differences at the bottom of the income distribution.¹⁹

¹⁹ Jenkins (1999).

The measures of income inequality used in this study can be difficult to interpret. For example, differences in the Gini coefficient do not necessarily indicate differences in inequality according to Lorenz ranking. That is, despite variation in the Gini coefficient, say between two regions, we can not say that one region has a more unequal distribution than another does if the Lorenz curves of the two regions happen to cross. In most of the studies of the relationship between income inequality and health, there has been little discussion of the fallibility of particular measures of income inequality. I use a number of different measures of income inequality in an attempt to ensure that results are not unique to a particular measure.

The Gini coefficient can be calculated when reported income is zero however, the GE class of indices cannot be calculated when income is zero. When conducting regression analysis, I report results where I use the entire data set including observations where income is reported as zero, and also where I trim the data set by excluding observations where income is zero as well as the top and bottom 1 percent of the income distribution.

4.3.1 Descriptive Results

The percentage of respondents in each self assessed health status category and means and standard deviations for the SF-36 measures of health are presented in Tables 4.1 and 4.2 respectively. As expected, a higher proportion of younger persons report that their self assessed health status is excellent or very good compared to older persons. Younger persons also report better health compared to older persons according to the general health and physical summary SF-36 measures. However, this is not true of the SF-36 mental health summary measure, as older persons tend to report better mental health than do younger persons.

Generally, a higher proportion of persons in higher income deciles reported excellent or very good health than persons in the lower income deciles except for persons in the first (lowest) income decile. This unusual relationship between the self assessed status of persons in the lowest income decile compared to persons in higher income deciles was also present for SF-36 measures of health and is discussed in more detail in Section 4.4.

Persons with higher educational qualifications reported better health than persons with no or lesser educational qualifications. Smokers reported poorer health compared to those who had never smoked. There were no large differences in reported health by marital status except perhaps for the widowed and never married categories, though these differences are probably driven by differences in the age distribution for these groups.²⁰

In Table 4.3, summary statistics for key variables are presented. By design, the mean and standard deviation of both SF-36 mental and physical summary measures are close to 50 and 10 respectively (see ABS Cat No 4263.0).

²⁰ There were a larger number of older persons in the widowed category and reported health tended to be poor whilst the never married category contained a higher proportion of younger persons who tend to report good health.

Table 4.1
Descriptive Statistics - Self Assessed Health Status

	Self Assessed Health Status (%)				
	Excellent	Very Good	Good	Fair	Poor
Age					
Age 15-24	23.78	40.52	26.65	7.92	1.13
Age 25-34	21.52	41.30	27.34	8.34	1.50
Age 35-44	21.15	39.95	27.88	9.08	2.04
Age 45-54	19.95	34.63	28.59	12.88	3.96
Age 55-64	13.91	27.81	31.16	19.71	7.41
Age 65-74	11.18	24.51	30.84	23.15	10.32
Age 75+	10.07	21.05	28.11	27.08	13.69
Gender					
Male	19.69	36.26	27.91	12.23	3.90
Female	19.26	35.94	28.51	12.52	3.76
Equivalent Income					
Decile 1	20.39	34.34	28.71	12.53	4.03
Decile 2	12.65	24.63	30.26	22.10	10.36
Decile 3	11.61	24.05	30.94	23.21	10.91
Decile 4	15.48	33.33	30.09	15.92	5.18
Decile 5	18.49	37.54	28.86	12.71	2.40
Decile 6	20.37	36.84	30.11	10.23	2.44
Decile 7	21.15	40.58	28.78	7.68	1.81
Decile 8	20.96	42.01	27.25	8.72	1.07
Decile 9	24.15	42.21	25.96	6.77	0.91
Decile 10	26.85	42.69	22.87	6.51	1.08
Educational Attainment					
Degree or higher	29.45	41.01	23.49	4.79	1.27
Diploma + Skilled	21.06	36.95	28.77	9.97	3.25
Basic Skilled	21.57	36.09	30.26	9.91	2.17
No Higher Quals	16.98	32.18	31.06	14.82	4.97
Smoking Status					
Na	31.83	39.13	22.35	5.78	0.91
Smoker	12.39	33.68	33.93	15.27	4.73
Ex-smoker	18.30	34.78	27.91	14.31	4.70
Never smoked	22.29	37.75	26.16	10.58	3.22
Employment Type					
No self employed	19.06	35.87	28.48	12.62	3.98
Self employed >= 1	26.35	39.95	23.93	8.41	1.36
Marital Status					
Married	18.68	36.34	28.59	12.59	3.80
Defacto	18.32	39.23	29.49	10.75	2.22
Separated	16.58	33.66	29.20	14.10	6.45
Divorced	19.78	30.55	27.95	14.86	6.87
Widowed	11.75	24.28	29.63	22.81	11.54
Never married	23.13	38.63	26.87	9.55	1.82
Employment Status					
NA	10.80	23.30	29.84	24.56	11.50
Employed	22.18	41.31	27.36	8.08	1.08
Unemployed	18.14	30.76	34.02	13.69	3.38
Not in Labour Force	17.86	30.91	22.03	16.39	6.74
Total	19.47	36.10	28.22	12.38	3.83

Table 4.2

Descriptive Statistics – SF-36 Measures of Health

SF-36						
	General Health		Mental Health		Physical Health	
	Mean	SD	Mean	SD	Mean	SD
Age						
Age 15-24	73.51	18.28	48.9	10.30	53.01	7.41
Age 25-34	76.15	17.78	49.44	9.86	53.04	7.61
Age 35-44	74.64	18.73	49.38	9.93	52.11	8.51
Age 45-54	71.46	20.98	50.22	9.86	49.85	9.63
Age 55-64	66.31	22.78	50.98	10.09	46.28	10.85
Age 65-74	62.52	23.30	51.48	10.06	42.63	11.54
Age 75+	60.72	22.74	51.46	10.57	38.41	12.45
Gender						
Male	71.45	20.52	50.76	9.57	50.25	9.83
Female	71.97	20.47	49.14	10.42	49.85	10.18
Equivalent Income						
Decile 1	71.23	20.43	48.64	10.87	50.33	10.03
Decile 2	63.24	23.83	48.12	11.84	45.28	12.26
Decile 3	62.32	23.37	48.57	11.17	44.74	12.04
Decile 4	68.73	21.70	49.70	10.33	47.97	11.07
Decile 5	72.23	19.87	50.08	9.91	50.10	9.87
Decile 6	73.96	18.45	50.07	9.78	51.39	9.21
Decile 7	74.83	18.48	50.36	9.55	52.00	8.14
Decile 8	75.02	17.57	50.71	9.04	51.90	8.16
Decile 9	77.14	17.52	51.08	8.84	52.55	7.81
Decile 10	76.35	17.37	51.05	8.94	52.62	7.42
Smoking Status						
Smoker	68.74	20.39	48.38	11.07	50.18	9.72
Ex-smoker	71.25	21.22	50.57	9.60	48.77	10.69
Never smoked	73.58	19.91	50.33	9.65	50.70	9.69
Employment Type						
No self employed	71.46	20.60	49.87	10.11	49.90	10.10
Self employed ≥ 1	76.01	17.99	50.47	8.95	52.32	8.13
Marital Status						
Married	72.07	20.26	50.58	9.38	49.82	9.87
Defacto	72.57	19.14	49.14	10.15	51.46	8.71
Separated	69.25	21.65	45.71	12.06	50.37	10.49
Divorced	69.87	22.78	49.13	11.12	48.29	11.40
Widowed	63.78	23.61	50.87	11.10	41.72	12.71
Never married	73.30	19.36	48.93	10.59	52.58	8.19
Employment Status						
NA	61.86	23.11	51.48	10.24	41.19	12.02
Employed	75.78	17.51	50.37	9.29	52.55	7.62
Unemployed	70.18	19.96	48.27	11.49	51.38	8.80
Not in Labour Force	65.64	23.63	47.64	11.49	47.44	11.57
Total	71.72	20.49	49.91	10.05	50.04	10.01

Table 4.3
Summary Statistics

	Mean	Standard Deviation	Number
Self assessed health status	2.45	1.05	35325
SF-36 General Health	71.72	20.49	16080
SF-36 Mental Health	49.91	10.05	15870
SF-36 Physical Health	50.04	10.01	15870
OECD equivalent income	23275	28484	35325
Log of Equivalent income	9.82	0.779	34231
Age	41.33	17.57	35325

Table 4.4
Means by Region

	All Observations				Trimmed 1% + Zeros			
	Statistical Division		Statistical Local Area		Statistical Division		Statistical Local Area	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
SAHS	2.47	0.12	2.45	0.22	2.49	0.13	2.46	0.22
SF-36								
General Health	71.7	3.16	71.8	4.30	71.5	3.38	71.6	4.33
Mental Health	50.3	1.34	49.7	1.86	50.3	1.48	49.7	1.87
Physical Health	49.5	1.36	50.2	2.09	49.4	1.39	50.1	2.04
Mean Log Income	9.74	0.18	9.84	0.26	10.17	0.15	10.25	0.22
Income Inequality								
Gini Coefficient	0.38	0.04	0.37	0.06	0.33	0.03	0.32	0.04
Entropy (-1)					0.23	0.05	0.24	0.09
Entropy (0)					0.19	0.03	0.18	0.05
Entropy (1)					0.19	0.04	0.17	0.04
Entropy (2)					0.21	0.05	0.19	0.06

The mean and standard deviation of health, income inequality indices, and the log of income are reported by region for both levels of geography in Table 4.4. It might be expected that mean income inequality indices at the more disaggregated level of geography (SLA) would be lower than those calculated at the SD level. This would be the case if persons with similar income levels and household characteristics tended to live in the same area. It is the case that mean income inequality indices for SLAs tend to be lower than for SDs. However, these differences are not significant at the 5 percent level.

4.4 Regression Results

Equation (1) is the model typically employed to test whether income inequality is affecting individual health. Equation (1) was estimated with different measures of health status regressed against age, sex, income, regional income inequality indices, education, employment status, smoking status, marital status, and whether anyone in the household was self employed.

Ordered probit regressions were estimated when self assessed health status was the dependent variable. In these regressions, self assessed health status was ordered from poor health to excellent health and therefore positive coefficients on explanatory variables indicate a positive relationship with health. When education was included as an explanatory variable in regressions on self assessed health status, only half the sample was available, as only half the sample was required to answer educational attainment questions.

Tobit regressions were run when SF-36 measures of health were used as the dependent variable (these measures are bounded at 0 and 100). In these regressions, education could not be included as an independent variable as it was not asked of this

group of respondents. In all regressions, smoking status and marital status were used to control for lifestyle differences that may affect health.

An important aspect of the ordered probit and tobit regressions is that when using grouped variables such as measures of regional income inequality it is likely that the standard errors on these variables will be biased downwards.²¹ In all regressions, the STATA cluster option, which uses Huber-White sandwich estimates of the variance covariance matrix, is used to correct for possible autocorrelation across observations within grouped variables.²²

4.3.1 Regression Results – Income Inequality Indices

Coefficients and t-statistics on income inequality indices measured at the Statistical Division (SD) level of geography for ordered probit and tobit regressions are reported in Table 4.5a. Similarly, coefficients on income inequality indices measured at the Statistical Local Area (SLA) level of geography (the more disaggregated level) are reported in Table 4.5b. Full regressions results for ordered probit regressions on self assessed health status including and excluding education variables are reported in Table 4.6 whilst full tobit regression results on the three SF-36 measures of health are reported in Table 4.7.²³

²¹ See Moulton (1990).

²² Correcting for clustering did make a difference in this study. In a number of regressions, coefficients on income inequality indices were significant before correction but not after.

²³ Regressions were also run on a data set that trimmed the top and bottom 4 percent of the income distribution. Trimming at the 4 percent level results in all zero income observations being excluded. Results from these regressions did not differ substantially from those reported for the data set where zero income observations were excluded as well as the top and bottom 1 percent of the income distribution.

Table 4.5a
Coefficients on Estimates of Income Inequality Measured at the Statistical Division Level *

	Gini Coefficient		Entropy (-1)		Entropy (0)		Entropy (1)		Entropy (2)	
	Coef	tstat	Coef	tstat	Coef	t-stat	Coef	tstat	Coef	tstat
Self Assessed Health Status (Ordered Probit)										
All observations	-1.48	2.55								
Trimmed 1% plus 0s	-0.53	0.62	-0.94	2.92	-1.88	1.70	-0.19	0.28	0.31	0.49
SF-36 General Health (Tobit)										
All observations	-9.3	0.93								
Trimmed 1% plus 0s	-17.8	1.45	-15.1	2.75	-22.5	2.05	-10.4	0.97	-0.03	0.00
SF-36 Mental Health (Tobit)										
All observations	-12.7	2.87								
Trimmed 1% plus 0s	-12.9	2.55	-10.5	4.62	-15.5	3.42	-6.97	1.50	0.59	0.17
SF-36 Physical Health (Tobit)										
All observations	2.27	0.63								
Trimmed 1% plus 0s	2.27	0.43	-0.63	0.26	0.66	0.14	1.54	0.35	1.88	0.43

Omitted Variables: never married, never smoked, age 15-25, Equivalent income decile 1, Education group no higher qualifications, Employment status – Not in Labour Force, no one in Income Unit self employed, male. Self assessed health status is ordered from poor health through to excellent health. Tobit regressions using SF-36 variables do not include measures of educational attainment.

* This table contains only the coefficients and t-statistics on the various measures of income inequality. Full regression results for some of the models are presented in Tables 4.6 and 4.7. Coefficients on other explanatory variables did not vary between the regressions on each measure of health.

Table 4.5b
Coefficients on Estimates of Income Inequality Measured at the Statistical Local Area Level *

	Gini Coefficient		Entropy (-1)		Entropy (0)		Entropy (1)		Entropy (2)	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Self Assessed Health Status (Ordered Probit)										
All observations	0.28	1.08								
Trimmed 1% plus 0s	0.45	1.22	0.17	1.01	0.32	1.06	0.29	0.94	0.15	0.73
SF-36 General Health (Tobit)										
All observations	2.66	0.62								
Trimmed 1% plus 0s	1.56	0.26	3.01	1.20	4.03	0.77	2.32	0.44	1.31	0.36
SF-36 Mental Health (Tobit)										
All observations	-1.95	1.01								
Trimmed 1% plus 0s	-2.46	0.87	-0.79	0.59	-1.99	0.87	-1.89	0.83	-0.90	0.56
SF-36 Physical Health (Tobit)										
All observations	2.19	1.14								
Trimmed 1% plus 0s	2.59	1.10	2.07	1.86	3.26	1.72	2.18	1.08	1.01	0.68
Omitted Variables: never married, never smoked, age 15-25, Equivalent income decile 1, Education group no higher qualifications, Employment status – Not in Labour Force, no one in Income Unit self employed, male. Self assessed health status is ordered from poor health through to excellent health. Tobit regressions using SF-36 variables do not include measures of educational attainment. * This table contains only the coefficients and t-statistics on the various measures of income inequality. Full regression results for some of the models are presented in Tables 4.6 and 4.7. Coefficients on other explanatory variables did not vary between the regressions on each measure of health.										

From Tables 4.5a and 4.5b it can be seen that some income inequality indices are significant in regressions on measures of health status when income inequality is

measured at the Statistical Division level of geography.²⁴ No income inequality indices calculated at the Statistical Local Area level of geography were significant in health regressions. This result lends some support to Wilkinson's (1997) suggestion that the level at which income inequality is measured matters and in particular, that measuring income inequality at fine levels of geography does not capture differences across society. However, support for Wilkinson's hypothesis is somewhat qualified as the relationship between income inequality measured at the more aggregate geographical level and health is not robust to the use of different measures of health and income inequality.

Gini coefficients are significant when the entire data set (including zero income observations) is used for self assessed health status and SF-36 Mental health regressions where Gini coefficients are calculated at the Statistical Division level. When zero income observations and the top and bottom 1 percent of the income distribution are excluded (the trimmed data set), Gini coefficients are no longer significant. For the trimmed data set the GE(-1) index is significant in regressions on self assessed health status, SF-36 General health and SF-36 Mental health as is the GE(0) index for SF-36 Mental Health. The GE(-1) index is most significant in the SF-36 Mental Health regressions. SF-36 Mental health and self assessed health status are highly correlated as are SF-36 Mental Health and SF-36 General Health. It may be the case that the significant relationship that is observed in the self assessed health status and SF-36 General health regressions is primarily a mental health phenomenon, where these two measures are proxying for mental health. Alternatively, it may also be the case that

²⁴ All these regressions were re-estimated where instead of 30 or more observations being observed in each Statistical Division 100 or more observations had to be observed. This had almost no effect on the results and did not effect the significance of the various income inequality coefficients.

income inequality is not contemporaneously related to physical and general health but is related with a lag. For example, income inequality may contemporaneously affect mental health, which over time affects physical and general health. Wilkinson's hypothesis that income inequality increases psychosocial stress may also fit with the observed mental health and income inequality relationship if we accept that mental health measures are better measures of psychosocial stress than other measures of health.

The GE(-1) income inequality index places more emphasis on differences in the bottom of the income distribution. I estimated a regression to test whether changes in the GE(-1) index were having an equal effect on the mental health of people belonging to different parts of the income distribution. In this regression, I interacted a dummy variable, which equalled one for people in the bottom 50 percent of the income distribution and was zero for those in the top 50 percent of the income distribution, with the GE(-1) income inequality variable. The coefficient on the GE(-1) variable was -8.46 (t-statistic of 3.85) while the coefficient on the interaction term was -4.34 (t-statistic of 4.206).²⁵ I conclude from this regression that changes in the GE(-1) index appear to affect the mental health of people differently depending on their position in the income distribution. In particular, those at that bottom of the income distribution appear to be more adversely affected by an increase in income inequality.

²⁵ I also examined this effect by estimating two separate regressions, one for those in bottom half of the income distribution and one for those in the top half. The results of these regressions, where all coefficients are able to change, were very similar to those presented in a dummy variable approach.

4.4.2 Regression Results – Other Explanatory Variables

There is a large literature that explores the relationship between socio-economic variables and health status. In Chapter 5, I have discussed in detail the relationships between education and health, and income and health. In Chapter 3, I have considered the relationship between labour force status and health. In this section, I note some data set specific issues that arise in the education, income and health relationships, and examine the effect of other socio-economic variables on health focusing on those not discussed elsewhere in the thesis.

Table 4.6 show regressions for self assessed health status including a Gini coefficient calculated at both levels of geography and with and without education variables. This was done for two reasons. First, to see if education was having an independent and significant effect on health; and secondly, because only half the sample was available when using education as an explanatory variable. Education was highly significant whilst the coefficient on the Gini coefficient was insignificant regardless of whether education was included. It appears likely then that although education is an important explanatory variable, regression results for the SF-36 health measures are unlikely to change if education variables were able to be included.

One interesting feature of these regressions was that the coefficients on the second and third income deciles are negative and significant compared to the first income decile indicating poorer health for this groups compared the first income decile.

²⁶ Upon closer investigation I discovered that there were a significant number of people

²⁶ I also estimated regressions where age dummy variables were interacted with the log of income. The results of these regressions suggest that income has the biggest impact on the health of persons aged 45 to 74 years.

reporting zero or negative income (which was coded as zero). Of this group reporting zero income, many were self-employed. When looking at the self assessed health status of persons who are in income units (households) where one or more persons is self employed these persons tend to report better health than the rest of the sample.²⁷ The peculiar income effect persists even after attempting to account for income reporting problems by including a dummy variable for self-employed persons.²⁸ A regression analysis excluding all the income units that contained self-employed persons was also undertaken. The results of this analysis did not vary when compared to the results of analyses presented in this paper.

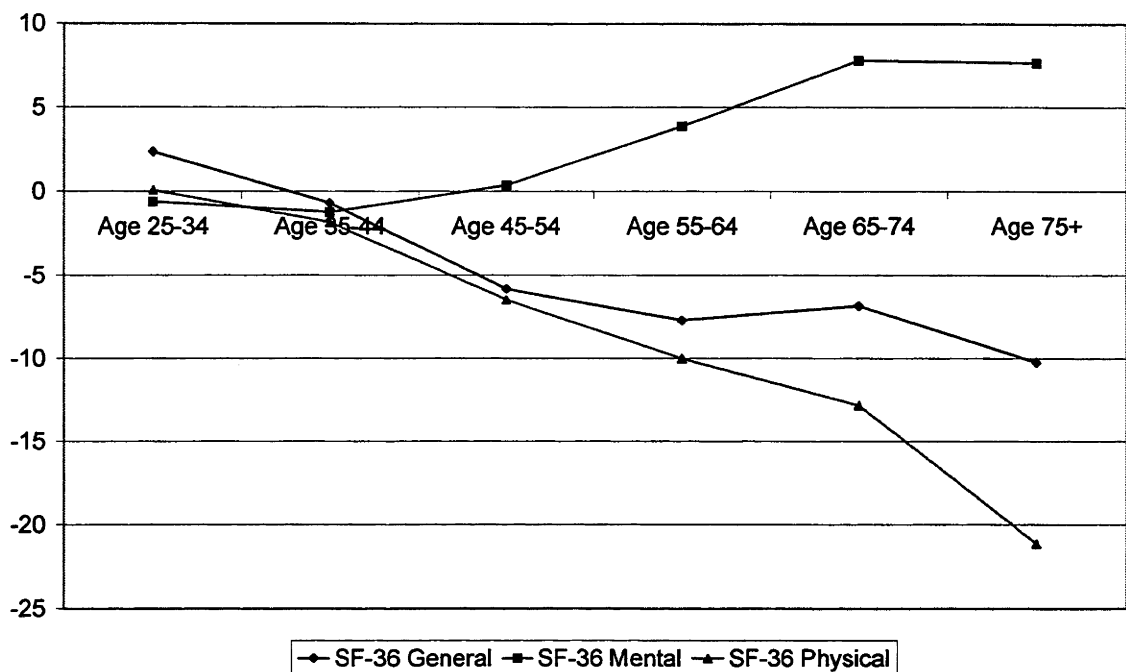
A negative relationship between age and health was found for both self assessed health status and the SF-36 Physical and General health measures. This was not the case when using the SF-36 mental health measure as the dependent variable. For the SF-36 mental health variable, older age groups were associated with better mental health. In Table 4.7b, I present for each SF-36 health measure the percentage difference (compared to the mean) of the effect of each explanatory variable. For example, SF-36 General Health for persons in the age group 65 to 74 years is 6.82 percent lower than the mean. In Figure 4.1, I present age profiles for all SF-36 variables based on the percentage differences. Figure 4.1 clearly shows the quite distinct age pattern of SF-36 Mental Health compared to SF-36 Physical and General health.

²⁷ It is hard to disentangle other influences such as employment versus non-employment and age from the self-employment variable.

²⁸ This raises the possibility that current income (as measured by gross personal income) may not be the best measure of purchasing ability. An alternative, such as consumption maybe a better measure of relative purchasing ability than income in this circumstance. Unfortunately, there were no measures of consumption in the data set.

Figure 4.1

Age Profiles for SF-36 Variables – Percent Difference from Means



The marital status-separated group was associated with a large negative effect on SF-36 Mental health. Other studies (see Goldberg and Williams, 1988 for a review) have also found a strong negative effect on mental health of the marital status category separated. This is discussed further in Chapter 3.

For SF-36 General and Physical health, apart from the large age effects, the smoking status groups were also relatively important. For example, SF-36 General Health was 7.53 percent lower for the smoking status group compared to those who had never smoked. Other studies have also found that smokers and ex-smokers have significantly lower SF-36 scores see for example, Wilson *et al.* (1999) and Woolf *et al.* (1999).

Table 4.6

Ordered Probit Regressions - Self Assessed Health Status - Trimmed 1% and Zeros

Regression	Ordered Probit (Region SLA)				Ordered Probit (Region SD)			
	1		2		3		4	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Age								
Age 25-34	-0.04	-1.65	-0.11	-3.34	-0.03	-2.50	-0.09	-3.75
Age 35-44	-0.12	-4.48	-0.21	-5.87	-0.11	-4.63	-0.19	-5.01
Age 45-54	-0.31	-9.54	-0.39	-9.94	-0.29	-11.31	-0.34	-9.17
Age 55-64	-0.45	-13.10	-0.54	-12.00	-0.42	-14.84	-0.50	-18.21
Age 65-74	-0.40	-10.09	-0.43	-8.58	-0.37	-10.39	-0.39	-9.30
Age 75+	-0.61	-12.74	-0.66	-9.57	-0.55	-11.67	-0.58	-8.97
Smoking								
na	0.35	9.22	0.00	-0.01	0.34	12.77	-0.01	-0.16
Smoker	-0.36	-20.07	-0.36	-15.09	-0.36	-22.91	-0.36	-19.15
Ex-smoker	-0.10	-5.80	-0.09	-4.17	-0.10	-8.22	-0.11	-5.91
Marital Status								
Married	0.02	1.08	0.06	1.90	0.02	1.41	0.04	1.50
Defacto	-0.08	-2.43	-0.03	-0.58	-0.06	-2.31	-0.01	-0.23
Separated	0.01	0.15	0.05	0.75	-0.01	-0.14	0.03	0.54
Divorced	0.06	1.68	0.07	1.26	0.07	1.88	0.06	1.36
Widowed	0.07	1.49	0.14	2.27	0.08	2.22	0.16	3.02
Female	0.03	1.98	0.07	3.36	0.04	3.17	0.08	4.44
Self employed	0.10	3.13	0.11	2.24	0.10	3.00	0.11	2.43
Education								
Degree or higher			0.22	7.38			0.24	7.16
Diploma +			0.11	4.81			0.11	6.83
Basic Skilled			0.08	1.57			0.10	2.29
Employment Status								
NA								
Employed	0.30	14.51	0.35	11.46	0.30	16.90	0.35	15.96
Unemployed	0.25	6.53	0.34	5.89	0.27	8.16	0.35	6.05
Equivalent Income								
Decile 2	-0.17	-4.73	-0.14	-2.64	-0.16	-5.86	-0.15	-3.33
Decile 3	-0.16	-4.30	-0.13	-2.20	-0.15	-5.51	-0.15	-3.24
Decile 4	0.02	0.54	0.04	0.80	0.03	0.82	0.05	1.28
Decile 5	0.16	4.47	0.16	3.17	0.15	5.17	0.14	3.31
Decile 6	0.16	4.43	0.13	2.58	0.15	5.41	0.12	3.53
Decile 7	0.21	5.93	0.21	4.18	0.21	6.24	0.20	5.79
Decile 8	0.21	5.75	0.19	3.52	0.21	7.86	0.17	4.80
Decile 9	0.30	7.87	0.23	4.72	0.30	9.41	0.22	5.94
Decile 10	0.37	9.59	0.33	5.90	0.38	10.83	0.31	6.83
Gini Coefficient	0.23	0.89	0.45	1.22	-0.46	-0.77	-0.53	-0.62
Inter 1	-1.78	0.09	-1.66	0.14	-2.00	0.20	-1.99	0.29
Inter 2	-0.91	0.09	-0.80	0.13	-1.12	0.20	-1.12	0.29
Inter 3	0.02	0.09	0.17	0.14	-0.19	0.20	-0.15	0.30
Inter 4	1.09	0.09	1.21	0.14	0.87	0.20	0.88	0.30
Log Likelihood	-36879		-17803		-45487		-21780	
No of Obs	27154		13116		33436		16047	

Omitted Variables: Never married, Never smoked, age 15-25, Equivalent income decile 1, Education category no higher qualifications, male. Self assessed health status is ordered from poor health through to excellent health.

Table 4.7a

Regressions SD Level – Trimmed 1% and Zeros

	SF-36 General Health Tobit		SF-36 Mental Health Tobit		SF-36 Physical Health Tobit	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Age						
Age 25-34	1.69	2.99	-0.30	-1.00	0.04	0.18
Age 35-44	-0.50	-0.69	-0.61	-1.49	-0.91	-4.01
Age 45-54	-4.16	-5.72	0.18	0.46	-3.23	-11.85
Age 55-64	-5.53	-6.28	1.94	3.28	-5.01	-10.82
Age 65-74	-4.89	-4.98	3.90	7.66	-6.42	-11.01
Age 75+	-7.34	-4.77	3.82	4.84	-10.57	-24.62
Smoking						
na						
Smoker	-5.40	-11.62	-1.51	-6.23	-1.16	-5.77
Ex-smoker	-0.78	-2.06	-0.13	-0.91	-0.80	-3.69
Marital Status						
Married	0.85	1.46	0.99	4.08	-0.34	-1.35
Defacto	-1.13	-1.45	0.18	0.49	-1.06	-2.66
Separated	0.41	0.28	-2.40	-4.27	0.26	0.42
Divorced	1.83	2.15	0.32	0.76	-0.78	-1.69
Widowed	2.69	2.25	1.25	2.11	-0.69	-0.93
Female	2.05	6.48	-1.26	-6.95	0.46	3.28
Self employed	1.15	1.42	0.02	0.08	0.43	1.50
Employment Status						
NA						
Employed	7.59	10.43	1.91	4.54	3.27	11.41
Unemployed	6.58	6.78	1.90	3.74	3.35	7.27
Equivalent Income						
Decile 2	-3.22	-3.36	-0.56	-1.29	-1.06	-2.21
Decile 3	-3.53	-3.47	-0.64	-1.47	-1.27	-2.82
Decile 4	0.16	0.14	0.57	1.63	0.13	0.26
Decile 5	2.26	2.32	1.35	2.69	0.70	1.36
Decile 6	2.70	2.77	1.34	3.47	1.06	2.83
Decile 7	2.91	3.07	1.71	5.20	1.14	3.55
Decile 8	2.77	2.86	1.92	4.22	1.08	3.06
Decile 9	4.85	5.03	2.28	5.21	1.53	3.25
Decile 10	3.72	4.53	1.97	5.25	1.91	4.48
Gini Coefficient	-17.37	-1.42	-12.94	-2.56	2.27	0.43
Constant	73.17	16.86	51.84	28.22	49.23	28.08
se	20.66	108.87	9.81	121.42	8.99	84.71
Log Likelihood	-64241		-55840		-54520	
No of Obs	15285		15083		15803	

Omitted Variables: Never married, Never smoked, age 15-25, Equivalent income decile 1, Education group no higher qualifications, Employment status – Not in Labour Force, male..

Table 4.7b

Regressions SD Level – Trimmed 1% and Zeros

	SF-36 General Health Tobit	SF-36 Mental Health Tobit	SF-36 Physical Health Tobit
	% Difference from mean	% Difference from mean	% Difference from mean
Age			
Age 25-34	2.36	-0.60	0.08
Age 35-44	-0.70	-1.22	-1.82
Age 45-54	-5.80	0.36	-6.45
Age 55-64	-7.71	3.89	-10.01
Age 65-74	-6.82	7.81	-12.83
Age 75+	-10.23	7.65	-21.12
Smoking			
na			
Smoker	-7.53	-3.03	-2.32
Ex-smoker	-1.09	-0.26	-1.60
Marital Status			
Married	1.19	1.98	-0.68
Defacto	-1.58	0.36	-2.12
Separated	0.57	-4.81	0.52
Divorced	2.55	0.64	-1.56
Widowed	3.75	2.50	-1.38
Female	2.86	-2.52	0.92
Self employed	1.60	0.04	0.86
Employment Status			
NA			
Employed	10.58	3.83	6.53
Unemployed	9.17	3.81	6.69
Equivalent Income			
Decile 2	-4.49	-1.12	-2.12
Decile 3	-4.92	-1.28	-2.54
Decile 4	0.22	1.14	0.26
Decile 5	3.15	2.70	1.40
Decile 6	3.76	2.68	2.12
Decile 7	4.06	3.43	2.28
Decile 8	3.86	3.85	2.16
Decile 9	6.76	4.57	3.06
Decile 10	5.19	3.95	3.82

Omitted Variables: never married, never smoked, age 15-25, Equivalent income decile 1, Education group no higher qualifications, Employment status – Not in Labour Force, male. See Table 4.3 for means of variables.

4.4.3 Results Summary

The regression analysis suggests that health status and income inequality are not robustly related in this Australian data set. The relationship between health status and income inequality was sensitive to the choice of health status measure, trimming the data set, and the measure of income inequality. Kennedy *et al.* (1998) suggest that for the US self assessed health status is robustly related to the Gini coefficient. However, similarly to the results presented here Weich *et al.* (2000a) find that self assessed health status is not robustly related to different measures of income inequality in the UK. In another paper Weich *et al.* (2000b) find that measures of mental health are moderately related to income inequality particularly for those “with the highest incomes within regions”. In this study, while SF-36 mental health is only related to particular measures of income inequality (those that emphasise the bottom of the income distribution) the effect is strong in these particular cases. Unlike, Weich *et al.* (2000b) I find that when SF-36 mental health is related to income inequality the effect is stronger in the bottom of the income distribution compared to the top half.

I conclude from this analysis that for Australia in general health is not robustly related to income inequality but that particular measures of health (mental health) are exhibiting a strong relationship to particular measures of income inequality which emphasise changes in the bottom half of the income distribution. It may be for example, that changes in the bottom half of the income distribution represent more carefully changes that matter most for psycho-social stress and by extension mental health.²⁹

²⁹ It is important to note that while I have identified a possible negative relationship between income inequality and mental health the magnitude of this relationship is relatively small. For example, a 50

4.4.4 Deaton and Paxson's Model

Most examinations of the income inequality and health relationship have been empirical in nature. That is, an empirical regularity has been tested for followed by possible explanations of the empirical regularity. One of the explanations of the income inequality and health relationship, due largely to Wilkinson, involves interpreting income distribution as a ranking mechanism. Crudely speaking, in areas where there are larger differences in the income distribution most people feel themselves to be of a lower rank in society, particularly compared to the top of the income distribution and this adversely affects their health. Thus, all persons except those at the very top of the income distribution are affected by an increase in income inequality. Deaton and Paxson's (1999) model is an attempt to formalise mathematically the relationship between relative income and health.

Regressions were run to estimate the Deaton and Paxson (1999) model.³⁰ In Deaton and Paxson's model, the variance of log income is the measure of income inequality. Regressions were run using self assessed health status as the dependent variable rather than SF-36 variables so I could control for educational attainment. Following on from equation (5), in a cross section data set the Deaton and Paxson model takes the following form

$$h_{ij} = \beta X_{ij} + \alpha LI_{ij} + \gamma Var(LI_j) + \delta LI_{ij} Var(LI_j) + \varepsilon_{ij} \quad (6)$$

percent increase in the GE(0) measure from 0.23 to 0.33 of income inequality would only decrease SF-36 Mental health by 1. This is a relatively small decrease given the size of the increase in inequality and that the standard deviation of SF-36 Mental Health is 10.

³⁰ Income inequality measures were calculated at the Statistical Division level in all these regressions.

where LI_{ij} is the log of equivalised income and $Var(LI_j)$ is the variance of log income.

Before estimating Equation (6), I estimated two regressions where I used the Gini coefficient and the variance of log income as the measures of income inequality (see Table 4.8.). The regression including the Gini coefficient as the measure of income inequality was used to test whether using log income would vary results compared to using a series of income dummies to control for the level of income. In both regressions, the Gini coefficient was insignificant. In regressions where the variance of log income was included as the measure of income inequality the coefficient on the variance of log income was significant and negatively related to health. The variance of log income is more similar to the GE(0) index, which in early regressions was more strongly associated with health than the Gini coefficient. Deaton and Paxson (1999) found that the variance of log income and the Gini coefficient were significantly related to health, though surprisingly both were positively related to health.

I then estimated Equation (6) to test Deaton and Paxson model. Results are reported in Table 4.8. This model includes an interaction term between log income and the variance of log income. The coefficient on the interaction term was positive but not significant. This sign of this coefficient accords with Deaton and Paxson's model whereby an increase in income inequality leads to a steeper gradient between income and health.

Table 4.8

Regressions - Self Assessed Health Status SD – Trimmed 1% and Zeros

Regression	Ordered Probit (Region SD)					
	1		2		3	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Age						
Age 25-34	-0.10	-4.15	-0.10	-4.25	-0.10	-4.25
Age 35-44	-0.20	-5.31	-0.20	-5.67	-0.20	-5.69
Age 45-54	-0.36	-9.56	-0.37	-9.92	-0.37	-9.97
Age 55-64	-0.53	-19.65	-0.54	-20.39	-0.54	-20.30
Age 65-74	-0.44	-10.01	-0.45	-10.32	-0.45	-10.33
Age 75+	-0.63	-9.72	-0.64	-9.88	-0.64	-9.91
Smoking						
na	0.01	0.09	0.01	0.08	0.01	0.07
Smoker	-0.36	-18.95	-0.36	-18.73	-0.36	-18.77
Ex-smoker	-0.11	-6.00	-0.11	-6.07	-0.11	-6.05
Marital Status						
Married	0.04	1.35	0.03	1.20	0.03	1.21
Defacto	-0.02	-0.54	-0.02	-0.61	-0.02	-0.61
Separated	0.02	0.40	0.02	0.42	0.02	0.42
Divorced	0.05	1.12	0.05	1.12	0.05	1.12
Widowed	0.14	2.93	0.14	2.94	0.14	2.95
Female	0.08	4.52	0.08	4.62	0.08	4.63
Self employed	0.11	2.46	0.11	2.48	0.11	2.48
Education						
Degree or higher	0.24	7.08	0.25	7.79	0.25	7.72
Diploma + Skilled	0.11	6.98	0.11	7.34	0.11	7.37
Basic Skilled	0.10	2.38	0.10	2.39	0.10	2.39
Employment Status						
NA						
Employed	0.40	19.31	0.40	19.41	0.40	19.30
Unemployed	0.36	6.30	0.36	6.39	0.36	6.38
Log of Income	0.18	9.36	0.19	10.12	0.14	1.05
Gini Coefficient	-0.60	-0.70				
Variance of Log			-0.69	-2.81	-1.99	-0.66
Interaction					0.13	0.43
Inter 1	-0.22	0.38	-0.25	0.22	-0.78	1.31
Inter 2	0.64	0.38	0.62	0.22	0.08	1.31
Inter 3	1.61	0.38	1.59	0.22	1.05	1.31
Inter 4	2.64	0.38	2.62	0.21	2.08	1.30
$\partial / \partial (\ln(y))$					0.19	1.54
$\partial / \partial (Var(\ln(y)))$					-0.66	-1.05
Log Likelihood	-21810		-21803		-21803	
No of Obs	16047		16047		16047	

Omitted Variables: never married, never smoked, age 15-25, Equivalent income decile 1, Education group no higher qualifications, Employment status – Not in Labour Force, male. Self assessed health status is ordered from poor health through to excellent health.

To see the full effect of log income and the variance of log income on self assessed health status the derivatives with respect to these variables are evaluated at their means and presented in Table 4.8. My estimates of Deaton and Paxson's (1999) model are a little difficult to interpret given the insignificance of key variables. However, I did find that signs of coefficients on key variables were as predicted by their model.

It is interesting to compare the results for Deaton and Paxson's model with earlier results. In earlier regressions, it was found that the mental health of people in the bottom half of the income distribution was more adversely affected by changes in the GE(-1) income inequality index than the mental health of those in the top half of the income distribution. This is consistent with the positive (admittedly insignificant) coefficient on the interaction of log income and the variance of log income arising out of Deaton and Paxson's model. I estimated Deaton and Paxson's model using SF-36 Mental health as the dependant variable rather than self assessed health status and found that the coefficients on the variance of log income and on the interaction of log income and the variance of log income were both insignificant.

The heavily qualified support for Deaton and Paxson's (1999) model found in this study is contrary to findings in Deaton and Paxson's own work. Deaton and Paxson found that income inequality was having a protective effective on health contrary to the predictions of their model. At best the results of this study suggest that relative income may be related to health but that Deaton and Paxson's statistical framework is either inadequate (the model is miss-specified) or the relationship is weak.

4.5 Income Inequality and Health Conclusions

The results of this study differ from those found by other authors such as Kennedy *et al.* (1998). Whilst some income inequality indices had an independent and negative effect on health status, other indices did not. I conclude that for Australia, the relationship between health and income inequality is generally not robust in the face of applications of different measures of health, income inequality, and trimming the data set. There was some evidence of a relationship between mental health and income inequality indices that emphasise the lower half of the income distribution.

When income inequality was measured at the more aggregate level (Statistical Division), results varied across the different measures of health. In self assessed health status, SF-36 general health and SF-36 mental health regressions the GE(-1) index was significant and negative. Other measures of income inequality were generally not related to these health status measures. All income inequality indices were not significantly related to SF-36 physical health. I found that educational attainment was having an independent, highly significant effect on self assessed health status, and that other important variables were age, income, and smoking status.

I found that the income inequality and health relationship was not robust to different approaches to trimming the data set. In particular, there was a significant negative relationship between the Gini coefficient (measured as the SD level of region) and self assessed health status when all observations were included. However, when zero income observations and the top and bottom 1 percent of the income distribution were excluded this relationship was insignificant. Many studies arbitrarily exclude zeros and trim their data sets as I have done in this study. Therefore, since it is clear that trimming the data makes a difference to results we need to be very careful in comparing studies. Variation in results in the face of trimming the data set is also more

evidence that the relationship between income inequality and health is not robust in Australia.

I did find qualified support for Wilkinson's hypothesis that the regional level at which income inequality was measured matters. In this study, income inequality measured at a relatively disaggregated level of region had no effect on health, whilst income inequality measured at a more aggregate level of region did have an effect on self assessed health status and SF-36 mental health for some income inequality indices.

In a recent paper by Ross *et al.* (2000) it was reported that income inequality was not related to Canadian mortality whilst it was related to USA mortality. Ross *et al.* (2000) suggested that the lack of a relationship in Canada might be due to Canada's health and social welfare system offsetting the negative health effects of income inequality. If this were the case, a similar reason could be used to explain why there is no (robust) relationship between income inequality and health status in Australia as the Australian health and social welfare system is similar to Canada's. However, the significant relationship between income inequality indices that emphasise difference in the bottom of the income distribution and mental health may provide us with another reason for why we observe a health and income inequality relationship in some countries but not others.

It may be the case that changes in the bottom of the income distribution adversely affect all persons mental health and that in countries such as the USA these mental health effects have had more general health effects over time. In countries such as Australia and Canada changes in the bottom of the income distribution may be more recent and therefore are only having a contemporaneous effect on mental health but

potentially affecting general health in the longer term.³¹ This may also be true for Britain where Weich *et al.* (2000b) find a relationship between income inequality and mental health.

In interpreting the relationship I found between mental health and income inequality indices that emphasise the bottom of the income distribution I am implicitly suggesting that other measures of income inequality and health are miss-specified versions of the correct model. This suggests that the correct model is one that relates mental health to income inequality measures that emphasise the bottom of the income distribution. Clearly such a suggestion is preliminary and highly speculative but is in keeping with the newness of the developing health and income inequality literature.

The results of this analysis are also preliminary, particularly given the potential difficulties in measuring income. In this study, even after controlling for age and other important characteristics I found that people in the lowest income decile are associated with better health than are persons in the second and third income deciles. This is highly likely to be indicative of income measurement issues and a natural way to extend the analysis of this paper is to seek better measures of income or perhaps attempt to estimate more appropriate measures of income such as permanent income. It is also important to consider using other health cross-sections and to include dummy variables

³¹ There is also the question of why health is related to different measures of income inequality in the USA but not in Australia. In Australia, only income inequality measures reflecting changes in the bottom of the income distribution are related to health. It could be the case that income inequality measures for the USA have changed across all parts of the income distribution, thus a change in income inequality at the top of the income distribution is highly correlated with a change at the bottom of the income distribution. In Australia changes maybe more focused on the bottom half of the income distribution and not correlated with changes in the top.

for regions. This would allow us to disentangle fixed regional contributions to health from variations in regional income inequality.

This Chapter took the opportunity to estimate a new and interesting model of the income inequality and health relationship developed by Deaton and Paxson (1999). I found some support for Deaton and Paxson's model. Models such as this are an important development in this literature as we try to understand better an interesting but perhaps not as robust – as first thought – empirical phenomenon.

Appendix 4A: Auxiliary Health and Income Inequality Tables

Table 4A.1: Variable Definitions

Variable	Definition
Self Assessed Health Status (SAHS)	Responses to the self assessed health status question were scored as follows (1=excellent, 2=very good, 3=good, 4=fair, 5=poor).
SF-36	There were three SF-36 measures of health used in this analysis. The general health dimension and the physical and mental health summary measures. See Australian Bureau Statistics (1995) for a more detailed description of these variables.
Equivalent Income	Equivalent income was used as both a continuous variable and coded according to a person's equivalent income decile. The equivalent income measure took into account different household types by applying OECD equivalence scales at the income unit level. I also use the log of equivalent income and the variance of log equivalent income by geographical region.
Age	Age is defined in 7 groups, age 15 to 24 years, age 25 to 34 years, age 35 to 44 years, age 45 to 54 years, age 55 to 64 years, age 65 to 74 years and age 75 years and over. When SF-36 measures are used the first age group becomes 18 to 24 years.
Sex	Coded as females =1 and males = 0 in regressions.
Educational Attainment	There were four education groups: bachelor's degree or higher, Diploma or skilled, Basic skilled and no higher qualifications.
Smoking Status	There were 4 smoking status categories: smoker, ex-smoker, never smoked and a group for who response was not obtained.
Marital Status	There were 6 marital status groups; married, defacto, separated, divorced, widowed, and never married.
Employment Status	Employment status was represented by 3 groups: employed, unemployed, and not in the labour force.
Self Employed	This was a dummy variable equal to 1 if one or more persons in the income unit were self employed otherwise the variable was 0.

5. The Relationship between Education and Health in Australia and Canada

5.1 Introduction

The relationship between education and health has been studied widely by economists, sociologists and health researchers. Whilst there is general acceptance of a positive relationship between education and health, explanations of this relationship are still much debated.

In order to frame effective health policy, it is important to determine not only if there is an association between education and health but also if there is a positive causal relationship. If there is a causal relationship, public health policy makers will need to consider the effects of education policy when forming optimal health policy. It is possible that one of the most effective public health policies is to increase the general level of education in the population.

In their review of education and health studies, Grossman and Kaestner (1997) discuss three broad explanations of the relationship between education and health. The first is that education improves health, the second that education and health are related through their relationship to a third variable, and the third that health improves education. Grossman and Kaestner (1997) note, “the three explanations are not mutually exclusive”, and this makes it difficult to identify the most significant explanation.

There are two theories for why education causes health. One suggests that additional education increases an individual’s ability to produce health given a set of inputs, technical efficiency. A related explanation is allocative efficiency: here

additional education improves an individual's ability to make the best choice of inputs with which to produce health.¹ In this Chapter, health production functions are estimated for Australia and Canada to examine technical and allocative efficiency. By comparing results for Australia and Canada, I gain more insights into how education might affect health and further establish the robustness of relationships. Importantly, the similarities of the Australian and Canadian data sets used in this study allow me to very carefully compare results. When estimating health production functions I also consider the impact of partners' education on health production. This aspect of the relationship between education and health is not often considered but clearly could be significant.

The second explanation of the relationship between education and health is that individuals who invest in education have low rates of time preference (a low discount rate) and individuals with a low rate of time preference will also invest more in health. In this case, there is not necessarily a direct relationship between education and health; the association is because of their relation to a third variable, such as time preference.²

One way to think about technical and allocative efficiency and time preference is in terms of heterogeneity. Technical and allocative efficiency may capture heterogeneity in health production while time preference is associated with heterogeneity in the discount rate. For technical and allocative efficiency, the heterogeneity in health

¹ That is, given a set of inputs individuals with higher education will choose a more efficient combination of inputs in producing health than would individuals with less education.

² The third variable explanation doesn't have to be related to time preference. An alternative common third variable might be ability.

production is captured by education where for time preference the origin of heterogeneity is less clear.

The third explanation for why education and health are related is that health causes education; I do not consider the issue of reverse causation in this Chapter. However, I do discuss a model developed by Berger and Leigh (1986) that allows for health in an earlier period to affect education. In this Chapter, I am primarily interested in clarifying the efficiency and time preference explanations of how education affects health and providing some preliminary empirical evidence of their relative importance.³

The Chapter is structured as follows: In Section 5.2, efficiency and time preference explanations of the education and health relationship are set out. The data underlying my analysis is discussed in Section 5.3 followed by an examination of the association between education and health in Australia and Canada including a shift-share analysis in Section 5.4. In Section 5.5, I present empirical evidence for each explanation of the association and the Chapter concludes with a discussion of the methodological issues in Section 5.6.

5.2 Models of the Education and Health Relationship

5.2.1 Technical Efficiency in Health Production

The technical efficiency explanation of the education health relationship arises directly out of Grossman's (1972) model of health (human) capital. In Grossman's

³ This empirical analysis in this Chapter focuses on the 25 years plus age group. This may reduce some of the potential for reverse causation as most investment in education has already taken place by age 25.

health capital model, individuals maximise their lifetime utility with respect to wealth, time, and technical constraints.

Following Grossman (1972) the health capital model can be represented algebraically as

$$U = U(\phi_0 H_0, \dots, \phi_n H_n, Z_0, \dots, Z_n) \quad (1)$$

$$h_i = \phi_i H_i \quad (2)$$

$$H_{i+1} - H_i = I_i - \delta_i H_i \quad (3)$$

$$I_i = I_i(M_i, TH_i : E_i) \quad (4)$$

$$Z_i = Z_i(X_i, T_i : E_i) \quad (5)$$

$$TW_i + TL_i + TH_i + T_i = \Omega \quad (6)$$

$$\sum \frac{P_i M_i + V_i X_i}{(1+r)^t} = \sum \frac{W_i TW_i}{(1+r)^t} + A_0 \quad (7)$$

The arguments of the utility function (equation 1) are healthy time $\phi_i H_i$ and other goods Z_i (usually represented as a single composite good). As this is a household production model, individuals produce these goods under the technical constraints of each production function, equations 4 and 5. In equations 4 and 5 M_i and TH_i are market goods and time used to produce health investment, X_i and T_i are market goods and time used to produce other goods, and E_i is education or human capital. The prices of inputs M_i and X_i are P_i and V_i respectively and appear in the wealth constraint, equation 7. The other variables in the wealth constraint are W_i , TW_i , A_0 and r ; the wage rate, time working, non-labour sources of income and the market interest rate respectively. The arguments of the time constraint (equation 6) are TL_i , time lost to sickness, Ω total time available, and TH_i and T_i defined earlier.

In this model, health is a capital stock that depreciates over time but can be increased through investment: equation 3 is a net investment identity and represents this relationship (δ_t is the depreciation rate in equation 3). In Grossman's model health can be thought of as both an investment and consumption good. Individuals consume health (healthy time) directly as well as invest in health to increase future returns from the health capital stock. There is an assumed relationship between the stock of health and healthy time as represented by equation 2. It is assumed that there is a concave relationship between the health stock and healthy time where an additional unit of health stock increases the amount of healthy time at a declining rate.

Grossman makes specific assumptions about the way education affects health production (equation 4) and the production other goods (equation 5). He assumes that increases in education lead to input neutral outward shifts in the production functions.⁴ Thus, as education increases factor (input) proportions will remain constant: that is, Grossman is assuming increases in education induce Hicks neutral technological change.⁵

It is easy to quibble with the long set of assumptions Grossman uses to set up his model. However, one thing the model does do well is point to potential econometric

⁴ Given Hicks neutrality and assuming the health production function is linear in inputs, education can be included as an additional variable in an estimated production function as education will increase the production of health independently of other inputs.

⁵ An implication of the Grossman model is that if there is an increase in demand for health driven by an increase in education this increase in demand can be exactly offset by an increase in the supply of health because of the decreasing cost of producing health. Therefore, an increase in education may induce no change in the amount of inputs used (demanded) for health investment production despite changes in the

issues in directly estimating health production functions. The key point is that some of the inputs into the health production function are choice variables and therefore when directly estimating a production function these variables are not exogenous and coefficients are likely to be correlated with regression error. Rosenzweig and Schultz (1983) show how biased coefficients on health inputs can arise in the direct estimation of health production functions and in what they term augmented health production functions. Rosenzweig and Schultz (1983) define augmented health production functions as combinations of reduced form demand equations (such as those that can be derived from Grossman's model) and some health production inputs. They suggest that the coefficients on health input variables from augmented health production functions can't be interpreted as reflecting just the technical relationship between inputs and health.⁶

One way to avoid the problems associated with directly estimating health production functions - in the case of the Grossman model is to use reduced form equations, health demand equations. In estimating health production functions by a set of reduced form equations or by instrumenting, one has to use prices and other exogenous variables, or find appropriate instruments with which to identify endogenous health inputs. The exogenous variables required are often not available (as is the case in this Chapter) for such an estimation strategy and finding appropriate instruments is difficult and often requires strong and less than plausible assumptions. It is also the case

demand for health.

⁶ In addition to the biases arising out of estimating an augmented health production function, Rosenzweig and Schultz (1983) also show how heterogeneity in the health technology of individuals can also lead to biases in appropriately estimated standard health production functions.

that even when data on the price of health inputs is available prices often do not vary across individuals in cross section data sets. Thus, while direct estimation of the production function is problematic estimation of the full model is often difficult due to data constraints and identification issues.⁷

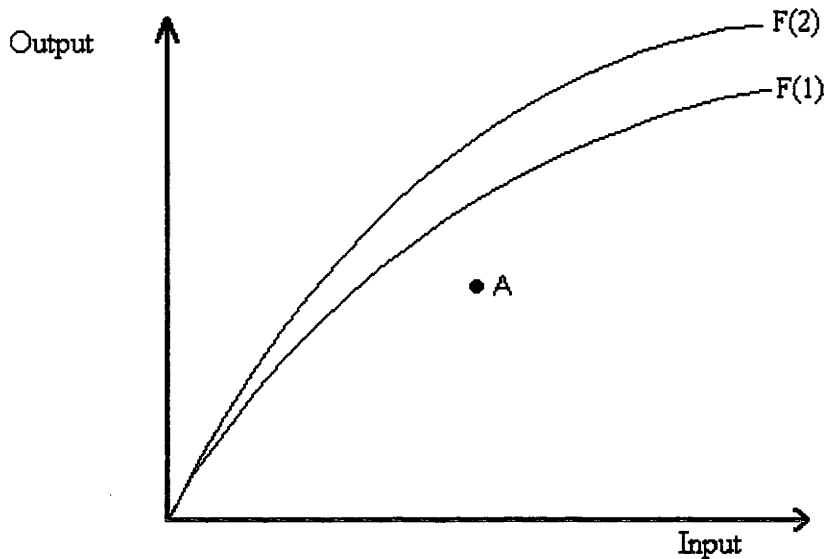
It is worth relating the health production literature to the firm production literature to gain a better understanding of the explanation of how education might affect health. Household production can be treated similarly to firm production and the terms used to describe firm production applied to household production. In the literature on firm production, technical efficiency refers to the case where firms are operating on their production function. That is, firms are producing as much output as possible given their inputs or alternatively they are using the smallest amount of inputs possible given their output.

When Grossman discusses technical efficiency in the context of health production he suggests that the more highly educated operate with reference to a different production function to the less educated. This is different to technical efficiency as defined for firm production. In the context of technical efficiency as defined for firm production more education makes individuals more productive, less education does not mean individuals are technically inefficient since with their production function (technology) they may be producing as much health as is possible.

⁷ Difficulties in estimating more theoretically pure versions of health production functions is probably what explains the more commonly estimated augmented production functions in the health production literature (see for example, Ettner 1996). There have been of course many worthwhile attempts to estimate full Grossman style models, for a review see Grossman (2000).

Figure 5.1

Technical Efficiency and Pure Productivity



This can be illustrated using a one input - one output production relationship. We can think of the single input as a composite of all health inputs and of output as health. In Figure 5.1 $F(2)$ is the production function for a high education group and $F(1)$ for a low education group. Individuals in the low education group may well be operating on their production function $F(1)$ and given their technology this means they are technically efficient. An individual with low education operating at point A is technically inefficient as they could reduce the (health) input they are using to produce the same output (health) or increase current output given input. Similarly, there could be high education individuals operating below their production function. Thus, differences in technical efficiency as described by Grossman are perhaps more accurately described as pure productivity effects. To remain consistent with the existing health production literature I will continue to use the term technical efficiency throughout this Chapter though it is important to keep in mind that this has a specific

meaning in this literature.

5.2.2 Allocative Efficiency in Health Production

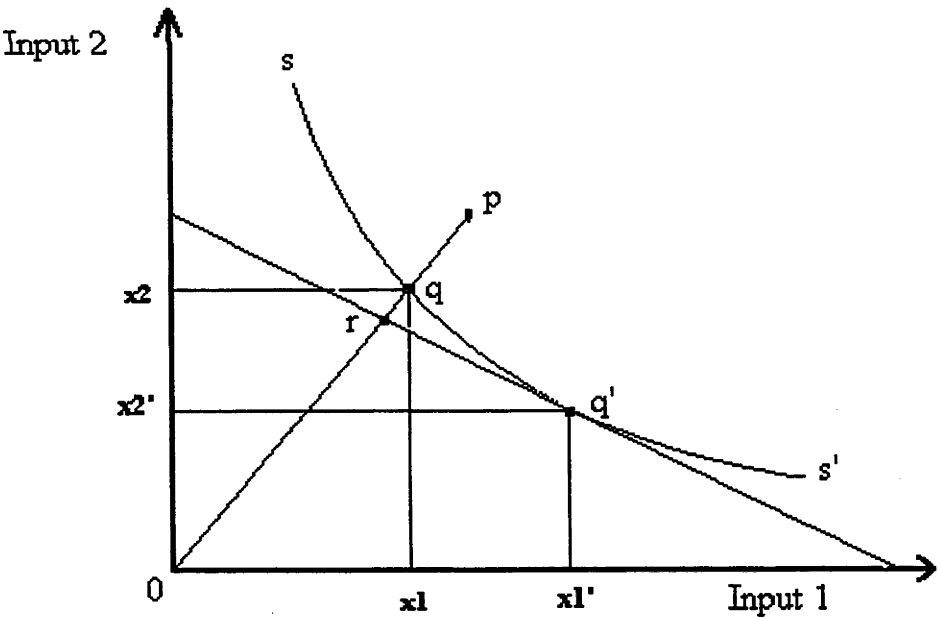
An explanation related closely to technical efficiency is allocative efficiency. Allocative efficiency suggests that more highly educated individuals have a better health knowledge and this leads them to choose better mixes of health inputs than less educated individuals, which results in better health for the more highly educated. Kenkel (1991) examined allocative efficiency by studying how education is related to different health behaviours. It is well accepted that not only are more educated people healthier, but they also consistently choose better health behaviours. For example, they smoke less and exercise more. Kenkel (1991) used information on individuals' knowledge of the effects of smoking, drinking and exercise to see if after incorporating this knowledge the effect of schooling was attenuated or diminished. Kenkel found that whilst the more highly educated do use health information more effectively there was still a direct effect of education on health that was not explained by the allocative efficiency hypothesis.

Allocative efficiency (similarly to technical efficiency) can be defined in the context of firm production. We can think of individuals (like firms) having the same underlying technology but being allocatively inefficient by not using a cost minimising set of inputs. Allocative efficiency can be most easily demonstrated using a one output / two inputs diagram, see Figure 5.2.⁸ In Figure 5.2, the individual operating at point q is

⁸ In Figure 5.2 the line SS' represents an isoquant and all points on this line represent different combinations of the two inputs requires to produce the same amount of output.

allocatively inefficient but technically efficient. They could produce no more output (health) from the inputs they are using but they could further reduce costs by moving to point q' . We could think of one health input as medical care and the other as a composite of all other health inputs. Allocative inefficiency arises because individuals do not appear to understand the budget constraint that is; they do not accurately understand the relative price of inputs. In practice, the effect of this misunderstanding or lack of information would be a decrease in real income or wealth. It also means that these individuals would use inputs in different proportions to allocatively efficient individuals.

Figure 5.2
Allocative and Technical Efficiency



What is implied in some discussions of allocative efficiency is that people with different amounts of education have different underlying production functions which

leads them to use more of some inputs. However, this is technical efficiency rather than allocative efficiency. The only difference between this technical efficiency effect and the one described earlier is that the effect of more education on health is non-neutral. That is, we have relaxed the assumption of homotheticity imposed on the production function in the standard Grossman model.

Both allocative inefficiency and non-neutral variation in technical efficiency lead to differences in health production input proportions. Therefore, differences in input proportions (between education groups) are not necessarily a test of allocative versus technical efficiency. This can only be done if the extra assumption is made that the health investment production function is homothetic.⁹

It is worth reflecting on whether the distinction between allocative and technical efficiency has any relevance to public health policy.¹⁰ Both arguments suggest that education is causally related to health and that increases in education would increase health. However, distinguishing between these two explanations may be important for public health policy given differences in education across the population. For example, putting aside the influence of other variables such as income, technical efficiency suggests that the only way the health of the less educated can be improved when

⁹ The assumption that health is constantly increasing in all inputs may also be problematic. For example, medical care is likely to have a positive marginal product over a range of the health stock and a zero or possibly negative effect beyond this range.

¹⁰ Testing for allocative efficiency as Kenkel did may not distinguish between allocative efficiency and non-neutral technical efficiency. For example, individuals who process health knowledge more effectively may use this knowledge to better determine the relative price of health behaviour, allocative efficiency. Alternatively, they may be better at producing health given this knowledge (a non-neutral change in their production function), technical efficiency.

compared to the more educated is to increase health inputs for the less educated.

Allocative efficiency as posited in this Chapter suggests that a more appropriate response to health inequities driven by educational differences might be to provide more information to the less educated about the relative price of various health inputs.

5.2.3 Time Preference, Education and Health

Another interpretation of the empirical relationship between health and education is that individuals who invest relatively more in schooling will also invest more in health, a time preference effect. For time preference, there is no direct effect of education on health; instead, there is a third variable to which both education and health is related. If the time preference explanation holds an observed relationship between education and health is at least partly spurious.

Fuchs (1982) used estimates of individuals' inter-temporal interest rates to examine time preference and the health and education relationship. He derived estimates of inter-temporal interest rates by surveying persons and asking time-money trade off questions. Fuchs (1982) then estimated regressions on health and included inter-temporal interest rates as an explanatory variable: he found little evidence for time preference in these regressions. However, Farrell and Fuchs (1982) found that additional schooling between the ages of 17 and 24 did not influence smoking behaviour. They viewed this as evidence that schooling and smoking behaviour were caused by a third variable, time preference. They drew this conclusion based on the idea that the additional education did not influence a health habit.

Examining whether particular health habits or behaviours are related to time preference is one way we may be able to gain insights into how health might be related

to education. Evans and Montgomery (1994) tested whether smoking behaviour could be used as an instrument for education in wage equations. If smoking and education were correlated because they both have strong time preference components and smoking was not related to ability, smoking would prove a useful instrument for education in wage equations. They found that smoking was a good instrument for education and they suggested that this was consistent with a time preference explanation for why people smoked and invested relatively less in education. Since there is evidence of smoking and education being related through a common time preference component, this relationship can be used to try to disentangle a time preference component of education when examining the effect of education on health.

Berger and Leigh (1986) took a different approach to Fuchs in attempting to disentangle the effect of education on health. They estimate the following two-equation model.

$$E_1 = X_1\beta_1 + Y_1\beta_2 + H_1\beta_3 + \varepsilon_{s1} \quad (8)$$

$$H_2 = X_2\alpha_1 + E_1\alpha_2 + Z_2\alpha_3 + H_1\alpha_4 + \varepsilon_{s2} \quad (9)$$

In this model: H is health, E is education, X a vector of variables affecting health and education, Y a vector of variables affecting only education, and Z is a vector of variables affecting health. This is a two period model where education in period one affects health in period two. Berger and Leigh estimate this model by using predicted education from equation 8 to instrument for education in health equation 9. They also include the error term from equation 8 and the interaction of the error term and instrumented education. This allows them to gauge the effect on health of unobservables in the education equation, and the interaction of education and

unobservables. Unobservables in the schooling equation can be thought of as a time preference indicator as other potential determinants of education are captured by the explanatory variables included in the education equation. Berger and Leigh concluded that their results were consistent with a direct effect of education on health and not the time preference explanation.

The strength of Berger and Leigh's model is that it allowed them to estimate a direct effect of schooling on health. However, the identification of the direct education effect swings on the power of the instruments used to identify schooling effects.¹¹ Grossman (2000) points out that the some of the instruments used to identify the education effect are likely to be correlated with time preference weakening somewhat Berger and Leigh's conclusions. Grossman concludes that the debate over time preference versus technical and allocative efficiency is largely unresolved.¹²

¹¹ Berger and Leigh used two data sets and different instruments and assumptions in analysis of each data set. In one data set, they merged with individual data aggregate US State level data on education expenditures per capita. In this data set they did not have a past health variable and had to assume that X_1 and X_2 from equations (8) and (9) were the same and that β_3 was equal to zero. In the other data set, they had more information available and used IQ and family background variables to instrument or identify education. In this instance, it appears likely that these variables would be correlated with time preference and thus be correlated with the error term in equation (8).

¹² A variation on the time preference explanation is that individuals who invest in education are after this investment more likely to invest in health. Here education doesn't directly, though in can in part, affect health rather education leads individuals to be more forward looking by lowering their current time preference. Individuals with a lower time preference will invest more in health capital for the future rather than consume health today. This model, which Grossman (2000) discusses in the context of Becker and Mulligan (1994), is difficult to identify and separate from an allocative efficiency argument or a more straightforward time preference determination process. However, it is no less plausible than other models of the education and health relationship. I don't discuss endogenous determination of the discount rate in

The policy implications arising out of Fuchs' time preference explanation of how education and health might be related are clear and appear diametrically opposed to those arising out of the efficiency explanations. The time preference explanation suggests that policies such as increasing the level of education in the population would be largely ineffective in improving public health. If time preference is the most important explanation of why education is related to health, policies which influenced individuals forward looking behaviour would clearly be much more effective in improving the health of the less educated.

5.3 The Data

5.3.1 Australian Data

The Australian Bureau of Statistics (ABS) 1995 National Health Survey is described in Section 2.2.¹³ As noted in Chapter 2, approximately 23,800 dwelling households were surveyed and of these households, approximately half were 'invited' to answer the Short Form 36 health status questionnaire (SF-36). Households selected to respond to the SF-36 were not asked questions about their education, alcohol consumption, health insurance or supplementary women's health questions. In this Chapter, I use that half of the sample where individuals were required to answer questions about their education.

Health is measured using self assessed health status. As noted in Chapter 2, Self

this Chapter. Instead, I focus on efficiency and (Fuchs's) time preference explanations.

¹³ See ABS (1995) Cat no 4363.0.

assessed health status is becoming an increasingly common measure of health in empirical research. However, it does have some limitations, see Sections 2.6 and 4.3.

The income measure used in this analysis is household equivalent income. Household income was equivalised using a modified Henderson equivalence scale, see ABS (1995) for more detail. A continuous household income measure was also constructed using the latest OECD equivalence scale.¹⁴

Education was measured using reported highest educational attainment. The eight categories of educational attainment available in the data set are collapsed to three categories for most of the analysis. Education categories were constructed in the following way. The bachelor degree plus level of education was composed of higher degree, post graduate diploma and bachelors degree, the skilled level of education was composed of the categories diploma, associate diploma, skilled and basic vocational, the no higher education group consisted of persons reporting no higher qualifications. A measure of smoking status was used where the categories were smoking, smoked or never smoked. An exercise index composed of four categories was used in this analysis. The exercise index was constructed by combining nine questions on exercise, see ABS (1995) for more details. Other information included marital status, labour force status, age and gender.

Measures of occupation and employment type were used in testing the robustness of the health equation but are not reported in this Chapter.

¹⁴ See Klaas De Vos *et al.* (1997) for the latest OECD equivalence scale. When using the continuous measure of income only age, marital status, smoking status, education and self employment could be used

5.3.2 Canadian Data

The Canadian National Population Health Survey (CNPHS) was collected over a one-year period from 1994 to 1995. This survey was constructed as follows; *“The sample design considered for the household component of the NPHS was a stratified two-stage design. In the first stage, homogeneous strata are formed and independent samples of clusters are drawn from each stratum. In the second stage dwelling lists are prepared for each cluster and dwellings, or households, are selected from the lists.”* See Statistics Canada (1995) for more details. The response rate for households in this survey was 88.7 percent.

Some of the variables drawn from this survey were the same as those found in the Australian National Health Survey: variables that were the same were self assessed health status, age and sex. Other variables such as highest educational attainment, marital status, labour force status (working status in the CNPHS), smoking status, and physical activity were able to be closely matched to their Australian counterparts. For highest educational attainment the Canadian responses were: no schooling, elementary schooling, some secondary schooling, secondary school graduation, other beyond high school, some trade school etc, some community college, some university, diploma/certificate trade school, diploma/certificate, community College, cegep, bachelor degree, master degree & doctorate. These responses were collapsed into three categories similar to the Australian categories: bachelor degree and higher forming one category, any qualifications post secondary school forming the second category, and secondary school or less the third category. There was less detail available on the

as regression controls.

Canadian marital status variable however the categories were still very similar to the Australian categories. In the Canadian data the measure of exercise is a physical activity indicator, for more details on its construction see Statistics Canada (1995).

One variable which was a little different between the two surveys was the income variable. In the Canadian survey, I have used the derived five-category income measure. This variable is based on income ranges conditional on household size (see Statistics Canada, 1994 for more details). Thus, there is considerable variation in the number of persons in each category with the majority of persons being in the middle income categories. For equivalised Australian household income, the number of persons in each income category is approximately the same as they are coded in income deciles.¹⁵ This means that in the Australian data the range of income between deciles can vary dramatically.

Measures of employment status in the Canadian data were reported differently to those in the Australian data. However, they represent similar groups: unemployed, employed and those not in the labour force. Smoking status was reported in considerably more detail in the Canadian survey. It was possible to collapse the Canadian categories so that they closely resembled the Australian categories of smoking, smoked and never smoked.

5.3.3 Descriptives

In Table 5.1a, I report the distribution of self assessed health status and

¹⁵ They are not exactly the same because of sample restrictions and because the income deciles are constructed using weighted estimates.

education responses. Canadian self assessed health status is slightly higher than that reported for Australia whilst there are also more individuals with higher qualifications in the Canadian data set. In Table 5.1b, I report self assessed health status responses by education for Australia and Canada. The patterns of responses are similar for both countries: those with higher educational qualifications report better health status.

Table 5:1a
Descriptive Statistics – Canada and Australia

Persons aged 25 or more	Australian NHS 1994-95	Canadian NHS 1994-95
	Percentage of sample	Percentage of sample
Self Assessed Health Status		
Excellent	19.23	21.79
Very Good	33.69	36.82
Good	29.71	27.25
Fair	12.93	11.08
Poor	4.45	3.07
Education		
Bachelor +	13.47	13.78
Skilled	32.29	40.49
No Higher	54.24	45.79

Table 5.1b
Descriptive Statistics - Self Assessed Health Status by Education

Persons aged 25 or more	Self Assessed Health Status (%)				
	Excellent	Very Good	Good	Fair	Poor
Australian NHS					
Education					
Bachelor +	28.96	40.61	24.03	4.98	1.42
Skilled	21.06	35.99	29.29	10.31	3.35
No Higher	15.72	30.60	31.37	16.46	5.86
Canadian NHS					
Education					
Bachelor +	34.85	40.16	19.34	4.38	1.26
Skilled	23.46	40.35	25.88	8.09	2.31
No Higher	16.46	32.68	30.85	15.73	4.28

5.4 The Association between Education and Health

5.4.1 *The Association between Education and Health*

I begin by examining the association between education and health in Australia and Canada. By establishing the existence and strength of a relationship between education and health, I provide impetus for examining in detail potential explanations of this relationship.

In Table 5.2, I present the results of ordered probit regressions for Australia and Canada where self assessed health status was regressed on age, income, sex, marital status, smoking status, an exercise index, labour force status and education. An ordered probit model was used because the self assessed health status variable has a natural ordering from poor through to excellent health. A detailed description of the data that underlies this analysis is contained in Section 5.3. The samples for these regressions were restricted to persons aged 25 or more years to consider persons that would have probably completed higher education.

All variables were related to health in the expected way: self assessed health declines with age, increases with income, and increases with the level of educational attainment.¹⁶ In Australian and Canadian regressions I used three collapsed education attainment categories outlined in Section 5.2 to capture differences in education.

¹⁶ There were other variables that I could have included in this regression for example, occupation and employment type. However, there is an issue of collinearity in these data sets both in terms of education and occupation categories being closely related and also older age groups are coded as not applicable for occupation and employment type making it difficult to identify age, employment and occupation effects.

Table 5.2

Ordered Probit Regressions on Self Assessed Health Status

Australian National Health Survey 1994-95			Canadian National Population Health Survey 1994-1995		
Variables	Coefficient	t statistic	Variables	Coefficient	t statistic
Age 30-34	0.041	1.170	Age 30-34	-0.066	-1.734
Age 35-39	-0.051	-1.416	Age 35-39	-0.186	-4.761
Age 40-44	-0.064	-1.700	Age 40-44	-0.244	-5.910
Age 45-49	-0.177	-4.578	Age 45-49	-0.366	-8.658
Age 50-54	-0.205	-4.958	Age 50-54	-0.428	-9.479
Age 55-59	-0.356	-7.914	Age 55-59	-0.539	-11.525
Age 60-64	-0.326	-6.734	Age 60-64	-0.445	-9.056
Age 65-69	-0.188	-3.658	Age 65-69	-0.392	-7.688
Age 70-74	-0.313	-5.710	Age 70-74	-0.442	-8.344
Age 75-79	-0.306	-4.846	Age 75-79	-0.465	-7.886
Age 80+	-0.465	-6.753	Age 80+	-0.499	-8.270
Male	-0.171	-8.791	Male	-0.050	-2.536
Income D 2	-0.195	-4.371	Low middle	0.100	2.421
Income D 3	-0.217	-5.057	Middle income	0.215	5.549
Income D 4	-0.004	-0.087	Upper income	0.383	9.598
Income D 5	0.081	1.858	High income	0.501	10.609
Income D 6	0.061	1.389			
Income D 7	0.120	2.764			
Income D 8	0.109	2.522			
Income D 9	0.131	3.093			
Income D 10	0.215	5.007			
Smoker	-0.279	-11.804	Smoker	-0.297	-12.413
Ex-smoker	-0.103	-4.810	Ex-smoker	-0.120	-5.217
Married	0.124	4.143	Has partner	-0.052	-2.031
Defacto	0.086	1.810	Is separated	-0.074	-2.195
Separated	0.080	1.455			
Divorced	0.112	2.392			
Widowed	0.226	4.513			
High exercise	0.670	15.758	Moderate exer	-0.158	-5.116
Med exercise	0.359	14.864	Inactive exer	-0.384	-14.455
Low exercise	0.187	8.699	Currently wking	0.385	2.397
Employed	0.436	15.489	Not Cur wking	0.343	2.086
Unemployed	0.368	7.145	No wk 12mths	-0.093	-0.574
Bachelor +	0.207	6.934	Bachelor +	0.237	7.472
Skilled	0.117	5.667	Skilled	0.086	4.065
Cut 1	-1.543	0.054	Cut 1	-2.320	0.170
Cut 2	-0.673	0.052	Cut 2	-1.414	0.169
Cut 3	0.302	0.051	Cut 3	-0.441	0.168
Cut 4	1.327	0.052	Cut 4	0.659	0.168
Observations	14148		Observations	13246	
Log Likelihood	-19202.12		Log Likelihood	-17345.58	
Omitted Australian categories: age 25-29, income decile 1, never smoked, no exercise, out of labour force or na, single, no higher education. Omitted Canadian categories: age 25-29, low income, never smoked, single, active exercise, Na or ns labour force, no higher education.					

Regressions were also run where all the available education attainment categories for each country's data set were included.¹⁷ Likelihood ratio tests indicated that restricted regressions (regressions where only three education categories were used) were not statistically different from unrestricted regressions.¹⁸ Given that this restriction holds, I use three education categories to characterise education differences in the analysis that follows.¹⁹

Perhaps the most immediate and striking result from the regressions is that the coefficients on education categories for Australia are very similar to those for Canada. In addition, it is also interesting that the association between education and health can be effectively captured using the same three categories of educational attainment in both countries.

To examine whether the magnitude of the relationship between education and health was similar in Australia and Canada marginal effects were calculated. The base case for this exercise was married males aged 35 to 39 who were in the medium exercise category, and the middle income category. The marginal effects on all self assessed health status categories of an increase in educational attainment are presented in Table 5.3a.

¹⁷ There were eight education categories in the Australian data and twelve education categories in the Canadian data.

¹⁸ Australian results LR Stat 7.63, Chi-squared (5) prob 0.1776, Canadian results LR statistic 9.13, Chi-squared (5) prob=0.1665.

¹⁹ Grossman (1975) found that the education health gradient was significant even at high levels of education, as cited in Fuchs (1982).

For Australia, the probability of reporting excellent health (the highest category of self assessed health status) increases for the skilled education category compared to the no higher education category by 4.1 percentage points or 14.2 percent. For Canada, the probability of reporting excellent health increases by 2.7 percentage points or 11.5 percent for the same change in education categories. The probability of reporting excellent health increases for the higher education category compared to no higher education for Australia and Canada by 7.5 and 7.8 percentage points or 25.6 and 33.7 percent respectively. The results of the ordered probit regressions suggest that not only is education and health related similarly for both countries, but that in both cases the relationship is substantial in size.²⁰

Table 5.3a
Marginal Effects Ordered Probit Regressions on Self Assessed Health Status

	Poor	Fair	Good	Very Good	Excellent
Australia					
Skilled	-0.274	-1.215	-2.544	-0.096	4.130
Bachelor +	-0.439	-2.030	-4.502	-0.503	7.474
Canada					
Skilled	-0.247	-1.062	-1.828	0.441	2.697
Bachelor +	-0.580	-2.683	-5.117	0.550	7.829

The base case is married males aged 35 to 39 who where in the medium exercise category, no higher education, and the middle income category.

²⁰ The relationship between health and other variables was also very similar between countries, for example, the relationship between health and smoking and age categories.

5.4.2 Blinder-style Decomposition

In Section 5.3.3 I noted that for Canada self assessed health status was slightly higher compared to Australia, and that there were also slightly higher proportions in the higher education categories. To examine whether the difference in health status between the two countries could be explained by the difference in their distributions of education, I undertook a Blinder (1974) style decomposition. The health regressions for Australia and Canada can be represented by Equations 10 and 11.

$$H_i^A = \beta_0^A + \sum_{j=1}^2 \beta_j^A E_{ji}^A + \sum_{k=1}^m \beta_k^A O_{ki}^A + \varepsilon_i^A \quad (10)$$

$$H_i^C = \beta_0^C + \sum_{j=1}^2 \beta_j^C E_{ji}^C + \sum_{k=1}^m \beta_k^C O_{ki}^C + \varepsilon_i^C \quad (11)$$

Where H_i^C and H_i^A are the health status of Canadians and Australians respectively, E_{ji} is education, O_{ki} the set other explanatory variables, and the β s the coefficients to be estimates. The health and education variables are the same for Australia and Canada however; the other explanatory variables vary between countries. This was the reason I was not able to undertake a full Blinder decomposition.

Predicted probabilities for two different cases were calculated taking into account that both countries have the same dependent variable and set of education variables. First, predicted probabilities were recalculated for self assessed health status categories for Australia where Canadian coefficients on education categories were used (see equation 12). In this case, I am examining whether the health returns to education in Canada would affect the average level of health in Australia.

$$H_i^A = \beta_0^A + \sum_{j=1}^2 \beta_j^C \bar{E}_{ji}^A + \sum_{k=1}^m \beta_k^A \bar{O}_{ki}^A + \varepsilon_i^A \quad (12)$$

There was virtually no difference in predicted probabilities between a base case (the base case is calculated at the mean of explanatory variables) and the case using Canadian returns to education, see Table 5.3b. This result emphasises the similarities of health returns to education in Australia and Canada.

Second, another set of predicted probabilities for Australia was calculated where the full set of Australian coefficients were used but the Canadian distribution of education (see equation 13). In this case, I am interested in whether variation in the distribution of education between Australia and Canada drives differences in health.

$$H_i^A = \beta_0^A + \sum_{j=1}^2 \beta_j^A \bar{E}_{ji}^C + \sum_{k=1}^m \beta_k^A \bar{O}_{ki}^A + \varepsilon_i^A \quad (13)$$

There was a small change in the predicted probabilities for Australian self assessed health status categories compared to the base case, see Table 5.3b. For example, the predicted proportions in two upper most health status categories increased by 1.6 percent. This means that the difference between these two categories for Australia and Canada falls from 6.9 percent to 5.3 percent.

Table 5.3b

Blinder-Style Decomposition of Ordered Probit Regressions on Self Assessed Health Status for Australia

	Predicted Probabilities for Australian Self Assessed Health Status Categories				
	Poor	Fair	Good	Very Good	Excellent
Australia					
Base Case at the mean of all variables	2.87	12.30	32.67	35.58	16.58
Case 1, Canadian Education Coefficients	2.89	12.35	32.72	35.53	16.50
Case 2, Canadian Education Distribution	2.61	11.61	31.98	36.18	17.63
Canada					
Base Case at the mean of all variables	1.74	9.71	29.45	39.88	19.22

In their review of education and health studies, Grossman and Kaestner (1997) cite more than thirteen US studies that also find that education and health are strongly related. In these studies, health is measured a number of different ways including self assessed health status, the measure of health used in this Chapter. Grossman (2000) concludes that the review conducted by Grossman and Kaestner (1997) “suggests that years of formal schooling completed is the most important correlate of good health”.

5.5 Empirical Evidence for Models of Education and Health

In the following section, I present empirical evidence for technical and allocative efficiency and time preference explanations of the relationship between education and health.

5.5.1 Technical and Allocative Efficiency

I begin by putting to one side time preference and examining the two efficiency explanations. The first explanation – technical efficiency – suggested that education increased the amount of health available to the highly educated individual for a given level of inputs. If I estimate a health production function and assume that the function is linear and homogenous then the coefficient on education captures the shift in technical efficiency per unit of education.

The second explanation – allocative efficiency – was that more highly educated persons were more able to combine inputs efficiently given prices. If technical efficiency is considered in conjunction with assuming health production functions are linear and homogenous in inputs, one way of distinguishing between the two efficiency explanations is to estimate health production functions conditional on education and compare coefficient vectors. Variation in coefficient vectors arising out health production functions estimated conditional on education suggests that inputs vary in their influence on health by education.²¹ However, if individuals with different amounts of education have different underlying production technologies, ie non-neutral technical efficiency, coefficient vectors would also vary between education groups.²² In this case, we cannot distinguish between (non-neutral) technical efficiency and allocative

²¹ If the health production function was linear and homogenous the only observed variation in coefficient vectors between the conditional regressions should be in the constant.

²² We could also use the idea that if an increase in education improves technical efficiency and the health production function is assumed linear and homogenous, factor inputs will continue to be used in the same proportions. Thus, if input proportions conditional on education are compared they should be the same if the technical efficiency homogeneity assumption is correct.

efficiency.

Three regressions were run for Australia and Canada conditional on the collapsed education categories, see Tables 5.4 and 5.5.²³ These conditional regressions contain the same explanatory variables reported in the earlier unconditional regressions, see Table 5.4. The regressions are probably best characterised using Rosenzweig and Schultz's (1983) notion of augmented health production functions, and therefore it is difficult to interpret the estimated functions as production functions as such.²⁴ However, given the unavailability of suitable data to estimate Grossman style health production functions these regression at least give us some insights into the overall pattern of the relationship between health inputs and health.

Likelihood ratio tests of whether coefficients vary between the conditional on education regressions for Australia and Canada rejected the null that they do not vary. Despite the rejection of this restriction, interestingly some coefficients vary little between education groups in particular; those on smoking status, exercise, and labour force status. The largest variation in coefficients appears to be between age and income coefficients, particularly for Australia. In the Canadian regressions, there is a small amount of variation in all coefficients and thus the null hypothesis that all the coefficients are the same is not rejected by as much as in the Australian case. The Canadian and Australian results are suggestive of either allocative efficiency or non-neutral technical efficiency - keeping in mind the caveats surrounding the specification

²³ As before the samples are restricted to persons aged 25 or more years.

²⁴ The coefficients on inputs represent choices (preferences) as well as a technical relationship between inputs and outputs.

of the health production function.

It is instructive to look in more detail at some of the interesting variations in coefficients arising from the conditional on education regressions to identify the sources of differences in health between education groups. Variations in age are particularly interesting as these variations may provide insights into patterns of health investment and depreciation. For Australia, by examining the pattern of age coefficients we see that age-health profiles by education category were quite similar until age 70-74. However, the bachelor plus education category appeared to have a much larger relative decline in health associated with age 75 years and more. This particular age effect may in part be a selection effect. If at younger ages those with no higher education are less healthy, it may be the case that these individuals also have higher mortality rates. Whilst for more highly educated people mortality rates may not increase until old age and thus (as a group) they experience a relatively larger decline in health at these ages. It is also appears to be the case that average health is better for the more educated over the entire lifecycle and therefore as a group they experience a more dramatic decline in health at very old age before dying.

Table 5.5

Ordered Probit regression conditional on Educational Category - Canada

Canadian National Population Health Survey 1994-1995						
Variables	Bachelor +		Skilled		No Higher	
	Coefficient	t statistic	Coefficient	t statistic	Coefficient	t statistic
Age 30-34	-0.044	-0.451	-0.041	-0.769	-0.100	-1.515
Age 35-39	-0.199	-1.971	-0.130	-2.336	-0.238	-3.601
Age 40-44	-0.142	-1.384	-0.184	-3.074	-0.355	-5.094
Age 45-49	-0.326	-3.137	-0.339	-5.406	-0.414	-5.940
Age 50-54	-0.287	-2.411	-0.354	-5.127	-0.550	-7.763
Age 55-59	-0.502	-3.806	-0.400	-5.455	-0.684	-9.638
Age 60-64	-0.588	-3.761	-0.339	-4.220	-0.536	-7.495
Age 65-69	-0.527	-3.109	-0.208	-2.451	-0.507	-6.931
Age 70-74	-0.233	-1.304	-0.285	-2.942	-0.572	-7.745
Age 75-79	-0.400	-1.825	-0.245	-2.245	-0.601	-7.499
Age 80+	-0.638	-2.990	-0.309	-2.694	-0.606	-7.402
Male	0.050	0.943	-0.105	-3.434	-0.038	-1.272
Low middle	0.104	0.545	0.173	2.331	0.063	1.207
Middle	0.254	1.646	0.241	3.599	0.200	3.949
Upper income	0.486	3.296	0.384	5.692	0.371	6.824
High income	0.482	3.182	0.546	7.044	0.504	6.825
Smoker	-0.357	-4.898	-0.343	-9.239	-0.257	-7.224
Ex-smoker	-0.098	-1.651	-0.122	-3.334	-0.123	-3.558
Has partner	0.020	0.238	0.010	0.252	-0.107	-2.954
Is separated	-0.040	-0.416	0.021	0.392	-0.148	-2.913
Moderate exer	-0.234	-3.000	-0.135	-2.875	-0.155	-3.203
Inactive exer	-0.499	-7.047	-0.362	-8.873	-0.371	-9.181
Currently	0.211	0.506	0.533	2.360	0.309	1.119
Not Cur	0.238	0.551	0.417	1.803	0.320	1.139
No wk 12mths	-0.252	-0.592	0.056	0.245	-0.180	-0.650
Cut 1	-2.573	0.462	-2.093	0.243	-2.555	0.285
Cut 2	-1.812	0.457	-1.276	0.240	-1.582	0.284
Cut 3	-0.780	0.455	-0.283	0.240	-0.622	0.283
Cut 4	0.372	0.455	0.865	0.240	0.418	0.283
Observations	1825		5363		6058	
L Likelihood	-2138.9		-6877.49		-8277	

Omitted Canadian categories: age 25-29, low income, never smoked, single, active exercise, Na or ns labour force, no higher education.

For Australia and Canada, there is stronger income-health gradient for those with less education. In Australian regressions, two issues make this gradient hard to judge. First, there is the unusual positive relationship to health of the first income decile when compared to the next two income deciles.²⁵ Second, the Australian income dummy variables represent household equivalent income deciles and therefore the range of income in each decile can vary. In Appendix 5B, I explore the relationship between income and health for Australia in more detail.

I noted in the Introduction to this Chapter that while models are often said to be representing households they are mostly estimated across individuals. As an extension to the above analysis, in Appendix 5A I examine the effect of partners' education to see if it is individual education or some broader notion of household education that primarily affects health.

5.5.2 Time Preference

In order to examine the time preference hypothesis regressions were estimated where the sample was disaggregated according to a time preference indicator, smoking status. If smoking status captures individual differences in time preference, and time preference is the primary explanation of the observed health and education relationship, we would expect the health gradient on education to diminish in these conditional regressions.

²⁵ I have tried to capture this effect in Chapter 4 by including variables on self employment in the household expecting, in part, that this was an income reporting problem. However, the result persisted despite these adjustments.

In Table 5.6, the coefficients on education categories are reported for regressions conditional on smoking status for Australia and Canada. For both countries, in most of the conditional regressions, the education gradient remained largely unchanged and was similar to the education gradient obtained from unconditional regressions. However, there were some differences between education coefficients for the regressions conditional on the smoking group compared to other conditional regressions. In the smoking group regressions, the skilled education category is no longer significantly different from the no higher education category. It may be the case that the smoking group is more homogeneous in terms of time preference and this has led to a reduction in the education gradient for this group. It may also be the case that education is still capturing heterogeneity in time preference in the smoked and never smoked groups.

Table 5.6

Education Coefficients from Ordered Probits conditional on Smoking Status*

	Never Smoked		Smoked		Smoking	
	Coefficient	t statistic	Coefficient	t statistic	Coefficient	t statistic
Australian						
Bachelor +	0.216	5.273	0.196	3.549	0.188	2.460
Skilled	0.127	3.986	0.169	4.661	0.024	0.574
No Obs	6484		4285		3379	
Log Likelihood	-8659.32		-5837.66		-4650.48	
Canadian						
Bachelor +	0.298	6.127	0.226	4.030	0.167	2.447
Skilled	0.156	4.094	0.100	2.707	0.014	0.401
No Obs	4699		4402		4194	
Log Likelihood	-5889.47		-5757.97		-5647.61	

* In this table, I only report the coefficients on education. The coefficients on other variables were similar to those in regressions reported in Table 5.2. Omitted Australian categories: age 25-29, income decile 1, never smoked, no exercise, out of labour force or na, single, no higher education. Omitted Canadian categories: age 25-29, low income, never smoked, single, active exercise, Na or ns labour force, no higher education.

5.5.3 A Lifecycle View - Gross Health Investment Profiles

The final way I examine the education and health relationship is to think about this relationship in a lifecycle setting. As discussed earlier, in the Grossman model or more generally in inter-temporal maximisation models, health can be treated as a capital stock that can be increased through investment but also declines in each period because of depreciation. Consider the following equation

$$H_t - H_{t-1} = I_{t-1} - \delta_{t-1}H_{t-1} \quad (10)$$

This is simply an identity where net investment equals gross investment minus depreciation from the last period. The difficult part is that in most analyses we never observe health investment though we do observe proxies for the stock of health.²⁶

It is easy to re-arrange equation 10 so that

$$I_{t-1} = H_t - (1 - \delta_{t-1})H_{t-1} \quad (11)$$

Thus, if I know the depreciation profile and the health stock from period to period I can derive a gross investment profile. Even when I don't know the exact depreciation profile as long as it is unchanged between education groups I can still make inferences about the investment profiles of different education groups by examining changes in the stock of health.²⁷ If I observe variation in investment profiles across

²⁶ If we assume that the depreciation rate is close to zero and our health measure is a measure of the change in health status, we can still use change in health status to estimate the investment production function.

²⁷ In estimating this relationship from a cross-section there are some potentially substantial cohort effects which have to be assumed away.

education groups this might indicate differences in time preference. If the investment profiles were the same, this might suggest that more education simply increases technical efficiency by raising the level of investment across the age profile.

Viewing human capital over the lifecycle by examining age earning profiles is a common way of exploring human capital. The author is not aware of similar approaches to examining health capital. There are of course some differences to the method of examining health capital presented in this section and a typical examination of human capital. For example, earnings can be thought of as the return to human capital investment whilst measures of health can be thought of as a direct measure of the stock of health. Some measures of health, such as disability free days, might be more accurately thought of as a flow of services arising from the stock of health. However, as long as the relationship between the stock of health and the flow of services is proportional, measures of the flow of health services can also be used to examine changes in the stock of health.

In Figures 5.3a and 5.3b, I present age-health profiles by education group for Australia and Canada respectively. The age-health profiles were calculated as the mean of self assessed health status by age, and as expected, mean health status declines with age. What is most striking about both figures is that the difference in self assessed health by education groups is present at age 25 to 29 and remains roughly constant across all age groups. That is, whatever drives the relationship between education and health is present at a relatively early age and in both countries.

I derived gross investment profiles for Australia and Canada by assuming that each education group had a common exponential depreciation profile and by using the

relationship presented in equation 11. An exponential depreciation profile suggests that health stocks depreciate at an ever-increasing rate.²⁸ I calculate the depreciation profile by calculating the exponential of the set of numbers -3.4 to -1.2 by increments of 0.2. I could just as easily assumed a common linear depreciation profile. This would have changed the shape of the set of investment profiles presented in Figures 5.3c and 5.3d but it does not affect our ability to compare different education groups investment profiles.

Gross Investment profiles for Australia and Canada are presented in Figures 5.3c and 5.3d respectively. There was remarkably little variation in the gross investment profiles by education group. This was not surprising given that the difference in mean self assessed health is so constant across age groups and the assumed common exponential depreciation profile.

²⁸ It could also be argued that the depreciation profile of the stock of health could vary by education group.

Figure 5.3a: Australian Mean Self Assessed Health Status by Age

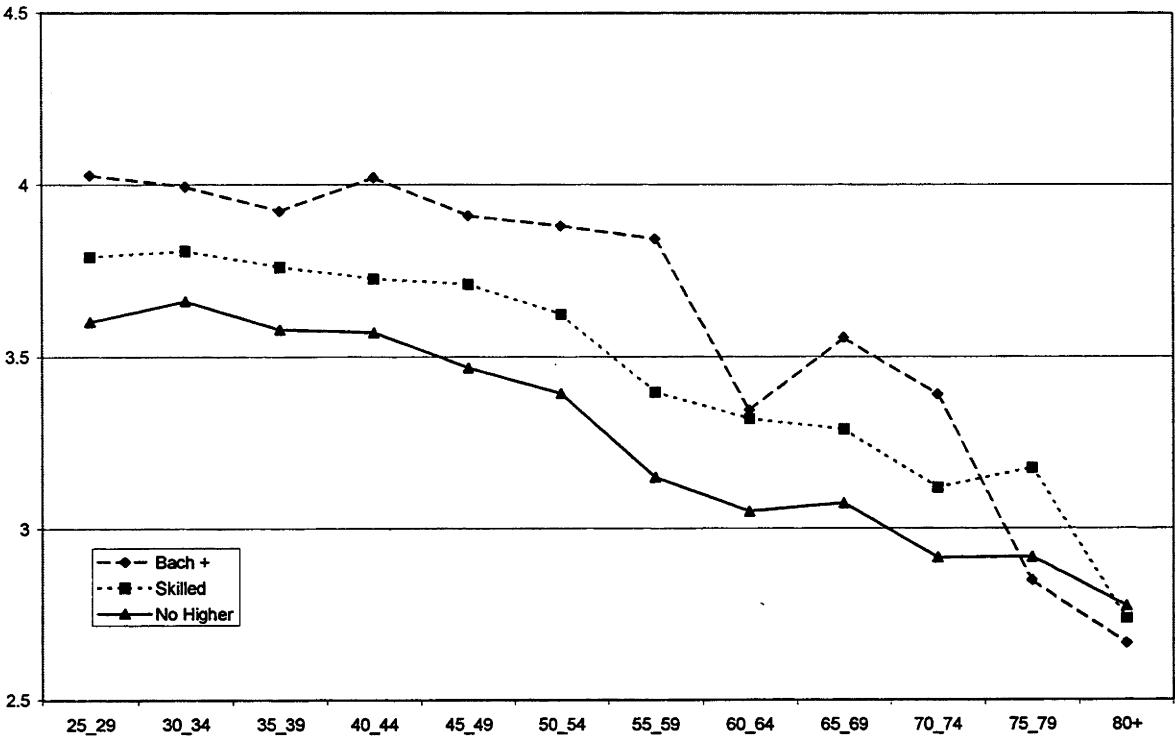


Figure 5.3b: Canadian Mean Self Assessed Health Status by Age

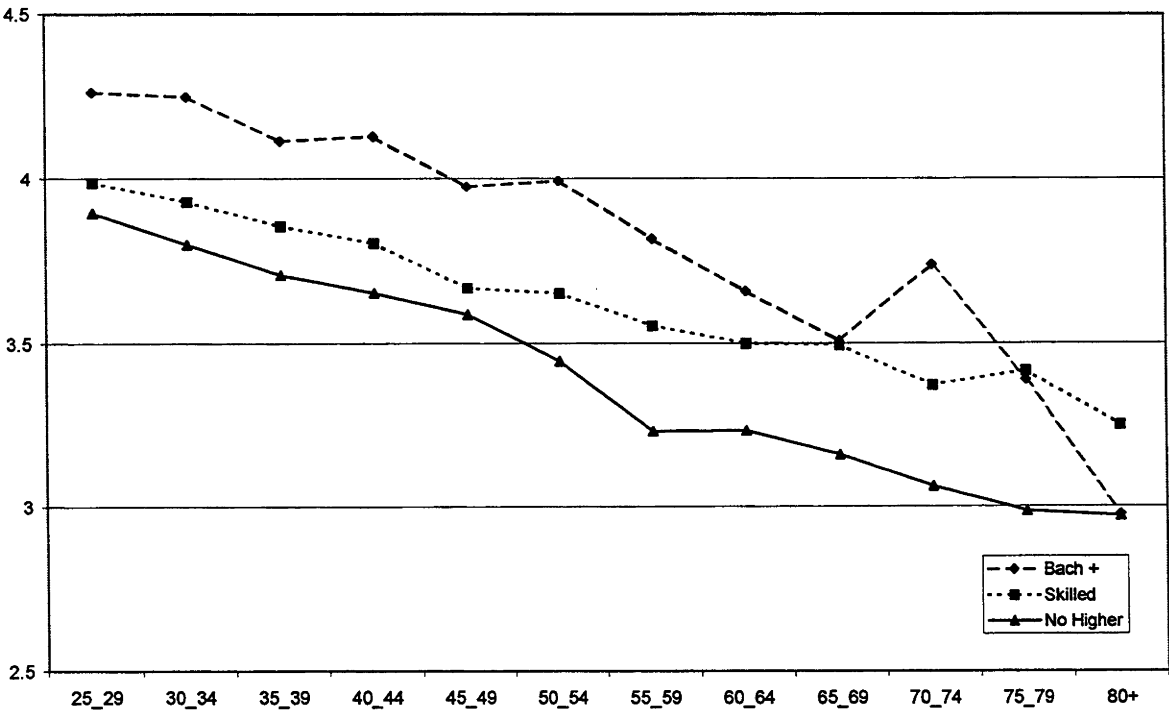


Figure 5.3c: Australian Derived Health Investment Profiles

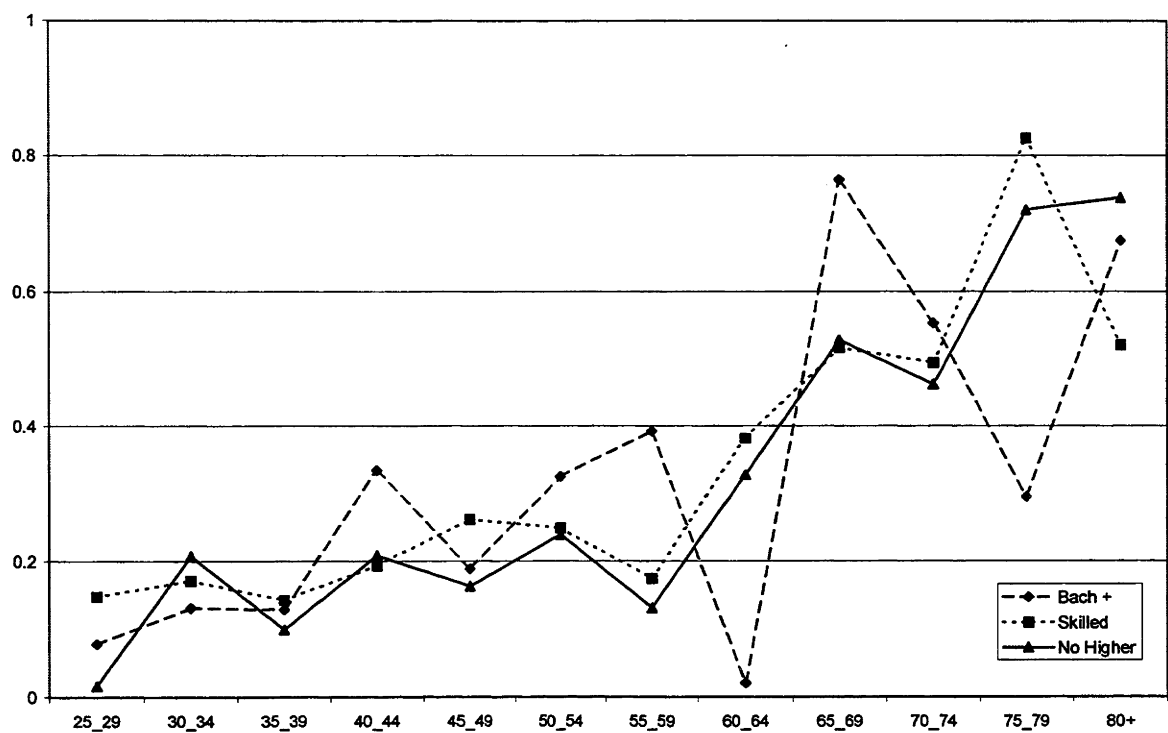
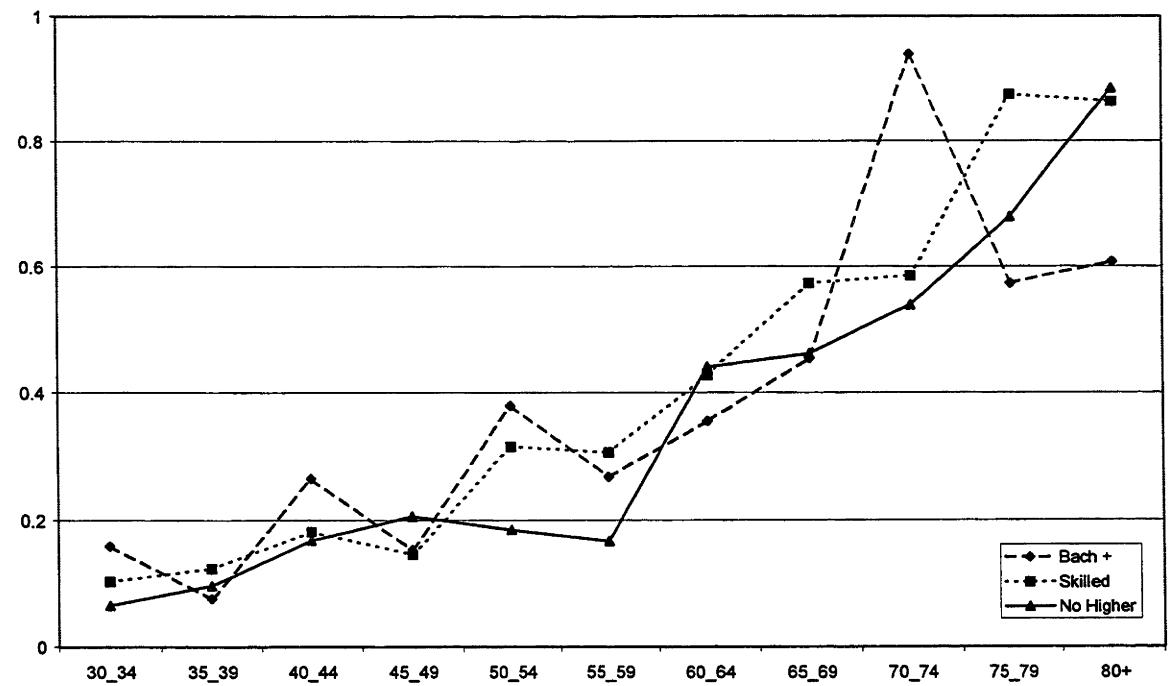


Figure 5.3d: Canadian Derived Health Investment Profiles



5.6 Health and Education Conclusions

This Chapter has highlighted a number of interesting features of the education and health relationship. It has shown that the association between health and education in Australian and Canada is very similar. This is perhaps not surprising given similarities in the Canadian and Australian health care systems, and general economic conditions.

After clarifying the differences between technical and allocative efficiency and time preference explanations of the relationship between education and health, I presented some empirical evidence for each. In both Canadian and Australian data sets it was difficult to identify the underlying health production relationship given a lack of suitable instruments and data to identify preferences. However, I was able to show that the association of health to other important socio-economic variables does vary by education group and this may imply that the underlying production structure varies by education or that education groups interpret relative prices of inputs differently.

I examined whether the education of other household members was important in explaining the health of individuals. Regressions on Australian data showed that male health was not significantly associated with the partner's education level: however, female health was associated with the partner's education level. These preliminary results suggest that examinations of the effect of education on health may need to consider the effect of the education of other household members upon an individual's health.

I attempted to isolate time preference heterogeneity by estimating regressions conditional on smoking status where smoking status was used as a time preference

indicator. If the education and health relationship disappeared in these conditional regressions, this would be evidence that education is proxying for time preference. I found in one group (those who were smoking) that education coefficients did diminish in size and statistical significance. In other conditional regressions, the education effect remained at a similar level to the unconditional regressions. In the unconditional regressions smoking was included as an additional variable thus if smoking was working as a time preference indicator the education effect should have already been some what attenuated in these regressions.²⁹ This was in fact the case; the exclusion of smoking status from the unconditional regression did lead to the coefficients on the education dummy variables increasing. Thus, it appears that there is at least some time preference component in the education and health relationship.

Lastly, I examined the age-health profiles of different education groups and derived gross investment profiles. The most striking aspect of this exercise was that the differences in health between education groups were present at a young age and that the differences remained largely unchanged for all age groups. This resulted in investment profiles that were very similar across education groups. These results held for both the Canadian and Australian data. The lack of variation in investment profiles is suggestive of an efficiency effect as a time preference effect would probably see the less educated invest less at younger ages compared to older ages.

²⁹ In an unconditional regression, where smoking status was excluded the coefficients on bachelor or higher and skilled education categories increased to 0.285 and 0.135 respectively.

Appendix 5A: The Effect of Partners' Educational Attainment on Health

I noted in the introduction to this Chapter that while models are often said to be representing households they are mostly estimated across individuals. As an extension to the earlier analysis, I included partners' education to see if it is individual education or some broader notion of household education that primarily affects health. I was only able to undertake this analysis using the Australian data as in this survey information were collected via personal interview from all adults in the household. By using the information collected from all adults in the household, I was able to construct a data set of couples.³⁰

In regressions for males, the coefficients on their partner's educational attainment categories were insignificant, see table 5A.1. However, in regressions for females the coefficients on their partners' education categories were significant. I also estimated male and female regressions including interactions between their respective educational attainment categories. Likelihood Ratio tests indicated that I could exclude these interaction terms.

My results for males are consistent with Taubman and Rosen (1982) who also found that for married men their female partner's health was not significantly related to married males' health. The results for females suggest that the effect of a partner's

³⁰ This exercise also is in keeping with models of household production of health, see for example, Jacobson (2000) and fits well with other studies that have examined how maternal education affects children Barrera (1990).

education is at least as important as their own education in contributing to health.³¹ It appears then that the educational attainment of partners may be important for an individual's health but that this effect varies between males and females. This suggests that models of individual health production may need to be extended to include other relevant persons' human capital, or to a more general household model rather than individual production model.

Table 5A.1
Ordered Probits for Australian NHS including Partners Education*

	Males		Females	
	Coefficient	t statistic	Coefficient	t statistic
Own				
Bachelor +	0.284	5.237	0.137	2.463
Skilled	0.225	6.705	0.081	2.205
Partners				
Bachelor +	0.069	1.257	0.136	2.528
Skilled	0.066	1.794	0.142	4.246
No Obs	4868		4868	
Log Likelihood	-6581.92		-6547.97	

* In this table, I only report the coefficients on education and partners education. The coefficients on other variables were similar to those in regressions reported in Table 5.2. Categories omitted in the full regressions included: age 25-29, income decile 1, never smoked, no exercise, out of labour force or na, single, no higher education.

³¹ I have no clear reason why the effect of partner education is not symmetric.

Appendix 5B: Health and Income in Australia

In this appendix, the association between income and health in Australia is briefly examined. Regressions conditional on collapsed education categories are estimated using a continuous measure of equivalent household income rather than grouped by decile measure. These regressions are probit regressions on a collapsed version of self assessed health status where excellent health is coded as one and all other reported health states as zero. This simplified regression was run to facilitate the comparison of the effect of income on health.³²

In one set of conditional probit regressions income, the square of income, and the cube of income are included. In a second set of conditional regressions, the log of income was used. In this case, the curvature of the relationship between income and health is more strictly imposed than when using higher order income terms.

In Figure 5B.1, I show the predicted probabilities that arise out of the conditional regressions across income. The regression results for other variables were the same, as those presented in Tables 5.3 and 5.4, the only difference being that income was now continuous rather than grouped. This exercise indicates that the range over which household income is associated with health does not vary considerably by education group. It appears from these regressions that while there is an income gradient for all

³² If I assume that health has an upper boundary that is an optimum at which health can not be improved upon: I can think of the self assessed health status category excellent as representing this optimum. Then, conditional on education I can look at the additional income required for a given proportion of the sample to be in optimal health. This exercise can also tell us about the shape of the income profile in the intervening range for example, whether there are declining health returns to income. It also gives some

education groups the more highly educated, in particular those with a degree maintain relatively better health. This is suggestive of a productive and or allocative efficiency effects.³³

I also used two non-parametric techniques to estimate the relationship between income and reported excellent health.³⁴ The first non-parametric technique used follows Fan (1992) as cited in Deaton (1997) where a locally weighted regression approach was used.³⁵ A quartic kernel was employed in deriving the weighting pattern for the series of local regressions and a band-width of 10000 dollars. I also estimated this relationship using the Stata package Lowess technique due to Cleveland (1979). Both techniques produced very similar results.

I have only presented the relationship for up to 55000 dollars as after this point, the data becomes sparse and the non-parametric techniques produce very volatile

indication over what range income is important to health for individuals with different education.

³³ It also suggests that an income redistribution policy would not eliminate health inequalities and that an education policy would potentially be more effective if education is related to health in a causal sense. Admittedly, these results also suggest a substantial amount of income could be removed from relatively wealthy people and this would have very little impact on their health status.

³⁴ I estimated the relationship non-parametrically so I could relax the restrictive non-linear transformations imposed on the data by the estimated log and polynomial income relationships discussed earlier.

³⁵ The Fan (1982) estimator is set out in Deaton (1997) as follows. A grid is set and for each point in the grid (each x) a weighted regression is estimated using a kernel. That is, $\theta_i(x) = (1/h)K((x-x_i)/h)$ is the kernel where h is the band width. A locally weighted regression parameter then estimates

$$\beta(x) = [X' \Theta(x) X]^{-1} X' \Theta(x) y$$

where the $\Theta(x)$ matrix is a diagonal matrix containing the $\theta_i(x)$ weights. The predicted value at this particular x is then estimated and the procedure repeated across the chosen grid.

predicted probabilities, see Figure 5B2.

It is clear from the non-parametric exercise that the unusual feature of very low income being associated with good health persists across education groups. It is also apparent that the gap between education groups remains across all levels of income, and in particular, at points where the relationship can be estimated robustly. This exercise suggests that the income health gradient is in fact fairly similar across all education groups.

One final point to note about this exercise is that individual income as an explanatory variable was unable to remove completely the effect of education. That is, the bachelor and more education group had higher levels of health at higher levels of income compared to those with less education but the same levels of income. If excellent health does represent optimal health this suggests that approximately 30 percent of the bachelor and more education group could achieve optimal health at high levels of income while only approximately 20 percent of those with no higher education can reach optimal health at the same level of income. This may be indicative of an exogenous productivity shift driven by education.

Figure 5B.1

Probability of Reporting Excellent Health over Equivalised Household Income - Australian National Health Survey

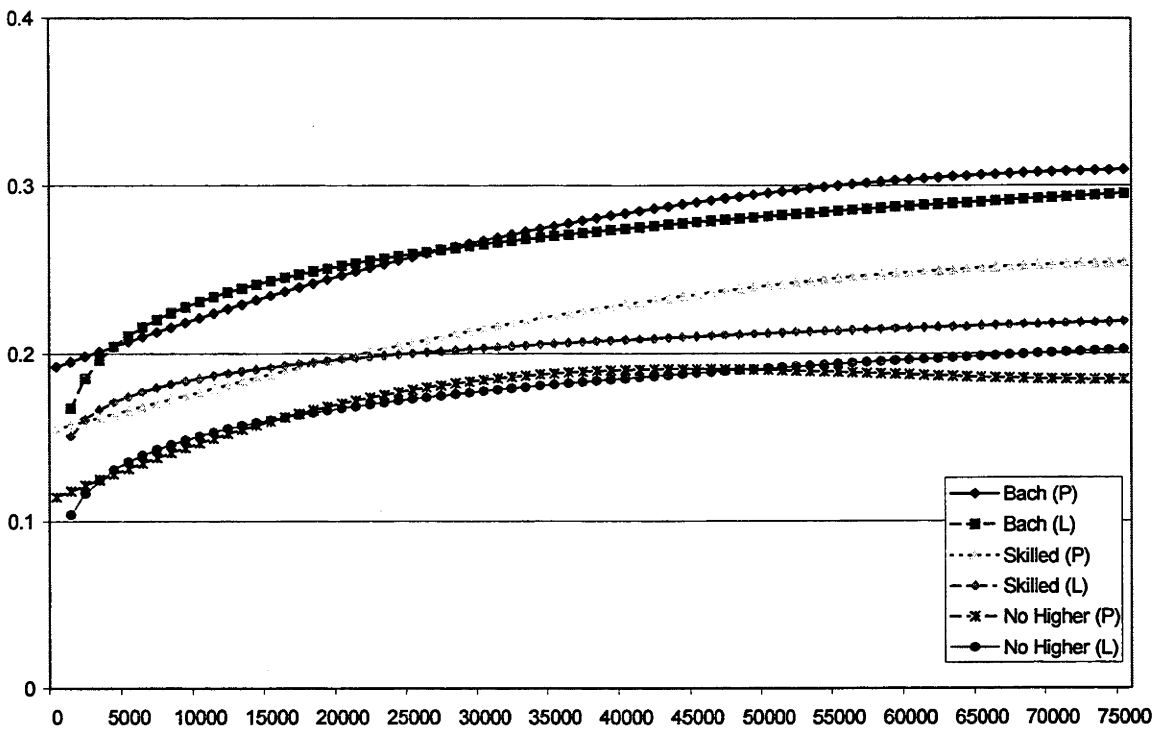
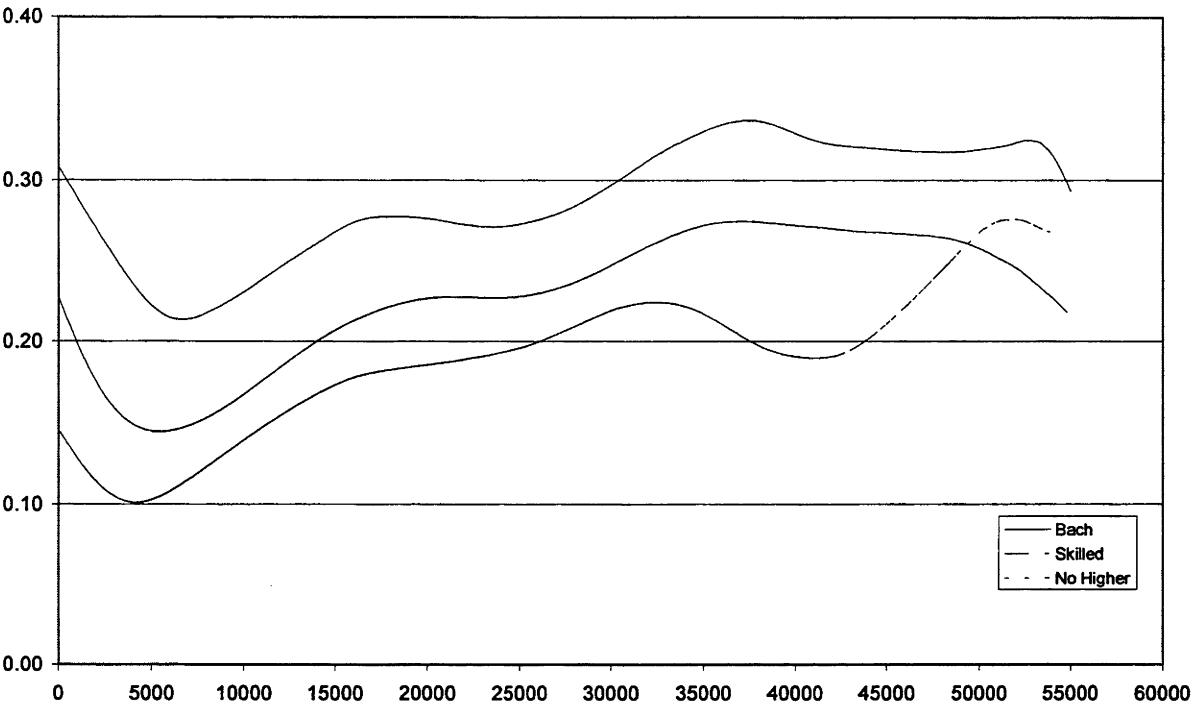


Figure 5B.2

Non Parametric Estimation of Excellent Health over Income



6. Conclusions and Suggestions for Future Research

6.1 Conclusions

That economic conditions might affect the health of individuals is not surprising or controversial. An important step is to determine what particular aspects of economic life are most important to the health of individuals. In this thesis, I found that income, education, and labour force status are all independently significant predictors of individual health.

In estimating the effect of these economic variables upon health, health has to be measured. Health is a complex concept and can represent a variety of different aspects of well being. A commonly used measure of health and one that I examined in detail is self assessed health status. I found that self assessed health status was a reasonably reliable measure of health, in terms of estimating the average health of population, but that errors in reporting health were not random across a typical population. For example, older persons tend to revise their self assessed health status more frequently than do younger persons suggesting that there is more error in the measures of self assessed health for older persons. This result held even after considering the effect of a wider distribution of health states for older persons. The presence of non-random measurement error has important implications for empirical research that uses self assessed health status either as a dependant or independent explanatory variable.

I also found evidence that the mode of administration of the survey and the ordering of questions on health surveys affect the propensity to revise one's reported health. These issues need to be considered when comparing the results of health status

questions from different studies.

An interesting feature of the examination of the relationship between unemployment and mental health for Australian immigrants was the effect of labour force status on couples' health. Whilst the mental health of immigrants and their partner's mental health were strongly positively associated, the effect of labour force status on partners mental health was less clear. A tentative conclusion with respect to partner's labour force status was that it appears that when males are unemployed and their partner employed this has a negative effect on male mental health compared to males who are unemployed and have a partner who is also unemployed. However, females appear to be unaffected by their partners labour force status. A more robust conclusion that can be drawn from the analyses of individuals and couples is that immigrant employment is a strong predictor of good mental health compared to both unemployment and being out of the labour force.

That unemployment has adverse mental health consequences for immigrants largely regardless of their partners' labour market outcomes is important for current Australian immigration policy. My study suggests that policies that restrict immigrant access to labour market programs, assuming that these labour market programs reduce the probability of unemployment, may have counter-productive health consequences, which may have health care cost implications.

An examination of the issue of causality between immigrant mental health and labour force status found that causality ran primarily from labour force status to mental health, and not vice versa. This result was largely consistent with previous findings from the unemployment and mental health, and the immigrant and mental health,

literature.

Another interesting feature of my study of Australian immigrants was the patterns of adjustment to the immigration and unemployment experience. In this study, psychological disadvantage was highest 6 months after arrival compared to immigration after 18 months and after 42 months. Unemployed immigrants also displayed a pattern of adjustment to the duration of unemployment similar to that found in other studies of unemployment and mental health. That is, mental health was poorest for those who had been unemployed for 2 to 6 months and slightly better for those unemployed for more than 6 months. However, immigrants who are unemployed for longer than 6 months still reported poorer mental health compared to employed immigrants.

In measuring the effect of unemployment on immigrants, I was careful to control for the effect of income. A new and interesting idea emerging in the public health literature is that not only is income important for health but also the distribution of income. I followed a strand of this literature and examined whether regional income inequality measured using five different income inequality indices was associated with different measures of health status. The results of my study differed to those of other authors such as Kennedy *et al.* (1998). Whilst some income inequality indices had an independent and negative effect on health status other indices did not. Income inequality measured at a relatively disaggregated level of region had no effect on health, whilst income inequality measured at a more aggregate level of region did have an effect on self assessed health status and SF-36 mental health for some income inequality indices.

Results not only varied across measures of income inequality they also varied across the different measures of health. In regressions using self assessed health status, SF-36 general health and SF-36 mental health the coefficient on the GE(-1) income inequality index was significant and negative. Other measures of income inequality were generally not related to these health status measures. All income inequality indices were not significantly related to the SF-36 measure of physical health.

I also found that the relationship between income inequality and health status was not robust to different approaches to trimming the data set. In particular, there was a negative relationship between the Gini coefficient (measured as the aggregate level of region) and self assessed health status when all observations were included. However, when zero income observations and the top and bottom 1 percent of the income distribution were excluded this relationship disappeared. Many studies arbitrarily exclude zeros and trim their data sets as I have done in this study. Since it is clear that trimming the data makes a difference to results, this suggests the need for care in comparing studies. It is also more evidence that the relationship between income inequality and health is not particularly robust in Australia.

The significant relationship found between mental health and income inequality indices that emphasis difference in the bottom of the income distribution may provide us with a reason for why we observe a health and income inequality relationship in some countries such as the USA but not others such as Canada and Australia. It may be that changes in the bottom of the income distribution adversely affect all persons' mental health, and that in countries such as the USA these mental health effects have, over time, affected general health. In countries such as Australia and Canada changes in the bottom of the income distribution may be more recent and therefore only be impacting

contemporaneously on mental health but potentially impact on general health in the longer term.

I also took the opportunity to estimate a new and interesting model of the income inequality and health relationship developed by Deaton and Paxson (1999). I found some support for Deaton and Paxson's model that suggests that relative income rather than individual income is what matters for health. Models such as this are an important development in this literature as we try to understand better an interesting empirical phenomenon, which is perhaps not as robust as first thought.

In the studies of unemployment and mental health and income inequality and health, I consistently found that education was an important independent predictor of health. In Chapter 5, I examined a number of interesting features of the education and health relationship in Australia and Canada. I found that the association between health and education in Australian and Canada was very similar. This is perhaps not surprising given similarities in the Canadian and Australian health care systems and general economic conditions.

After clarifying the differences between three possible explanations of the education and health relationship, I presented some empirical evidence for each explanation. In both the Canadian and Australian data sets it was difficult to identify the underlying health production relationship given a lack of suitable instruments and data to identify preferences. However, I was able to show that the association of health to other important socio-economic variables does vary by education group. This may imply that the underlying production structure varies by education, or that education groups interpret the relative prices of health inputs differently.

I attempted to isolate a time preference explanation of the education and health relationship by estimating regressions conditional on smoking status where smoking status was used as a time preference indicator. If it were the case that the education and health relationship disappeared in these conditional regressions, this would be evidence that education is proxying for time preference. I found that for one group, those who were smoking, the education relationship was attenuated. In the other conditional regressions, the education effect remained at a similar level to the unconditional regressions. In the unconditional regressions smoking was included as an additional variable; thus if smoking was working as a time preference indicator the education effect should have already been somewhat attenuated in these regressions. This was in fact the case; the exclusion of smoking status from the unconditional regression did lead to the coefficients on the education dummy variables increasing. Thus, it appears that there is at least some time preference component in the education and health relationship.

I also examined the age-health profiles of different education groups and derived gross health investment profiles. The most striking aspect of this exercise was that the differences in health between education groups were present at a young age and the differences remained largely unchanged for all age groups. This resulted in investment profiles that were very similar across education groups. These results held for both the Canadian and the Australian data. The lack of variation in investment profiles is suggestive of an efficiency effect from education to health as a time preference effect would probably see the less educated invest less at younger ages compared to older ages.

6.2 *Suggestions for Future Research*

An overall conclusion that can be drawn from my study is that in Australia economic factors such as employment, income and education play an important role in the health of individuals. This result appears robust despite acknowledged difficulties in measuring health. Apart from issues of measurement, another overall issue to emerge is how best to disentangle the direction of causality. Given the difficulties in identifying good quality instruments in health studies perhaps the most productive studies of the effects of economic variables are those of a natural experiment nature. My examination of the reliability of self assessed health status is one example of the use of survey data in a natural experiment style of study.¹

Longitudinal data allow a more careful examination of the direction of causality than do cross-sectional data. In examining the relationship between unemployment and immigrant mental health using longitudinal data, I was able to conclude tentatively that causality flows primarily from unemployment to immigrant mental health. I used cross-section data sets to examine the relationships between income inequality and health and education and health and hence can not confidently ascribe causality in these cases.

There are many difficulties in separating out the effects of education on health, income on health, health on income, education on income and so on, particularly in cross-section data sets. For example, in Mincerian (1974) inspired analyses of earnings (see Currie and Madrian (1999) for a review), health is occasionally included as an

¹ The powerful US Rand study is probably the best example of the power of the natural experiment approach to studying health economics. A move towards this style of analysis in health economics brings economists closer to other health researchers who are more familiar with the experiment based style of research.

explanatory variable, in addition to education and experience. However, if earnings or income also affect health it is not clear what effects are being identified in the earnings equation. As a simple illustration of the possible impact of health on earnings, I estimated income functions for males and females separately with and without health variables. Full regression results are presented in Appendix 6A. The effects of education, age, and health variables on earnings for males and females are presented in Table 6.1.

Table 6.1
Income Regressions*

OLS	Females	Males	Females	Males
	Coefficient (t-stat)	Coefficient(t-stat)	Coefficient(t-stat)	Coefficient(t-stat)
Age	0.053 (4.35)	0.058 (8.39)	0.053 (4.36)	0.058 (8.35)
Age Squared	-0.001 (3.88)	-0.001 (7.85)	-0.001 (3.88)	-0.001 (7.75)
Education				
Higher Degree	0.411 (13.13)	0.423 (19.75)	0.399 (12.70)	0.410 (18.92)
Other Post Secondary	0.143 (4.87)	0.088 (5.24)	0.132 (4.51)	0.083 (4.93)
Self Assessed Health				
Very Good			-0.056 (1.81)	-0.015 (0.72)
Good			-0.113 (3.29)	-0.064 (2.96)
Fair			-0.109 (1.91)	-0.103 (3.17)
Poor			-0.201 (1.48)	-0.110 (1.50)

*The dependant variable is personal income measured as Gross Personal Income from all sources. This income measure should be a reasonable proxy for earnings given that the sample is restricted to persons aged 25 to 64, who are full-time employees. The omitted category for the independent variables are education category no post secondary; self assessed health status category excellent; and State category NSW. See Appendix 6A, Table 6A.1 for full regression results.

Table 6.1 shows that individual incomes increase with education and age as expected and that the effect of these variables on incomes is mostly unaffected by the inclusion of health status. Health status is related to income in the expected way: incomes fall with poorer health. Whilst this simple example is only intended to

illustrate possible endogeneity and omitted variable effects it does provide some evidence of complex inter-relationships between variables. For example, if health does affect earnings or incomes what does this mean for the relationship between income and health discussed in Chapter 4? Similarly, why are education and health related to incomes in a largely orthogonal way (education effects are not substantially reduced when health is included) when the analysis in Chapter 5 suggests that education is an important determinant of health? Bound (1991) has suggested that the attention bias associated with the measurement error in self assessed health status, discussed in detail in Chapter 2, may offset the endogeneity bias. Clearly though, disentangling measurement error and endogeneity issues remains an important area of future research for health economics.

Another important aspect of individuals' health that arose throughout my thesis, and is related to the issue of causality, is the inter-temporal nature of health. Grossman's (1972) model of health capital is perhaps the best known model in health analysis that explicitly deals with ideas such as health declines with age and increases with income and health behaviours. Though this model assumes wages and education are exogenous, the above discussion suggests that this might not be the case.

In many public health and economic studies of health, measures of health are often contemporaneously related to socioeconomic variables. This is also true of most of the analysis presented in this thesis, except for the analysis of longitudinal data in Chapter Three. To better understand the impact of economic factors on health we need to be able understand how these variables affect persons over the course of their lives. For example, many studies of child health show the importance of economic factors. If an individual's health is adversely affected when they are young, are increased

investments in health in later years able to offset the earlier negative influences? Such analyses would appear particularly important when considering policies designed to influence individual and public health such as the policy consequences of increasing public education to improve health. These and other important questions can only be answered with careful empirical analyses of data sets that have a substantial longitudinal component, and which allow us to control for socioeconomic variation.

Appendix 6A: Auxiliary Tables

Table 6A.1

Incomes Regressions*

OLS	Females	Males	Females	Males
	Coefficient (t-stat)	Coefficient(t-stat)	Coefficient(t-stat)	Coefficient(t-stat)
Age	0.053 (4.35)	0.058 (8.39)	0.053 (4.36)	0.058 (8.35)
Age Squared	-0.001 (3.88)	-0.001 (7.85)	-0.001 (3.88)	-0.001 (7.75)
Education				
Higher Degree	0.411 (13.13)	0.423 (19.75)	0.399 (12.70)	0.410 (18.92)
Other Post Secondary	0.143 (4.87)	0.088 (5.24)	0.132 (4.51)	0.083 (4.93)
Self Assessed Health				
Very Good			-0.056 (1.81)	-0.015 (0.72)
Good			-0.113 (3.29)	-0.064 (2.96)
Fair			-0.109 (1.91)	-0.103 (3.17)
Poor			-0.201 (1.48)	-0.110 (1.50)
State				
Queensland	-0.064 (1.60)	-0.016 (0.65)	-0.069 (1.71)	-0.021 (0.87)
Victoria	-0.035 (0.73)	-0.095 (3.24)	-0.044 (0.91)	-0.097 (3.33)
South Australia	-0.076 (1.66)	-0.112 (4.17)	-0.085 (1.86)	-0.117 (4.32)
Western Australia	-0.080 (1.53)	-0.007 (0.23)	-0.088 (1.65)	-0.009 (0.32)
Tasmania	-0.040 (0.57)	-0.095 (2.28)	-0.052 (0.75)	-0.098 (2.35)
Northern Territory	0.037 (0.77)	0.021 (0.66)	0.042 (0.84)	0.018 (0.57)
ACT	0.016 (0.34)	0.021 (0.72)	0.017 (0.36)	0.020 (0.66)
Constant	9.103 (37.8)		9.029 (37.1)	
No of Observations	1748	3268	1748	3268
Adjusted R Squared	0.11	0.16	0.11	0.16

*The dependant variable is personal income measured as Gross Personal Income from all sources. This income measure should be a reasonable proxy for earnings given that the sample is restricted to persons aged 25 to 64, who are full-time employees. The omitted category for the independent variables are education category no post secondary; self assessed health status category excellent; and State category NSW.

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