INDIVIDUAL-LEVEL PREDICTORS OF HEALTH AND WELL-BEING: AN INTEGRATION OF THE SOCIAL SCIENCES

A thesis submitted to the University of Manchester for the degree of Doctor of Philosophy (PhD) in the Faculty of Medical and Human Sciences

2015

Hilda Osafo Hounkpatin

School of Medicine

Institute of Population Health
LIST OF CONTENTS

LIST OF CONTENTS ..................................................................................................................2
LIST OF TABLES ..........................................................................................................................8
LIST OF FIGURES ..........................................................................................................................9
LIST OF ABBREVIATIONS ..............................................................................................................10
THESIS ABSTRACT ......................................................................................................................12
DECLARATION ...............................................................................................................................13
COPYRIGHT STATEMENT ..............................................................................................................13
RATIONALE FOR SUBMITTING THE THESIS IN THE ALTERNATIVE FORMAT .........................14
ACKNOWLEDGEMENTS .................................................................................................................15
DEDICATION ........................................................................................................................................15
CHAPTER 1 .................................................................................................................................16
  1.0 Introduction ..........................................................................................................................16
  1.1 Overview ..................................................................................................................................16
  1.2 Explaining the Precise Association between Income and Health and Well-Being 17
      1.2.1 Theoretical framework: The hypothesis debate ..............................................................18
      1.2.2 Distinguishing between the different hypotheses: A review of the literature ..22
  1.3 Individual Heterogeneity in the Inequality-Health and Well-Being Association...24
  1.4 The Greater Role of Personality Measures as Indicators of Overall Health and Well-Being ...........................................................................................................................................28
      1.4.1 The use of personality trait measures in health and well-being research..............28
      1.4.2 The magnitude of personality trait change.................................................................28
      1.4.3 Theories of personality trait change: Exploring the evidence ...............................30
      1.4.4 Personality traits and well-being outcomes: A causal relationship?.................33
  1.5 Overview of Thesis ...............................................................................................................34
  1.6 Note on Collaboration and Published Material ..................................................................35
CHAPTER 2 ...................................................................................................................................37
  2.0 Methods ..................................................................................................................................37
CHAPTER 2

2.1 Choice of Datasets and Samples

2.1.1 The English Longitudinal Study of Ageing (ELSA)

2.1.2 The Wisconsin Longitudinal Study (WLS)

2.1.4 The Longitudinal Internet Studies for the Social Sciences (LISS)

2.2 Statistical Techniques

2.2.1 Multiple linear regression models

2.2.2 Marginal and conditional models

2.2.3 Structural equation modelling

2.4 Prediction versus Causal Explanation

2.5 Model Selection and Goodness of Fit Statistics

2.6 Handling Missing Data

CHAPTER 3

3.0 Why does Income Relate to Depressive Symptoms? Testing the Income Rank Hypothesis Longitudinally

3.1 Abstract

3.2 Introduction

3.3 Methods

3.3.1 Data

3.3.2 Statistical analyses

3.4 Results

3.4.1 Rank groups and income

3.4.2 Comparison of models

3.5 Discussion
CHAPTER 4  ......................................................................................................................... 80

4.0 Does Income Relate to Health due to Psychosocial or Material Factors? Consistent Support for the Psychosocial Hypothesis Requires Operationalization with Income Rank not the Yitzhaki Index ................................................................. 80

4.1 Abstract ..................................................................................................................... 80

4.2 Introduction ............................................................................................................. 80

4.3 Methods .................................................................................................................. 84

4.3.1 Participants and procedure ............................................................................. 84

4.3.1.1 ELSA ........................................................................................................... 85

4.3.1.2 LISS ........................................................................................................... 85

4.3.2 Self-rated health .............................................................................................. 89

4.3.2.1 Self-rated health ......................................................................................... 89

4.3.2.2 Allostatic load .......................................................................................... 89

4.3.2.3 Actual income, the Yitzhaki Index, and income rank .............................. 89

4.3.2.4 Potential covariates .................................................................................... 91

4.3.3 Statistical analysis ........................................................................................... 91

4.4 Results ................................................................................................................... 93

4.5 Discussion ............................................................................................................. 99

CHAPTER 5  ......................................................................................................................... 103

5.0 An Existential-Humanistic View of Personality Change: Co-occurring Changes with Psychological Well-Being in a Ten Year Cohort Study ................................................................. 103

5.1 Abstract .................................................................................................................. 103

5.2 Introduction ........................................................................................................... 103

5.3 Materials and Methods ...................................................................................... 106

5.3.1 Participants and procedure ............................................................................ 106

5.3.2 Measures ......................................................................................................... 107

5.3.2.1 Big Five personality traits ......................................................................... 107

5.3.2.2 Psychological well-being ............................................................................ 108

5.3.2.3 Life satisfaction ......................................................................................... 108

5.3.2.4 Depression ............................................................................................... 109
5.3.2.5 Hostility. .................................................................109
5.3.2.6 Socioeconomic variables. .........................................110
5.3.3 Statistical procedure. ..................................................110
5.4 Results ........................................................................113
5.5 Discussion ....................................................................123
5.6 Limitations .....................................................................124
5.7 Conclusion .....................................................................126
CHAPTER 6 ........................................................................127
6.0 Which Personality Traits Lead to Life Satisfaction? Lagged Changes in Neuroticism Negatively Predict Life Satisfaction Changes in a Large Representative Cohort Survey ........................................................................127
6. 1 Abstract ........................................................................127
6.2 Introduction .....................................................................128
6.2.1 Research on personality change ......................................129
6.2.2 Introducing bivariate latent change score (LCS) to personality psychology. 130
6.2.3 Theoretical models of the role of personality in life satisfaction .................132
6.2.4 The current study ..........................................................133
6.3 Methods ..........................................................................134
6.3.1 Participants and procedure ............................................134
6.3.2 Measures .................................................................135
6.3.2.1 Life satisfaction .......................................................135
6.3.2.2 Personality .............................................................136
6.3.2.3 Affect ....................................................................137
6.3.3 Analytical strategy .......................................................138
6.3.3.1 Measurement model ................................................138
6.3.3.2 Bivariate latent change score models .................................138
6.3.3.3 LCS mediation models .............................................144
6.4 Results ........................................................................147
6.4.1 Measurement component of LCS model .................147
6.4.2 Association between changes in personality traits and changes in life satisfaction

6.4.2.1 Neuroticism and life satisfaction ................................................................. 148

6.4.2.2 Extraversion and life satisfaction ............................................................... 155

6.4.2.3 Openness and life satisfaction ................................................................. 155

6.4.2.4 Agreeableness and life satisfaction ......................................................... 155

6.4.2.5 Conscientiousness and life satisfaction .................................................... 156

6.4.3 Mediation effects of changes in negative affect on the association between lagged changes in personality and changes in life satisfaction ........................................ 156

6.5 Discussion ....................................................................................................... 157

6.6 Limitations and Future Directions ................................................................. 159

6.7 Conclusion ....................................................................................................... 162

CHAPTER 7 ............................................................................................................. 163

7.0 Discussion ....................................................................................................... 163

7.1 Overview .......................................................................................................... 163

7.2 Chapter Summary ............................................................................................ 164

7.3 Limitations ....................................................................................................... 166

7.3.1 Sample ......................................................................................................... 166

7.3.2 Measures ...................................................................................................... 167

7.3.3 Methodological limitations ........................................................................ 169

7.4 Theoretical Implications .................................................................................. 170

7.4.1 The mechanism underlying the association between income/wealth and health and well-being ................................................................. 170

7.4.2 Mechanisms underlying personality change .............................................. 171

7.4.3 Do personality traits predict life satisfaction? .......................................... 172

7.5 Methodological Implications .......................................................................... 173

7.6 Practice and Policy Implications ................................................................... 174

7.6.1 Psychological interventions to improve health and well-being ................. 174

7.6.2 Personality change as markers of change in well-being ......................... 176
7.7 Proposals for Future Research

7.7.1 Using self-defined reference groups and perceived rank measures to better understand impact of relative deprivation

7.7.2 Instrumentation study to determine causal association between income rank, personality traits and health and well-being.

7.7.3 Using a ‘simplex’ and ‘SIMEX’ approach to isolate measurement error from psychological measures.

7.7.4 Determining the nature of the association between personality change and change in psychological well-being.

7.8 Final Conclusions

References

Appendix I: Fit Statistics Comparing Contemporaneous and Lagged Models of the Association between Income-Related Predictors and Health

Appendix II: Fit Statistics for Competing Models of the Association between Income-Related Predictors and Self-rated Health and Allostatic Load

Total word count: 56,697
LIST OF TABLES

Table 1 The Big Five personality domains and their components ..............................................27
Table 2 Summary statistics of study samples ...........................................................................62
Table 3 Comparison of test statistics for models of depressive symptoms .........................70
Table 4 Estimation of adjusted coefficients using best statistical model for predicting current and future depressive symptoms in (a) WLS and (b) ELSA ..................................73
Table 5 Descriptive statistics across time waves for ELSA and LISS .....................................87
Table 6 Fit statistics comparing contemporaneous and lagged models of the association between income-related predictors and health .................................................................95
Table 7 Fit statistics of competing models of the association between income-related predictors and self-rated health and allostatic load ..............................................................98
Table 8 Summary statistics across sample measured at two time points ..............................112
Table 9 Estimation of PWB change on changes in socioeconomic and personality variables .................................................................................................................................115
Table 10 Estimation of changes in life satisfaction, depression, and hostility on changes in socioeconomic and personality variables .................................................................119
Table 11 Individual differences in personality traits ...............................................................121
Table 12 Descriptive statistics of personality, negative affect, positive affect, and life satisfaction measures for analytic sample .................................................................136
Table 13 Model fit statistics and parameter estimates for LCS model ...............................149
LIST OF FIGURES

Figure 1 Increasing income values increase health values but by decreasing amounts. . . .19
Figure 2 A measurement error model........................................................................45
Figure 3 Measurement components for latent change score. ..................................47
Figure 4 Structural equation model framework..........................................................48
Figure 5 Plot of rank against constant relative risk aversion (CRRA) for the reference
groups in (a) WLS and (b) ELSA.. ........................................................................69
Figure 6 Path diagram of bivariate measurement error models, together with the
corresponding latent change scores $\Delta P_{T2-T1}, \Delta P_{T3-T2}$ (for personality) and $\Delta LS_{T2-T1}, \Delta LS_{T3-T2}$
(for life satisfaction) ....................................................................................................139
Figure 7 Path diagram of basic bivariate LCS model (including paths to explain the
changes in latent change scores over time)..................................................................141
Figure 8 Path diagram of basic LCS mediation model (including paths to explain the
changes in latent change scores over time).................................................................145
Figure 9 A simple path diagram illustrating the mediation effect of negative affect on the
influence of lagged changes in neuroticism on changes in life satisfaction ..............157
LIST OF ABBREVIATIONS

AIC = Akaike Information Criterion
BFI = Big Five Inventory
BIC = Bayesian Information Criterion
CBT = Cognitive Behavioural Therapies
CES-D = Centre for Epidemiologic Studies Depression
CFA = Confirmatory Factor Analysis
CFI = Comparative Fit Index
CRRA = Constant Relative Risk Aversion
DF = Degrees of Freedom
ELSA = English Longitudinal Study of Ageing
EU = European Union
GCE = General Certificate of Education
HSE = Health Survey for England
IPIP = International Personality Item Pool
IPW = Inverse Probability Weighting
LCS = Latent Change Score
LISS = Longitudinal Internet Studies for the Social Sciences
MAR = Missing at Random
MCAR = Missing Completely at Random
MLE = Maximum Likelihood Estimation
MNAR = Missing Not at Random
NVQ = National Vocational Qualification
OLS = Ordinary Least Squares
PANAS = Positive and Negative Affect Scale
PHG = Parahippocampal Gyrus
PWB = Psychological Well-Being
R= Rank (of Income)
RD = Relative Deprivation (Yitzhaki Index)
RMSEA = Root Mean Squared Approximation Index
SEM = Structural equation models
SRMR = Standardised Root Mean Square Residual
SWB = Subjective Well-Being
TLI = Tucker-Lewis Index
UK = United Kingdom
US = United States
VIFs = Variance inflation factors
WLS = Wisconsin Longitudinal Study
THESIS ABSTRACT

A thesis submitted to the University of Manchester for the degree of Doctor of Philosophy

Candidate: Hilda Osafo Hounkpatin

Thesis Title: Individual-level predictors of health and well-being: An integration of the social sciences

Date: September 2015

Background: The public health and economic literature on individual-level social determinants of health and well-being has largely focused on the role of income. However, it is not clear whether an individual’s income relates to their health and well-being due to material or psychosocial factors. The psychological literature on individual-level social determinants of health and well-being has been concerned with the role of psychosocial factors such as social comparisons and personality variables. However, the use of personality measures as predictors of health and well-being has been limited due to traditional perspectives that personality traits are stable over time. This thesis takes an interdisciplinary approach to advance the understanding of individual-level predictors of health and well-being in these disciplines.

Methods: Large scale cohort data were utilised for the analyses in this thesis. Marginal and conditional regression models were used to i) assess whether psychosocial factors associated with income predicted health better than material factors, and ii) determine the specification which best represented the psychosocial influence of income on health. Conditional models were also used to compare the predictive value of changes in income and changes in personality traits for a range of well-being outcomes. Structural equation models examined the nature of the association between changes in personality traits and changes in well-being.

Results: Regression models and goodness of fit statistics indicated that psychosocial factors associated with income, specifically an individual’s rank within a comparison group, predicted health better than material factors. Conditional models further indicated that other psychosocial factors such as an individual’s personality traits explained more variation in well-being outcomes than changes in income. Structural equation models indicated that observed changes in personality traits were not due to measurement error and that change in the personality trait neuroticism may be causally associated with changes in well-being.

Conclusions: The findings here integrate and advance the public health, economic and psychological literature on individual-level predictors of health and well-being, through identifying a psychological pathway through which income relates to health and by determining the relative contribution of economic and psychological factors such as personality trait change on health and well-being outcomes. Furthermore, the nature of the association between personality traits and well-being is explored.
DECLARATION

No portion of the work referred to in this thesis has been submitted in support of an application for another degree or qualification at this or any other university or other institute of learning.

COPYRIGHT STATEMENT

i. The author of this thesis (including any appendices and/or schedules to this thesis) owns any copyright or related rights in it (the “Copyright”) and s/he has given The University of Manchester the right to use such Copyright for any administrative, promotional, educational, and/or teaching purposes.

ii. Copies of this thesis, either in full or in extracts, may be made only in accordance with the regulations of the John Rylands University Library of Manchester. Details of these regulations may be obtained from the Librarian. This page must form part of any such copies made.

iii. The ownership of any patents, designs, trademarks and any and all other intellectual property rights except for the Copyright (the “Intellectual Property Rights”) and any reproductions of copyright works, for example graphs and tables (“Reproductions”), which may be described in this thesis, may not be owned by the author and may be owned by third parties. Such Intellectual Property Rights and Reproductions cannot and must not be made available for use without the prior written permission of the owner(s) of the relevant Intellectual Property and/or Reproductions.

iv. Further information on the conditions under which disclosure, publication and exploitation of this thesis, the Copyright and any Intellectual Property Rights and/or Reproductions described in it may take place is available from the Head of School of Medicine.
RATIONALE FOR SUBMITTING THE THESIS IN THE ALTERNATIVE FORMAT

This thesis has been granted permission to be submitted in the alternative thesis format. It was agreed among the supervisory team that the alternative format would be suitable for this thesis because the specific area of research undertaken in this project had yet to be explored extensively and therefore presented an opportunity to produce a number of individual research papers on a common theme. Subsequently, the four empirical chapters within this thesis are presented in format suitable for publication. Two of the empirical chapters (Chapters 3 and 5) have been published and two (Chapters 4 and 6) are currently under review at peer-reviewed journals.
ACKNOWLEDGEMENTS

Firstly, I would like to thank my supervisory team, Professor Graham Dunn and Professor Alex Wood for their thorough guidance, encouragement, and invaluable support throughout this program. I am grateful to them for their scientific input and commitment to this project and for helping me become a better researcher. I would also like to thank Professor Gordon Brown and Dr Christopher Boyce for their collaboration and advice. They have all greatly contributed to my development as a researcher.

I would like to acknowledge the Medical Research Council for providing the funding which has made it possible for me to pursue and complete this research. I would like to recognise the UK Data Service, CentERdata, and the Wisconsin Longitudinal Study staff for providing access to the data used in this research. I would also like to thank the administrative staff and IT services at the University of Manchester for helping me with numerous queries and issues I have encountered along this journey. I would like to thank my colleagues and friends in Coupland Building 1 for their advice and pleasant distractions. Thank you to Michael Bossons for leaving the computer clusters open until late so that I could use the printers.

Finally, I would like to thank my family and friends. I am especially grateful to my parents and Kanyin Sowemimo for their unwavering love, motivation, and support. Their constant encouragement and belief in me has enabled me to reach this far.

DEDICATION

This thesis is dedicated to my mum.
CHAPTER 1

1.0 Introduction

1.1 Overview

This thesis takes an inter-disciplinary approach to advance understanding of the individual-level social predictors of health and well-being. A primary interest within the social sciences (particularly the fields of economics and public health) has been the role of an individual’s income on their health and well-being. This research has concluded that an individual’s income is positively correlated to their health (e.g., Backlund, Sorlie, & Johnson, 1996) and well-being (e.g., Argyle, 1999), but that the effect of an individual’s income on their health and well-being is also dependent on the incomes of other individuals (Clark, Frijters, & Shields, 2008) because individuals evaluate their income relative to that of others. However, it is not clear (a) whether an individual’s income contributes more to their health and well-being than their relative income and (b) what specification should be used to model the effects of relative income on health and well-being. It is important to determine whether it is an individual’s income or their income relative to others’ that contributes more to their health and well-being so that effective policies and interventions can be designed to improve their health and well-being. Moreover, when assessing the relative contributions of actual and relative income on health and well-being, it is important to identify and use the best specification to model the effect of relative income in order to prevent misleading conclusions.

Research from the field of psychology can help determine the best specification to model the effect of relative income on health. Specifically, psychological research suggests that is the rank of an individual’s income within a comparison group that relates to an individual’s health and well-being because people make judgements based on rank position rather than any other specification (Stewart, Chater, & Brown, 2006). In addition to proposing an exact mechanism through which an individual’s income relates to their health
and well-being, the psychological literature has also provided extensive evidence that an individual’s personality trait is associated with health and well-being (DeNeve & Cooper, 1998; Steel, Schmidt, & Shultz, 2008) and may even predict health and well-being better than income (Boyce, Wood, & Powdthavee, 2013). However, the use of personality measures in health and well-being has been limited due to the traditional perspective that personality traits are fixed (Costa & McCrae, 1980) and therefore not suitable targets for interventions. Furthermore, it is not clear whether the association between personality traits and health and well-being may be confounded by omitted variables. A better understanding of the magnitude of personality trait change and the nature of the association between personality traits and well-being may be achieved by using analytical techniques more commonly used in economic research which better control for omitted variable bias.

This thesis therefore integrates and advances the economic, psychological and public health literature on individual-level social predictors of health and well-being through examining (a) whether the rank of an individual’s income predicts well-being better than an individual’s actual income, (b) whether the rank of an individual’s income predicts well-being better than an alternative measure of relative income that is currently widely used, (c) how much an individual’s personality trait changes over time relative to how much their income and other socio-economic factors change over time, and (d) whether the association between personality and well-being persists after controlling for omitted variable bias.

1.2 Explaining the Precise Association between Income and Health and Well-Being

The question of how income influences health and well-being outcomes has generated wide interest across the social sciences. Over the last two decades, economists, epidemiologists, and psychologists have embarked on research to understand the exact mechanism through which income positively relates to health. Competing hypotheses have now been proposed to explain the association between income and health (Wagstaff & van
Doorslaer, 2000). These are the absolute income hypothesis, the relative position hypothesis and the relative income or relative deprivation hypothesis. The next section gives a brief overview of the different hypotheses.

1.2.1 Theoretical framework: The hypothesis debate.

It has been observed that individuals with higher income tend to have better health and societies with a more equal distribution of incomes are generally healthier than societies with a wide income distribution (Subramanian & Kawachi, 2004).

Proponents of the absolute income hypothesis argue that income inequality within a society appears to affect population health only because each individual’s health is a product of the individual’s income and a concave (or non-linear) function by which the individual’s income is transformed to health (Gravelle, 1998; Preston, 1975; Rodgers, 1979). Equation 1.1 below illustrates this relationship:

\[ h_i = f_I(y_i) \quad (Eqn \ 1.1) \]

where \( h_i \) is the health of individual i, \( y_i \) the income of individual i and \( f_I \) is a concave function by which an individual’s income is transformed to their health (Wagstaff & van Doorslaer, 2000).

This absolute income hypothesis therefore suggests that an individual’s health depends only on their own material resources, and that more money confers better health, albeit with diminishing returns. Figure 1 shows how a one unit increase in income will improve the health of a poorer individual by a greater magnitude than it would the richer individual further to the right of the curve. Consequently, a more egalitarian population may be expected to have better health than a less egalitarian population simply because the poor health outcomes of the poor outweigh the health benefits of the wealthy (Gravelle, 1998).
Figure 1 Increasing income values increase health values but by decreasing amounts. (a) The curve becomes flatter moving from left to right, suggesting that an increase in income from far below average to below average will result in a higher health increase than an increase from above average to far above average. (b) For some adverse health outcomes (for example diabetes and ulcers), the relationship is convex, so that the flatter part of the curve is at higher incomes. This is due to the different biological mechanism and risk factors of disease. Taken from Pham-Kanter, 2009.

On the other hand, the income inequality hypothesis posits that, in addition to the effects of absolute income, the income gap between the rich and poor poses an additional effect on health. The income inequality hypothesis proposes that an unequal distribution of income causes a downward shift in the income-health curve (Subramanian & Kawachi, 2004), such that at the same income level, less health benefits are experienced in a less equal compared to a more egalitarian population. Income inequality is believed to relate to population health through eroding social cohesion which in turn reduces public goods and services (Kawachi, Fujisawa, & Takao, 2007; Kawachi & Kennedy, 1999). However, income inequality also relates to health at the individual-level through a psychosocial
pathway whereby an unequal income distribution causes individuals to make social comparisons with one another (Kawachi et al., 2007; Kawachi & Kennedy, 1999). The making of social comparisons often results in negative emotions such as feeling inadequate, social anxiety and stress which subsequently influence health (Wilkinson, 2001). Two further hypotheses can be considered under the individual-level psychosocial pathway of income inequality: the relative income hypothesis and the relative position (or relative rank) hypothesis.

There are slightly different variants of the relative income hypothesis. One variant proposes that it is the deviation of an individual’s income from the mean income of the population that results in poor health effects (Wilkinson, 1997). In equation form (Eqn 1.2):

$$h_i = f_I(y_i - y_p)$$  \hspace{1cm} (Eqn 1.2)

where $h_i$ is the individual’s health, $f_I$ is a concave function, $y_i$ is the individual’s income and $y_p$ is the mean income of the comparison group. Another variant suggests that it is the sum of the income gap between an individual’s income and the incomes of all individuals with higher incomes in the comparison group divided by the total number of individuals in the comparison group that relates to health (Kondo, Kawachi, Subramanian, Takeda, & Yamagata, 2008; Yitzhaki, 1979). Finally, an alternative variant suggests that it is the extent to which an individual’s income falls below the poverty line (an income of less than $1.00 a day or an income less than half of the community median income) that determines one’s health (Wagstaff & van Doorslaer, 2000). This can be described as

$$h_i = f_I(g_i, z)$$  \hspace{1cm} (Eqn 1.3)

where $h_i$ is the health of the individual, $f_I$ is the concave function, $g_i$ is the individual’s income gap and $z$ is the poverty line. However, this specific variant is less applicable for middle and high income countries (which is the focus of this thesis) where individuals generally have incomes above the poverty line.
The relative position hypothesis suggests that it is an individual’s social position within a comparison group that relates to their health (Wilkinson, 1996). This hypothesis may be more adequately described as the relative rank hypothesis. The relative rank hypothesis draws on evidence from primate studies which indicate that low ranking animals in conflict with more dominant members of the same species experience high levels of stress (Sapolsky, 2004; Shivley, Laber-Laird, & Anton, 1997) and cognitive science findings which indicate that individuals use rank position rather than any other specification when evaluating how their income compares to others’ (Stewart et al., 2006). It is expected that individuals are more likely to rank how their income compares to others’ rather than calculating the difference between their incomes and that of others’ because it is a less cognitively demanding yet effective process (Kahneman & Tversky, 1979, 2000).

Although the different hypotheses are closely related, it is important to distinguish between them in order to determine the exact mechanism through which income relates to health, particularly as the implications associated with some of the hypotheses may be very different. For example, if an individual’s income relates to health solely due to their absolute income levels (as suggested by the absolute income hypothesis) then this would suggest that income only relates to health due to material factors and that policies that increase an individual’s income should improve their health and well-being, regardless of the incomes of others’. Alternatively, if income relates to health due to social comparisons (as suggested by the relative income or relative rank hypotheses), then policies which target an individual’s income will only have an effect on their health if the incomes of others’ within their reference group remain the same. Instead, interventions which help reduce both the tendency to make comparisons and negative emotions arising from these comparisons may be more effective at improving an individual’s health and well-being. Although both the relative income and relative rank hypotheses propose a psychosocial effect on health, it is important to distinguish between these two hypotheses (and their specifications of relative deprivation) since it is plausible that the association between
health and well-being and each of these hypotheses may not be the same. Moreover, if people make income comparisons based on the ranks of their incomes and that of others’ and this is not adequately captured by specifications used to model the relative income hypothesis, then contrasting the absolute income hypothesis and the relative income hypothesis may erroneously lead to the conclusion that income does not have a psychosocial effect on health. It is therefore vital to discriminate between the hypotheses in order to determine the exact mechanism through which income inequality affects health.

1.2.2 Distinguishing between the different hypotheses: A review of the literature. Subramanian & Kawachi (2004) and Wagstaff & van Doorslaer (2000) have argued that multilevel studies containing both individual level data on income and health as well as aggregate income inequality measures have the potential to determine if income inequality has additional contextual effect on health and further discriminate between the relative income and relative rank hypotheses (both of which are consistent with the income inequality hypothesis). Existing multilevel studies on the association between income inequality and individual health and have produced mixed findings (Lynch et al., 2004; Subramanian & Kawachi, 2004; Wilkinson & Pickett, 2006). Recently, Kondo, Sembajwe, et al. (2009) and Kondo et al., (2012) have conducted meta-analyses using multilevel studies on the association between income inequality and mortality or self-rated health published between January 1995 and July 2008 and have concluded that income inequality has a modest independent effect on health. They have suggested that mixed findings may be due to threshold and lagged effects of income inequality, period effects (such as globalisation) and the geographic unit and study sample size used (Kondo, Sembajwe, et al., 2009; Kondo et al., 2012).

Although reviews by Kondo, Sembajwe, et al., (2009), Wilkinson & Pickett (2006), Pickett & Wilkinson (2015) indicate income inequality has an independent effect on individual health, there is still a debate over the exact pathway through which income inequality affects health and the relative importance of this mechanism compared to role of
absolute income (Wilkinson & Pickett, 2009a). A large number of studies have produced evidence for a contextual effect of social cohesion on individual health (for example, Kawachi, Kennedy, Lochner & Prothrow-Stith, 1997; Kawachi, Kennedy & Glass, 1999; Ichida et al., 2009; Kim, Park, Peterson, 2013), though some studies have found that this effect is partly due to individual-level social cohesion and trust (for example, Kim, Subramanian, & Kawachi, 2006; Subramanian, Kim, & Kawachi, 2002). Furthermore, the effect of societal social cohesion (measured as social trust and social capital) on self-rated health has been noted to vary across individuals, depending on the individual’s levels of trust and civic participation (Poortinga, 2006; Subramanian et al., 2002). This suggests that psychosocial processes at the individual-level are more accurate predictors of the effect of income inequality on individual health. However, studies that have specifically assessed the effect of relative income (as a measure of social comparisons) on health have been less conclusive (Adjaye-Gbewonyo & Kawachi, 2012). For example, studies that have used data from Nordic countries (Yngwe, Kondo, Hagg, & Kawachi, 2012; Yngwe, Fritzell, Burstrom, & Lundberg, 2005; Yngwe, Fritzell, Lundberg, Diderichsen, & Burstrom, 2003) and the United States (Eibner & Evans, 2005; Eibner, Sturm, & Gresenz, 2004) have yielded evidence for an effect of relative income on health, while studies from the United Kingdom and elsewhere have found no (Li & Zhu, 2006; Lorgelly & Lindley, 2008) or weak (Gravelle & Sutton, 2009; Jones & Wildman, 2008; Wildman, 2003) evidence for this mechanism. The heterogeneous findings may therefore partly reflect differences in the magnitude of income differences of individuals within a reference group in different countries. However, inconsistent results have been reported for studies within the same country (for example: Li & Zhu, 2006 and Ling, 2009; Kondo et al., 2008 and Kondo, Kawachi, et al., 2009) suggesting that the effect of relative deprivation may vary across different outcome health variables and different reference groups used (Adjaye-Gbewonyo & Kawachi, 2012). Furthermore, the mixed findings may also be due to the use of different analytic methods.
While a number of studies have looked specifically at the effect of relative income, very few studies have investigated an effect of relative rank on health. Eibner and Evans (2005) have assessed the effect of centile rank on mortality in the US and did not observe a significant association. Using two different samples, Li and Zhu (2006) and Subramanyam, Kawachi, Berkman, & Subramanian (2009) have found percentile income rank is positively associated with self-rated health. Furthermore, studies from the psychological literature (Boyce, Brown, & Moore, 2010; Daly, Boyce, & Wood, 2015; Wood, Boyce, Moore, & Brown, 2012) have provided support for a positive association between income rank and mental distress, subjective well-being and health. More recently, Elgar et al. (2013) have assessed and compared the effect of family (material) affluence, family relative affluence, and family rank affluence on psychosomatic (i.e. feeling nervous, down or low) and somatic (e.g., difficulty sleeping, headache) symptoms in adolescents and found that rank affluence was significantly associated with these symptoms and better explained variation in these symptoms than absolute and relative affluence. The authors also observe an interaction effect between rank affluence and absolute affluence, such that rank was more strongly related to outcomes at lower levels of absolute affluence. These findings, together with evolutionary studies providing support for the importance of social rank within a hierarchy (Raleigh, Brammer, & McGuire, 1983; Yeh, Frickle, & Edwards, 1996) and cognitive findings on how individuals make judgements, suggest that income may affect health by acting as a proxy for income rank. Further studies which directly contrast the effects of absolute income, relative income and relative rank on health and well-being and use different study populations and outcome measures can help identify the exact mechanism through which income relates to health.

1.3 Individual Heterogeneity in the Inequality-Health and Well-Being Association

Both the relative income and relative rank hypothesis are consistent with Leon Festinger’s (1954) theory of social comparison, which models how individuals often make
upward comparisons with one another. Having low income compared to others will trigger such comparisons, which can often be distressful as they prompt an individual to evaluate themselves based on other’s abilities or performances. While the effects of stress are mediated and often protected by the body’s biological homeostatic stress response (Brunner, 1997; Sapolsky, 2004), recurrent and prolonged formation of income comparisons can have serious consequences on both physical and mental health and well-being (e.g., Sapolsky, 2004; Tsigos & Chrousos, 2002). Whether individuals experience negative consequences such as depression after experiencing chronic stress will depend partly on whether they feel they have no control over their situation due to their own inadequacies (Willner & Goldstein, 2001). Gilbert and Allan (1998) and Willner and Goldstein (2001) have also argued that perceptions of defeat and entrapment mediate the association between stress and depression. To the extent that an individual’s personality determines both the frequency at which they make income comparisons and how negatively they respond to unfavourable income comparisons (for example, Budria & Ferrer-i-Carbonell, 2012; Van der Zee, Oldersma, Bunk, & Bos, 1998), it is plausible that any effect of relative income or relative rank will vary across individuals.

An individual’s personality can be defined as a combination of their characteristic patterns of thoughts, feelings and actions that form an individual’s unique character (Roberts, Wood, & Caspi, 2008). The field of personality psychology has focused on personality traits as predictors of health and well-being and have identified five core dimensions which account for an individual’s personality traits (John & Srivastava, 1999; McCrae & John, 1992), thus facilitating the integration of personality traits into research on individual-level predictors of health and well-being. These dimensions - also known as the ‘Big Five’ or ‘Five Factor’ model - are: neuroticism, extraversion, openness to experience, agreeableness and conscientiousness. Table 1 provides a summary of the definition of each of these, as well as traits and tendencies of people with the specified personalities.
Recently, a handful of empirical studies have demonstrated that the effect of an individual’s absolute income on their mental health (Jokela & Keltikangas-Jarvinen, 2011) and well-being (Boyce & Wood, 2011; Soto & Luhmann, 2013) is in fact moderated by their personality traits. For example, income was more strongly associated with depression and life satisfaction for moderately neurotic individuals than their less neurotic peers and highly conscientious individuals benefitted more from an equivalent increase in income compared to less conscientious individuals (Boyce & Wood, 2011; Soto & Luhmann, 2013). Similarly, personality traits have been found to moderate the association between other indicators of social class and health behaviours (Chapman, Fiscella, Duberstein, & Kawachi, 2009) and mortality (Hagger-Johnson et al., 2012). There is also some evidence to suggest that personality traits not only moderate, but also mediate the association between income and health and well-being. For example, Diener, Tay, Oishi (2013) have argued that a positive association between income and well-being is more likely to occur if an individual feels optimistic about their future. Together these findings suggest that personality traits play an important role on the association between income and health and well-being. If certain personality characteristics are necessary for income to have an effect on well-being then this would indicate that personality measures should be more widely used as predictors of health and well-being. The next section discusses the use of personality trait variables as predictors of health and well-being.
<table>
<thead>
<tr>
<th>Big Five Factor</th>
<th>Personality Description</th>
<th>American Psychology Association Dictionary Description</th>
<th>Basic Tendencies</th>
<th>Characteristic Adaptations/ Traits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neuroticism</td>
<td>A chronic level of emotional instability and proneness to psychological distress</td>
<td>Depression (tendency to experience dysphonic affect—sadness, hopelessness, guilt)</td>
<td>Low self-esteem, pessimistic attitudes, hostile, moody, prone to experiencing anxiety</td>
<td></td>
</tr>
<tr>
<td>Extraversion</td>
<td>An orientation of one’s interests and energies toward the outer world of people and things rather than the inner world of subjective experience; characterised by positive affect and sociability</td>
<td>Gregariousness (a preference for companionship and social stimulation)</td>
<td>Self-confident, sociable, enthusiastic, adventurous, energetic, having numerous friendship</td>
<td></td>
</tr>
<tr>
<td>Openness to Experience</td>
<td>The tendency to be open to new aesthetic, cultural or intellectual experiences</td>
<td>Having a need for variety, novelty, and change</td>
<td>Artistic, unconventional, interest in travel, having wide interests and hobbies</td>
<td></td>
</tr>
<tr>
<td>Agreeableness</td>
<td>The tendency to act in a cooperative, unselfish manner</td>
<td>Compliance (a willingness to defer to others during interpersonal conflict)</td>
<td>Warm, sympathetic, forgiving and trusting, believing in cooperation</td>
<td></td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>The tendency to be organized, responsible and hard-working</td>
<td>Achievement striving – a strong sense of purpose and high aspiration levels</td>
<td>Efficient, having leadership skills, well organised and good work ethic</td>
<td></td>
</tr>
</tbody>
</table>

– adapted from Costa and McCrae (1992) and Heckman (2011).
1.4 The Greater Role of Personality Measures as Indicators of Overall Health and Well-Being

1.4.1 The use of personality trait measures in health and well-being research.

In addition to the moderating role of personality variables on the association between income and health and well-being, personality measures have been directly linked to economic, health and well-being outcomes (DeNeve & Cooper, 1998; Steel et al., 2008). For example, evidence from psychological literature suggests high levels of conscientiousness has been consistently positively associated with educational attainment and job performance (Barrick & Mount, 1991) (and in turn high earning potential) as well as well-being (DeNeve & Cooper, 1998; Steel et al., 2008), chronic and infectious disease progression (Ironson, O'Cleirigh, Weiss, Schneiderman, & Costa, 2008) and longevity (Jokela et al., 2013). Weaker evidence also exists for the association between the remaining traits and career success (Sutin, Costa, Miech, & Eaton, 2009) and health outcomes (Jokela et al., 2013).

However, despite the evidence supporting a strong association between personality measures and economic, health and well-being outcomes, the use of personality measures has been limited in disciplines outside psychology, at least partly due to the earlier perspective that personality traits were stable after the age of 30 (Costa & McCrae, 1980, 1988). A growing body in the psychological literature has now indicated that personality does in fact change beyond the onset of adulthood and across all age ranges (for example, Srivastava, John, Gosling, & Potter, 2003) thus elucidating personality variables as possible targets for interventions and policies aimed at improving health and well-being. Nevertheless, before personality change measures can be used in health and well-being research, it is important to understand how much personality changes and what this change represents. The sections below consider the magnitude and theories of personality change.

1.4.2 The magnitude of personality trait change.
In order to fully understand personality change, it is necessary to examine all three indices of personality change and continuity (Roberts & Mroczek, 2008). These indices are: mean-level change, rank-order stability and individual differences in personality change. Mean-level change is often referred to as absolute or normative change and occurs when a group of individuals show similar patterns in personality change over time (Roberts, Walton, & Viechtbauer, 2006; Specht, Egloff, & Schmukle, 2011). Rank order stability refers to whether individuals retain the same position within a distribution, with respect to their personality traits (Specht et al., 2011). Individual differences in personality change describe the deviation of an individual’s change in personality from the sample-mean level pattern of personality change (Roberts & Mroczek, 2008). Together these indices provide a comprehensive understanding of personality development. For example, a sample can have high rank-order stability but still show mean level change indicating that most individuals show similar patterns of change in trait dimensions over time (Roberts & DelVecchio, 2000). On the other hand, a sample which does not show mean-level change in personality traits may include individuals who change their personality traits to a similar degree in opposite directions (Roberts & DelVecchio, 2000).

Personality development can be characterised as showing a curvilinear pattern of rank-order stability (with rank-order stability increasing after childhood and reaching a plateau during midlife) (Roberts & DelVecchio, 2000), small but significant mean-level change (Bleidorn, Kandler, Riemann, Angleitner, & Spinath, 2009; Roberts et al., 2006) - specifically mean-level increases in extraversion, openness, agreeableness and conscientiousness and mean-level decreases in neuroticism- and considerable individual differences in the pattern of development (Bleidorn et al., 2009) across the lifespan. Although the magnitude of mean-level change in traits can be described as small - effect sizes (denoted by \(d\)) (Cohen, 1988) ranging from \(d = 0.06\) to \(d = 0.41\) - Roberts, Walton, & Viechtbauer, (2006) have highlighted that changes of such magnitude are important for at least two reasons: firstly, small changes in personality may result in significant changes in
human outcomes and secondly, small changes may amount to changes as large as one standard deviation over the entire lifespan. Moreover, changes of larger magnitude may exist at the individual level. While a number of studies have found reliable individual differences in personality change (for example, Mroczek & Spiro, 2003; Vaidya, Gray, Haig, Mroczek, & Watson, 2008), there is a lack of studies that have directly estimated the magnitude of personality change at the individual level. A more recent study by Boyce, Wood, & Powdthavee (2013) uses an econometric approach to investigate the magnitude of personality trait change and concludes that an individual’s personality changes at least as much socioeconomic indices which are widely considered as variable. The finding by Boyce et al., (2013) suggests that personality change may have an applied value in economic and public health research, through acting as an indicator of an individual’s well-being. However, it is not clear whether such findings would extend to different populations and what intra-individual personality change represents. Further examinations of intra-individual personality change using similar analytical approaches for different study samples are needed to improve understanding of the magnitude and underlying causes of personality change at the individual level.

1.4.3 Theories of personality trait change: Exploring the evidence.

At least six main theories have overtly considered the mechanisms of personality change over time. These theories are the Five Factor theory, the genotype → environment theory, the social investment principle, the sociogenomic model, the paradoxical theory and the existential-humanistic theory. These theories can be divided into theories that favour a biological mechanism of personality change and those that support an environmental influence on personality change.

The Five Factor theory (McCrae & Costa, 2008) proposes that individuals are genetically predisposed to experiencing normative personality changes in certain directions, independent of their environment and life experiences. Specifically, individuals tend to become less neurotic and more agreeable, more conscientious (Roberts, Wood, &
Smith, 2005) as they age. The Five Factor theory contends that these changes occur solely due to biological maturation and that environmental conditions affect personality traits only in very rare situations (McCrae & Costa, 2008). Much of the argument for the Five Factor theory stems from cross-sectional studies showing similar age patterns of mean-level personality change cross-culturally (McCrae et al., 1999). However, studies indicating that cultural changes within countries are associated with differential patterns of personality development (Roberts et al., 2005) and cultures that differ in normative timing of life events such as marriage differ in the timings of personality change (Bleidorn et al., 2013) suggest that other factors besides genetics influence personality change.

Another theory which focuses on biological process of personality change is the ‘genotype → environment’ theory (Scarr & McCartney, 1983). Unlike the Five Factor theory, the genotype → environment theory proposes that environmental conditions contribute to personality, but these environmental influences are genetically-determined and act only as mediators of personality change rather than having a direct influence on personality change (Specht et al., 2014). For example, individuals who have certain (genetically-determined) personality characteristics are likely to select certain professions which will cause further increases in those traits (Roberts et al., 2008). This theory is consistent with the findings by Bleidorn et al (2013), since each individual may be genetically-predisposed to change their personality traits, but the exact timing of this will depend on their environmental conditions. However, the theory has been contradicted by longitudinal studies of personality development in twins which found that both genetic and environmental factors independently contribute to personality change (Bleidorn et al., 2009). Furthermore, there is some indication that environmental influences are more important predictors of individual differences in personality change (Specht et al., 2014). Such empirical evidence is perhaps more in line with the sociogenomic model (Roberts & Jackson, 2008; Roberts et al., 2008) which also considers gene-environment interactions as drivers of personality change. This model takes the view that personality traits are
‘inherited’ but that environmental conditions are necessary both for the expression of these
traits and any changes in their expression. However, unlike the genotype → environment
theory, the sociogenomic model does not imply that these environmental conditions are
genetically-determined. Environmental changes associated with, for example, role-
transitions are thought to first cause changes in personality states (i.e., thoughts and
feelings) (Roberts & Jackson, 2008; Specht, Egloff, & Schmukle, 2013). Through
prolonged effects of personality states, these environmental changes consequently result in
changes in personality traits.

On the contrary, the social investment theory postulates the environment and life
experiences alone drive personality changes. According to this theory, investments in
social roles such as marriage or work are associated with a set of expectations which an
individual must follow in order to be successful in the role. By committing to the role, the
individual is therefore expected to gain certain characteristics that are conducive to
success, such as becoming more agreeable, less neurotic and more conscientious (Roberts
et al., 2005). Successful adaptation in these roles would therefore be associated with
personality changes in this direction. A number of studies have now provided direct
evidence for the social investment principle, including studies which find that investment
in work (for example Hudson, Roberts, & Lodi-Smith, 2012; Specht et al., 2011) and
romantic relationships (Lehnart, Neyer, & Eccles, 2010) predict mean-level changes in
personality traits in a direction consistent with the social investment principle. However,
Specht et al. (2011) have found that certain life events are associated with personality
changes in the opposite direction to those predicted by the theory, suggesting further
research is needed to understand which and how certain social roles are associated with
personality change.

The paradoxical theory (Caspi & Moffitt, 1993) focuses on individual differences
in change and argues that personality change is more likely to occur when all the following
conditions are simultaneously present: (a) the individual is presented with a new
unpredictable situation (b) the individual seeks to transform this ambiguous situation into a familiar one (c) previous responses are discouraged and (d) there is clear information on how to respond adaptively in this situation (Caspi & Moffitt, 1993). This theory predicts that personality change is unlikely to occur if conditions (c) and (d) are not met. According to this theory, it can be expected that personality change will occur only if there is clear information on how to respond adaptively. The theory of self-regulated personality change (Denissen, van Aken, Penke, & Wood, 2013) further suggests that the expected personality change is likely to occur if the individual wants to change and the direction of personality change will depend on the values of the individual. If the individual values personality characteristics that are considered adaptive for a social role, then the individual’s personality will change in this direction. If the individual values alternative personality characteristics and/or has low self-control, then the individual’s personality will change towards these characteristics. Therefore, the self-regulatory perspective of personality change stresses the importance of an individual’s motivation or ability to regulate themselves in order to obtain characteristics that are considered valuable by society. Contrary to this, the existential-humanistic theory implies that it is the individual’s determination to develop in ways that are consistent with their true self (rather than society) that provokes personality change. Striving for self-fulfilment and meaningfulness to one’s existence drives personality to change (Wong, 2006), in ways which allow the individual to existentially engage with the world around them.

1.4.4 Personality traits and well-being outcomes: A causal relationship?  

The theories of personality change suggest that personality trait change is a meaningful process, which enables individuals to fulfil their goals and achieve well-being. A large body of evidence now exists which suggests that changes in personality co-occur with changes in well-being (Boyce et al., 2013; Specht et al., 2013). Two studies by Soto (2013) and Specht et al. (2013) have found that individuals who had higher initial levels of well-being were more likely to experience subsequent positive changes to their personality
traits and individuals who had higher levels of emotional stability, extraversion, agreeableness and conscientiousness experienced subsequent increases in well-being. This finding suggests that personality traits and well-being variables prospectively influence one another. However, we cannot infer from these studies whether personality change is causally associated with changes in health and well-being as associations between individual differences in personality and within-person change in well-being may be confounded by person-specific variables. More conservative statistical techniques which reduce bias due to omitted variables are needed to explore whether changes in an individual’s personality influence subsequent changes in their well-being. The study of whether changes in personality lead to subsequent changes in well-being will greatly advance knowledge of the association between personality traits and well-being by determining whether the association between personality traits and life satisfaction is only due to individual differences in omitted variables.

1.5 Overview of Thesis

The overarching aim of this thesis was to integrate and advance perspectives across the social sciences to better understand individual-level predictors of health and well-being. Chapter 2 summarises the methodologies used in the empirical studies. Chapters 3 and 4 integrate psychological research into rank with the public health/economic research on the association between income and health and well-being. Chapter 3 provides a direct test of the relative rank hypothesis in two midlife samples and expands the literature on the role of income rank to a measure of depression. Chapter 3 further contributes to the literature by addressing two key methodological issues in the previous studies investigating the effect of income on health in order to allow a more stringent test of the relative rank hypothesis. Chapter 4 provides the first direct comparison of the absolute income, relative income and relative rank hypotheses to ascertain the exact mechanism through which income relates to health. Chapters 5 and 6 extend the psychological literature on the
importance of personality variables for health and well-being. First, Chapter 5 examines the magnitude and predictive value of personality change over time and compares this to the magnitude and predictive value of change in income. Thus, Chapter 5 illustrates the relative contribution of personality change (a psychological predictor) and income change (an economic predictor) to health and well-being outcomes. Chapter 5 additionally explores what personality change represents by comparing the predictive value of personality change for a range of different well-being outcomes. Chapter 6 assesses the nature of the association between personality and well-being, through using more advanced statistical techniques which reduce bias due to omitted variables. The thesis then concludes with an overview and general discussion of the findings of Chapters 3-6 (Chapter 7).

1.6 Note on Collaboration and Published Material

This current thesis is produced in the alternative format option, whereby research chapters are written and presented in a format suitable for publication in academic peer-reviewed journals. The alternative format was chosen for this thesis in order to allow work to be submitted for publication during the course of the PhD program. As a result, Chapter 3 (Why does income relate to depressive symptoms: Testing the income rank hypothesis longitudinally) and Chapter 5 (An existential-humanistic view of personality change: Co-occurring changes with psychological well-being in a ten year cohort study) have been published by Social Indicators Research. Chapter 4 (Does income relate to health due to psychosocial or material factors? Consistent support for the psychosocial hypothesis requires operationalization with income rank not the Yitzhaki Index) is currently under review at Social Science & Medicine and Chapter 6 (Which personality traits lead to life satisfaction? Lagged changes in neuroticism negatively predict life satisfaction changes in a large representative cohort survey) is currently under review at Journal of Personality & Social Psychology. The author of this thesis completed the research presented in this thesis in collaboration with other individuals. The author’s supervisory team, Professor Graham
Dunn and Professor Alex Wood provided input in the research development and write-up of the thesis. They are therefore listed as co-authors in each research paper. Professor Gordon Brown, from the University of Warwick, contributed to the methodology and write-up of Chapter 3, and is also recognised as a co-author here. Dr Christopher Boyce is recognised as co-author for Chapters 5 and 6, for his input in the development and write-up of these studies. All analyses were undertaken solely by the author. Similarly, all the write-up was the work of the author, though others provided feedback and suggestions on earlier drafts.
CHAPTER 2

2.0 Methods

This chapter provides an overview of the data and statistical procedures used in this thesis. The background and design of each dataset utilised is outlined, followed by descriptions and assumptions of the statistical techniques used to analyse the data. Generic examples of research questions are also provided to illustrate the appropriate use of the different methodologies.

2.1 Choice of Datasets and Samples

This thesis makes use of publicly archived large-scale cohort data that can be accessed online through resources such as the UK Data Service and CentERdata. Publicly archived data facilitates the use of existing (secondary) data in health-related research. The use of secondary data offers a number of advantages. Secondary data are instantly available, are often free of charge and can provide data on a range of variables for a large number of individuals (Hussein, 2011). However, the main disadvantages of using secondary data are that the researcher does not have control over the data collection process and much of the data contained in secondary data may not be relevant or suitable to answer the specific research question (Hussein, 2011). The datasets utilised in this thesis were specifically selected due the availability of validated measures of personality, well-being, health and socioeconomic variables at multiple time points. Data in which the same variables are measured over time is known as longitudinal data. Longitudinal data allows the study of association between changes in these variables over time, as well as prospective effects of one variable on another variable. Additionally, longitudinal data can reveal pathways through which variables are related. The datasets utilised in this thesis were the English Longitudinal Study of Ageing (ELSA), the Wisconsin Longitudinal Study
(WLS), and the Longitudinal Internet Studies for the Social Sciences (LISS). The following sections describe the background and design of each of these datasets.

2.1.1 The English Longitudinal Study of Ageing (ELSA).

ELSA is a nationally representative cohort of individuals aged 50 and over and living in England. The main purpose of ELSA was to provide data to improve understanding of the health, well-being and economic status of individuals as they age (Steptoe, Breeze, Banks, & Nazroo, 2013). The initial sample for ELSA consisted of 12,099 individuals who participated in the Health Survey of England during 1998, 1999 and 2001. Participants were first interviewed in 2002 and have been interviewed every two years since then. Refreshment cohorts were added to the initial sample during Waves 3 (2006) and Waves 4 (2008). Data has been collected using both face-to-face interviews and self-completion questionnaires. During Waves 2 (2004), Waves 4 (2008) and Waves 6 (2012), participants who gave their consent additionally underwent clinical assessment by a nurse. Objective measures of health, such as diastolic and systolic blood pressure, body mass index, forced expiratory volume and biomarkers of disease were obtained during the clinical assessment. Data for Wave 7 of ELSA is not yet available.

2.1.2 The Wisconsin Longitudinal Study (WLS).

WLS is a cohort of a random sample of 10,317 individuals who graduated from high schools in Wisconsin in 1957. WLS consists of a representative sample of white, non-Hispanic high school graduates. The WLS provides data on family background, socioeconomic variables, mental health and psychological well-being from adolescent years to late adulthood and death (Herd, Carr, & Roan, 2014). Participants first provided data in the form of questionnaires in 1957. In 1964, parents of participants were asked to provide follow-up data on behalf of the participant, via mail questionnaires. Participants were then asked to provide follow-up data via telephone surveys during 1975. During 1992-1993 and 2004, participants completed telephone and mail questionnaires about their
income, employment status, health and well-being. An additional wave of data collection began in 2011, but is not yet available.

2.1.4 The Longitudinal Internet Studies for the Social Sciences (LISS).

LISS is a cohort of a nationally representative sample of approximately 5,000 Dutch households in the Netherlands. LISS aims to provide a representative study of the lives and living conditions of the Dutch population (Knoef & deVos, 2009). Households were randomly selected from municipal registers in 2007 and selected for inclusion in the panel if at least one member of the household was 18 years or older. Participants have been administered online surveys every month since October 2007. Each online survey consisted of questions on sociodemographic variables. Participants also provided data on self-rated health (via online surveys) during the months of November and December 2007-2013. During May/June 2008 and May/August 2009-2013, participants were also asked (via online surveys) to rate their personality. The initial (2007) sample was slightly underrepresentative of elderly individuals in the Netherlands (Knoef & deVos, 2009). As a result, refreshment samples were added to the initial sample during 2009, 2011-2012 and 2013-2014 to ensure representativeness of the sample. A particular advantage of the LISS panel for this thesis was the availability of three waves of personality and well-being data, which allowed us to adopt a specific structural equation modelling technique to enhance our understanding on the association between personality and well-being.

2.2 Statistical Techniques

This thesis uses different types of statistical models to predict health and well-being outcomes from socioeconomic and personality variables. The models used in this thesis have been chosen as they are most suited to the structure of the data and the specific research question. This section describes the different models used in the thesis.

2.2.1 Multiple linear regression models.
Multiple linear regression models were used to predict both current and future depressive symptoms from income and income rank (plus covariates) in Chapter 3. In a multiple regression model, an outcome variable $Y$ is predicted from a linear combination of explanatory variables ($X$) as below:

$$Y_i = \alpha_i + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \epsilon_i$$  \hspace{1cm} (Eqn 2.1)

where $\alpha$ is the intercept and is equal to the value of the outcome variable $Y$ when the values of all explanatory variables ($X$) are equal to 0, $\beta_k$ is the regression coefficient for the $k$th explanatory variable ($X_k$) and $\epsilon$ is random error. The regression coefficient is the change in $Y$ per unit change in $X$ when the remaining explanatory variables in the model are held constant. The intercept and regression coefficients of a multiple linear regression are estimated using the ordinary least squares (OLS) method. OLS selects the estimates that minimize the sum of squared residuals (Wooldridge, 2003) by first squaring the deviation of the observed values of each variable from the expected value for that variable, then summing the squared deviations of all the variables in the model and minimizing this value. The fit of the regression model can then be assessed by calculating the deviation between the expected values of $Y$ and the observed values of $Y$. The deviance between each expected and observed $Y$ value is then squared and summed to provide an indication of the goodness of fit of the model (Hutcheson, 2011). A large residual sum of squares indicates that the model is not a good fit for the data because the data is far from the predicted values.

Multiple regression models have the advantage that multiple explanatory variables can be included into the model. This also means that a unique effect of a variable on an outcome variable can be estimated since the effects of other variables affecting the outcome are controlled. A multiple regression model was thereby appropriate to predict a cross-sectional association between depressive symptoms from income and income rank (as well as other predictor variables such as employment and marital status). Similarly, it was useful to predict future depressive symptoms from current levels of depressive
symptoms, current income and current socio-demographic variables. However, multiple linear regression models make certain assumptions. The first assumption is that the relationship between the parameters of the model is linear, although this assumption is flexible (Wooldridge, 2003) and non-linear functions of variables (such as polynomials or logarithmic transformations) may be included in the model. Secondly, the error term $\varepsilon$ is assumed to (a) be independent of the explanatory variables in the model and (b) have the same variance for all values of the explanatory variables. The assumption of independent error limits the use of multiple linear regression models for analysis of longitudinal data since observations from the same individual can be expected to be correlated and also have correlated errors. Therefore, it was not suitable to use a multiple regression model to assess the effect of income and income rank on depressive symptoms over time (as in Chapter 4) or to assess the effect of within-person changes in income or personality variables on within-person changes in depressive symptoms over time (as in Chapter 5). Marginal and conditional models are better suited than linear regression models to account for non-independence of repeated observations (and the errors associated with these observations). Marginal and conditional models are described in the next sections.

2.2.2 Marginal and conditional models.

Marginal and conditional models are two distinct approaches that have been developed to account for non-independence of observations in longitudinal data (Liang & Zeger, 1986; Zeger, Liang, & Albert, 1988). Marginal and conditional models differ in their assumptions and focus of analysis.

Marginal models provide population-averaged estimates of the association between variables across different time points. In a marginal model, the clustered nature of the data is accounted for but differences between subjects are not directly estimated. The marginal model predicts the outcome $Y$ across time $t$ from a set of covariates $X$ across time $t$:

$$ Y_{it} = \alpha + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \varepsilon, \quad t = 1, 2 \ldots T \quad (\text{Eqn 2.2}) $$
where $Y_{it}$ is the outcome variable for a specific individual $i$ across time $t$, $\alpha$ is equal to the value of $Y$ across time when the value of all explanatory variables $X$ is equal to 0 and $\beta_k$ is the change in $Y$ per unit change in the $k$th explanatory variable, $X_k$, over time when all other explanatory variables are held constant. The marginal model then estimates the within-cluster correlation of the residuals and uses this correlation to generate weights of the observations (Hanley, Negassa, Edwardes, & Forrester, 2003). A weighted combination of observations is then used to generate parameter estimates and standard errors (Hanley et al., 2003). The advantage of the marginal model is that it provides efficient estimates of regression parameters with accurate standard errors (Hanley et al., 2003), even when the within-subjects correlation structure is misspecified (Liang & Zeger, 1986).

A marginal model is appropriate to use when ‘between-subject’ effects are of interest (Agresti, 2010). For example, a marginal model will yield efficient parameter estimates if the focus of the analysis is to compare the effect of a variable (for example, socioeconomic status) on health status for two randomly selected individuals. However, conditional models will be more efficient if the focus of analysis is estimating within-subject effects – for example, estimating effect of change in individual’s socioeconomic status on change in their health status over time. Conditional models provide individual-specific estimates of the association between variables. In a conditional model, differences across subjects are explicitly modeled (Hanley et al., 2003), rather than controlled. Conditional models also assume that the within-subject independence of observations is due to unobserved heterogeneous factors (Gardiner, Luo, & Roman, 2009). A conditional model that assumes these unobserved heterogeneous factors are random and independent of the explanatory variables of the regression is known as a random-effects model (Gardiner et al., 2009; Wooldridge, 2003; Zeger et al., 1988). In a random-effects model (which is equivalent to a marginal model for continuous outcome variables), the unobserved effect is estimated along with the remaining parameters of the model.
(Wooldridge, 2003). The results of a random effects model therefore present a weighted estimate of between- and within-subject effects. In a random-effects model, an outcome variable \( Y \) for a specific individual \( i \) across time \( t \) is estimated as below:

\[
Y_{it} = \alpha + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + u_i + \epsilon_{it} \tag{Eqn 2.3}
\]

where \( \alpha \) is equal to the value of \( Y \) over time when the value of all explanatory variables \( X \) is equal to 0, \( \beta_k \) is the change in \( Y \) per unit change in \( X_k \) over time for a specific individual \( i \), given a set of explanatory variables and \( u_i \) is the unobserved factors causing the within-subject correlation of residuals for individual \( i \) (i.e., the subject-specific effects on the repeated observations), again holding all the other explanatory variables constant. A random-effects model may be preferred to a marginal model if the cluster-specific estimates and the variation of the cluster-specific estimates are of interest. For models with linear continuous outcome variable, the regression coefficients of a random-effects model is identical to the regression coefficients of a marginal model (Verbeke, Molenberghs, & Rizopoulos, 2010). In Chapter 4, a random-effects model was used to provide mean estimates of the effect of income rank on depressive symptoms (a continuous variable) over time for a given sample. Although the variation at cluster-level was not the main interest of the study in Chapter 4, a random-effects model was preferred due to the lack of tests to assess fit of marginal models (Skrondal & Rabe-Hesketh, 2004).

In Chapter 5, a fixed-effects regression model was used to estimate the association between changes in well-being outcome variables with changes in socioeconomic and personality variables. A fixed-effects regression model is an alternative type of a conditional model. In a fixed-effects model, the unobserved factors are assumed to be time invariant and correlated with the explanatory variables of the model. The fixed-effects approach adjusts for the correlation between the explanatory variables and unobserved factors by subtracting the average of each variable from the corresponding variable at each time point. For example, if the outcome \( Y \) for a specific individual \( i \) at a single time point \( t \) is given by:
\[ Y_{it} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + u_i + \varepsilon_{it} \quad (Eqn\ 2.4) \]

and across time the average value for \( Y \) is:

\[ \bar{Y}_i = \bar{\alpha}_i + \bar{\beta}_1 \bar{X}_{1i} + \bar{\beta}_2 \bar{X}_{2i} + \bar{\beta}_3 \bar{X}_{3i} + u_i + \bar{\varepsilon}_i \quad (Eqn\ 2.5) \]

Then the fixed-effects model is:

\[ Y_{it} - \bar{Y}_i = (X_{1it} - \bar{X}_{1i}) \beta_1 + (X_{2it} - \bar{X}_{2i}) \beta_2 + (X_{3it} - \bar{X}_{3i}) \beta_3 + (u_i - \bar{u}_i) + (\varepsilon_{it} - \bar{\varepsilon}_i) \quad (Eqn\ 2.6) \]

where \( Y_{it} - \bar{Y}_i \) is the deviation of \( Y \) from the mean \( Y \) over time, \( \beta_k \) is the effect of deviation of explanatory variable \( X_k \) from mean \( X_k \) over time on deviation of \( Y \) from mean \( Y \) over time and \( (\varepsilon_{it} - \bar{\varepsilon}_i) \) is the deviation of the error term from the mean error over time.

The fixed-effects approach eliminates the effect of the unobserved factors (which is considered to be fixed for each individual), as well as other time-invariant observed variables such as gender or ethnicity. In the case of a two-wave panel, the fixed-effects regression is equivalent to a first-difference estimation that subtracts observations at Time 2 from observations at Time 1. The first-difference model is:

\[ \Delta Y_i = \beta_1 \Delta X_{1it} + \beta_2 \Delta X_{2it} + \beta_3 \Delta X_{3it} + \Delta \varepsilon_{it} \quad (Eqn\ 2.7) \]

where \( \Delta Y_i \) is the change in outcome variable \( Y \) from Time 1 to Time 2 for an individual \( i \), \( \beta_k \) is the effect of change in an explanatory variable \( X_k \) from Time 1 to Time 2 for individual \( i \) and \( \Delta \varepsilon_i \) is the change in error term from Time 1 to Time 2 for individual \( i \). A fixed-effects model (or a first-difference model) may be selected instead of a random-effects model when the focus of analysis is on the association between within-subject changes in an explanatory variable (for example, change in an individual’s socioeconomic status) and within-person changes in an outcome variable (for example, change in an individual’s depressive symptoms). The fixed-effects approach is suitable when assessing the association between changes in variables at the individual-level because the effects of unobserved time-invariant subject-specific factors are controlled for in the analysis. In this case, the fixed-effects approach will yield more accurate subject-specific regression coefficients than a random-effects model.
2.2.3 Structural equation modelling.

An assumption of regression models is that explanatory variables are measured without error (Hox, 2013). However, this is often not the case as most variables are measured with both systematic (i.e. error due to an unreliable instrument) and random (i.e. fluctuations over time) error (Goldstein, Kounali, & Robinson, 2008). Random measurement error can be particularly problematic when assessing changes in variables over time (for example in a fixed-effects model), since any observed changes in variables may be due to changes in measurement error (Angrist & Pischke, 2008). Structural equation models (SEM) can be used to account for measurement error in observed variables (Hoyle, 2012). SEM consists of two parts: a confirmatory factor analysis (CFA) measurement model and a structural model (i.e. a model for the assumed explanatory or causal relationships between latent variables or factors). CFA models the relationship between the scores of observed variables and their underlying true (latent) construct and then partials out the true score of the observed measure from measurement error (Hoyle, 2012; Kline, 2013). The measurement model typically consists of repeated measures of an observed variable. Each variable then acts as an indicator of the latent (uncontaminated) underlying construct as in Figure 2:

![Figure 2](image)

*Figure 2* A measurement error model. L1 is the latent underlying construct, X1 – X3 are observed variables of the construct and ε1–ε3 is the random error associated with the observed variable at each time point.
CFA partials out the variance in these indicators into two parts: a common variance and a unique variance. The common variance is shared among all the indicators and is taken to be the variance that is due to the underlying latent factor. The unique variance is due to measurement error (Hoyle, 2012). When only one scale is used to measure a construct at each time point, the items of the scale may be summed and the summed or average score of the items can be used as a single indicator for the latent factor at each time point (Coffman & MacCallum, 2005; Hoyle, 2012). However, having only one indicator per factor can be problematic since the number of estimated parameters must be equal to or less than the number of observed variances and covariances in the model in order for a model to be identified (Hoyle, 2012). Therefore, certain restrictions may be introduced to ensure model identification. For example, restricting the paths from the factor to its respective indicator to be 1 and restricting the measurement error variances at each time point to be equal reduces the number of parameters that need to be estimated (Hoyle, 2012). The true (uncontaminated) change in construct across time can then be estimated by introducing a second-order latent variable which represents the true change in construct (McArdle, 2009). This second-order latent variable is defined by a path from the latent variable for the construct at Time 1 and a path from the second-order variable to the latent variable for the construct at Time 2 as shown in Figure 3. The second-order latent variable (i.e. the change score) is not contaminated by measurement error since it is defined by latent variables. A path from the latent variable at Time 1 to the latent variable at Time 2 is included to ensure that the change score capture the variance in the latent variable at Time 2 that is not shared by the latent variable at Time 1 (McArdle, 2009).
Figure 3 Measurement components for latent change score. L1 and L2 are the latent underlying constructs at Time 1 and Time 2 respectively, X1 and X2 are observed variables of the construct at Time 1 and Time 2 respectively and $\varepsilon_1$-$\varepsilon_2$ is the random error associated with the observed variable at each time point. $\Delta L$ is the second-order latent variable representing true change in L between Time 1 and Time 2. Error variances of L1 and L2 are set to be equal and loadings from L1 to X1 and L2 to X2 are set to ‘1’ to allow model identification.

The structural model can then be used to assess the relationship between latent variables (Kline, 1998; Lei & Wu, 2007). For example, in Chapter 6, a SEM framework was used to estimate paths between latent change scores for life satisfaction and latent change scores for personality traits after adjusting for measurement error. Figure 4 displays a simple diagram relating change scores for a personality trait to change scores for life satisfaction.
Figure 4 Structural equation model framework. OP1 and OP2 are observed variables of personality trait at Time 1 and Time 2 respectively, OL1 and OL2 are observed variables of life satisfaction at Time 1 and Time 2 respectively, P1 and P2 are latent personality trait variables at Time 1 and Time 2 respectively, L1 and L2 are latent life satisfaction variables at Time 1 and Time 2 respectively. ∆P is the true change in personality trait from Time 1 to Time 2, ∆L is the true change in life satisfaction from Time 1 to Time 2, EP$_{T1}$ and EP$_{T2}$ are random errors associated with personality at Time 1 and Time 2 respectively, EL$_{T1}$ and EL$_{T2}$ are random errors associated with life satisfaction at Time 1 and Time 2 respectively. ∆L and ∆P were specified to co-vary here.

In addition to accounting for measurement error in observed variables, SEM has the advantage that specified paths between variables can be assessed. For example, in SEM, the direction of the association between two variables and mediational pathways can be assessed (MacKinnon, 2008; Selig & Preacher, 2009). These features of SEM can enhance understanding of the nature of the association between variables and allow stronger causal inferences to be made than can be made from regression models.
2.4 Prediction versus Causal Explanation

This thesis aims to assess risk factors or causes of health and well-being outcomes. As a result, explanatory models rather than predictive models are used in the analyses in this thesis. Unlike predictive models which are concerned with determining whether a set of independent variables relate to an outcome measure, explanatory models aim to establish whether the association between an independent variable and an outcome measure is causal (Sainani, 2014). For explanatory modeling, it is therefore important to consider whether any significant associations are due to chance or due to other variables (i.e. confounders) which are related to both the independent variable of interest and the outcome variable (Sainani, 2014).

In order to reduce the risk of obtaining a spurious association between an outcome variable and independent variables, independent variables were selected for inclusion in the analytical models based on theoretical models and empirical evidence from previous research. Confounding was adjusted for by including in the model variables which may modify the association between the independent variable(s) of interest and the outcome variable. However, there will likely always be some residual confounding as it may not be possible to control for all possible confounders, particularly as some confounders may be unobserved. The results obtained using explanatory models may therefore be biased by confounding variables which have not been controlled for in the models. Even though some explanatory models are able to control for unobserved time-invariant person-specific factors which may confound the association of interest as well as measurement error (e.g., structural equation models), these models are still susceptible to bias arising from time-varying variables that have not been controlled for in the model.

2.5 Model Selection and Goodness of Fit Statistics

In Chapters 3 and 4, different models were compared to determine which specification of income better predicted health. Two main factors must be considered when
selecting a preferred model: how well the model fits the true data and the complexity of the model (i.e. whether it consists of many parameters). Generally, a parsimonious model is the preferred model, unless the more complex model provides a sufficiently improved fit over the parsimonious model (Kuha, 2004). However, with large sample data, parsimonious models are more likely to be rejected as having poor statistical fit (Kuha, 2004). In this thesis, Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) have been utilized as model selection criteria. The AIC and BIC are the two most widely used theory-based penalized criteria. Both criteria penalize models for added parameters, although the theoretical basis of the two criteria differs. The BIC is based on the Bayes factor, which indicates the strength of the evidence provided by the data to support a specific model over an alternative. The BIC criterion assumes the existence of a true model among the candidate models (Burnham & Anderson, 2004). An advantage of the BIC is that it is a consistent selection criterion in the sense that the probability of the BIC selecting the true model approaches 1 as the sample size becomes very large (Tang, He, & Tu, 2012). On the contrary, the AIC considers the distance between the densities of the true model and a candidate model and in doing so assesses the expected predictive performance of the model (Kuha, 2004). The AIC selects the model with the smallest average squared error for the specified sample size, but is not a consistent selection criterion (Tang et al., 2012) since the preferred model may change with sample size (Burnham & Anderson, 2004). The two criteria cannot be directly compared and currently there isn’t a model selection procedure that possesses the strengths of both the AIC and BIC (Yang, 2005). We have used BIC as the main criterion to select the best model in Chapters 3 and 4 as the BIC consistently selected the same model as the best-fitting model across different reference groups and datasets, whereas the AIC was less consistent across different reference groups and datasets.
2.6 Handling Missing Data

Missing data often arises in longitudinal data. Rubin (1976) has proposed that there are three mechanisms through which missing data can arise. Data can be missing completely at random (MCAR), missing at random (MAR) or missing not at random (MNAR) (Rubin, 1976). Data is MCAR when the missing values of a variable do not depend on the values of that variable or any other variables/predictors in the dataset. When the missing values of a variable X depend on other variables in the dataset but not on the values of variable X, the data is described as MAR. Data is MNAR when the missing values of a variable depend on the values of that variable. When data is MCAR, analyses using only complete cases (i.e., those who provide data on all variables of interest) will produce unbiased parameter estimates. However, missing data estimation approaches are required to yield unbiased estimates when data is either MAR or MNAR. In this thesis we assume that the missing data are MAR and use inverse probability weighting (IPW) and maximum likelihood estimation (MLE) to account for the missing data.

IPW (Robins, Rotnitzky, & Zhao, 1995) adjusts for missing data by assigning probability weights to the observed cases. This is achieved by regressing a binary variable indicating whether a case is missing on explanatory variables in a model. The fitted model estimates the predicted probability that each case will be observed. The inverse of the predicted probability is used as a weight for each case in the analysis. IPW is easy to implement and is particularly useful in cases where data is missing from a large number of variables for each individual (Hofler, Pfister, Lieb, & Wittchen, 2005).

MLE uses all available data to derive estimates that have the highest probability of originating from a normally distributed population (Allison, 2012). The procedure accounts for missing data by ‘borrowing’ information about the correlation between variables in complete cases to produce the most likely estimates of the parameters of interest. The estimate that best fits the data (i.e., has the highest log-likelihood) is selected as the maximum likelihood estimate (Allison, 2012). MLE is a widely used, straightforward
procedure to handle missing data. A main advantage of MLE is that it is fast and reliable method. MLE produces efficient estimates under a single model and always produces the same results for the same dataset (Allison, 2012).
3.0 Why does Income Relate to Depressive Symptoms? Testing the Income Rank Hypothesis Longitudinally


3.1 Abstract

This paper reports a test of the relative income rank hypothesis of depression, according to which it is the rank position of an individual’s income amongst a comparison group, rather than the individual’s absolute income, that will be associated with depressive symptoms. A new methodology is developed to test between psychosocial and material explanations of why income relates to well-being, and allows a conservative test of the income rank hypothesis as applied to depressive symptoms. We used data from a cohort of 10,317 individuals living in Wisconsin who completed surveys in 1992 and 2003. The utility assumed to arise from income was represented with a Constant Relative Risk Aversion (CRRA) function to overcome limitations of previous work in which inadequate specification of the relationship between absolute income and well-being may have inappropriately favoured relative income specifications. We compared models in which current and future depressive symptoms were predicted from: (a) income utility alone, (b) income rank alone, (c) the transformed difference between the individual’s income and the mean income of a comparison group and (d) income utility, income rank and distance from the mean jointly. Model comparison overcomes problems involving multi-collinearity amongst the predictors. A rank-only model was consistently supported. Similar results were obtained for the association between depressive symptoms and wealth and rank of
wealth in a cohort of 32,900 British individuals who completed surveys in 2002 and 2008. We conclude that it is the rank of a person's income or wealth within a social comparison group, rather than income or wealth themselves or their deviations from the mean within a reference group, that is more strongly associated with depressive symptoms.

3.2 Introduction

Depression is a devastating condition which disproportionately affects low income groups (Chung, McCollum, Elo, Lee, & Culhane, 2004; McBarnette, 1996). The condition presents at different levels, depending on the number and severity of symptoms experienced. In addition to producing direct suffering, high levels of depressive symptoms can result in low self-esteem, relationship conflict, poor health, and suicide (Block-Joy & Hudes, 2010), as well as conferring a substantial financial burden on the state (Layard, 2006). A number of hypotheses have been proposed to explain why low income increases risk of high levels of depressive symptoms. The absolute income hypothesis suggests that it is the actual amount a person earns that protects them from depressive symptoms through conferring an ability to purchase goods and services that promote mental health, albeit with diminishing results (Lynch et al., 2004; Preston, 1975; Rodgers, 1979). In contrast, various versions of the relative income hypothesis (Kondo et al., 2008; Wagstaff & van Doorslaer, 2000; Wilkinson, 1992, 1996) suggest that in addition to having direct effects (i.e., the ability to purchase more material goods), income may relate to depressive symptoms through the social position that it confers.

Previous studies of the income-depression relationship have indicated that the indirect effect of income (measured as an individual’s income relative to that of others within a comparison group) is important for depression (Cifuentes et al., 2008; Eibner et al., 2004; Kahn, Wise, Kennedy, & Kawachi, 2000; Messias, Eaton, & Grooms, 2011; Rai, Zitko, Jones, Lynch, & Araya, 2013). However, it is not clear what specification of relative income relates to depression. In this paper we focus on one particular form of the relative...
income hypothesis, which proposes that it is specifically the rank of an individual’s income within a reference group that should matter (Wagstaff & van Doorslaer, 2000; Wood, Boyce, et al., 2012), and test it against an alternative specification of the relative income hypothesis in order to understand the exact mechanism through which relative income determines depressive symptoms. The income rank hypothesis has particular relevance to understanding the link between income and depressive symptoms because it has been suggested that individuals have an evolutionary propensity to experience depressive symptoms when they are cued to see themselves as of low social rank compared to others (Gilbert, 2006; Gilbert & Allan, 1998; Price, Sloman, Gardner, Gilbert, & Rohde, 1994). This income rank hypothesis (Boyce et al., 2010) is distinguished from other versions of the relative income hypotheses such as the reference income hypothesis according to which people are concerned with how their income compares to the mean income of a reference group. The income rank hypothesis combines social psychology research on the impact of unfavourable social comparisons on well-being (Festinger, 1954) with psychiatric research showing that cognitions associated with low rank are proximal causes of depressive symptoms (Taylor, Gooding, Wood, & Tarrier, 2011) and primate studies showing that animals are highly sensitive to rank position (Raleigh et al., 1983; Yeh et al., 1996). Specifically, subordinate animals in competition with more dominant members of the same species have lower levels of the hormone serotonin than the dominant members (Raleigh et al., 1983; Yeh et al., 1996). For many animals, and humans over the course of evolution, these hormonal differences are believed to have conferred a survival advantage through motivating such behaviours as social withdrawal, decreased appetite and sexual drive, and hypervigilance, all of which may be appropriate reactions to being of low rank within a hostile hierarchy (Sapolsky, 2004). Gilbert and colleagues (Gilbert, 2006; Gilbert & Allan, 1998; Price et al., 1994) have noted the similarity of these reactions to symptoms of human depression, in which serotonin is also known to play a role (Coppen & Doogan, 1988; Cryan & Leonard, 2000). Gilbert et al. suggest that genes predisposing to depressive
symptoms have been inherited from our ancestors (Price et al., 1994), for whom depression-like behaviour in response to low social rank served as an adaptive mechanism for surviving competitive social situations. For example, by withdrawing oneself and reducing appetite and sexual behaviour so as not to compete for food and potential mates, subordinate members were able to signal a ‘no-threat’ status to the more dominant members. As a result, individuals who were able to respond in this way were more likely to survive, thus passing on their genes to future generations. While these hard-wired responses previously conferred an evolutionary advantage, such reactions to low rank can have maladaptive consequences for the individual in modern societies where having a low social rank persists over a longer duration and can result in perceptions of defeat and entrapment (Taylor et al., 2011). To the extent that social comparisons result in stress, people may also experience homeostatic responses releasing various hormones including cortisol (Hill, Greer, & Felsenfeld, 1967; Mason, 1968; Taylor et al., 2011; Wood, Boyce, et al., 2012); such hormones have also been associated with risk of depressive symptoms (Anda et al., 1993; Jacobs, 1994; Willner & Goldstein, 2001) when the response is prolonged.

Although the study of the importance of income position for various forms of well-being, including depression, has a long history (for example the Whitehall study by Martikainen, Adda, Ferrie, Davey-Smith, Marmot, 2003; and more recently the study by Elgar et al., 2013), there has been no previous direct test of the income rank hypothesis concerning the relationship between income and depression that additionally controls for the effect of absolute level of income. More recently a growing body of work has assessed the effect of income rank on other indicators of well-being, whilst controlling for absolute income (Boyce et al., 2010; Daly et al., 2015; Wood, Boyce, et al., 2012). For example, Wood et al. (2012) found that both income and income rank within a geographic community are related to general psychopathology. However, when general psychopathology was jointly regressed on income and rank, additionally controlling for
covariates, only income rank remained a predictor. This suggests that the relationship between income and general psychopathology is better explained by income rank. However it is not clear whether these results would hold for a measure of depression specifically. More importantly, whilst Wood et al.’s (2012) methodology allows comparison of the income rank and absolute income hypotheses, the method has two key limitations. Firstly, income was logarithmically transformed before being used to predict general psychopathology. Use of a logarithmic transformation is typical when income/well-being associations are examined, and reflects the assumption that subjective well-being is a negatively accelerating function of income. However, when effects of absolute income and rank of income are compared, misleading coefficients on the relative rank variable might result if well-being is not a linear function of logarithmically transformed income (because the rank variable might capture any non-linearity). This could lead to the erroneous conclusion that the association between income and well-being is due to income rank position, when in fact the results merely reflect the fact that the true relationship between absolute income and well-being is not perfectly logarithmic. Here, in order to adequately capture the non-linear relationship between income and degree of depressive symptoms, we use the more flexible utility function commonly adopted within economics – the constant relative risk aversion (CRRA) formulation – to transform absolute income. Secondly, in previous applications of the methodology used by Wood et al. (2012), the logarithmic transformation of income, income rank, and income’s distance from the mean income of a comparison group have been entered simultaneously into regressions. While this approach has the advantage of providing a direct test of the income rank hypothesis while controlling for the predictions of rival hypotheses, the approach may be problematic due to the co-linearity between measures of absolute income and relative position (Gravelle & Sutton, 2009), making it difficult to separate the effects of the two and reducing confidence in the stability of the findings. Here in contrast we compare the relative fit of the income rank model with that of the income model and distance from the
mean model as a means of overcoming this limitation and determining which of the hypotheses better explain the effect of income on depressive symptoms. In adopting the approach here we therefore provide a more direct and conservative test of the income rank hypothesis as well as applying it for the first time to depressive symptoms.

Finally, earlier studies have focused mainly on the effect of income on health, while there is a lack of studies on the effect of wealth. Wealth is a measure of long-term socioeconomic position whereas income is an indicator of current socioeconomic position and more likely to vary over time. It is therefore possible that the association between wealth and health is different to that of income and wealth. There is evidence that suggests wealth is a stronger predictor of health than current income (Benzeval & Judge, 2001), which may be expected since many health conditions are driven by long-term risk factors (Aittomaki, Martikainen, Laaksonen, Lahelma, & Rahkonen, 2010). Using a dataset which contains measures for both income and wealth, we assessed which was the stronger predictor of depressive symptoms and used this measure in our analyses.

### 3.3 Methods

#### 3.3.1 Data.

Two waves of data from the Wisconsin Longitudinal Study (WLS) (1992 and 2003) and the English Longitudinal Study of Ageing (ELSA) (2004 and 2008) were analysed to examine the association between income and depressive symptoms. Both populations consisted of individuals in their middle to late adulthood. These datasets are particularly suitable for our analyses as they both contain validated measures of depressive symptoms as well as a large sample size and continuous measures of individual income.

The WLS included 10,317 randomly-sampled individuals who had graduated from high schools in Wisconsin in 1957. Individuals were re-contacted and interviewed in 1992-1993 and 2003-2005. Subjects were included in our study if they responded to questions about depressive symptoms, income, and socio-demographic factors. Subjects were
excluded if any information on depressive symptoms, household income, household size or any of the employed covariates was missing. The final sample consisted of 6,494 individuals at Time 1 (62.9% of the original sample) of which 51.7% were females, and 4,812 individuals at Time 2 (51.3% females) – a retention rate of 74%. Subjects who were included in our study were generally more educated than those who were not; 31% of subjects included in our study achieved education above high school level, while 12% of excluded subjects achieved education above high school. The mean total annual household income was $66,586.20 for subjects included in our study and $49,133.76 for those excluded at Time 1. Individuals who were included in our study at Time 1 but excluded at Time 2 did not differ by age from those who were included at both time points, although there were proportionately fewer females and subjects with health conditions (cancer, chronic liver or heart trouble, high blood pressure) included at both Time 1 and Time 2. This was partly due to the fact that some subjects who had a physical health condition died before Time 2 \( (n = 363) \). A logistic regression was performed to determine whether physical health status at Time 1 predicted whether or not the subject was included in Time 2 analyses; the regression showed that cancer and chronic liver problems were significant predictors of inclusion at Time 2. The WLS sample is representative of white Americans with at least complete high school education but under-representative of African-American, Asian and Hispanic populations.

ELSA is a nationally representative cohort study of individuals aged 50 years and over living in England. Participants were interviewed every two years from 2002 through 2008 and data were collected in questionnaire format. All participants who completed the mail questionnaires and provided data for all demographic, economic and depressive symptoms variables as well as all the employed covariates were included in our study. The final sample for our analysis at Wave 1 (2002) and 4 (2008) consisted of 11,264 and 6,425 individuals respectively. This reflects a response rate of 46.8% at Wave 1 and an attrition rate of 57.0% at Wave 4. At Wave 1, the mean wage for individuals who did not provide
data on depressive symptoms was lower than for participants who did provide these data. There were no differences in demographics. Subjects who were included in both waves of our study (i.e., subjects who continued through to Wave 4) were generally older, more educated and had a mean net wealth four times higher than subjects who were included at Wave 1 but were excluded at Wave 4. Table 2 presents descriptive statistics for the two populations.

3.3.1.1 Measurement of depressive symptoms. Both studies used the Centre for Epidemiologic Studies Depression (CES-D) measure at both waves. The CES-D is a well-validated self-reported inventory where participants rate the frequency of depressive symptoms experienced in a week. Questions used included “how many times during the past week did you feel bothered by things that don’t usually bother you?”, “how many days during the past week did you think your life had been a failure?” and “how many days during the past week did you feel you could not shake off the blues even with the help from your family and friends?”. The measure of depressive symptoms was included as a continuous rather than binary outcome to account for the deviation of each individual from the CES-D cut off point and represent the full continuum of depressive symptoms (Wood, Taylor, & Joseph, 2010). The CES-D has been shown to correlate highly with clinical ratings of depressive symptoms (McDowell & Kristjansson, 1996; Radloff, 1977) and to have a 100% sensitivity and 88% specificity for identifying individuals with clinical depressive symptoms in older populations (Beekman et al., 1997). Depression scores were standardized prior to analysis to facilitate interpretation of effect sizes.

3.3.1.2 Income, wealth, income rank, wealth rank and distance from mean income measures. Both respondent and total household incomes in the last 12 months were available as continuous variables. In WLS, household income rather than respondent personal income was used due to the higher correlation of household income (both untransformed and CRRA-transformed) with depressive symptoms ($r = -.12$ and $r = -.11$ respectively).
### Table 2 Summary statistics of study samples

<table>
<thead>
<tr>
<th></th>
<th>WLS Time 1</th>
<th>WLS Time 2</th>
<th>ELSA Time 1</th>
<th>ELSA Time 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>%</td>
<td>N</td>
<td>%</td>
</tr>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>3135</td>
<td>48.3</td>
<td>2344</td>
<td>48.7</td>
</tr>
<tr>
<td>Female</td>
<td>3359</td>
<td>51.7</td>
<td>2468</td>
<td>51.3</td>
</tr>
<tr>
<td><strong>Date of Birth</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WLS</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1937</td>
<td>104</td>
<td>1.6</td>
<td>66</td>
<td>1.4</td>
</tr>
<tr>
<td>1938</td>
<td>1018</td>
<td>15.7</td>
<td>716</td>
<td>14.9</td>
</tr>
<tr>
<td>1939</td>
<td>5068</td>
<td>78.0</td>
<td>3792</td>
<td>78.8</td>
</tr>
<tr>
<td>1940</td>
<td>304</td>
<td>4.7</td>
<td>238</td>
<td>5.0</td>
</tr>
<tr>
<td>ELSA</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1966-1975</td>
<td>17</td>
<td>0.2</td>
<td>9</td>
<td>0.1</td>
</tr>
<tr>
<td>1956-1965</td>
<td>229</td>
<td>2</td>
<td>130</td>
<td>2</td>
</tr>
<tr>
<td>1946-1955</td>
<td>2992</td>
<td>26.6</td>
<td>1919</td>
<td>29.9</td>
</tr>
<tr>
<td>1936-1945</td>
<td>3377</td>
<td>30</td>
<td>2105</td>
<td>32.8</td>
</tr>
<tr>
<td>1926-1935</td>
<td>2816</td>
<td>25</td>
<td>1606</td>
<td>25</td>
</tr>
<tr>
<td>1916-1925</td>
<td>1567</td>
<td>13.9</td>
<td>620</td>
<td>9.6</td>
</tr>
<tr>
<td>1906-1915</td>
<td>266</td>
<td>2.4</td>
<td>36</td>
<td>0.6</td>
</tr>
<tr>
<td><strong>Highest educational achievement</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WLS</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High school</td>
<td>4480</td>
<td>69</td>
<td>3199</td>
<td>66.5</td>
</tr>
<tr>
<td>Associate degree</td>
<td>181</td>
<td>2.8</td>
<td>137</td>
<td>2.8</td>
</tr>
<tr>
<td>First degree</td>
<td>1067</td>
<td>16.4</td>
<td>823</td>
<td>17.1</td>
</tr>
<tr>
<td>Masters</td>
<td>581</td>
<td>8.9</td>
<td>489</td>
<td>10.2</td>
</tr>
<tr>
<td>MD/PhD</td>
<td>185</td>
<td>2.8</td>
<td>164</td>
<td>3.4</td>
</tr>
<tr>
<td>ELSA</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No qualifications</td>
<td>4723</td>
<td>41.9</td>
<td>2293</td>
<td>35.7</td>
</tr>
<tr>
<td>Some qualification</td>
<td>1501</td>
<td>13.3</td>
<td>821</td>
<td>12.8</td>
</tr>
<tr>
<td>‘O’ Level/nvq1/nvq2</td>
<td>1821</td>
<td>16.2</td>
<td>1170</td>
<td>18.2</td>
</tr>
<tr>
<td>‘A’ level/nvq3</td>
<td>708</td>
<td>6.3</td>
<td>443</td>
<td>6.9</td>
</tr>
<tr>
<td>Higher education below degree</td>
<td>1238</td>
<td>11.0</td>
<td>816</td>
<td>12.7</td>
</tr>
<tr>
<td>University degree</td>
<td>1273</td>
<td>11.3</td>
<td>882</td>
<td>13.7</td>
</tr>
<tr>
<td><strong>Marital Status</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married</td>
<td>5378</td>
<td>82.8</td>
<td>3823</td>
<td>79.4</td>
</tr>
<tr>
<td>Remarried</td>
<td>0</td>
<td>0.0</td>
<td>0</td>
<td>0.0</td>
</tr>
<tr>
<td>Separated</td>
<td>41</td>
<td>0.6</td>
<td>4</td>
<td>0.1</td>
</tr>
<tr>
<td>Divorced</td>
<td>662</td>
<td>10.2</td>
<td>457</td>
<td>9.5</td>
</tr>
<tr>
<td>Widowed</td>
<td>138</td>
<td>2.1</td>
<td>342</td>
<td>7.1</td>
</tr>
<tr>
<td>Never married</td>
<td>275</td>
<td>4.2</td>
<td>186</td>
<td>3.9</td>
</tr>
<tr>
<td><strong>Employment Status</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed</td>
<td>5756</td>
<td>88.6</td>
<td>2280</td>
<td>47.4</td>
</tr>
<tr>
<td>Unemployed</td>
<td>738</td>
<td>11.4</td>
<td>2532</td>
<td>52.6</td>
</tr>
<tr>
<td><strong>Household income ($)</strong></td>
<td>66586.2</td>
<td>69006.9</td>
<td>204205.4</td>
<td>232880.2</td>
</tr>
<tr>
<td><strong>Total net wealth (£)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### Housing Tenure

<table>
<thead>
<tr>
<th>Tenure</th>
<th>6087</th>
<th>54.0</th>
<th>4385</th>
<th>68.3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Owner</td>
<td>2936</td>
<td>26.1</td>
<td>930</td>
<td>14.5</td>
</tr>
<tr>
<td>Has mortgage</td>
<td>2120</td>
<td>18.8</td>
<td>1027</td>
<td>16.0</td>
</tr>
<tr>
<td>Rent</td>
<td>121</td>
<td>1.1</td>
<td>83</td>
<td>1.3</td>
</tr>
<tr>
<td>Live rent free</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Retirement status

<table>
<thead>
<tr>
<th>Status</th>
<th>508</th>
<th>7.8</th>
<th>729</th>
<th>15.1</th>
<th>0</th>
<th>0.0</th>
<th>0</th>
<th>0.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Retired and working</td>
<td>324</td>
<td>5.0</td>
<td>2353</td>
<td>48.9</td>
<td>5437</td>
<td>48.3</td>
<td>4038</td>
<td>62.9</td>
</tr>
<tr>
<td>Completely retired</td>
<td>5662</td>
<td>87.2</td>
<td>1730</td>
<td>36.0</td>
<td>5827</td>
<td>51.7</td>
<td>2387</td>
<td>37.2</td>
</tr>
<tr>
<td>Not retired at all</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note.* In WLS, household income (in dollars) adjusted for household number was studied. In ELSA, net wealth (in British pounds) was used instead.

Since ‘unequivalized’ household income (i.e., income values prior to adjusting for household size) was more strongly correlated to depressive symptoms levels than equivalized household income, unadjusted income was used in all analyses in WLS. Similar results were obtained using both methods. An income value of 1 was allocated to respondents who had negative household incomes (n = 6). Household income values in WLS were transformed using the CRRA utility function below:

\[ u = \frac{y^{1-\rho} - 1}{1-\rho} \]

where for values of \( \rho \) not equal to 1, \( u \) is utility, \( y \) is total income and \( \rho \) is the elasticity of marginal utility with respect to income and is assumed to be constant, and when \( \rho \) is 1, the function is equal to the logarithm of income. This function has been used for example by Layard, Nickell, and Mayraz (2008) to examine subjective well-being as a function of income (i.e., to illustrate how the effect of income on well-being diminishes with increasing income). Layard et al. (2008) predict well-being from estimated parameters in large empirical datasets and find that the function yields the best estimates when constant \( \rho = 1.26 \). For our study, we derived different specifications of the CRRA function by varying the values of \( \rho \) used to construct the function. We then use the specification which gives the best fit for predicting depressive symptoms as our income model. Plotting scatter graphs of utility (CRRA) against household income revealed a smooth curve, suggesting
no outlying subjects. Utility scores were then standardized to have zero mean and one unit standard deviation prior to analyses.

For ELSA, net total wealth rather than total household income was used as the former was more strongly correlated to and better predicted depressive symptoms: the correlation between depressive symptoms at Time 1 and transformed total household income was $r = -.21$ while the correlation between depressive symptoms at Time 1 and transformed net wealth was $r = -0.26$. At Time 2, the correlations between depressive symptoms and total household income and net wealth were $r = -.14$ and $r = -.21$ respectively. Participants with a negative value ($n = 457$) for net total wealth were allocated a net value of 1, so that these subjects could be included in the analyses. Utility scores were then calculated as described above. Plotting two-way scatter graphs for utility and net wealth revealed that there were no outlying subjects.

3.3.1.3 Income rank and wealth rank. A relative rank measure was calculated for each individual using the formula below (Brown, Gardner, Oswald, & Qian, 2008; Stewart et al., 2006):

$$R_i = \frac{i-1}{n-1}$$

where $i$ is the ranked position of the individual’s income within the reference group for WLS and $i$ is the ranked position of the individual’s wealth within the reference group for ELSA, $n$ is the number of people in the reference group and an individual’s relative rank is a value between 0 and 1, given by the proportion of people that have a lower income in the comparison group in WLS and the proportion of people that have lower wealth in the comparison group in ELSA.

It was assumed that people generally compare themselves to people who surround them and to those with similar characteristics. Individuals were therefore ranked in terms of their position within groups of individuals of the same gender as themselves and with similar levels of education: A 6 category exploratory variable was created to compare individuals of similar education and gender (i.e., males with only high school education,
females with only high school education, males with associate-level degree, females with associate level degree, etc.). Although it is difficult to determine to whom individuals compare themselves, gender and education have been central in the formation of reference groups (Singer, 1981; Subramanyam et al., 2009). As there was a sufficient number of participants in each educational group (no qualifications, some qualification, General Certificate of Education (GCE): Ordinary level (O-level), General Certificate of Education (GCE): Advanced level (A-level), below degree, university degree), a 12 category variable was created for the ELSA dataset.

3.3.1.4 Distance from the mean. For each time point, the difference between the best-fitting CRRA specification for income and the best-fitting CRRA specification for mean reference income was calculated. For ELSA, the best-fitting CRRA specification for mean reference wealth was used instead.

3.3.1.5 Covariates. Demographic and economic measures were used as covariates. Socio-demographic variables included in the WLS study were gender, age, age squared, household size, level of highest education since high school (none [high school], associate degree, bachelor degree, masters degree, doctorate or professional degree) marital status (married, separated, divorced, widowed, never married), current employment status (employed or not employed), and retirement (not retired at all, retired and working, completely retired). From ELSA, gender, age, age squared, household size, employment status (employed or self-employed), marital status (married, remarried, legally separated, divorced, widowed, never married), educational attainment (no qualifications, some qualification, GCE ‘O’ level or National Vocational Qualification (NVQ) 1 or 2 , ‘A’ level or NVQ3, below degree, university degree or NVQ 4 or NVQ 5), tenure (owner, paying mortgage, renting, living rent free), retirement (not retired, fully retired, semi-retired) were used. In WLS, a variable for the degree of negative income reported (i.e. a value of 0 for subjects with income of $0 or above and reported negative income as a positive value,
ranging from $0 to $14400 for those with negative incomes) was constructed and included in the analyses.

3.3.2 Statistical analyses.

Statistical analysis was performed to investigate which of income rank (as a measure of social position), transformed absolute income, or transformed deviation of absolute income from the mean income within the reference group best predicted depressive symptoms in 52-56 year olds and then depressive symptoms ten years later. We first obtain the best specification for income as a predictor of depressive symptoms: Least squares regression was performed to fit models containing the effect of income and all socio-demographic covariates using different estimates of $\rho$ to obtain the CRRA function that best fit the data (as determined by the log-likelihood or, equivalently, the Bayesian Information Criterion, BIC – see below).

Depressive symptoms at Time 1 was regressed on transformed income at Time 1 and Time 1 covariates. Depressive symptoms at Time 2 was then regressed on Time 1 levels of depressive symptoms and Time 1 transformed income and Time 2 covariates. The regression was then repeated to include income rank and demographics (without income) and then transformed deviation from the mean income and demographics (without income and income rank). For both time points, our variable for depressive symptoms was jointly regressed on transformed income and income rank (and demographics). Finally, our variable for depressive symptoms was simultaneously regressed on transformed income, income rank and transformed deviation from mean.

Goodness of fit tests were used to determine the best model explaining the income-depressive symptoms relationship. The Bayesian Information Criterion (BIC), also known as Schwarz Information Criterion, was used to choose the best-fitting model. The BIC is a large-sample asymptotic estimator which uses the log-likelihood adjusted for the number of observations and regressors (Gravelle & Sutton, 2009; Raftery, 1996) to approximate the Bayesian probability of a model. The model with the lowest BIC has the highest
Bayesian posterior probability and is taken as the preferred model, according to the available data. This criterion is widely used for model selection purposes, with a BIC decrease of 2 or more units indicating some evidence for the model and a decrease of 6 or more indicating strong evidence (Gravelle & Sutton, 2009; Raftery, 1996). It should be noted that the BIC values here do not allow for the fact that \( \rho \) is being estimated; the BIC estimates for the income model would be higher if this was adjusted for. The R-squared value was additionally used to examine the amount of variation captured by the model.

Results from the CRRA model using the optimum value of \( \rho \), as well as the model using the logarithm of income (if different to the optimum) are presented here (Table 3). The BIC, R-squared, Akaike Information Criterion (AIC, an alternative goodness of fit test) values are also presented in the results.

Bootstrapping was then performed to determine the statistical significance of the differences in the goodness of fit measures for two non-nested models with identical degrees of freedom. This process re-samples the distribution without computational error (Jeong, 2006) producing consistent results and allowing us to confirm a model truly has higher explanatory power than an alternative model (Davidson & MacKinnon, 1997; Jeong, 2006). The BIC values can be informally compared for models containing either the CRRA function of income or income rank but cannot be compared using a conventional significance testing since they are produced by non-nested models. Sampling variability in the variation of the difference was therefore examined using the bootstrap (Efron & Tibshirani, 1993). One thousand bootstrap samples (i.e. samples with replacement) of the same size of the original data set were obtained, and for each sample the two competing models were fitted and the BIC statistics extracted. The difference between these two BIC values was computed (that for income minus the one after fitting the effects of income rank) and the distribution of the differences across bootstrap samples examined. If the rank model is preferred, the true difference will be positive and we therefore report the proportion of the differences with a value greater than zero (the complement of this – the
probability of the difference being equal to or less than zero - provides a one sided p-value on which to evaluate statistical significance).

The analyses were repeated in ELSA using a measure of wealth and wealth rank instead of income and income rank.

3.4 Results

3.4.1 Rank groups and income.

In order to determine whether our value for rank was sufficiently different to the transformed measure of absolute income, scatter graphs were plotted to observe the variation in rank for the same income value and vice versa. Figure 5 shows that the range in rank for a given income level at Time 1 was considerable, with the largest range at about $40,000. Income values for a rank of .2, .4, .6, .8 and 1 ranged from approximately $16,000-$35,000, $25,000-$49,000, $34,000-$64,000, $48,000-$95000, and $145,000-$300,000 respectively at Time 1 in WLS. The plots show that transformed income and income rank are sufficiently non-linearly related to be used as different indicators. Additionally, the gaps occur mostly around the middle to bottom of the distribution, where differences between income rank and income is particularly of interest. Similar results are seen for wealth in ELSA.
Figure 5 Plot of rank against constant relative risk aversion (CRRA) for the reference groups in (a) WLS and (b) ELSA. CRRA can be seen to be clearly distinguishable from rank, indicating that two individuals with the same income measure may have different ranks within their reference group. Largest vertical differences are observed at the middle of the distribution, where differences are of particular interest.

3.4.2 Comparison of models.

Table 3 presents the test statistics of the income model using the CRRA specification with the best-fitting value of $\rho$, the income model using the logarithm of income and the income rank model for each time point in WLS. Test statistics for the analyses using the wealth measure in ELSA are also presented in Table 3. For each time point the function with the lowest BIC for regression of depressive symptoms on income (including mentioned covariates) was selected as the best fitting model. In Table 3 we see that for WLS at Time 1, the function for income which gave the best fit was the CRRA model when $\rho = 0.20$ ($BIC: 18277.21$) rather than the model using the logarithmic function ($BIC: 18308.05$).
Table 3 Comparison of test statistics for models of depressive symptoms

<table>
<thead>
<tr>
<th>Predictor</th>
<th>f(predictor)</th>
<th>Rank</th>
<th>f(predictor) + Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BIC</td>
<td>AIC</td>
<td>R squared</td>
</tr>
<tr>
<td><strong>WLS</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Time 1</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Linear : Log (income)</td>
<td>18308.05</td>
<td>18186.04</td>
<td>0.03</td>
</tr>
<tr>
<td>Standardized CRRA (ρ = 0.20)</td>
<td>18277.21</td>
<td>18155.20</td>
<td>0.04</td>
</tr>
<tr>
<td>CRRA-transformed distance from the mean</td>
<td>18270.47</td>
<td>18148.46</td>
<td>0.04</td>
</tr>
<tr>
<td><strong>Time 2 on Time1</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Linear : Log (income)</td>
<td>11736.65</td>
<td>11613.56</td>
<td>0.29</td>
</tr>
<tr>
<td>Standardized CRRA (ρ = 0.40)</td>
<td>11731.77</td>
<td>11608.67</td>
<td>0.29</td>
</tr>
<tr>
<td>CRRA-transformed distance from the mean</td>
<td>11733.16</td>
<td>11610.06</td>
<td>0.29</td>
</tr>
<tr>
<td><strong>ELSA</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Time 1</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Linear : Log (net wealth)</td>
<td>30836.18</td>
<td>30674.94</td>
<td>0.12</td>
</tr>
<tr>
<td>Standardized CRRA (ρ = 0.80)</td>
<td>30807.11</td>
<td>30645.86</td>
<td>0.12</td>
</tr>
<tr>
<td>CRRA-transformed distance from the mean</td>
<td>30807.11</td>
<td>30645.86</td>
<td>0.12</td>
</tr>
<tr>
<td><strong>Time 2 on Time1</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model</td>
<td>2010</td>
<td>2011</td>
<td>2012</td>
</tr>
<tr>
<td>-------------------------------------------</td>
<td>------------</td>
<td>------------</td>
<td>------------</td>
</tr>
<tr>
<td>Linear : Log(net wealth)</td>
<td>16402.10</td>
<td>16246.44</td>
<td>16395.12</td>
</tr>
<tr>
<td>Standardized CRRA (ρ = 0.60)</td>
<td>16397.38</td>
<td>16241.72</td>
<td>16395.12</td>
</tr>
<tr>
<td>CRRA-transformed distance from the mean</td>
<td>16396.69</td>
<td>16241.03</td>
<td>16395.12</td>
</tr>
</tbody>
</table>

Note. For each time wave, two specifications are presented to model the absolute income hypothesis \(f(\text{income})\) – the logarithm of income and CRRA specification using the estimate of \(\rho\) that gives the lowest BIC. Each of these models and the CRRA-transformed deviation from the mean model are then compared to the income rank model to assess the best fitting model for each time point. For ELSA results using net wealth are presented.
Even when compared to the model with the best fitting function for income, a model containing rank without income had a lower BIC (BIC: 18268.93) and therefore overall best fit. This rank model also provided a better fit than the CRRA-transformed deviation of income from the mean income of the reference group (BIC: 18270.47). Table 3 shows that similar results were obtained in ELSA; In ELSA, the optimum model for regressing wealth on current depressive symptoms (Time 1) was the CRRA model when \( \rho = 0.80 \) (BIC: 30807.11). Once again, even when compared to both this specification and the CRRA-transformed deviation from the mean (BIC: 30807.11), the model with the lowest BIC was the rank model (BIC: 30795.79), supporting the wealth rank hypothesis. The rank model produced a BIC value that was 11.32 less than the BIC of the wealth model, which (under some assumptions) corresponds to a Bayes factor of 287. In other words, the odds in favour of the rank model given the data are 287. Thus, the goodness of fit statistics provide strong evidence that rank is a better predictor of current depressive symptoms. Table 4 shows that the goodness of fit test results were confirmed with the regression analyses, which showed that rank was consistently a significant predictor of current depressive symptoms for both datasets. In WLS, a one standard deviation increase in household income was associated with a 0.08 standard deviation decrease in risk of depressive symptoms, while moving from top to bottom rank (within a reference group of people of the same education and gender) reduced risk of depressive symptoms by 0.29 standard deviations and a change in CRRA-transformed distance from the mean was associated with a 0.08 standard deviation decrease in depressive symptoms. Jointly regressing the CRRA function and income rank on depressive symptoms showed that the CRRA function was no longer significant while income rank remained significant (\( p = 0.004 \)). However, this model had a higher BIC than the models including the CRRA function and income rank alone and did not explain any more variation in depressive symptoms. This is unsurprising as BIC penalises for additional regressors.
<table>
<thead>
<tr>
<th>Predictor Variables</th>
<th>Depressive Symptoms</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Time 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(a) Standardized CRRA</td>
<td>-0.08</td>
<td>-0.00</td>
<td>0.28</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.014; p &lt; 0.001)</td>
<td>(0.029; 0.898)</td>
<td>(0.083; 0.001)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rank</td>
<td>-0.29</td>
<td>-0.28</td>
<td>-0.25</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.045; p &lt; 0.001)</td>
<td>(0.096; 0.004)</td>
<td>(0.096; 0.010)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRRA-transformed</td>
<td>-0.08</td>
<td>-0.29</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>distance from the mean</td>
<td>(0.013; p &lt; 0.001)</td>
<td>(0.080; p &lt; 0.001)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(b) Standardized CRRA</td>
<td>-0.16</td>
<td>-0.05</td>
<td>-0.14</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.016; p &lt; 0.001)</td>
<td>(0.035; 0.177)</td>
<td>(0.033; p &lt; 0.001)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rank</td>
<td>-0.43</td>
<td>-0.32</td>
<td>-0.32</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.040; p &lt; 0.001)</td>
<td>(0.089; 0.000)</td>
<td>(0.089; p &lt; 0.001)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRRA-transformed</td>
<td>-0.16</td>
<td>0.03</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>distance from the mean</td>
<td>(0.016; p &lt; 0.001)</td>
<td>(0.211; p &lt; 0.001)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Time 2 on Time 1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(a) Depressive symptoms (T1)</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.012; p &lt; 0.001)</td>
<td>(0.012; p &lt; 0.001)</td>
<td>(0.012; p &lt; 0.001)</td>
<td>(0.012; p &lt; 0.001)</td>
<td>(0.012; p &lt; 0.001)</td>
<td></td>
</tr>
<tr>
<td>Standardized CRRA (T1)</td>
<td>-0.03</td>
<td>0.07</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.014; 0.025)</td>
<td>(0.036; 0.067)</td>
<td>(0.103; 0.400)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rank (T1)</td>
<td>-0.14</td>
<td>-0.33</td>
<td>-0.36</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(b)</td>
<td>Depressive symptoms (T1)</td>
<td>0.39</td>
<td>0.39</td>
<td>0.39</td>
<td>0.39</td>
</tr>
<tr>
<td>------------------------</td>
<td>-----</td>
<td>-------------------------</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.012; p &lt; 0.001)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CRRA-transformed distance from the mean</td>
<td></td>
<td>-0.03</td>
<td></td>
<td></td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.014; 0.016)</td>
<td></td>
<td></td>
<td>(0.029; 0.866)</td>
<td>(0.151; 0.132)</td>
</tr>
<tr>
<td>Standardized CCRA (T1)</td>
<td></td>
<td>-0.13</td>
<td>-0.14</td>
<td>-0.14</td>
<td>-0.23</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.048; 0.007)</td>
<td></td>
<td></td>
<td></td>
<td>(0.096; 0.161)</td>
</tr>
<tr>
<td>Rank (T1)</td>
<td></td>
<td>-0.04</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.015; 0.016)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. (1) Model containing income/wealth + mentioned covariates (2) Model containing rank + mentioned covariates (3) Model containing CRRA-transformed distance from mean + mentioned covariates (4) Model containing income/wealth + rank + mentioned covariates (5) Model containing income/wealth + rank + CRRA-transformed distance from mean + mentioned covariates. For each predictor variable, the top row provides the estimate of the regression coefficient, the row beneath shows the corresponding (standard error; p-value).
Simultaneously regressing depressive symptoms on CRRA, CRRA-transformed deviation from the mean and rank also produced a significant coefficient on the rank variable ($p = 0.010$) and CRRA-transformed distance from the mean ($p < 0.001$), although this regression indicated multi-collinearity in the predictors since the CRRA function became significant in the opposite direction. Similarly, in ELSA, jointly regressing the CRRA-transformed wealth and rank on depressive symptoms resulted in CRRA-transformed wealth losing significance, while moving from bottom to top rank was associated with a 0.32 ($p < 0.001$) standard deviation decrease in depressive symptoms. Regressing depressive symptoms on CRRA-transformed wealth, CRRA-transformed deviation from the mean and rank jointly suggested multi-collinearity as CRRA-transformed deviation from the mean became significant in the opposite direction.

In Table 3 we show that the income model which best predicted future depressive symptoms from Time 1 income was the CRRA model when $\rho = 0.40$ for WLS ($BIC: 11731.77$). This model had reduced fit when compared to the model containing income rank alone ($BIC: 11726.50$). Consistently in ELSA, the optimum wealth model (the CRRA specification when $\rho = 0.60$) proved to fit slightly less well than the rank model ($BIC: 16397.38$ and $16395.12$ respectively). For both datasets, the rank model consistently better predicted future depressive symptoms than did CRRA-transformed distance from the mean. As before, the results of the regression analyses in Table 4 confirmed the results. For WLS, joint regression of the CRRA function and income rank resulted in the CRRA function losing significance and rank remaining significant. Similarly, jointly regressing future depressive symptoms on CRRA, CRRA-transformed deviation from the mean and rank resulted in only rank remaining a significant predictor. However, in ELSA joint regression resulted in the CRRA function, CRRA-transformed deviation from the mean and rank losing significance, indicating multi-collinearity. We counteract this with a bootstrapping test to assess the probability that the rank model is a better fit than the income model (i.e. a BIC difference of $> 0$). Results showed that the proportion of the
bootstrapped BIC differences greater than 0 for current depressive symptoms was 0.95 and 0.88 for WLS and ELSA respectively, providing some evidence that the rank model is generally better than the income or wealth model. For predicting future depressive symptoms, the proportion of the bootstrapped BIC differences greater than 0 was 1.00 and 0.82 for WLS and ELSA respectively.

Contingency analyses were performed to check the robustness of results. Regression was repeated excluding subjects with negative income values. Results obtained were similar, although effect sizes of rank were slightly larger in ELSA. Furthermore, the effect of rank within the overall population was also examined. Similar results were found at all time periods as when stratifying rank by gender and education. Similarly, consistent results were observed for the regression analyses using total personal income in both datasets and total household income in ELSA (though household income was not a significant predictor of future depressive symptoms in ELSA). Regressions were also repeated using depressive symptoms as a dichotomised variable and with income rank by education and yielded consistent results. Additionally, the regressions at both time points were repeated to include physical health variables (at Time 1), which did not attenuate the results. Probability weights were also created and used in the regression to predict future depressive symptoms, in order to account for the fact that physical health was a predictor of inclusion at Time 2 analyses. The latter produced similar results. Finally, inverse probability weighting was also used to handle missing data for the variables of interest at Time 1 and Time 2; we first created a variable to indicate whether data for depressive symptoms at Time 1 were missing. Regressing this variable on CRRA, rank, CRRA-transformed distance from the mean and demographic variables indicated that rank, distance from the mean, household size, gender, education, marital and retirement status predicted whether the respondent provided data on their depressive symptoms. The variable indicating whether data on depressive symptoms were missing was then regressed on these significant predictors and the inverse probability of this regression was stored and
used as probability weights in our complete case regression analysis. The results using these weights were similar to those obtained using complete case analysis.

3.5 Discussion

The results provide the first direct evidence that the relationship between income and depressive symptoms is best explained by an individual’s income rank position within a reference group. We provide a strict test of this income rank hypothesis by accounting for the direct effect of various functions of income. We show that the CRRA function represents the effect of income on depressive symptoms better than the logarithmic function, highlighting the need to fully control for the exact form of the relationship between income and well-being when comparing absolute income against relative income specifications. Consistent with the results from the study by Gravelle and Sutton (2009), we find that addition of the rank variable to the model containing the CRRA specification does not improve the fit of the model and in the case of ELSA, results in both wealth and rank losing significance. This result is consistent with Gravelle and Sutton’s conclusion that the high correlation between different indicators of socioeconomic status will present a problem in many datasets. We therefore suggest that the best way to assess whether rank has an effect on depressive symptoms above and beyond the direct effect of income or wealth is to compare the fit of two theoretical models. Here we show that the model with the lowest BIC for all time points in both WLS and ELSA was the rank model. This was confirmed with bootstrapping and sensitivity analyses. We therefore conclude that the income rank model (and wealth rank model in ELSA) is statistically and theoretically a better model for risk of depressive symptoms, providing evidence to support Marmot’s argument of the role of psychosocial factors on individual health (Marmot & Wilkinson, 2001).

The study has a number of advantages - the use of a pooled dataset, reported actual values of income rather than income categories, and use of a reliable measure of depressive
symptoms. Although a self-report measure of depressive symptoms is used here, the CES-D has been shown to have high sensitivity and specificity, allowing those at risk of clinical depressive symptoms to be identified. Furthermore the analysis was conducted on two datasets to see if the results were consistent in different populations and therefore generalizable to mid-life populations. Similarly, we use two different measures of utility (wages and net wealth) and find consistent results. An obvious limitation which must be considered is that it is difficult to know exactly to whom people compare themselves (Pham-Kanter, 2009). More suitable reference groups could be one’s social circle or work colleagues, rather than people of similar education or gender. More accurate results could be obtained using questionnaires that inquire about reference groups or defining exact metrics along which the participants make social comparisons and including members of these social comparison groups as participants (Pham-Kanter, 2009).

Through this study we show that the income-depressive symptoms relationship is likely due to psychosocial factors rather than material factors. Although we find that income rank is a better predictor of depressive symptoms than income, it must be noted that rank still explains a relatively small percentage of variability in depressive symptoms (4% and 12% in WLS and ELSA respectively). Income, however specified, only explains a small amount of well-being relative to psychological characteristics (Boyle et al., 2013). Furthermore, the current research suggests an explanation of the Easterlin paradox (Easterlin, 1973; Easterlin, McVey, Switek, Sawangfa, & Zweig, 2010) where whilst income within a country is related to well-being at a point in time, increases in national income do not relate to aggregate increases in well-being. If the income/well-being relationship is better represented by rank position, at a given time point those of higher rank will have higher well-being, but increasing population income will have no impact on national well-being as there will still by definition be the same proportion of people at high and low rank. Taken together, whilst the current results provide an explanation as to why the well-observed income-depressive symptoms relationships exists, and what it
represents, greater improvements in well-being may be achieved through focusing on improving social good rather than economic success.
CHAPTER 4

4.0 Does Income Relate to Health due to Psychosocial or Material Factors?

Consistent Support for the Psychosocial Hypothesis Requires Operationalization with Income Rank not the Yitzhaki Index

Currently under review at Social Science and Medicine

4.1 Abstract

Research on why income influences health has produced mixed findings. Many, but not all, studies suggest that the relationship between income and health is due to income indicating psychosocial position rather than the associated material benefits. The inconsistent findings may be partly due to the use of the Yitzhaki Index, a function which calculates the accumulated income shortfall for an individual relative to those with higher income, in order to represent the psychosocial position conferred by income. The current study tests whether an alternative specification – income rank – provides more consistent conclusions regarding the psychosocial effect of income on health. We used data from two nationally representative samples: 12,576 observations from 8,392 participants across three waves (2004, 2008, and 2012) of the English Longitudinal Study of Aging (ELSA) and 29,237 observations from 8,441 individuals across seven waves (2007-2013) of the Longitudinal Internet Studies for the Social Sciences (LISS). Multilevel regression models indicated that income rank was a stronger and more consistent predictor than both the Yitzhaki Index and actual income of self-rated and objective health as well as health changes over time. The psychosocial hypothesis is more consistently supported when income rank is used to test it.

4.2 Introduction

A large body of research has investigated why an individual’s income negatively relates to their health. Two distinct hypotheses have been offered to explain the association
between income and health at the individual level. The materialist hypothesis posits that individuals with lower income are less likely to have good health than individuals with higher income because they lack material resources that are conducive to good health (Lynch, Davey-Smith, Kaplan, & House, 2000). This hypothesis can be contrasted with the *psychosocial hypothesis* (Subramanian & Kawachi, 2004; Wilkinson & Pickett, 2006, 2009b) which proposes that individuals with less income often have worse health than individuals with higher income due to negative upward social comparisons (Kondo et al., 2008; Runciman, 1966) which can result in frustration, shame, stress (Kondo et al., 2008) and subsequently ill health.

The literature comparing the materialist and psychosocial effects of an individual’s income on their health has mostly used actual income to represent the materialist hypothesis. This is normally contrasted with the psychosocial hypothesis as represented by the Yitzhaki Index (Yitzhaki, 1979). This function represents the average difference between an individual’s income and the income of all individuals with higher income within the same reference group. Studies using the Yitzhaki Index to assess the psychosocial hypothesis have yielded mixed results, with many studies finding the Yitzhaki Index relates to health (for example, Eibner & Evans, 2005; Eibner, Sturm, & Gresenz, 2004; Kondo et al., 2008; Subramanyam, Kawachi, Berkman, & Subramanian, 2009; Yngwe, Kondo, Hagg, & Kawachi, 2012; Yngwe, Fritzell, Burstrom, & Lundberg, 2005; Yngwe, Fritzell, Lundberg, Diderichsen, & Burstrom, 2003), while many others (for example Gravelle & Sutton, 2009; Jones & Wildman, 2008; Li & Zhu, 2006; Lorgelly & Lindley, 2008; Wildman, 2003) find no or only weak evidence for an association (see Adjaye-Gbewonyo & Kawachi, 2012, for a review of empirical studies published between 2000 and 2010 that test the effect of Yitzhaki Index on health measures). The mixed findings have been attributed to a number of different factors, such as the use of different outcome measures, countries, size and choice of reference groups, statistical methods,
different time lags between income and health measures, as well as the presence of a threshold effect of income differences on health (Kondo, Kawachi, et al., 2009).

Meanwhile, a new line of evidence (Boyce et al., 2010; Daly et al., 2015; Hounkpatin, Wood, Brown, & Dunn, in press; Wood, Boyce, et al., 2012) has consistently suggested that it is the rank (ordinal position) of an individual’s income that is psychosocially important for their health. For example, Daly et al. (2015) compared the effects of income and income rank on self-rated health, obesity, and allostatic load, and they found that income rank was significantly associated with each health measure in two British populations, even after controlling for the effects of actual income. Moreover, when controlling for income rank, actual income no longer related to health, suggesting that income only relates to health through acting as a proxy for income rank. This parallels findings with mental health and depressive symptoms as the outcome (Elgar et al., 2013; Hounkpatin, Wood, et al., in press; Wetherall, Daly, Robb, Wood, & O’Connor, 2015; Wood, Boyce, et al., 2012) as well findings from a study by Subramanyam et al. (2009) which indicated that percentile income rank significantly predicted self-rated health in a US population after controlling for actual income. The income rank specification is consistent with the psychosocial hypothesis but differs from the Yitzhaki Index in that it proposes that health is not necessarily related to the magnitude of the difference, but rather the position of income on the income distribution within a comparison group.

The first motivation of the income rank hypothesis was from primate studies indicating that low ranking animals in conflict with more dominant members of the same species experience high levels of stress (Sapolsky, 2004; Shivley et al., 1997) as evidenced by decreased levels of serotonin in their serum (Raleigh et al., 1983; Yeh et al., 1996). Reduced secretion of serotonin is believed to have allowed the subordinate animal to behave in a hyper vigilant and withdrawn manner so as to increase their chances of survival under hostile conditions. Humans continue to display similar reactions in response to cognitions associated with low social rank (Gilbert, 2006; Price et al., 1994). While
these hard-wired responses to low rank were adaptive under evolutionary conditions, such reactions may adversely affect health in modern day, particularly if prolonged (Gilbert, 2006; Taylor et al., 2011).

The second motivation for the rank hypothesis was from cognitive science findings that people always judge relative magnitude based on rank position rather than any other specification (Stewart et al., 2006). Judgements normally rely on heuristics, rules of thumb that balance cognitive processing cost with accuracy (Kahneman & Tversky, 1979, 2000). It has been suggested that when making relative judgements (such as one’s income position relative to others) people first bring a distribution of similar stimuli to mind (e.g., other individual’s income) from memory or salient features of the environment, sequentially compare the target (e.g., one’s income) with each of the other stimuli in the set (e.g., the incomes of others), and simply keep track of the number of stimuli higher than the target stimuli (that is, one’s rank within the income distribution). This ranking process provides a balance between the low cognitive costs (and low informational value) of making non-relative judgements and the high cognitive costs (but high informational value) of calculating both rank position and relative distance (as with the Yitzhaki Index), whilst still capturing most of the relevant information through taking into account the main features of the distribution (e.g., skew). This model has been shown to predict judgements of personality (Wood, Brown, Maltby, & Watkinson, 2012), fairness of sentencing (Aldrovandi, Brown, & Wood, 2013), indebtedness (Aldrovandi, Wood, Maltby, & Brown, 2015), willingness to pay for food (Aldrovandi, Brown, & Wood, in press), educational satisfaction (Brown, Wood, Ogden, & Maltby, 2015), emotion (Melrose, Brown, & Wood, 2013; Wood, Brown, & Maltby, 2011), alcohol use (Taylor, Vlaev, Maltby, Brown, & Wood, in press; Wood, Brown, & Maltby, 2012), pain (Watkinson, Wood, Lloyd, & Brown, 2013) and health benefits of exercise (Maltby, Wood, Vlaev, Taylor, & Brown, 2012).
If people have an evolutionary sensitivity to rank position and judge their social position based on rank position, using the Yitzhaki Index - which measures rank plus the magnitude of income difference - may erroneously lead to a rejection of the psychosocial hypothesis. For example, when using the Yitzhaki Index a psychosocial effect of income may not be apparent for a comparison group of individuals with similar incomes as income differences will only be minimal. However, a psychosocial effect would be observed for the same group of individuals when using a pure rank specification. We are unaware of any previous studies in adults that have directly contrasted the health effects of the Yitzhaki Index and income rank specifications. Although a study by Elgar et al. (2013) indicated that rank affluence (within region) better predicted psychosomatic symptoms in an adolescent sample than actual family affluence or Yitzhaki Index, it is not clear whether such findings might extend to an adult population and to objectively as well as subjectively measured health outcomes. In the present study, we directly compare the effects of Yitzhaki Index and income rank on two health measures, self-rated health and allostatic load, using data from two nationally representative but culturally different adult samples. Due to co-linearity issues associated with predicting health jointly from income and income rank or Yitzhaki Index (Gravelle & Sutton, 2009), we primarily compare the predictive fit of each of the income-related predictors. We hypothesised that: (H1) A model using income rank will better predict both self-rated and objective health than one that uses the Yitzhaki Index, suggesting that income rank is the better representation of psychosocial position, and (H2) use of income rank would provide more consistent support for the psychosocial hypothesis across measures and datasets than the Yitzhaki Index.

4.3 Methods

4.3.1 Participants and procedure.
The analysis was performed on two separate datasets: the English Longitudinal Study of Ageing (ELSA) and the Longitudinal Internet Studies for the Social Sciences (LISS) panel.

4.3.1.1 ELSA. ELSA is a nationally representative sample of non-institutionalized individuals aged 50 years and older and living in England. The ELSA sample was drawn from households who participated in the Health Survey for England (HSE) during 1998, 1999, and 2001. Participants were asked to complete questionnaires about their socio-demographics and health every two years. During Wave 2 (2004), Wave 4 (2008) and Wave 6 (2012), participants who gave consent were also visited by a nurse for assessment of objective measures of health such as blood pressure, lung function and anthropometric indices. Seventy-eight percent of the initial sample (9,432 out of 12,100 participants) completed questionnaires at Wave 2 (2004) and 7,666 participants (63.35% of the initial sample) additionally underwent clinical assessment by a nurse. Eleven thousand and fifty participants completed questionnaires during Wave 4, and 10,601 participants completed questionnaires during Wave 6. Eight thousand six hundred and forty-three and 8,054 participants also underwent clinical assessment at Wave 4 and Wave 6 respectively. We used data from three waves (2004, 2008, and 2012) for the current study. Our analytic sample consisted of 8,392 participants (mean age 68.36 years, 55.144% female) who completed self-report questionnaires on at least one occasion and 7,277 participants (mean age 68.81 years, 54.36% female) who underwent clinical assessment on at least one occasion. Our analytic sample was slightly older and had slightly higher average level of income than those who did not respond to measures of interest.

4.3.1.2 LISS. The LISS panel is a sample of approximately 5,000 households in the Netherlands who were randomly selected from municipal registers in 2007. Refreshment samples were recruited during 2009, 2011-2012, and 2013-2014 to ensure the representativeness of the sample. Participants completed online surveys each month which asked questions about their socio-demographic and income status. Internet service and
personal computers were provided to households who did not have access to the internet or a computer. During the months of November and December of 2007-2013 participants were additionally asked to rate their health. Participants were included in our analyses if they provided data on socio-demographics, income and self-rated health during at least one of the 7 waves. Six thousand six hundred and ninety-eight individuals (78.90% of the initial sample) provided data on their subjective health during November and December 2007 (Wave 1), 5,961 participants provided data on their self-rated health during November and December 2008 (Wave 2). After refreshment samples were added in 2009, data on self-rated health was available for 6,109, 5,718, 5,072, 5,780 and 5,379 participants during waves 3-7 respectively. The final sample for our analyses consisted of 8,441 individuals (mean age 49.49 years, 53.20% female) who provided a total of 29,237 observations across all waves. Individuals who were included in our study were generally older, had slightly lower income and more likely to be married but did not differ in levels of self-rated health. Table 5 provides the means and standard deviations of the variables of interest for the two analytic samples.
Table 5 Descriptive statistics across time waves for ELSA and LISS

### ELSA

<table>
<thead>
<tr>
<th></th>
<th>Wave 2</th>
<th>Wave 4</th>
<th>Wave 6</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Mean (SD)</td>
<td>N</td>
</tr>
<tr>
<td>Age</td>
<td>8361</td>
<td>65.58 (10.46)</td>
<td>5606</td>
</tr>
<tr>
<td>Female</td>
<td>8361</td>
<td>1.55 (0.48)</td>
<td>5606</td>
</tr>
<tr>
<td>No qualifications (proportion)</td>
<td>8361</td>
<td>0.42 (0.49)</td>
<td>5606</td>
</tr>
<tr>
<td>Married (proportion)</td>
<td>8361</td>
<td>0.56 (0.50)</td>
<td>5606</td>
</tr>
<tr>
<td>Employment status</td>
<td>8361</td>
<td>0.32 (0.47)</td>
<td>5606</td>
</tr>
<tr>
<td>Retired</td>
<td>8361</td>
<td>0.51 (0.50)</td>
<td>5606</td>
</tr>
<tr>
<td>Equivalised Income (£)</td>
<td>8361</td>
<td>288.98 (278.37)</td>
<td>5606</td>
</tr>
<tr>
<td>Self-rated health</td>
<td>8361</td>
<td>3.18 (1.13)</td>
<td>5606</td>
</tr>
<tr>
<td>Allostatic load</td>
<td>6875</td>
<td>1.98 (1.58)</td>
<td>4844</td>
</tr>
</tbody>
</table>

### LISS

<table>
<thead>
<tr>
<th></th>
<th>Wave 1</th>
<th>Wave 2</th>
<th>Wave 3</th>
<th>Wave 4</th>
<th>Wave 5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Mean (SD)</td>
<td>N</td>
<td>Mean (SD)</td>
<td>N</td>
</tr>
<tr>
<td>Age</td>
<td>5959</td>
<td>45.52 (15.53)</td>
<td>4996</td>
<td>46.77 (16.07)</td>
<td>4615</td>
</tr>
<tr>
<td>Female</td>
<td>5959</td>
<td>0.53 (0.50)</td>
<td>4996</td>
<td>0.54 (0.50)</td>
<td>4615</td>
</tr>
<tr>
<td>Primary education (proportion)</td>
<td>5959</td>
<td>0.00 (0.01)</td>
<td>4996</td>
<td>0.00 (0.03)</td>
<td>4615</td>
</tr>
<tr>
<td>Married (proportion)</td>
<td>5959</td>
<td>0.61 (0.49)</td>
<td>4996</td>
<td>0.62 (0.49)</td>
<td>4615</td>
</tr>
<tr>
<td>Employment status</td>
<td>5959</td>
<td>0.53 (0.50)</td>
<td>4996</td>
<td>0.52 (0.50)</td>
<td>4615</td>
</tr>
</tbody>
</table>
### LISS

<table>
<thead>
<tr>
<th></th>
<th>Wave 6</th>
<th>Wave 7</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Mean (SD)</td>
</tr>
<tr>
<td>Age</td>
<td>5060</td>
<td>50.85 (17.31)</td>
</tr>
<tr>
<td>Gender</td>
<td>5060</td>
<td>0.53 (0.50)</td>
</tr>
<tr>
<td>Primary education (proportion)</td>
<td>5060</td>
<td>0.00 (0.05)</td>
</tr>
<tr>
<td>Married (proportion)</td>
<td>5060</td>
<td>0.59 (0.49)</td>
</tr>
<tr>
<td>Employment status</td>
<td>5060</td>
<td>0.45 (0.50)</td>
</tr>
<tr>
<td>Retired</td>
<td>5060</td>
<td>0.22 (0.42)</td>
</tr>
<tr>
<td>Net Income (€)</td>
<td>5060</td>
<td>2972.58 (3485.07)</td>
</tr>
<tr>
<td>Household size</td>
<td>5060</td>
<td>2.60 (1.30)</td>
</tr>
<tr>
<td>Self-rated health</td>
<td>5060</td>
<td>3.10 (0.77)</td>
</tr>
</tbody>
</table>

*Note. N = number of observations. SD = standard deviation.*
4.3.2 Measures.

4.3.2.1 Self-rated health. In ELSA, self-rated health was assessed using a single item: “Would you say your health is...”, to which participants responded with either “excellent”, “very good”, “good”, “fair” or “poor”. Scores were reverse coded and treated as a continuous measure ranging from 1 (“poor”) to 5 (“excellent”). Similarly, in LISS, participants were asked “How would you describe your health, generally speaking?”, to which they responded on a 5-Likert scale ranging from 1 (“poor”) to 5 (“excellent”). Test-retest reliability (calculated as the correlation between variables across time) for our measure of self-rated health was $r = .86$ in ELSA and $r = .91$ in LISS.

4.3.2.2 Allostatic load. For ELSA an indicator of high risk allostatic load was calculated using selected biomarkers of immune function (C-reactive protein and fibrinogen), cardiovascular functioning (systolic and diastolic blood pressure), respiratory functioning (peak expiratory flow), metabolic functioning (the ratio of total blood cholesterol to high density lipoprotein (HDL) cholesterol, triglycerides, glycated haemoglobin), and an index of body fat (waist measurement). A binary variable indicating high risk levels was generated for each biomarker. Levels of C-reactive protein, fibrinogen, systolic blood pressure, total blood cholesterol to HDL cholesterol, triglycerides, glycated haemoglobin and waist measurement in the upper quartile were considered high risk. Levels of diastolic blood pressure and peak expiratory flow in the lowest quartile were considered high risk. The nine binary variables were then summed to generate a continuous measure of high risk allostatic load, ranging from 0 (does not belong to high risk group for any of the biomarkers) to 9 (belongs to high risk group for all biomarkers). This measure of allostatic load has been used in previous studies by Read & Grundy (2012) and Daly, Boyce, & Wood (2015).

4.3.2.3 Actual income, the Yitzhaki Index, and income rank. Data on total household income was available for every wave in both datasets. ELSA additionally contained data on ‘equivalised total income’, which is the total income adjusted for family
size. In ELSA, equivalised total income was used rather than total household income since the former accounts for increased demand on resources for larger families. Individuals with negative equivalised income values in ELSA (referred to as income henceforth) were assigned a value income of £0 (in ELSA) so that they would be included in the analysis. Income was then transformed to a Constant Relative Risk Aversion (CRRA) utility function using the formula:

\[ u = \frac{y^{1-\rho} - 1}{1 - \rho} \]

where for values of \( \rho \) not equal to 1, \( u \) is utility, \( y \) is income and \( \rho \) is the elasticity of marginal utility with respect to income and is assumed to be constant. When \( \rho = 1 \), the function is equal to log-transformed income. This function has been used to more adequately account for the highly non-linear association between income and well-being (for example Layard, Nickell, & Mayraz, 2008; Hounkpatin, Wood, Brown & Dunn, in press), which may not be captured by the commonly used logarithmic function. Using the CRRA function allows us to represent the exact shape of the relationship between income and health. This is important in order to ensure that any significant coefficient on the income rank or Yitzhaki Index is not due to these variables representing non-linearities in the relationship between income and health that are not fully captured by the logarithmic function. Use of the CRRA function therefore allows a more accurate estimation of the association between actual income and health as well as preventing bias on the coefficient on the relative income measures.

The Yitzhaki Index (RD; Yitzhaki, 1979) and income rank (R; Brown, Gardner, Oswald, & Qian, 2008; Stewart, Chater, & Brown, 2006) within education group and region were calculated as the social psychology literature suggests individuals compare themselves to these groups (Goethals & Darley, 1977; Singer, 1981). In LISS, only education was used as a reference group since geographical data was not available. The Yitzhaki Index of an individual \( i \) was calculated as:
\[ \text{RD} = \frac{1}{N} \sum_u (y_u - y_i), \forall (y_u > y_i) \]

where \( y_i \) is the income of the individual \( i \), \( y_u \) is the income of an individual \( u \) with higher income than individual \( i \) and \( N \) is the total number of individuals within the reference group. RD is therefore the average difference in income between individual \( i \) and other members in the same reference group who have higher income. The income rank, \( R \), of an individual \( i \) is given by:

\[ R_i = \frac{j - 1}{n - 1} \]

where \( j - 1 \) is the number of individuals within individual \( i \)’s reference group who have incomes lower than individual \( i \) and \( n \) is the number of people within that reference group.

### 4.3.2.4 Potential covariates.

Age, gender, household size (log-transformed), employment status (employed or unemployed), retirement status (retired or not retired), marital status (married, remarried, legally separated, divorced, widowed, never married in ELSA; married, separated, divorced, widowed, never married in LISS) and level of education achieved (no qualifications, National Vocational Qualification [NVQ] 1, GCE ‘O’ level or NVQ 2, ‘A’ level or NVQ3, below degree, university degree or NVQ 4 or NVQ 5 in ELSA; not yet started education, primary school, intermediate secondary school/junior high school, higher secondary education or senior high school, intermediate vocational education or junior college, higher vocational education or college, university level in LISS) and year effects were controlled for in all analyses. In ELSA, government office region (North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South East, South West) was additionally controlled for in all analyses.

### 4.3.3 Statistical analysis.

Analysis was performed using STATA Version 11 (StataCorp, 2009). Given the clustered nature of the data (observations clustered within individuals who are nested in regions in ELSA and observations clustered within individuals who are nested within
households in LISS), we fitted 3-level multilevel models to assess the association between health measures and each of the income-related predictors (CRRA-transformed actual income, Yitzhaki Index and income rank). To make full use of the longitudinal nature of the data, we additionally modelled the association between each health outcome and lagged income-related predictors. Values of income-related predictors at four-year and one-year time lag were used for the analysis in ELSA and LISS respectively, since data on our variables of interest were collected every four years in ELSA and yearly in LISS. The lagged models contained significantly fewer observations (N = 12,576 for analyses on self-rated health in ELSA; N = 10,717 for analyses on allostatic load in ELSA; N = 29,237 for analyses on self-rated health in LISS) as subjects who did not provide data on income at both current and lagged periods were dropped from the analysis. We use the maximum likelihood estimation option of the `xtmixed` command in STATA to account for missing data (Rabe-Hesketh & Skrondal, 2008). Maximum likelihood estimation borrows information about the correlation between variables from complete cases to derive the most likely parameter estimates (Allison, 2012).

We first derived the CRRA specification that best explained the effect of actual income on each health variable by varying the values of $\rho$ used to construct the CRRA function. Goodness of fit statistics indicated that the best-fitting specification to represent the effect of contemporaneous actual income on self-rated health across all time waves was $\rho = .60$ in ELSA and $\rho = .70$ in LISS. In ELSA, the best-fitting specification for the effect of actual income on allostatic load was achieved when income was CRRA-transformed using $\rho = .80$. Goodness of fit statistics indicated the best-fitting CRRA specification for the effect of lagged actual income on self-rated health in ELSA and LISS was $\rho = .60$ and $\rho = .70$ respectively. The best-fitting CRRA specification for the effect of lagged actual income on allostatic load in ELSA was $\rho = .50$. We then, for each combination of income measure (the potential predictor) and outcome, compared the fit of three models to assess whether the association between health and income was best explained by
contemporaneous income, lagged income, or both. Model 1 predicted health from contemporaneous income plus covariates, Model 2 predicted health from lagged income plus covariates and Model 3 predicted health from both contemporaneous and lagged income plus covariates. All models were compared primarily using the Bayesian Information Criterion (BIC). BIC is a goodness of fit test which penalizes models for added parameters (Burnham & Anderson, 2004; Raftery, 1996) – a lower value indicating a better fit. Both the BIC and an alternative fit statistic, Akaike Information Criterion (AIC) are presented here for completeness. A BIC/AIC difference of 2 is considered weak evidence that the model with the lowest BIC/AIC explains the data better than the competing model and BIC/AIC differences of 4-7 provide moderate evidence that the model with the lowest BIC/AIC performs better.

4.4 Results

Our first set of analyses were concerned with establishing; (a) whether health was best predicted from contemporaneous or lagged income, and (b) which income-related predictor (absolute, Yitzhaki, or rank) best accounted for this relationship. Considering each income-related predictor, in turn, we first fitted 3 regression models for each outcome variable in each sample. Model 1 predicted an outcome variable from contemporaneous values of one income-related predictor, plus covariates. Model 2 predicted an outcome variable from lagged values of the same income-related predictor, plus covariates. Model 3 predicted an outcome variable jointly from contemporaneous and lagged values of the income-related predictor. Goodness of fit statistics (the BIC and AIC) indicated that regardless of which of Models 1, 2 and 3 were considered, income rank (normally within region) consistently outperformed predictions using either actual income or the Yitzhaki Index (Table 6). Bootstrapping tests further indicated that the difference between the fit of the rank model and the Yitzhaki model was statistically significant (p-value ranging from $p < 0.001$ to $p = 0.004$) for each sample, health measure and reference group.
tests also indicated that the rank model was a significantly better predictor than the actual income model for self-rated health in LISS, but was not a significantly better predictor than the actual income model for self-rated health in ELSA. However, the rank model predicted self-rated health in ELSA better than the actual income model 88.8-93.9% of the time.

The choice of model (1, 2 or 3) was not so clear cut. The best-fitting model for the association between self-rated health and each income-related predictor in ELSA was the model predicting self-rated health from both contemporaneous and lagged values of the specified income-related predictor (Model 3). This shows that in ELSA, people’s subjective health is best predicted both by the rank of their income amongst others at the present time, as well as the rank of their income in the recent past. The latter finding implies that there may be some causality between income rank and health. The best-fitting model for the association between allostatic load and each income-related predictor in ELSA was the model predicting allostatic load from both lagged values of the specified income-related predictor (Model 3). This shows that in ELSA, people’s objective health is best predicted by the rank of their income amongst others in the recent past. The best-fitting model for the association between self-rated health and each income-related predictor in LISS was the model predicting self-rated health from contemporaneous values of the specified income-related predictor, although the improvement on Model 3 (particularly when using income rank) was trivial. This shows that in LISS, people’s self-rated health is best predicted from rank amongst others at the present time and possibly also from rank amongst others in the recent past and thus only suggestive of causality. All further analyses were based on Model 3.
Table 6 Fit statistics comparing contemporaneous and lagged models of the association between income-related predictors and health

<table>
<thead>
<tr>
<th></th>
<th>Contemporaneous model</th>
<th>Lagged model</th>
<th>Contemporaneous + Lagged model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BIC</td>
<td>AIC</td>
<td>BIC</td>
</tr>
<tr>
<td><strong>ELSA</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Self-rated health</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual income</td>
<td>32279.26</td>
<td>32056.07</td>
<td>32258.87</td>
</tr>
<tr>
<td>Yitzhaki Index (region)</td>
<td>32285.58</td>
<td>32062.39</td>
<td>32267.19</td>
</tr>
<tr>
<td>Yitzhaki Index (education)</td>
<td>32283.96</td>
<td>32060.77</td>
<td>32305.59</td>
</tr>
<tr>
<td>Rank (region)</td>
<td><strong>32267.52</strong></td>
<td><strong>32044.33</strong></td>
<td><strong>32230.38</strong></td>
</tr>
<tr>
<td>Rank (education)</td>
<td>32272.72</td>
<td>32049.53</td>
<td>32242.73</td>
</tr>
<tr>
<td><strong>Allostatic load</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual income</td>
<td>29340.00</td>
<td>29121.62</td>
<td>29331.74</td>
</tr>
<tr>
<td>Yitzhaki Index (region)</td>
<td>29339.01</td>
<td>29120.62</td>
<td>29336.71</td>
</tr>
<tr>
<td>Yitzhaki Index (education)</td>
<td>29338.35</td>
<td>29119.97</td>
<td>29342.93</td>
</tr>
<tr>
<td>Rank (region)</td>
<td><strong>29334.16</strong></td>
<td><strong>29108.49</strong></td>
<td><strong>29328.99</strong></td>
</tr>
<tr>
<td>Rank (education)</td>
<td>29337.17</td>
<td>29118.79</td>
<td>29330.79</td>
</tr>
<tr>
<td><strong>LISS</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Self-rated health</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual income</td>
<td>66912.42</td>
<td>66705.34</td>
<td>66917.16</td>
</tr>
<tr>
<td>Yitzhaki Index (education)</td>
<td>66890.53</td>
<td>66683.45</td>
<td>66897.01</td>
</tr>
<tr>
<td>---------------------------</td>
<td>----------</td>
<td>----------</td>
<td>----------</td>
</tr>
<tr>
<td>Rank (education)</td>
<td><strong>66879.02</strong></td>
<td><strong>66671.94</strong></td>
<td><strong>66882.61</strong></td>
</tr>
</tbody>
</table>

*Note.* For each health outcome, the fit of contemporaneous models of the association between each income-related predictor and health and the fit of lagged models of the association between each income-related predictor and health is compared to models predicting health from contemporaneous and lagged actual income-related predictor simultaneously. The best fitting parameter within each model is indicated in bold. N = 12,576 for models of self-rated health in ELSA, N = 10,717 for models of allostatic load in ELSA and N = 29,237 for models of self-rated health in LISS.
The results above show that when each is considered independently, income rank is a better fitting predictor of health than actual income or Yitzhaki Index. We next tested whether a combination of income predictors improved fit further (e.g., whether rank and absolute income together fit the data better than rank alone). Jointly regressing each of our health outcomes on actual income, rank, and Yitzhaki resulted in an inflation of the standard errors and VIFs with final values ranging from 4.71 to 19.44. Although previous work has taken variance inflation factors (VIFs) of <10 as indication that parameter estimates are not significantly biased by co-linearity, there was evidence of co-linearity in our models which is consistent with evidence suggesting parameter estimates from models with VIFs<10 may be biased by co-linearity (Tu & Gilthorpe, 2012). Given that the parameter estimates of our joint regression models are therefore unreliable and following on from recent recommendations (Hounkpatin, Wood, Brown, & Dunn, in press), we compared the fit of the rank model with the fit of the joint regression models predicting each health outcome from; (1) rank plus actual income, (2) rank plus Yitzhaki Index, and (3) rank plus actual income plus Yitzhaki Index. Here we are assessing whether predictions are improved by using combinations of predictors rather than using just income rank alone. For self-rated health in LISS and objective health (allostatic load) in ELSA both the AIC and BIC indicated that the rank model provided a better fit on the data than the models predicting each health outcome jointly from rank plus Yitzhaki Index and the models predicting each health outcome jointly from rank plus actual income (see Table 7). The BIC also indicated this for self-reported health in ELSA. Whilst the AIC statistics indicated a small improvement when the second indicators were added (only for self-rated health in ELSA), the AIC does not penalise models for number of parameters, and models with more parameters are naturally better fitting (thus, the AIC results here are almost certainly explained by over-fitting). The penalised goodness of fit statistics (the BIC values in Table 7) was totally consistent across all samples and outcome measures.
Table 7 Fit statistics of competing models of the association between income-related predictors and self-rated health and allostatic load

<table>
<thead>
<tr>
<th></th>
<th>Rank</th>
<th>Rank + Actual Income</th>
<th>Rank + Yitzhaki</th>
<th>Rank + Actual Income + Yitzhaki</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BIC</td>
<td>AIC</td>
<td>BIC</td>
<td>AIC</td>
</tr>
<tr>
<td><strong>ELSA, self-rated health</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Region</td>
<td>32172.55</td>
<td>31941.92</td>
<td>32185.07</td>
<td>31939.57</td>
</tr>
<tr>
<td>Education</td>
<td>32186.96</td>
<td>31956.33</td>
<td>32195.21</td>
<td>31952.36</td>
</tr>
<tr>
<td><strong>ELSA, allostatic load</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Region</td>
<td>29331.65</td>
<td>29105.99</td>
<td>29349.36</td>
<td>29109.03</td>
</tr>
<tr>
<td>Education</td>
<td>29333.34</td>
<td>29107.68</td>
<td>29350.40</td>
<td>29108.42</td>
</tr>
<tr>
<td><strong>LISS, self-rated health</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>66879.30</td>
<td>66664.00</td>
<td>66897.55</td>
<td>66665.62</td>
</tr>
</tbody>
</table>

*Note.* For each health outcome, the fit of the rank model is compared to models predicting health (1) jointly from rank and actual income (2) jointly from Rank and Yitzhaki Index and (3) jointly from rank + actual income + Yitzhaki Index. N = 12,576 for models of self-rated health in ELSA, N= 10,717 for models of allostatic load in ELSA and N = 29,237 for models of self-rated health in LISS. The best fitting of the combinations of the income parameters are indicated in bold.
We have demonstrated that the results are not simply due to the reference group used to calculate rank and Yitzhaki through using both education and region as reference groups in ELSA (where data was available on both). These were the two reference groups that we predicted would be the most psychologically valid based on previous work. As a robustness check, we also repeated all analysis using age as a reference group in both ELSA and LISS (<50, 50-54, 55-59, 60-64, 65-69, 70-74, 75-79, 80-84, 85-89, >89 in ELSA; 5 year age bands ranging from 0 to 100 years in LISS). The results are reported in Tables I and II of the online appendix. Rank within age group was consistently a better predictor of self-rated health in LISS and allostatic load in ELSA than both the Yitzhaki Index and actual income. Furthermore, the rank model consistently predicted self-rated health in LISS and allostatic load in ELSA better than any of the joint models. However, the best-fitting model to explain the association between self-rated health and income in ELSA was the model predicting self-rated health from both current and lagged income, although the improvement on the model predicting self-rated health from current and lagged rank was trivial. We attribute the minor differences in findings to the use of a less psychologically valid reference group, and our robustness check shows a high degree of convergence between the results using age as a reference group (see Online Appendix) and those using other reference groups in the main analysis (see Tables 6 and 7), thus improving confidence in the robustness of our findings.

4.5 Discussion

This study explored differences in the predictive value of two competing indicators of relative deprivation- the Yitzhaki Index and income rank position- on self-rated health and allostatic load. The findings contribute to the debate on the material and psychosocial effects of an individual’s income on their health by suggesting that the psychosocial effect is strongly supported when modelled by the rank specification.
The results support both our hypotheses. Income rank was a better predictor of self-rated health and allostatic load than the Yitzhaki Index for both samples and across two reference groups. In line with our second hypothesis, income rank more consistently predicted self-rated health and allostatic load than Yitzhaki Index in both samples after controlling for actual income. The findings demonstrate how support for the psychosocial hypothesis over the material hypothesis may depend on the specification used to model relative deprivation. Contrasting the associations of actual income and Yitzhaki Index with self-rated health and allostatic load may lead to the conclusion that material factors better explain the association between health and income, while contrasting the associations of actual income and income rank leads to the conclusion that psychosocial factors uniquely predict health outcomes and relate more strongly to health than material factors.

The results here support the role of income rank on health. Income rank negatively relates to both self-report and objective measures of health. Our findings are consistent with a growing body of literature comparing the material and psychosocial processes on health (for example Martikainen, Adda, Ferrie, Davey-Smith, & Marmot, 2003; Elgar et al., 2013; Daly, Boyce, & Wood, 2015; Boyce, Brown, & Moore, 2010; Wood, Boyce, et al., 2012), and contrast the studies by Eibner & Evans (2005) and Li & Zhu (2006) who report mixed findings for an effect of rank on health. A failure to find a significant effect of rank in the two outlier studies may be the result of using datasets in which information on individual income was only collected within a broad income band (as in the case of the study by Eibner & Evans, 2005), rather than the actual income level, which is less suitable for forming the rank variable, or the use of a deflated income per capita household income variable (as in the case of the study by Li & Zhu, 2006), which assumes that people compare relative spending power rather than simply how much they are earning relative to others. The current study additionally provides evidence to suggest that the association between an individual’s income and health is more closely related to their income rank position within a reference group than the magnitude of the difference in their income.
relative to those with higher income within the reference group. Previous studies that failed to find an effect of relative income on health using the Yitzhaki Index may have found a significant association had they used the income rank specification as a measure of relative deprivation instead. We suggest, as future research, that these earlier studies are revisited to see whether the results change if a rank measure of relative deprivation is used.

There are a number of limitations that must be considered. Firstly, although we use longitudinal data we do not make strong causal inferences about the association between income rank and health. It is possible that an individual’s health predicts their income. Additional statistical procedures such as instrumentation and the use of natural experiments would be needed to determine any causal association between income (rank) and health. Such instrumentation however is difficult as it requires data not commonly available in datasets. Certainly issues of causality are key to address in future work. Secondly, we use a composite measure of allostatic load since a summary score of biomarkers has been found to be more strongly associated with health than single biomarkers (Karlamangla, Singer, McEwen, Rowe, & Seeman, 2002). Future work may want to examine the relationship between income and specific health conditions. Thirdly, we model the effects of relative deprivation using measures of income rank and the Yitzhaki Index that we estimated from income levels within each reference group. It is unclear whether such ‘objective’ measures of relative deprivation translate to perceived sense of relative deprivation or the extent to which each individual is affected by having lower income (rank). Further studies such as those by Pham-Kanter (2009) and Miething (2013) that additionally ask participants to provide self-report measures of their income rank and indicate the extent to which they worry about their income rank may provide more accurate measure of the effect of relative deprivation on health. We encourage more widespread inclusion of these measures in large scale dataset collections. In conclusion, this study supports the role of psychosocial processes on health and highlights the effect of
psychosocial factors is most evident when modelled using the income rank specification rather than the Yitzhaki Index.
CHAPTER 5

5.0 An Existential-Humanistic View of Personality Change: Co-occurring Changes with Psychological Well-Being in a Ten Year Cohort Study.


5.1 Abstract

Increasingly, psychological research has indicated that an individual’s personality changes across the lifespan. We aim to better understand personality change by examining if personality change is linked to striving towards fulfilment, as suggested by existential-humanistic theories of personality dynamics. Using the Wisconsin Longitudinal Study, a cohort of 4,733 mid-life individuals across 10 years, we show that personality change was significantly associated with change in existential well-being, represented by psychological well-being (PWB). Moreover, personality change was more strongly related to change in PWB than changes in other well-being indicators such as depression, hostility and life satisfaction. Personality changed to a similar degree and explained greater variation in our well-being measures than changes in socioeconomic variables. The findings indicate the holistic development of an individual is accompanied by changes in personality, supporting a greater need to understand personality change and increasing room for use of personality measures as indicators of well-being and policy making.

5.2 Introduction

Within psychology, the view of personality as stable throughout life is rapidly changing to one where traits react fluidly to life circumstances (Caspi, 1998; Caspi & Bem, 1990; Roberts, Wood, & Caspi, 2008). Despite a mass of evidence that suggests an
individual’s personality changes across the complete lifespan (Lucas & Donnellan, 2011; Roberts, Walton, & Viechtbauer, 2006; Specht, Egloff, & Schmukle, 2011), core personality traits are still generally considered ‘relatively enduring’, particularly in disciplines outside psychology. As a result of this, the use of personality change measures in well-being research has been limited, with most studies utilising personality measures at one time point to predict well-being outcomes (Boyce & Wood, 2011; de Beurs et al., 2005; DeNeve & Cooper, 1998; Friedman, Kern, & Reynolds, 2010; Steel et al., 2008) and only a few studies exploring the effect of personality change on well-being.

Studies that have investigated personality change have found an association with subjective well-being measures such as life satisfaction (Boyce et al., 2013; Heller, Komar, & Lee, 2007; Specht, Egloff, & Schmukle, 2013; van Aken, Denissen, Branje, Dubas, & Goosens, 2006), self-rated health (Berg & Johansson, 2013; Magee, Heaven, & Miller, 2013; Turiano et al., 2012), self-efficacy (Hutteman et al., 2014), psychological turning points (Allemand, Gomez, & Jackson, 2010; Sutin, Costa, Wethington, & Eaton, 2010) as well as physical and mental health outcomes (Human et al., 2013; Mroczek & Spiro, 2007). Evidence for an association between well-being and personality has been taken to support the social investment perspective on personality development (Roberts & Wood, 2006; Roberts, Wood, & Smith, 2005) which suggests that committing and successfully adapting to social roles such as marriage and work drives personality development. Whilst the social investment theory considers the effect of societal-determined expectations and goals on personality change, it does not address the importance of striving for authentic, self-concordant goals for personality change. Such a relation forms the basis of an alternative explanation for personality change, proposed by existential and humanistic theories which have not previously been introduced into the contemporary empirical literature on the malleability of personality.

Taken together, the existential and humanistic theories propose that each individual has the freedom and responsibility to transcend the meaninglessness of their existence.
Personality change is thought to occur when the individual confronts meaninglessness in life and has to decide for themselves how to shape their life\(^1\). An individual who chooses to strive towards fulfilment may likely experience favourable personality changes (i.e., perhaps becoming more open to opportunities or more extraverted) as the individual recognises their capacity to choose their own future and is able to take full advantage of opportunities to find meaning to their existence. Alternatively, if the individual is consumed with feelings of despair and fails to engage with themselves and the world around them to achieve their full potential, then they are more likely to experience personality changes in the opposite direction (i.e., becoming less open and more introverted). Associating personality change with changes in such ways of functioning would be part of a theoretical movement from seeing personality change as a biological maturation or social investment process towards seeing such change as part of a holistic development of the person in ways that are right for the individual (existential well-being) (Deci & Ryan, 1985, 2000; Joseph & Linley, 2005).

The existential-humanistic theory of personality change can be tested using a measure of psychological well-being (PWB). Waterman (1993; 1984) defines PWB as concerned with the feelings associated with an individual’s strive to grow and fully develop oneself amid life challenges. PWB encompasses an individual’s perception of engagement with the self, environment and others (Keyes, Shmotkin, & Ryff, 2002; Ryan & Deci, 2001), thus capturing existential well-being. In terms of measurement, Ryff & Keyes (1995; 1989) operationalize PWB as comprising autonomy (the extent to which one is self-determining and independent), environmental mastery (competence in managing the environment and presented opportunities), personal growth (possessing feelings of continued developments), positive relations (having strong social ties), purpose in life

---

\(^1\) See Wong (2006) for a discussion on how this perspective of personality change emerges from the work of Victor Frankl, Abraham Maslow, Rolo May, and Carl Rogers.
In this paper we report on a study that seeks to better understand the relationship between personality change and well-being change through linking changes in personality to an individual’s existential engagement with the world, as represented by changes in PWB. We additionally aim to assess the use of personality change measures as well-being indicators and targets for intervention, through (a) quantifying the size of personality change relative to socioeconomic metrics commonly used in well-being research and (b) comparing the predictive value of changes in personality and socioeconomic factors on changes in PWB. In order to quantify an effect size as large or small, direct comparisons with effect sizes of other variables of interest must be made (Cohen, 1992; Glass, McGaw, & Smith, 1981). Recently, Boyce et al. (2013) have been the first to compare the magnitude of personality change with that of socioeconomic indicators that are widely considered changeable (e.g. income, marital employment status). They find that personality changes at least as much as socioeconomic factors across a wide age range. Here, we specifically examine whether personality changes more than socioeconomic factors during midlife. Furthermore, we examine how personality change relates to changes in other well-being measures such as depression, hostility, and life satisfaction in order to assess the importance of personality change for PWB over other well-being measures.

5.3 Materials and Methods

5.3.1 Participants and procedure.

Participants were from the Wisconsin Longitudinal Study (WLS), a cohort of 10,317 individuals who graduated from Wisconsin high schools in 1957 (Little, 1958; Sewell & Orenstein, 1965). The sample is representative of white Americans living in Wisconsin who were born in 1938-1940 and completed at least 12 years of schooling. The WLS contains both measures of personality and socioeconomic data, allowing us to make direct
comparisons of personality change and socioeconomic change in a large sample. Personality measures were collected during the 1992 and 2004 time waves. Therefore, our analyses only used data from these 2 waves. Participants who gave responses for all variables of principal interest at both time points ($N = 4,733$) were analysed for this study. This sample consisted of a similar proportion of males and females as in the main sample. Participants were approximately 53-54 and 64-65 years old in 1992 (Time 1) and 2004 (Time 2) respectively.

5.3.2 Measures.

5.3.2.1 Big Five personality traits. Personality traits were assessed based on the Big Five Inventory (BFI; John, Donahue & Kettle, 1991). Respondents were asked 29 questions on the five traits - namely neuroticism, extraversion, openness, agreeableness and conscientiousness - for which responses ranged from 1 ‘strongly agree’ to 6 ‘strongly disagree’. The neuroticism subscale consisted of 5 questions, and subscales for the remaining traits comprised 6 questions each. Examples of the questions asked are as follows: neuroticism (e.g., “do you agree that you see yourself as someone who is emotionally stable, not easily upset”), extraversion (e.g., “do you agree that you see yourself as someone who is talkative”), openness (e.g., “do you agree that you see yourself as someone who has an active imagination”), agreeableness (e.g., “do you agree that you see yourself as someone who is generally trusting”), conscientiousness (e.g., “do you agree that you see yourself as someone who does a thorough job”). Scores were summed for individuals who responded to at least one of the questions for each trait and then averaged by the number of questions answered. The BFI allows the five dimensions of personality to be measured efficiently and flexibly when there is no need for a more differentiated measurement of individual facets (John et al., 1991; John, Nauman, & Soto, 2010; John & Srivastava, 1999). The BFI is used widely in research settings and has been shown to be
reliable, easier to understand and shorter than other Big Five scales (Benet-Martinez & John, 1998; Soto, John, Gosling, & Potter, 2008).

5.3.2.2 Psychological well-being. Psychological well-being (PWB) was assessed through a 42-item version of Ryff’s PWB scales (Ryff & Keyes, 1995). For our analyses, we focused only on the questions which were asked at both time points (as in the study by Springer, Pudrovská, and Hauser, 2011, so that change in scores across the two time points could not be attributed to a difference in wording of the questions). A total of 19 questions were asked at both time points (4 questions for the purpose in life subscale and 3 questions for the remaining subscales). Sample items for each subscale were as follows: autonomy (e.g., “do you agree that you have confidence in your decisions even if contrary to general consensus?”), environmental mastery (e.g., “do you agree that you have been able to create a lifestyle that is much to your liking?”), personal growth (e.g., “do you agree that you have the sense that you have developed a lot as a person over time), positive relationships with others (e.g., “do you agree that you enjoy personal and mutual conversations with family and friends?”), purpose in life (e.g., “do you agree that you sometimes feel as if you’ve done all there is to do in life?”) and self-acceptance (e.g., “do you agree that, in general, you feel confident and positive about yourself?”). Responses ranged from 1-6, higher scores indicating higher well-being. An average score was calculated for each subscale at each time point if at least one of the questions were answered. Internal consistency was acceptable, with alpha coefficients as follows: autonomy (α = .60), environmental mastery (α = .65), personal growth (α = .64), positive relations (α = .65), purpose in life (α = .68), self-acceptance (α = .68), suggesting reliability of the instrument as a measure of PWB. Alpha coefficients are slightly lower than may be achieved using the full version of the scale, though the abbreviated scales have been shown to have a high correlation with the original scale (Ryff & Keyes, 1995).

5.3.2.3 Life satisfaction. A single item – “do you agree that when you look at the story of your life, you are pleased with how things have turned out?” - was used, to which
responses ranged from 1-6, a score of 1 corresponding to highest satisfaction. These scores were reversely coded for our analysis so that highest score would correspond to highest satisfaction. This measure is particularly useful as it requires participants to consider their satisfaction over their entire life course, thereby producing stable estimates. Although single item measures are less stable than multi-item scales, Lucas and Donnellan (2012) have estimated the reliability of single item life satisfaction measures from four large scale nationally representative longitudinal studies and have on average found estimates of .72, which exceeds the cut-off value of .70 as an acceptable reliability for measures with moderate levels of reliability (Lance, Butts, & Michels, 2006). Furthermore, research indicates single item measures correlate highly with multi-item life satisfaction measures (van Beuningen, 2012) and other indicators of well-being (Diener, Lucas, Schimmack, & Helliwell, 2009).

5.3.2.4 Depression. A 20-item version of the Centre for Epidemiological Studies-Depression (CES-D) was used. Respondents were asked how frequently they experienced depressive symptoms (sample item: “how many days this week did you feel lonely”). Scores were reverse coded as appropriate. Scores were summed for subjects who responded to at least 3 items and then averaged by the number of items answered. CES-D is a highly reliable measure, having 100% sensitivity and 88% specificity in detecting clinical depression as assessed by nurse-clinicians (McDowell & Kristjansson, 1996; Radloff, 1977). Alpha reliability for our measure of depression was $\alpha = .87$ and $\alpha = .86$ at Time 1 and Time 2 respectively.

5.3.2.5 Hostility. Hostility was assessed using a 3 item scale: “how many days during the past week did you feel irritable or likely to argue”, “how many days during the past week did you feel like telling someone off?”, and “how many days during the past week did you feel angry or hostile for several hours at a time?” Scores from the three items were summed and averaged for each individual. This scale gives a reliable measure of hostility, with alpha coefficient of .78.
5.3.2.6 Socioeconomic variables. Total annual household income was log-transformed prior to analyses. Household size and socioeconomic data such as current employment status (employed or unemployed), level of educational achievement (high school, <1 year college, college without bachelor degree, bachelor degree, graduate degree or above), marital status (married, separated, divorced, widowed, never married) and retirement (partly retired, completely retired, not retired at all) was controlled for in our analyses. Gender was accounted for as having a non-changing effect. Physical health (based on whether participants were ever diagnosed by a medical doctor as having long-standing illness such as cancer, chronic liver trouble, chronic heart trouble, anaemia, asthma, arthritis, diabetes, bronchitis/emphysema, circulation problems, back trouble, ulcers, allergies, kidney or bladder problems, colitis, high blood pressure and multiple sclerosis) was also controlled for in our analyses, as health status would be expected to affect both personality and well-being. Participants who did not provide physical health data at both time points (N = 206) were excluded from our regression analyses.

5.3.3 Statistical procedure.

Statistical analyses were conducted using STATA v.11 (StataCorp, 2009). Stability for each of the Big Five traits was estimated using the Pearson correlation between scores at the two time points. This panel consisted of a total of 9,466 observations, corresponding to 4,733 individuals. We created dummy variables for all categorical predictors (e.g., 5 dummy variables – ‘married’, ‘separated’, ‘divorced’, ‘widowed’ and ‘never married’ were...

---

Participants who did not respond to health questions had a lower mean income level, lower personality and PWB scores and higher hostility and depression scores than those who did. To assess whether including these individuals would alter our analysis results, we first regressed the odds of responding to physical health questions on well-being, personality and socioeconomic measures across our sample. We then estimated the predicted probability of this regression and repeated our difference score analysis, this time including a variable for the inverse of the predicted probability. Results were similar to our complete case analyses.
generated for marital status). To determine whether personality traits can be considered as
time-varying for statistical analyses purposes, we assessed the extent to which personality
variables varied between compared to within individuals by dividing the standard deviation
of the personality variable between individuals by the standard deviation within the
individual. A low between-to-within ratio suggests that a variable changes more within an
individual than between individuals over time and therefore can be incorporated into
analyses that focus on within-individual change (Boyce, 2010; Boyce et al., 2013; Plumper
& Troeger, 2007). A large between-to-within ratio indicates a time invariant variable.

We further compare our stability ratios for the personality variables with that of
socioeconomic indicators which are generally considered malleable, such as household
income and employment status. Table 8 presents a summary of our stability ratios for the
well-being, personality and socioeconomic variables across the sample.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Overall $\mu$</th>
<th>Overall $\sigma$</th>
<th>Between $\sigma$</th>
<th>Within $\sigma$</th>
<th>‘Between to within variation’ Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log-transformed household income</td>
<td>10.32</td>
<td>2.56</td>
<td>2.08</td>
<td>1.50</td>
<td>1.39</td>
</tr>
<tr>
<td>Household income ($)</td>
<td>69,778</td>
<td>71,413</td>
<td>61,252</td>
<td>36,720</td>
<td>1.67</td>
</tr>
<tr>
<td>Unemployment</td>
<td>0.28</td>
<td>0.45</td>
<td>0.27</td>
<td>0.36</td>
<td>0.73</td>
</tr>
<tr>
<td>Neuroticism</td>
<td>3.07</td>
<td>0.95</td>
<td>0.86</td>
<td>0.39</td>
<td>2.21</td>
</tr>
<tr>
<td>Extroversion</td>
<td>3.82</td>
<td>0.88</td>
<td>0.83</td>
<td>0.31</td>
<td>2.68</td>
</tr>
<tr>
<td>Openness</td>
<td>3.63</td>
<td>0.79</td>
<td>0.73</td>
<td>0.30</td>
<td>2.43</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>4.77</td>
<td>0.72</td>
<td>0.65</td>
<td>0.31</td>
<td>2.10</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>4.85</td>
<td>0.68</td>
<td>0.61</td>
<td>0.29</td>
<td>2.10</td>
</tr>
<tr>
<td>Married</td>
<td>0.82</td>
<td>0.39</td>
<td>0.35</td>
<td>0.15</td>
<td>2.31</td>
</tr>
<tr>
<td>Separated</td>
<td>0.00</td>
<td>0.06</td>
<td>0.04</td>
<td>0.04</td>
<td>1.06</td>
</tr>
<tr>
<td>Divorced</td>
<td>0.10</td>
<td>0.30</td>
<td>0.28</td>
<td>0.10</td>
<td>2.66</td>
</tr>
<tr>
<td>Widowed</td>
<td>0.05</td>
<td>0.21</td>
<td>0.17</td>
<td>0.12</td>
<td>1.44</td>
</tr>
<tr>
<td>Never married</td>
<td>0.04</td>
<td>0.20</td>
<td>0.20</td>
<td>0.02</td>
<td>11.56</td>
</tr>
<tr>
<td>Partly retired</td>
<td>0.11</td>
<td>0.31</td>
<td>0.21</td>
<td>0.23</td>
<td>0.93</td>
</tr>
<tr>
<td>Completely retired</td>
<td>0.25</td>
<td>0.43</td>
<td>0.25</td>
<td>0.35</td>
<td>0.72</td>
</tr>
<tr>
<td>Not retired</td>
<td>0.64</td>
<td>0.48</td>
<td>0.26</td>
<td>0.40</td>
<td>0.64</td>
</tr>
</tbody>
</table>

*Note.* Unstandardised score presented. $\mu$ = mean, $\sigma$ = standard deviation. $N = 9,466$. 


Next we examined whether changes in an individual’s personality, income, education, marital and physical health status was associated with change in their well-being. Personality and well-being scores were standardised across the entire population (to have a mean of 0 and standard deviation of 1) to facilitate interpretation of results. Difference scores were generated for each socioeconomic, well-being and personality variables, which represented the change in measure in that variable between Time 2 and Time 1 for each individual. For categorical variables, the difference in dummy variables was used such that an individual who was married at Time 1 but separated at Time 2 would have a value of ‘-1’ for the ‘married’ dummy variable, ‘1’ for the ‘separated’ dummy variable and ‘0’ for the remaining categories. Difference scores is the most efficient way to deal with unobserved confounders when using two panel data (Angrist & Pischke, 2008; Rogosa & Willet, 1983; Wooldridge, 2003).

Tables 9 and 10 present the results of our difference scores analysis. Specifically, we fit 3 models for each well-being measure; Model 1 estimates the association between changes in socioeconomic variables (i.e., changes in log-transformed income, unemployment, education, marital, retirement, physical health status) and change in the specified well-being variable. Model 2 estimates the association between change in the well-being variable and changes in the personality variables. Model 3 estimates the association between change in the specified well-being variable and changes in the personality variables, additionally adjusting for changes in the socioeconomic variables.

5.4 Results

Stability of personality scores across time were as follows: 0.68 for neuroticism, 0.74 for extraversion, 0.71 for openness, 0.61 for agreeableness, 0.62 for conscientiousness. These coefficients were comparable to those found in similar study by Roberts & DelVecchio (2000). Our stability coefficients represent the correlation between the mean personality score at Time 1 and Time 2 and therefore indicate that personality
measures across the sample are generally stable over time. However, the high stability coefficients do not preclude the possibility of personality changes within an individual (Ozer, 1986), which is the focus of our study. The less than perfect (i.e. $r < 1.0$) stability across the two time points further suggest there may be are individual-level changes in personality. In order to explore this, we examined the number of individuals who showed reliable change (i.e. true change not due to measurement error) in personality measures from Time 1 to Time 2 and the magnitude of this change. Table 11 illustrates the percentage of individuals who experienced true change in personality measures and the lowest and highest magnitude of change (in standard deviation) for these individuals. Our results in Table 11 shows that a proportion of the sample experience change in personality of considerable magnitude. Through the ‘between-to-within variation ratio’ in Table 8, we also show that even at midlife, personality changes as much as other indicators that have traditionally been used to predict human outcomes. Our between-to-within stability ratios were lower for personality traits than for the different categories of educational achievement and marital status in our sample, indicating that an individual’s personality is more likely to change from Time 1 to Time 2 than their educational achievement or marital status.
Table 9 Estimation of PWB change on changes in socioeconomic and personality variables

<table>
<thead>
<tr>
<th>Predictor variables</th>
<th>Outcome variables</th>
<th>Autonomy</th>
<th>Environmental mastery</th>
<th>Personal growth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 3</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td>(1a)</td>
<td>(2a)</td>
<td>(3a)</td>
</tr>
<tr>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Log-transformed income</td>
<td></td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Unemployed</td>
<td></td>
<td>0.11</td>
<td>0.10</td>
<td>0.09</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.06)</td>
<td>(0.06)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Neuroticism</td>
<td></td>
<td>-0.07*</td>
<td>-0.07*</td>
<td>-0.15**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Extroversion</td>
<td></td>
<td>0.09**</td>
<td>0.09**</td>
<td>0.12**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Openness</td>
<td></td>
<td>0.06*</td>
<td>0.05*</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 3</td>
<td>Model 1</td>
</tr>
<tr>
<td>----------------------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
</tr>
<tr>
<td></td>
<td>Socioeconomic model</td>
<td>Personality model</td>
<td>Joint regression for personality and socioeconomic variables</td>
<td></td>
</tr>
<tr>
<td>Agreeableness</td>
<td>0.02</td>
<td>0.02</td>
<td>0.08**</td>
<td>0.08**</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>0.09**</td>
<td>0.09*</td>
<td>0.14**</td>
<td>0.14**</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.06*</td>
<td>0.04*</td>
<td>0.05*</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.01)</td>
<td>(0.03)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Individuals</td>
<td>4504</td>
<td>4504</td>
<td>4504</td>
<td>4504</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.01</td>
<td>0.03</td>
<td>0.04</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. Standardised estimates (standard error) *significant at 5%  **significant at 1%. Model 1: Socioeconomic model additionally adjusted for education, household size, marital status, retirement status and physical health variables (not shown). Model 2: Personality model, not adjusting for education, household size, marital status, retirement status and physical health variables. Model 3: Joint regression for personality and socioeconomic variables, additionally adjusted for education, household size, marital status, retirement status and physical health variables (not shown).
<table>
<thead>
<tr>
<th>Predictor variables</th>
<th>Outcome variables</th>
<th>Positive Relations</th>
<th>Purpose in life</th>
<th>Self-acceptance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 3</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 3</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td>(1d)</td>
<td>(2d)</td>
<td>(3d)</td>
</tr>
<tr>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>No</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log-transformed income</td>
<td></td>
<td>0.01</td>
<td>0.01</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Unemployed</td>
<td></td>
<td>0.09</td>
<td>0.06</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Neuroticism</td>
<td></td>
<td>-0.10**</td>
<td>-0.10**</td>
<td>-0.08**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Extroversion</td>
<td></td>
<td>0.14**</td>
<td>0.14**</td>
<td>0.12**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Openness</td>
<td></td>
<td>0.03</td>
<td>0.03</td>
<td>0.08**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td></td>
<td>Agreeableness</td>
<td>Conscientiousness</td>
<td>Constant</td>
<td>Individuals</td>
</tr>
<tr>
<td>----------------------</td>
<td>---------------</td>
<td>-------------------</td>
<td>----------</td>
<td>-------------</td>
</tr>
<tr>
<td></td>
<td>0.15**</td>
<td>0.05*</td>
<td>-0.02</td>
<td>4505</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td></td>
<td>0.15**</td>
<td>0.05*</td>
<td>0.01</td>
<td>4505</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td></td>
<td>0.11**</td>
<td>0.11**</td>
<td>0.07*</td>
<td>4495</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.03)</td>
<td>(0.02)</td>
</tr>
<tr>
<td></td>
<td>0.11**</td>
<td>0.11**</td>
<td>0.07*</td>
<td>4495</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td></td>
<td>0.11**</td>
<td>0.10**</td>
<td>0.07*</td>
<td>4494</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td></td>
<td>0.11**</td>
<td>0.10**</td>
<td>0.07*</td>
<td>4494</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
</tbody>
</table>

Note. Standardised estimates (standard error) *significant at 5% **significant at 1%. Model 1: Socioeconomic model, additionally adjusting for education, household size, marital status, retirement status and physical health variables (not shown). Model 2: Personality model, not adjusting for education, household size, marital status, retirement status and physical health variables. Model 3: Joint regression for personality and socioeconomic variables, additionally adjusted for education, household size, marital status, retirement status and physical health variables (not shown).
Table 10 Estimation of changes in life satisfaction, depression, and hostility on changes in socioeconomic and personality variables

<table>
<thead>
<tr>
<th>Predictor variables</th>
<th>Life satisfaction</th>
<th>Depression</th>
<th>Hostility</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 3</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Log-transformed income</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Unemployed</td>
<td>-0.04</td>
<td>-0.05</td>
<td>-0.05</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Neuroticism</td>
<td>-0.06*</td>
<td>-0.06*</td>
<td>0.22**</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Extroversion</td>
<td>0.06*</td>
<td>0.06*</td>
<td>-0.09**</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Openness</td>
<td>0.01</td>
<td>0.02</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>0.05*</td>
<td>0.05*</td>
<td>-0.02</td>
</tr>
<tr>
<td>--------------</td>
<td>-------</td>
<td>-------</td>
<td>--------</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>0.05*</td>
<td>0.05*</td>
<td>-0.08**</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.02</td>
<td>-0.01</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.02)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Individuals</td>
<td>3511</td>
<td>3511</td>
<td>3511</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.01</td>
<td>0.01</td>
<td>0.03</td>
</tr>
</tbody>
</table>

*Note.* Standardised estimates (standard error) *significant at 5%  **significant at 1%. Model 1: Socioeconomic model additionally adjusted for education, household size, marital status, retirement status and physical health variables (not shown). Model 2: Personality model, not adjusting for education, household size, marital status, retirement status and physical health variables. Model 3: Joint regression for personality and socioeconomic variables, additionally adjusted for education, household size, marital status, retirement status and physical health variables (not shown).
Table 11 Individual differences in personality traits

<table>
<thead>
<tr>
<th></th>
<th>Decreased</th>
<th>Increased</th>
<th>No change</th>
<th>Magnitude of change in standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min</td>
<td>Max</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Neuroticism</td>
<td>16.7</td>
<td>7.3</td>
<td>76.0</td>
<td>1.0</td>
</tr>
<tr>
<td>Extraversion</td>
<td>8.4</td>
<td>6.3</td>
<td>85.3</td>
<td>1.0</td>
</tr>
<tr>
<td>Openness</td>
<td>4.6</td>
<td>3.0</td>
<td>92.4</td>
<td>1.0</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>10.0</td>
<td>11.1</td>
<td>78.9</td>
<td>0.8</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>11.5</td>
<td>6.9</td>
<td>81.6</td>
<td>0.8</td>
</tr>
</tbody>
</table>

Note. N = 4733. Percentages of individuals who decreased, increased, or showed no reliable change in personality and the magnitude of this change.

Table 9 demonstrates that personality change relates to significant changes in well-being. Models 2a - 2f in Table 9 show that personality alone explained 3-7 times more variation (indicated by R-squared values) in the PWB subscales in our sample than socioeconomic and health indicators together (Models 1a-1f). For example, in Model 2a in Table 9, personality change explained 3% of the variation in an individual’s level of autonomy, while changes in socioeconomic variables (Model 1a in Table 9) explained only 1% of the within-person variation. Similarly, personality change explained 7% of the within-person variation in environmental mastery (Model 2b), 5% of the within-person variation in personal growth (Model 2c), positive relations (Model 2d) and purpose in life (Model 2e), and 6% of the within-person variation in self-acceptance (Model 2f) over the ten year period. Socioeconomic variables together explained only 1% of the within-person variation in each of the PWB subscales (Models 1a, 1c - 1f). Our R squared values are similar to those found in similar models which estimate variation within individuals (Boyce, Wood, & Powthavee, 2013; Ferrer-i-Carbonell & Frijters, 2004) and are used
here to highlight the stronger relationship between well-being change and change in personality measures compared to change in socioeconomic factors. Furthermore, Models 1a - 1f in Table 9 indicates that change in log-transformed income and unemployment status were not significant predictors of change in any of the PWB subscales while Models 2a - 2f in Table 9 shows that personality change was significantly associated with change in each of the PWB subscales. For example, in the case of purpose in life (Model 2e), a one standard deviation increase in extroversion, openness, agreeableness and conscientiousness was significantly associated with a 0.12, 0.08, 0.11 and 0.11 standard deviation increase in purpose in life respectively, and a one unit increase in neuroticism was significantly associated with a 0.08 standard deviation decrease in purpose in life. In Models 3a - 3f, we further show that personality change remained significantly associated with changes in all PWB scales (effect sizes ranging from 0.04 to 0.15 standard deviations) even after controlling for changes in socioeconomic variables, whereas changes in socioeconomic indicators were only significantly associated with changes in positive relations (becoming partly retired being associated with a 0.08 standard deviation increase in positive relations compared to not being retired).

The importance of personality change for PWB is highlighted by examining how personality change relates to other well-being measures (life satisfaction, depression, hostility) compared to PWB. Models 2g - 2i in Table 10 shows that personality change explained only as much within-person variation in life satisfaction, twice as much variation in depression and three times as much variation in change in hostility than change in socioeconomic variables (Models 1g - 1f).
5.5 Discussion

This study extends earlier research suggesting that personality change is in fact meaningful. We use a midlife population, an age group for which research on personality development is limited. Midlife presents an important period for personality development (Lachman, 2004; Neugarten, 1968) as it is associated with many biological, physical, work, social and psychological changes, amongst others which in turn may result in changes in personality (see Roberts & DelVecchio, 2000 and Allemand, Zimprich, & Hertzog, 2007 for a discussion on mechanisms of trait consistency and change in midlife) as well as a period where individuals seek a sense of identity as they reflect on their lives. Obtaining clarity of self and striving towards a fulfilled life is associated with favourable changes in personality, and may be protective of any negative changes associated with midlife. Therefore, studying whether and how personality changes across midlife can give insight into how individuals are coping with midlife challenges.

Through our stability ratios in Table 8, we illustrate that personality changes to a similar extent as socioeconomic variables during midlife. In our sample, personality variables changed more than marital and education status and almost as much as income across 10 years. We further show that personality change is not only an indicator of change in life satisfaction as previously shown, but associated with changes in a wider range of measures over time, specifically PWB, even after adjusting for socioeconomic variables. In our sample, personality change explained up to 7 times as much within-person variation in PWB than socio-economic variables, 2 - 3 times as much within-person variation in depression and hostility and as much within-person variation in life satisfaction. The overall findings highlight the importance of personality change for PWB as well as the need to distinguish between the different well-being constructs (Kahneman & Deaton,
The results can be interpreted as some empirical support for existential-humanistic theories of personality change, which suggest that personality change is essential to an individual’s strive towards a fulfilled life; an increase in neuroticism indicating poor existential engagement with the world and increases in the remaining traits suggesting positive existential well-being. For all well-being measures, personality change was a better indicator of well-being change than change in socioeconomic variables. Taken together, the results show that an individual’s personality changes over time and that these changes are strongly related to changes in the individual’s existential well-being. These findings emphasise the importance of personality in psychological functioning during midlife, reiterating the need to integrate personality measures into well-being research.

5.6 Limitations

Our study examines the association between changes in personality and well-being using two time points. Therefore we do not model how these variables change continuously but rather across a 10 year period. However, this could be seen as an advantage as we study long term changes in personality rather than temporary changes due to life events. Secondly, the use of a single item measure is a limitation of the dataset. Single item measures of life satisfaction are considered less stable and correlate less strongly with socioeconomic variables such as income and education (Pinquart & Sorensen, 2000) than multi-item measures. However, this dataset was chosen as it is a large sample which provides data on life satisfaction, PWB and personality at two time points, allowing us to examine the association between these measures across time. A third limitation is that personality measures may be influenced by mental health status (Fergusson, Horwood, & Lawton, 1989; Hirschfeld et al., 1983) – a depressed individual may report higher scores for neuroticism than they would in their pre-morbid state, since
the individual’s mental state may result in more neurotic perceptions of themselves than usual. This would mean that an apparent change in self-reports of personality traits could be due to the effect of a mental disorder rather than associated changes in environmental circumstances or existential struggles. However, Fergusson et al. (1989) show that even after correcting for the effect of current mental state on neuroticism, neuroticism still remained a significant predictor of depression. Fourth, we excluded a large proportion of the sample (54%) from our analyses due to missing data. To explore if individuals included in our analyses were different to those excluded from the analyses, we regressed an inclusion variable (which indicates whether subjects are included in the analyses) on each of our well-being outcomes and all control variables. These regression models indicated that education, employment status and physical health were predictors of inclusion into the analyses. For each outcome variable, a weight was then generated from the inverse of the predicted probability of the model predicting inclusion into the analyses. These weights were then included in our difference score models to account for missing data. The ‘weighted’ models produced similar results to our complete case analyses (Tables 9 and 10), except for the regression predicting change in depression, which indicated that becoming unemployed was associated with a 0.20 standard deviation decrease in depression status \((p < 0.01)\), compared to a 0.06 standard deviation decrease in depression in the complete case analysis. However, despite the substantive difference in the regression coefficient for unemployment, the weighted model personality change explained the same amount of variation in depression status as in the complete case analysis. Fifth, our analysis can not make any causal inferences or direction about the personality-well-being relationship; whereas we have discussed the life choices people make as antecedents of personality change, it may be that certain personality traits facilitate the growth and
development process. More research would be needed to confirm the causal pathways between personality change and well-being. Furthermore, we note that associating PWB change and personality change is consistent with other theories of personality development. It is possible that other mechanisms may be driving the association between changes in well-being and changes in personality. For example, changes in personality traits and well-being measures may be driven by life experiences (which may or may not co-occur with changes in an individual’s strive to achieve a fulfilled life) or other time-varying confounders such as changes in an individual’s social ties or behaviours. The results presented here should be interpreted with caution as we are not able to adjust for all possible confounders of the association between changes in personality traits and well-being. We merely present the existential-humanistic theory as an alternative explanation for personality development.

5.7 Conclusion

Personality change has important implications for public policy making, particularly as they may provide intrinsic measures of how people are engaging with the world. While policy has focused on inevitable socioeconomic changes across time this research indicates that it is the concurrent personality changes that are more strongly related to well-being. Public health interventions aimed at targeting specific aspects of personality such as social support (Oddone, Hybels, McQuoid, & Steffens, 2011), cognitive training (Jackson, Hill, Payne, Roberts, & Stine-Morrow, 2012), self-regulation (Baumeister, Gailliot, DeWall, & Oaten, 2006) may be the key to helping individuals better cope with changes in life circumstances and improve their well-being as they mature.
CHAPTER 6

6.0 Which Personality Traits Lead to Life Satisfaction? Lagged Changes in Neuroticism Negatively Predict Life Satisfaction Changes in a Large Representative Cohort Survey

Currently under review at Journal of Personality and Social Psychology

6.1 Abstract

Research has found that personality traits predict, and even change in unison with, life satisfaction. However, it is not yet clear whether personality traits causally relate to life satisfaction. Theoretically, only neuroticism (comprising negative affect) and extraversion (comprising positive affect) should influence life satisfaction. These predictions appear to contrast empirical findings that each of the Big Five traits predicts life satisfaction. However, previous work has used methods that are either not able to control for between-person variables or not able to determine directionality, and therefore may have resulted in spurious inferences. The current study uses bivariate latent change score (LCS) models to address these limitations. We examine the influence of changes in personality traits on subsequent changes in life satisfaction in a representative Dutch sample ($N = 4,969$), with all participants providing data on both personality and life satisfaction measures on three separate occasions two years apart. Our LCS models indicated that, after controlling for person-specific factors, change in neuroticism led to a subsequent change in life satisfaction and change in life satisfaction levels led to a subsequent change in neuroticism. Changes in the remaining personality traits did not lead to changes in life satisfaction and were not influenced by changes in life satisfaction. Further, an LCS mediation model indicated that the influence of changes in neuroticism on subsequent changes in life satisfaction was substantially mediated by negative affect. Previously observed
associations between life satisfaction and openness, agreeableness, and conscientiousness may have been confounded by time-invariant third variables.

6.2 Introduction

The relationship between personality and life satisfaction has been a primary research topic within personality psychology over the last 20 years (for example McCrae & Costa, 1991; DeNeve & Cooper, 1998; Steel, Schmidt, & Shultz, 2008). Recent research has found that each of the Big Five personality traits change over the lifespan (Lucas & Donnellan, 2011; Roberts et al., 2006; Specht et al., 2011) and that these changes are associated with changes in life satisfaction (for example Boyce, Wood, & Powdthavee, 2013; Soto, 2013; Hounkpatin, Wood, Boyce & Dunn, 2015). The observation that personality traits change leads to new questions and provides a new method for answering old questions. A naturally emerging new question is whether personality change precedes life satisfaction change, whether changes in life satisfaction precede changes in personality traits or whether changes in personality traits and life satisfaction simply co-occur without any causality between them - perhaps because changes in both personality and life satisfaction are caused by a time-variant third variable. A new approach to answer old questions arises from the ability to relate within-person personality change scores (rather than baseline levels of personality which represent between person differences) to within-person changes in life satisfaction, through the use of new statistical methods within personality psychology. Such methods control for previous changes in both personality traits and life satisfaction variables to better eliminate the confounding effects of other variables. Whilst these methods are commonly used in other fields, they have not previously been used in personality psychology due to the traditional presumption that an individual’s personality traits do not change. This method can be used to provide more
definitive answers to old and controversial questions. The current paper aims to make three novel contributions to personality psychology: (1) To develop the emerging personality change literature through examining whether personality changes precede, not simply co-occur with life satisfaction changes; (2) to introduce a new method to personality psychology that takes advantage of personality changes to make stronger causal inferences regarding the association between personality change and life satisfaction change; and (3) to use this method to provide a more definitive answer to the long running question of which personality traits are most closely related to life satisfaction.

6.2.1 Research on personality change.

Traditionally personality traits were believed to be exclusively genetically determined and therefore non-changing, particularly after the age of 30 (Costa & McCrae, 1980, 1988) when individuals are believed to have matured and developed set personality traits. More recently, research has indicated that personality traits continue to change beyond the onset of adulthood and across all age ranges (Srivastava et al., 2003) as a result of environmental influences. Changes in an individual’s personality traits have now been found to be linked to changes in their life satisfaction levels (for example Boyce, Wood, & Powdthavee, 2013; Soto, 2013; Hounkpatin, Wood, Boyce & Dunn, 2015), suggesting that an individual experiences changes to their life satisfaction levels as they develop their personality. However, it is not yet clear whether changes in personality traits drive changes in life satisfaction (or vice versa or both) or whether such findings represent a correlational association whereby individuals who experience changes in personality traits also experience changes in life satisfaction because a third variable (e.g. time-varying between-person factors such as life experiences) drives changes in both personality traits and life satisfaction.
6.2.2 Introducing bivariate latent change score (LCS) to personality psychology.

That personality traits have been shown to change reliably over time, together with the availability of data on personality measures at three or more time points, allows the introduction of new statistical approaches to personality psychology, known as bivariate latent change score (LCS) models (McArdle, 2009; McArdle & Hamagami, 2001). LCS models offer an advance on other models (for example latent growth models, autoregressive models, and fixed-effects models) that have previously been used in this area of research and can be used to make stronger causal inferences about the association between personality traits and life satisfaction. For example, in latent growth and autoregressive models changes in life satisfaction from Time 1 to Time 2 are predicted from personality level at Time 1. Although this approach may be used to determine if personality traits have a prospective effect on change in life satisfaction, any results obtained using these models will be vulnerable to omitted variable bias because other between-person variables that may be associated with personality at Time 1 (Duckworth, Tsukayama, & May, 2010) are not controlled for appropriately. Therefore, an apparent association between personality at Time 1 and changes in life satisfaction between Time 1 and Time 2 may in fact be due to either time-invariant (e.g., biological factors such as gender or ethnicity) or time-variant (e.g., life experiences or characteristic adaptations such as self-regulation processes) third variables. These variables would have to be controlled for specifically in the analysis which is problematic as it is unlikely that data will be available for all relevant confounding variables and some of these variables will be unobserved (e.g., an individual’s genetic composition).
Designs which predict changes in life satisfaction from changes in personality traits (e.g., fixed-effects models) offer a better solution to omitted variable bias by eliminating the variance that is due to time-invariant third variables. In such designs, the effect of each variable at Time 2 is subtracted from the effect of the same variable at Time 1. Thus, subtracting the variance due to time-invariant third variables associated with personality at Time 2 from the variance due to time-invariant third variables associated with personality at Time 1 will result in removal of this effect since this effect is the same at both time points. However, such models do not account for measurement error, thus making it difficult to conclude whether findings from these studies represent an association between true (uncontaminated) changes in personality traits and life satisfaction or measurement error. Moreover, these models do not allow the direction of the association to be determined (Grimm, An, McArdle, Zonderman, & Resnick, 2012).

LCS models address limitations of these previous models by allowing the investigator to assess the association between lagged within-person changes in personality traits and within-person changes in life satisfaction, whilst additionally controlling for previous changes in life satisfaction. This approach establishes temporal precedence and reduces omitted variable bias since each individual is used as their own control, thus allowing the effect of person-specific time-invariant omitted variables to be cancelled out over time. LCS models further reduce bias due to time-variant third variables by making use of time-specific personality change; Any omitted confounding variable would have to change in unison with time-specific changes in the first construct as well as change in unison with subsequent time-specific changes in the second construct (Duckworth et al., 2010). An additional important advantage of the LCS model approach is that it accounts for measurement error (short-term fluctuations) in the observed personality and life
satisfaction variables so that any associations between changes in personality and changes in life satisfaction will not be attenuated (biased towards the null) by such errors. This is particularly useful as observed psychological variables have been found to contain considerable amount of measurement error (Chmielewski & Watson, 2009). Therefore, by using LCS models, we can isolate true changes in personality and life satisfaction variables and more accurately estimate how changes in personality relate to changes in life satisfaction.

6.2.3 Theoretical models of the role of personality in life satisfaction.

The primary model of subjective well-being (SWB; Diener, 1984) views this higher order construct as comprising individual differences in positive affect, negative affect, and life satisfaction (for example Larsen, Diener, & Emmons, 1985; Linley et al., 2009). Furthermore, there is some evidence to suggest a causal structure of SWB, whereby positive and negative affect influence life satisfaction (Kuppens, Realo, & Diener, 2008; Magee, Miller, & Heaven, 2013; Schimmack, Diener, & Oishi, 2002; Schimmack, Radhakrishnan, Oishi, Dzokoto, & Ahadi, 2002; Suh, Diener, Oishi, & Triandis, 1998). As extraversion and neuroticism comprise trait differences in the experience of positive and negative affect respectively (Augustine & Larsen, 2015), any changes in these variables would be expected to precede changes in life satisfaction. Specifically, neuroticism is composed of facets such as anxiety, fear, and self-consciousness (Augustine & Larsen, 2015) which predispose an individual to experience negative affect. For this reason, highly neurotic individuals tend to appraise situations as stressful or threatening (Bolger & Schilling, 1991; Mroczek, Spiro, Griffin, & Neupert, 2006) and also react more negatively to challenging situations than less neurotic individuals (Bolger & Schilling, 1991; McCrae & Costa, 2003). In contrast, extraversion is composed of facets such as excitement seeking
and cheerfulness which predispose an individual to experience positive affect. Highly extraverted individuals therefore seek positive experiences and respond more positively to situations and experiences (Gray, 1991; Lischetzke & Eid, 2006) than their introverted peers. The theoretical predictions of the relation between neuroticism and negative affect and the relation between extraversion and positive affect has been supported by empirical studies (for example Larsen & Ketelaar, 1991; Gross, Sutton, & Ketelaar, 1998; Hemenover, 2003; Hemenover, Augustine, Shulman, Tran, & Barlett, 2008) which find that neurotic individuals express more negative affect in response to negative stimuli than less neurotic individuals, while extraverted individuals experience more positive affect in response to positive stimuli than introverted individuals.

In contrast to the theoretical predictions of the association between personality traits and life satisfaction, a substantial cross-sectional literature has suggested that each of the Big Five traits predict life satisfaction (DeNeve & Cooper, 1998; Steel et al., 2008). The cross-sectional findings have been supported by longitudinal analyses in which changes in life satisfaction is predicted by baseline levels of personality (for example Specht, Egloff, & Schmukle, 2013; Soto, 2015; Magee, Miller, & Heaven, 2013), as well as studies which have associated changes in personality with changes in life satisfaction (for example Boyce, Wood, & Powdthavee, 2013; Hounkpatin, Wood, Boyce & Dunn, 2015). However, each of these research streams has used methods which are susceptible to bias either due to omitted third variables or measurement error. LCS models can be used to reduce omitted variable bias and hence improve our understanding of the nature of the association between personality traits and life satisfaction.

6.2.4 The current study.
We use bivariate LCS models to study the relationship between changes in personality traits and subsequent changes in life satisfaction. We additionally examine whether lagged changes in an individual’s level of life satisfaction lead to changes in their personality traits and whether there is a reciprocal association between changes in life satisfaction and changes in personality traits. A significant association between lagged changes in personality and changes in life satisfaction would indicate that changes in personality lead to changes in life satisfaction. A significant association between lagged changes in life satisfaction and changes in personality would suggest that changes in life satisfaction drive changes in personality traits. However, lack of a significant association between lagged changes in personality and changes in life satisfaction would indicate that the commonly observed association between changes in personality traits and changes in life satisfaction is not due to an effect of one construct on the other but rather due to individual differences in a third time-varying variable. Given that theoretical evidence suggests that only neuroticism and extraversion are structurally linked to positive and negative affect respectively (Augustine & Larsen, 2015; Gray, 1991) which in turn influence life satisfaction (Schimmack, Diener, et al., 2002; Schimmack, Radhakrishnan, et al., 2002), we predict that: (H1) changes in neuroticism and extraversion will precede changes in life satisfaction once third variables are better controlled for within this analysis and (H2) the influence of lagged changes in neuroticism and extraversion on changes in life satisfaction will be mediated by changes in negative and positive affect, respectively.

6.3 Methods

6.3.1 Participants and procedure.

Participants were part of the Longitudinal Internet Studies for the Social Sciences (LISS) panel, a representative random sample of the Dutch population. Participants
completed online surveys monthly. Surveys included questions on socio-demographics and psychological variables. An additional personality questionnaire was administered to all participants during May/August of 2009, 2011 and 2013\(^3\). Our analytic sample consisted of 4969 individuals who provided data on life satisfaction and personality variables at all three time points. Individuals who were included in our study were older and more likely to be male than those who did not respond to the variables of interest.

### 6.3.2 Measures.

#### 6.3.2.1 Life satisfaction. The *Satisfaction with Life Scale* (Diener, Emmons, Larsen, & Griffin, 1985; Pavot & Diener, 1993) assessed satisfaction with life as a whole. This scale consisted of the following 5 items: “in most ways my life is close to my ideal”, “the conditions of my life are excellent”, “I am satisfied with my life”, “so far I have gotten the important things I want in life”, “if I could live my life over, I would change almost nothing”. Respondents were asked to indicate how well each statement applied to them on a 7-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree). Responses to all 5 items were summed and divided by the total number of items responded. Higher scores represented higher life satisfaction. Cronbach’s alphas for the life satisfaction measure for our sample were .89, .89, and .88 at Time 1, Time 2, and Time 3 respectively. The test-retest reliability coefficient, as assessed by the intraclass correlation coefficient across the three time points was .68. This was calculated as the correlation

---

\(^3\) The personality questionnaire was also administered to all participants in May/June 2008. However, data from May/June 2008 was not used in the analysis since the analytic approach used here requires equal time intervals. However, similar results were obtained using a model in which Wave 1 was included in the analysis and the unequal time interval accounted for.
between measures within a participant over time. Table 12 provides the means and standard deviations of the life satisfaction variable for our analytic sample at each time point.

Table 12 Descriptive statistics of personality, negative affect, positive affect, and life satisfaction measures for analytic sample

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Neuroticism</td>
<td>2.57 (0.67)</td>
<td>2.54 (0.68)</td>
<td>2.49 (0.69)</td>
</tr>
<tr>
<td>Extraversion</td>
<td>3.27 (0.63)</td>
<td>3.25 (0.63)</td>
<td>3.23 (0.66)</td>
</tr>
<tr>
<td>Openness</td>
<td>3.49 (0.49)</td>
<td>3.45 (0.49)</td>
<td>3.44 (0.50)</td>
</tr>
<tr>
<td>Agreeableness</td>
<td>3.89 (0.48)</td>
<td>3.85 (0.50)</td>
<td>3.85 (0.51)</td>
</tr>
<tr>
<td>Conscientiousness</td>
<td>3.72 (0.53)</td>
<td>3.70 (0.52)</td>
<td>3.73 (0.52)</td>
</tr>
<tr>
<td>Negative Affect</td>
<td>2.05 (1.04)</td>
<td>2.8 (1.11)</td>
<td>2.04 (1.09)</td>
</tr>
<tr>
<td>Positive Affect</td>
<td>4.49 (0.99)</td>
<td>4.36 (1.00)</td>
<td>4.37 (1.03)</td>
</tr>
<tr>
<td>Life satisfaction</td>
<td>5.12 (1.07)</td>
<td>5.07 (1.10)</td>
<td>5.05 (1.10)</td>
</tr>
</tbody>
</table>

Note. N = 4969. Scores for personality traits range from 1 to 5. A score of 5 indicates high levels of the specified trait. Scores for life satisfaction, positive and negative affect range from 1 to 7. Higher scores indicate higher levels.

6.3.2.2 Personality. Personality was measured using the International Personality Item Pool (IPIP; Goldberg, 1992; Golberg et al., 2006) scale. Each personality trait was measured using 10 items. Respondents were asked how accurately each statement described them. Possible responses ranged from 1 (very inaccurate) to 5 (very accurate). Sample items included: “I get stressed out easily” (neuroticism), “I’m the life of the party” (extraversion), “I have a rich vocabulary” (openness to experiences), “I feel little concern
for others” (*agreeableness*; a reverse coded item), and “I’m always prepared” (*conscientiousness*). Reversely worded items were reverse-coded prior to generating the mean score for each personality trait measure. Cronbach’s alphas for each personality trait during Time 1, Time 2, and Time 3 were as follows: Neuroticism - .88, .88, .88; Extraversion- .87, .87,.87; Openness - .77, .77, .76; Agreeableness- .81, .81, .81; Conscientiousness- .79, .79,.78. Test-retest intraclass correlations across the three time periods were .75, .80, .76, .71, and .75 for neuroticism, extraversion, openness, agreeableness and conscientiousness respectively. Table 12 provides the means and standard deviations of the personality variables for our analytic sample at each time point.

### 6.3.2.3 Affect.

The Positive and Negative Affect Schedule (PANAS; Watson, Clark, & Tellegen, 1988) assessed the presence of positive affect and absence of negative affect in the individuals’ lives. Respondents were asked the extent to which 19 adjectives described how they were feeling at that moment. Possible responses ranged from 1 (not at all) to 7 (extremely). A positive affect score was formed by summing the responses to the adjectives ‘interested’, ‘strong’, ‘enthusiastic’, ‘proud’, ‘alert’, ‘inspired’, ‘determined’, ‘attentive’, ‘active’, ‘excited’ and dividing by the number of adjectives that were answered. A negative affect score was formed by summing the responses to the adjectives ‘distressed’, ‘upset’, ‘guilty’, ‘scared’, ‘hostile’, ‘irritable’, ‘ashamed’, ‘nervous’, ‘jittery’, ‘afraid’ and dividing by the number of adjectives answered. Cronbach’s alphas for positive affect at Time 1, Time 2 and Time 3 were as follows: .87, .87, and .87. Test-retest intraclass correlation for positive affect across the three time points was .54. Cronbach’s alphas for negative affect at Time 1, Time 2 and Time 3 were as follows: .93, .94, and .93. Test-retest intraclass correlation for negative affect across the three time points was .53.
Table 12 provides the means and standard deviations of the affect variables for our analytic sample at each time point.

6.3.3 Analytical strategy.

6.3.3.1 Measurement model. We first produced separate measurement models for each personality trait. The measured value of each personality trait (MP) was specified to be the sum of the true value of the personality trait (P) and random measurement error (EP). Similarly, the measured values for life satisfaction (ML) were the sum of the true value of life satisfaction (L) and random measurement error (EL). All measurement errors had a mean of 0 and the precision of the measurement processes for personality and life satisfaction (i.e. the variances of their measurement errors) is assumed to be the same for the three assessment waves. It is further assumed that, at any given wave the measurement errors for personality and life satisfaction are correlated and that these correlations are the same for all three waves of data. The variance in observed scores of each construct that is present at all assessment waves is isolated as the variance that is due to the underlying factor (Hoyle, 2012) (i.e., the true score).

6.3.3.2 Bivariate latent change score models. We used bivariate latent change score (LCS) models (McArdle, 2009), as shown in Figure 6, to examine the association between individual-level changes in each personality trait and individual-level changes in life satisfaction. Four LCS models were fitted for each personality trait. Each LCS model was based on the measurement model for the specified personality trait and the measurement model for life satisfaction. Additionally, each LCS model contained latent change scores between successive waves which represented true changes in personality ($\Delta P_{T2-T1}$, $\Delta P_{T3-T2}$ in Fig. 6) and life satisfaction ($\Delta L_{T2-T1}$, $\Delta L_{T3-T2}$) scores between the two waves. Figure 6 illustrates the bivariate measurement error models, together with the
corresponding latent change scores. We then introduced paths to allow latent personality change scores to be influenced by previous levels of both personality (path a in Fig. 6) and life satisfaction (path d in Fig. 6). We also introduced a path to evaluate the effect of the first personality change score, $\Delta P_{T2-T1}$, on the second personality change score, $\Delta P_{T3-T2}$ (path e in Fig. 6). Similar paths (paths b, c, and f) were also introduced for life satisfaction change scores. We refer to this model (as depicted in Fig. 6) as our minimal structural model (Model 1). The minimal structural model does not include any associations between change scores and thereby assumes that changes in personality traits do not influence changes in life satisfaction or vice versa.

*Figure 6* Path diagram of bivariate measurement error models, together with the corresponding latent change scores $\Delta P_{T2-T1}$, $\Delta P_{T3-T2}$ (for personality) and $\Delta L S_{T2-T1}$, $\Delta L S_{T3-T2}$ (for life satisfaction) (excluding paths to explain the changes in latent change scores over time. Squares represent measured personality (MP) or life satisfaction (MLS) variables at each time point. Ovals represent latent personality (P) and life satisfaction variables (LS) at each time point. EP and ELS are the measurement error present in each measured personality and life satisfaction variable respectively.
Figure 7 Path diagram of basic bivariate LCS model (including paths to explain the changes in latent change scores over time). Squares represent measured personality (MP) or life satisfaction (MLS) variables at each time point. Ovals represent latent personality (P) and life satisfaction variables (LS) at each time point. EP and ELS are the measurement error present in each measured personality and life satisfaction variable respectively. Each change score is influenced by initial levels of personality trait P (paths a, c), initial levels of life satisfaction LS (paths b, d) and prior changes in the same construct (i.e. \( \Delta P_{T2-T1} \) or \( \Delta LS_{T2-T1} \)) (paths e, f).
Next, we introduced a path to allow the second change score in life satisfaction, $\Delta L_{T3-T2}$, to be influenced by lagged change scores for personality, $\Delta P_{T2-T1}$. We refer to this model as Model 2. Model 2 assumes that changes in personality traits precede changes in life satisfaction. For Model 3, we instead introduced a path to allow the second change score in personality, $\Delta P_{T3-T2}$, to be influenced by lagged change scores for life satisfaction, $\Delta L_{T2-T1}$. Model 3 assumes that changes in life satisfaction precede changes in personality traits and hence this model is the reverse causation model. Finally, for Model 4 we introduce simultaneously a path to allow the second change score in personality, $\Delta P_{T3-T2}$, to be influenced by lagged change scores for life satisfaction, $\Delta L_{T2-T1}$ and another path to allow the second change score in life satisfaction, $\Delta L_{T3-T2}$, to be influenced by lagged change scores for personality, $\Delta P_{T2-T1}$. Model 4 assumes that lagged changes in personality influence changes in life satisfaction and lagged changes in life satisfaction influence changes in personality. Model 4 therefore represents a reciprocal causation model. All models were fitted using Mplus version 5 (Muthén & Muthén, 1998-2007). The fit of Models 1-4 were compared using two goodness-of-fit indices, Akaike’s Information Criterion (AIC) and Bayesian Information Criterion (BIC). The model with the lowest AIC and BIC is selected as the best fitting model. An AIC/BIC difference of 2 points suggest weak evidence that one model provides a better fit than a competing model, whereas larger differences indicate stronger support for the model with the lowest AIC/BIC (Burnham & Anderson, 2004). The fit of the best-fitting model was further evaluated using fit criteria suggested by Hu and Bentler (1999). A model with comparative fit index (CFI) > .95, root mean squared approximation index (RMSEA) < .06 and standardised root mean square residual (SRMR) < .08 is considered to fit the data well. Chi-squared ($\chi^2$) are additionally presented as they are the basis of these tests, however the Chi-squared is not itself
interpretable as it is likely to be significant simply as a function of sample size (a problem that is accounted for in the other fit indices; Hu and Bentler, 1999).

6.3.3.3 LCS mediation models. We then tested whether any significant associations between lagged changes in personality traits and changes in life satisfaction are mediated by positive or negative affect using LCS mediation models (MacKinnon, 2008; McArdle & Hamagami, 2001). The LCS mediation model, as shown in Figure 8, is based on the respective bivariate LCS model and additionally includes a measurement component for the mediator (i.e., positive or negative affect), latent change scores for the mediator, paths between the personality variables and the mediator and paths between life satisfaction and the mediator. For example, an LCS model examining a mediation effect of change in negative affect on the influence of lagged changes in neuroticism on changes in life satisfaction consisted of all the paths included in Model 2 and additionally contained paths to allow latent change scores in personality and life satisfaction to be influenced by previous levels of negative affect (paths j and k in Fig. 8, respectively) and paths to allow latent change scores in negative affect to be influenced by previous levels of personality and life satisfaction (paths g and h in Fig. 8 respectively). We also introduced a path to evaluate the effect of the first change score for negative affect ($\Delta NA_{T2-T1}$) on the second change score for negative affect, $\Delta NA_{T3-T2}$ (path l in Fig. 8). Next, we introduced a path to allow the first personality change score to influence the second change score for negative affect and a path to allow the second negative affect change score to influence the second life satisfaction change score. We additionally included paths from the first neuroticism change score to the first negative affect change score and from the first negative affect change score to the second life satisfaction score to account for an influence of current
change in personality on current change in negative affect and an influence of previous change in negative affect on change in life satisfaction.

Figure 8 Path diagram of basic LCS mediation model (including paths to explain the changes in latent change scores over time). Squares represent measured personality (MP), life satisfaction (MLS) and negative affect variables at each time point. Ovals represent latent personality (P) and life satisfaction variables (LS) at each time point. EP, ELS and ENA are the measurement error present in each measured personality, life satisfaction and negative affect variable respectively. Each change score is influenced by initial levels of personality trait P (paths a, c, g), initial levels of life satisfaction LS (paths b, d, h), initial levels of negative affect (paths i, j, k) and prior changes in the same construct (i.e. ΔP_{T2-T1} or ΔLS_{T2-T1}, ΔNA_{T2-T1}) - paths e, f, l.
6.4 Results

We fit 20 bivariate LCS models in total: four LCS models for each combination of a personality trait and life satisfaction variable. We first report the results of the measurement component of the models. Next, we focus on the component of the model that examines relations between individual-level wave-specific changes in personality and life satisfaction.

6.4.1 Measurement component of LCS model.

The measurement component indicated that a significant proportion of the observed changes in personality traits and life satisfaction measures were due to measurement error rather than true change. For example, the measurement model for life satisfaction indicated that approximately 25-29% of the variance in observed scores on life satisfaction was due to measurement error. Similarly, the measurement models for neuroticism, extraversion, openness, agreeableness and conscientiousness indicated that measurement error accounted for 19-21%, 16-17%, 20-22%, 24-26% and 18-20% of the change in observed scores, respectively. This supported the psychometric validity of the measures, in that 74% to 84% of the changes in personality scores were substantive, rather than driven by measurement error. The measurement error in personality change scores was also comparable in magnitude to the amount of measurement error observed in the more commonly used life satisfaction change scores. However, the 16% to 26% measurement error rates supports the use of the LCS method as it is important to remove this measurement error from the models as error of this magnitude could potentially drive any results observed. Each model estimated strong paths between successive latent variables (for example, LP_{T1} and LP_{T2}), suggesting high temporal stability in the measures over time.
6.4.2 Association between changes in personality traits and changes in life satisfaction.

6.4.2.1 Neuroticism and life satisfaction. The best-fitting model to explain the association between changes in neuroticism and changes in life satisfaction was one where lagged changes in neuroticism led to changes in life satisfaction (Model 2). Model 2 provided a better fit (AIC: 50560.87, BIC: 50678.06) than the reverse model, Model 3, where lagged changes in life satisfaction led to changes in neuroticism (AIC: 50573.29, BIC: 50690.49) and a reciprocal model, Model 4, where lagged changes in neuroticism led to changes in life satisfaction and lagged changes in life satisfaction led to changes in neuroticism (AIC: 50557.74, BIC: 50681.45). Model 2 also had considerably better fit than a model which did not include any associations between the first personality change score and second life satisfaction change score or any associations between the first life satisfaction change score and second personality change score (Model 1, AIC: 50575.87, BIC: 50686.55). The best-fitting model (Model 2) indicated that lagged changes in an individual’s level of neuroticism significantly influenced changes in their level of life satisfaction ($\beta = -0.50, p < .001$). A detailed list of the estimation results and fit statistics of the models can be found in Table 13.
Table 13 Model fit statistics and parameter estimates for LCS model

<table>
<thead>
<tr>
<th>Neuroticism</th>
<th>No lagged effects</th>
<th>LS→P</th>
<th>P→LS</th>
<th>Reciprocal</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β</td>
<td>SE</td>
<td>β</td>
<td>SE</td>
</tr>
<tr>
<td>Baseline P level with baseline LS level</td>
<td>-0.533***</td>
<td>0.013</td>
<td>-0.532***</td>
<td>0.013</td>
</tr>
<tr>
<td>P change score on lagged P score</td>
<td>-0.027</td>
<td>0.018</td>
<td>-0.036**</td>
<td>0.016</td>
</tr>
<tr>
<td>P change score on lagged LS score</td>
<td>-0.021</td>
<td>0.015</td>
<td>-0.013</td>
<td>0.013</td>
</tr>
<tr>
<td>LS change score on lagged LS score</td>
<td>-0.015</td>
<td>0.014</td>
<td>-0.018</td>
<td>0.013</td>
</tr>
<tr>
<td>LS change score on lagged P score</td>
<td>0.001</td>
<td>0.018</td>
<td>0.004</td>
<td>0.018</td>
</tr>
<tr>
<td>P change score on lagged P change score</td>
<td>0.306</td>
<td>0.173</td>
<td>0.272</td>
<td>0.151</td>
</tr>
<tr>
<td>LS change score on lagged LS change score</td>
<td>0.546**</td>
<td>0.235</td>
<td>0.535**</td>
<td>0.213</td>
</tr>
<tr>
<td>P change score on lagged LS change score</td>
<td>-0.327**</td>
<td>0.127</td>
<td>-0.290**</td>
<td>0.111</td>
</tr>
<tr>
<td>LS change score on lagged P change score</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Chi | 44.827 | 40.249 | 27.824 | 22.703 |
Df  | 10     | 9      | 9      | 8      |
CFI/ TLI | 0.998/0.997 | 0.998/0.997 | 0.999/0.998 | 0.999/0.998 |
RMSEA | 0.026  | 0.026  | 0.021  | 0.019  |
SRMR  | 0.018  | 0.018  | 0.017  | 0.016  |
AIC   | 50575.868 | 50573.291 | 50560.865 | 50557.744 |
BIC   | 50686.554 | 50690.4 | 50678.06 | 50681.452 |

Note. ***p < .001, **p < .01, p < .05. Associations are standardised in terms of personality and life satisfaction. P= personality; LS= Life satisfaction. Model fit statistics are also presented. Χ² =chi-square ; df= degrees of freedom; CFI = comparative fit index; TLI= Tucker-Lewis Index; RMSEA= root mean square error of approximation; SRMR = standardized root mean square residual. Associations are coded to match paths in Figure 7.
### Table 13 (continued) Model fit statistics and parameter estimates for LCS model

<table>
<thead>
<tr>
<th>Extraversion</th>
<th>No lagged effects</th>
<th>LS→P</th>
<th>P→LS</th>
<th>Reciprocal</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β</td>
<td>SE</td>
<td>β</td>
<td>SE</td>
</tr>
<tr>
<td>Baseline P level with baseline LS level</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.234***</td>
<td>0.018</td>
<td>0.232***</td>
<td>0.018</td>
</tr>
<tr>
<td>P change score on lagged P score</td>
<td>-0.023</td>
<td>0.020</td>
<td>-0.022</td>
<td>0.020</td>
</tr>
<tr>
<td>P change score on lagged LS score</td>
<td>0.011</td>
<td>0.020</td>
<td>0.011</td>
<td>0.020</td>
</tr>
<tr>
<td>LS change score on lagged LS score</td>
<td>-0.070**</td>
<td>0.026</td>
<td>-0.072**</td>
<td>0.025</td>
</tr>
<tr>
<td>LS change score on lagged P score</td>
<td>0.054**</td>
<td>0.024</td>
<td>0.056**</td>
<td>0.024</td>
</tr>
<tr>
<td>P change score on lagged P change score</td>
<td>0.690***</td>
<td>0.163</td>
<td>0.670***</td>
<td>0.172</td>
</tr>
<tr>
<td>LS change score on lagged LS change score</td>
<td>0.269</td>
<td>0.221</td>
<td>0.269</td>
<td>0.214</td>
</tr>
<tr>
<td>P change score on lagged LS change score</td>
<td>0.127</td>
<td>0.143</td>
<td>0.127</td>
<td>0.143</td>
</tr>
<tr>
<td>LS change score on lagged P change score</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chi</td>
<td>18.111</td>
<td></td>
<td>17.334</td>
<td></td>
</tr>
<tr>
<td>Df</td>
<td>10</td>
<td></td>
<td>9</td>
<td></td>
</tr>
<tr>
<td>CFI/TLI</td>
<td>0.999/0.999</td>
<td></td>
<td>0.999/0.999</td>
<td></td>
</tr>
<tr>
<td>RMSEA</td>
<td>0.013</td>
<td></td>
<td>0.014</td>
<td></td>
</tr>
<tr>
<td>SRMR</td>
<td>0.017</td>
<td></td>
<td>0.017</td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>48909.714</td>
<td></td>
<td>48910.937</td>
<td></td>
</tr>
<tr>
<td>BIC</td>
<td>49020.401</td>
<td></td>
<td>49028.135</td>
<td></td>
</tr>
</tbody>
</table>

**Note.** ***p < .001, **p < .01, p < .05.** Associations are standardised in terms of personality and life satisfaction. P= personality; LS= Life satisfaction. Model fit statistics are also presented. X^2=chi-square; df= degrees of freedom; CFI = comparative fit index; TLI= Tucker-Lewis Index; RMSEA= root mean square error of approximation; SRMR= standardized root mean square residual. Associations are coded to match paths in Figure 7.
Table 13 (continued) Model fit statistics and parameter estimates for LCS model

<table>
<thead>
<tr>
<th>Openness</th>
<th>No lagged effects</th>
<th>LS→P</th>
<th>P→LS</th>
<th>Reciprocal</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β</td>
<td>SE</td>
<td>β</td>
<td>SE</td>
</tr>
<tr>
<td>Baseline P level with baseline LS level</td>
<td>0.073***</td>
<td>0.019</td>
<td>0.073***</td>
<td>0.019</td>
</tr>
<tr>
<td>P change score on lagged P score</td>
<td>-0.045*</td>
<td>0.017</td>
<td>-0.047**</td>
<td>0.017</td>
</tr>
<tr>
<td>P change score on lagged LS score</td>
<td>0.038</td>
<td>0.025</td>
<td>0.040</td>
<td>0.025</td>
</tr>
<tr>
<td>LS change score on lagged LS score</td>
<td>-0.086**</td>
<td>0.026</td>
<td>-0.085**</td>
<td>0.027</td>
</tr>
<tr>
<td>LS change score on lagged P score</td>
<td>0.050**</td>
<td>0.018</td>
<td>0.049**</td>
<td>0.018</td>
</tr>
<tr>
<td>P change score on lagged P change score</td>
<td>0.046</td>
<td>0.161</td>
<td>0.041</td>
<td>0.160</td>
</tr>
<tr>
<td>LS change score on lagged LS change score</td>
<td>0.166</td>
<td>0.209</td>
<td>0.166</td>
<td>0.214</td>
</tr>
<tr>
<td>P change score on lagged LS change score</td>
<td>-0.064</td>
<td>0.112</td>
<td>-0.064</td>
<td>0.112</td>
</tr>
<tr>
<td>LS change score on lagged P change score</td>
<td>0.002</td>
<td>0.110</td>
<td>0.002</td>
<td>0.110</td>
</tr>
</tbody>
</table>

Chi 20.536 20.211 20.535 20.211
Df 10 9 9 8
CFI/TLI 0.999/0.999 0.999/0.999 0.999/0.999 0.999/0.999
RMSEA 0.015 0.016 0.016 0.018
SRMR 0.017 0.016 0.017 0.016
AIC 44059.379 44061.054 44061.378 44063.054
BIC 44170.065 44178.252 44178.576 44186.762

Note. ***p < .001, **p < .01, *p < .05. Associations are standardised in terms of personality and life satisfaction. P= personality; LS= Life satisfaction. Model fit statistics are also presented. X^2 = chi-square ; df= degrees of freedom; CFI = comparative fit index; TLI= Tucker-Lewis Index; RMSEA= root mean square error of approximation; SRMR = standardized root mean square residual. Associations are coded to match paths in Figure 7.
<table>
<thead>
<tr>
<th>Agreeableness</th>
<th>No lagged effects</th>
<th>LS→P</th>
<th>P→LS</th>
<th>Reciprocal</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β</td>
<td>SE</td>
<td>β</td>
<td>SE</td>
</tr>
<tr>
<td>Baseline P level with baseline LS level</td>
<td>0.108***</td>
<td>0.020</td>
<td>0.108***</td>
<td>0.020</td>
</tr>
<tr>
<td>P change score on lagged P score</td>
<td>-0.037**</td>
<td>0.016</td>
<td>-0.038**</td>
<td>0.016</td>
</tr>
<tr>
<td>P change score on lagged LS score</td>
<td>0.038</td>
<td>0.026</td>
<td>0.040</td>
<td>0.026</td>
</tr>
<tr>
<td>LS change score on lagged LS score</td>
<td>-0.145***</td>
<td>0.026</td>
<td>-0.144***</td>
<td>0.027</td>
</tr>
<tr>
<td>LS change score on lagged P score</td>
<td>0.080***</td>
<td>0.015</td>
<td>0.080***</td>
<td>0.016</td>
</tr>
<tr>
<td>P change score on lagged P change score</td>
<td>0.014</td>
<td>0.169</td>
<td>0.006</td>
<td>0.168</td>
</tr>
<tr>
<td>LS change score on lagged LS change score</td>
<td>-0.008</td>
<td>0.151</td>
<td>-0.013</td>
<td>0.152</td>
</tr>
<tr>
<td>P change score on lagged LS change score</td>
<td>-0.043</td>
<td>0.091</td>
<td>0.091</td>
<td>0.091</td>
</tr>
<tr>
<td>LS change score on lagged P change score</td>
<td>-0.105</td>
<td>0.080</td>
<td>-0.104</td>
<td>0.080</td>
</tr>
</tbody>
</table>

Chi | 19.185 | 18.956 | 17.527 | 17.291 |
Df | 10 | 9 | 9 | 8 |
CFI/ TLI | 0.999/0.999 | 0.999/0.999 | 0.999/0.999 | 0.999/0.999 |
RMSEA | 0.014 | 0.015 | 0.014 | 0.015 |
SRMR | 0.008 | 0.008 | 0.008 | 0.008 |
AIC | 45330.580 | 45332.351 | 45330.923 | 45332.686 |
BIC | 45441.267 | 45449.549 | 45448.120 | 45456.395 |

Note: ***p < .001, **p < .01, p < .05. Associations are standardised in terms of personality and life satisfaction. P= personality; LS= Life satisfaction. Model fit statistics are also presented. X² = chi-square; df= degrees of freedom; CFI = comparative fit index; TLI= Tucker-Lewis Index; RMSEA= root mean square error of approximation; SRMR = standardized root mean square residual. Associations are coded to match paths in Figure 7.
Table 13 (continued) Model fit statistics and parameter estimates for LCS model

<table>
<thead>
<tr>
<th>Conscientiousness</th>
<th>No lagged effects</th>
<th>LS→P</th>
<th>P→LS</th>
<th>Reciprocal</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β</td>
<td>SE</td>
<td>β</td>
<td>SE</td>
</tr>
<tr>
<td>Baseline P level with baseline LS level</td>
<td>0.195***</td>
<td>0.019</td>
<td>0.195***</td>
<td>0.019</td>
</tr>
<tr>
<td>P change score on lagged P score</td>
<td>-0.056***</td>
<td>0.020</td>
<td>-0.057**</td>
<td>0.021</td>
</tr>
<tr>
<td>P change score on lagged LS score</td>
<td>0.082**</td>
<td>0.029</td>
<td>0.082**</td>
<td>0.029</td>
</tr>
<tr>
<td>LS change score on lagged LS score</td>
<td>-0.107**</td>
<td>0.032</td>
<td>-0.107**</td>
<td>0.032</td>
</tr>
<tr>
<td>LS change score on lagged P score</td>
<td>0.063**</td>
<td>0.021</td>
<td>0.063**</td>
<td>0.022</td>
</tr>
<tr>
<td>P change score on lagged P change score</td>
<td>0.472**</td>
<td>0.215</td>
<td>0.470**</td>
<td>0.216</td>
</tr>
<tr>
<td>LS change score on lagged LS change score</td>
<td>0.119</td>
<td>0.226</td>
<td>0.121</td>
<td>0.227</td>
</tr>
<tr>
<td>P change score on lagged LS change score</td>
<td>-0.015</td>
<td>0.134</td>
<td>0.180</td>
<td>0.134</td>
</tr>
<tr>
<td>LS change score on lagged LS change score</td>
<td>0.134</td>
<td>0.134</td>
<td>0.181</td>
<td>0.135</td>
</tr>
</tbody>
</table>

| Chi                | 49.077            | 49.064            | 47.448            | 47.422            |
| Df                 | 10                | 9                 | 9                 | 8                 |
| CFI/TLI            | 0.997/0.996       | 0.997/0.995       | 0.997/0.995       | 0.997/0.995       |
| RMSEA              | 0.028             | 0.030             | 0.029             | 0.031             |
| SRMR               | 0.036             | 0.036             | 0.037             | 0.037             |
| AIC                | 45727.132         | 45729.119         | 45727.502         | 45729.476         |
| BIC                | 45837.818         | 45846.316         | 45844.700         | 45853.185         |
Note. ***p < .001, **p < .01, p < .05. Associations are standardised in terms of personality and life satisfaction. P= personality; LS= Life satisfaction. Model fit statistics are also presented. X^2=chi-square ; df= degrees of freedom; CFI = comparative fit index; TLI= Tucker-Lewis Index; RMSEA= root mean square error of approximation; SRMR = standardized root mean square residual. Associations are coded to match paths in Figure 7.
6.4.2.2 Extraversion and life satisfaction. The best-fitting model for the association between changes in extraversion and changes in life satisfaction was one where lagged changes in extraversion did not influence changes in life satisfaction and lagged changes in life satisfaction did not influence changes in personality traits (Model 1). Model 1 provided considerably better fit (AIC: 48909.71, BIC: 49020.40) than Model 2 (AIC: 48910.94, BIC: 49028.14), Model 3 (AIC: 48911.54, BIC: 49028.74) and Model 4 (AIC: 48912.76, BIC: 49036.47). Lagged changes in extraversion were not significantly related to changes in life satisfaction and lagged changes in life satisfaction were not significantly associated with changes in extraversion, suggesting lagged changes in extraversion did not drive changes in life satisfaction and lagged changes in life satisfaction did not lead to changes in extraversion.

6.4.2.3 Openness and life satisfaction. The association between changes in openness and changes in life satisfaction was best explained by a model where lagged changes in openness did not influence changes in life satisfaction and lagged changes in life satisfaction did not influence changes in openness (Model 1). Model 1 (AIC: 44059.38, BIC: 44170.07) was a better fit than Model 2 (AIC: 44061.05, BIC: 44178.25), Model 3 (AIC: 44061.38, BIC: 44178.58) or Model 4 (AIC: 44063.05, BIC: 44186.76). Each model indicated that lagged changes in openness were not significantly associated with changes in life satisfaction and/or lagged changes in life satisfaction were not significantly associated with changes in openness.

6.4.2.4 Agreeableness and life satisfaction. Model 1 (AIC: 45330.58, BIC: 45441.27) explained the association between changes in agreeableness and changes in life satisfaction better than Model 2 (AIC: 45332.35, BIC: 45449.55), Model 3 (AIC: 45330.92, BIC: 45448.12) or Model 4 (AIC: 45332.69, BIC: 45456.40), suggesting that lagged
changes in agreeableness did not influence changes in life satisfaction and lagged changes in life satisfaction did not influence changes in agreeableness.

6.4.2.5 Conscientiousness and life satisfaction. The best-fitting model for the association between changes in conscientiousness and changes in life satisfaction was Model 1 (AIC: 45727.13, BIC: 45837.82). This model provided considerably better fit than Model 2 (AIC: 45729.12, BIC: 45846.32), Model 3 (AIC: 45727.50, BIC: 45844.70) and Model 4 (AIC: 45729.48, BIC: 45853.19). Lagged changes in conscientiousness did not influence changes in life satisfaction and lagged changes in life satisfaction did not influence changes in conscientiousness.

6.4.3 Mediation effects of changes in negative affect on the association between lagged changes in personality and changes in life satisfaction.

We examined, using our LCS mediation model, whether the influence of lagged changes in neuroticism on changes in life satisfaction was mediated by negative affect. We did not examine mediation effects of positive or negative affect on the association between changes in the remaining traits personality traits and changes in life satisfaction since bivariate LCS models indicated that lagged changes in the remaining traits did not influence changes in life satisfaction and lagged changes in life satisfaction did not influence changes in the remaining traits for our sample.

Our LCS mediation model indicated that changes in negative affect were influenced by previous levels of negative affect (β = -0.25, p < .001), previous levels of neuroticism (β = 0.17, p < .001), and lagged changes in neuroticism (β = 0.17, p = .013). Changes in life satisfaction were influenced by previous levels of life satisfaction (β = -0.03, p = .012), lagged changes in negative affect (β = -0.24, p = .011), lagged changes in life satisfaction (β = 0.45, p = .008) and lagged changes in neuroticism (β = -0.42, p <
The mediation effect of negative affect on the influence of lagged changes in neuroticism on changes in life satisfaction is illustrated in Figure 9. Goodness of fit tests (AIC and BIC) indicated that the fit of the LCS mediation model to the data was considerably lower (AIC: 83291.41; BIC: 83525.81) than the fit of the bivariate LCS models (AIC: 50560.87, BIC: 50678.06), as can be expected due to the higher number of parameters included in the mediation model. However, the LCS mediation model provided overall good fit to the data (CFI = 0.998, TLI: 0.997, RMSEA = 0.019, SRMR = 0.016).

![Figure 9](image)

Figure 9 A simple path diagram illustrating the mediation effect of negative affect on the influence of lagged changes in neuroticism on changes in life satisfaction

6.5 Discussion

The current study uses bivariate proportional change LCS models to assess the longitudinal association between personality traits and life satisfaction levels after accounting for measurement error and controlling for time-invariant omitted variables.
Bivariate proportional change LCS models allowed us to examine whether lagged within-person changes in personality influenced within-person changes in life satisfaction. As hypothesized, changes in an individual’s neuroticism levels preceded changes in their levels of life satisfaction and this association was largely mediated by changes in the individual’s level of negative affect. However, we did not find evidence for an influence of lagged changes in extraversion on changes in life satisfaction. Similarly, changes in the remaining traits did not precede changes in life satisfaction and changes in life satisfaction did not precede changes in personality traits. Models 1-4 for the association between life satisfaction and the personality traits extraversion, openness, agreeableness and conscientiousness produced very similar path estimates, further suggesting that there were no significant prospective associations between changes in these traits and changes in life satisfaction.

The findings here advance our understanding of the nature of the association between personality traits and life satisfaction levels. Although previous work has demonstrated that personality trait change co-occurs with changes in life satisfaction, concerns regarding omitted variable bias, measurement bias or inability to assess directionality has made it difficult to conclude whether such associations are substantive. Our study suggests that previous observations of any cross-sectional or longitudinal association between life satisfaction and openness, agreeableness and conscientiousness may have been due to individual differences in time-invariant omitted variables. Our finding of an effect of lagged within-person change in neuroticism on within-person change in life satisfaction extends previous studies (Soto, 2015; Specht et al., 2013) examining individual differences in personality maturation and life satisfaction change by providing evidence to suggest that the association between individual differences in levels
of neuroticism and overall changes in life satisfaction is not confounded by other person-specific time-invariant variables.

Our findings also contribute to theories of personality change and is consistent with the social investment perspective (Roberts & Wood, 2006; Roberts et al., 2005) that individuals change their personality traits to allow them to successfully adapt to new roles. Our LCS mediation model indicated that lagged changes in neuroticism drive changes in life satisfaction by influencing changes in negative affect. An individual who becomes less neurotic likely perceives situations as less stressful and responds more adaptively to stressful events (Mroczek et al., 2006), which would lead to decreases in negative affect and subsequently increases in life satisfaction. This explanation is consistent with the neural basis of life satisfaction and neuroticism. Both life satisfaction and neuroticism have been found to be associated with parahippocampal gyrus (PHG) of the brain (Kong et al., 2015; Servaas, Riese, Ormel, & Aleman, 2014). Furthermore, life satisfaction has been found to be positively associated with regional gray matter volume in the PHG (Kong et al., 2015), while perceived stress (Li et al., 2014) and anxiety symptoms (Wei et al., 2015) are negatively associated with regional gray matter volume in the PHG.

6.6 Limitations and Future Directions

The LISS panel was a suitable dataset for our study as it included at least three waves of personality data from a large nationally representative sample. The availability of three waves allows us to fit a bivariate proportional LCS model, which accounted for measurement error in observed measures of the variables of interest. However, there are some limitations associated with the study. First, we expected to find that lagged changes in extraversion also influence changes in life satisfaction since extraversion has been structurally related to positive affect, although we found no evidence for this in the current
study. This may be due to the measures of extraversion in this study being more focused on sociability (for example being talkative, being the life of the party) rather than positive moods (for example being joyful). A significant influence of lagged changes in extraversion on changes in life satisfaction may have been observed if more items of the extraversion scale focused on trait positive affectivity. Alternatively, studies have suggested that the role of positive affect on life satisfaction is moderated by culture (Kuppens et al., 2008). It is possible that the positive affect component of extraversion does not influence life satisfaction in our sample due to cultural characteristics of the sample. Finally, theories of life satisfaction emerging from the positive affective component of extraversion may simply be incorrect, and driven by less stringent controls in earlier studies; More research is needed to test between these competing possibilities and our results on this trait should be treated with caution until such research is conducted.

Second, our measures of positive and negative affect asked respondents how affective they were feeling at the moment. The expectation is that mood in the moment would be driven by the more trait like neuroticism. However, using a momentary measure of negative affect rather than measuring negative affect over a recent period of time may weaken the power to detect our mediation as the momentary negative affect will in part be driven by chance factors in the environment at the time of questionnaire completion (although, in general, people higher in negative affect would be expected to be feeling more negative affect in any situation). More accurate effects for positive and negative affect may be achieved if a measure assessing affect over a longer duration was used. This was a basic limitation of the data, and relates to wider debates about the relative benefits of using pre-collected large, representative, and longitudinal samples verses smaller scale specifically-collected data which is less likely to be as representative, well-powered, or
long term. The over-reliance on collection of new data has been implicated in the replicability crisis in psychology (Pashler & Wagenmakers, 2012), and we note that an additional benefit of using this data is that the data is readily available to any researchers who wish to check our results, or test alternate explanations, without their needing to contact us. This, combined with the data being independently collected without our involvement, significantly reduces the potential for our (honest or otherwise) biases to have affected the results. The field needs to both continue to collect new data and make better use of existing resources, and future work is advised to follow up with additional measures of negative affect. However, here we felt that the relative benefits of using this data outweighed the ability to personally choose the measures. We note that this is a secondary analysis for our paper, which was significant, and that the added error in using a state measure of negative affect may have resulted in an underestimate of the effect. There is also an unintended benefit of using a state measure of negative affect, in that it reduces conceptual overlap between the predictor (neuroticism, comprising trait negative affect) and the mediator (the more state-like negative affect). The greater the time frame covered by any negative affect the more it becomes at trait measure and the analysis risks becoming a truism (although it would still have identified which sub-component of neuroticism drives the results). By using a pure state measure, we perform the more stringent test of whether negative affect measured in the moment is a strong enough proxy for the negative moods an individual is experiencing at that point in their life to provide mediation of trait neuroticism on life satisfaction. However, we acknowledge the limitation, and future research is encouraged to include two measures of negative affect, respectively covering how the person is feeling “right now” and “in general over the last month” so that the results can be replicated across each.
Third, although we present the strongest support to date for an unconfounded association between neuroticism and life satisfaction, we are not able to make any causal inferences about the association. The results here may be confounded by omitted time-variant third variables that are associated with changes in personality and life satisfaction. Thus we can say with greater confidence that we disprove the role of traits other than neuroticism in this sample, and only that we fail to disprove that neuroticism matters (rather that that we prove that it does), in line with the positivistic epistemology generally adopted by personality psychology. Building a greater knowledge base on this issue through future research would give progressively more confidence that the effect of lagged changes in neuroticism on changes in life satisfaction is not driven by other factors. Such variables may include characteristic adaptations such as self-regulatory processes which have been suggested to explain personality change (Denissen et al., 2013) and have also been linked to life satisfaction (Elliot, Thrash, & Murayama, 2011; Hill, Jackson, Roberts, Lapsley, & Brandenberger, 2011) or the experience of life events that drive changes to both personality and life satisfaction (Boyce, Wood, Daly, & Sedikides, 2015).

6.7 Conclusion

In the current study, we find that lagged changes in neuroticism influenced changes in life satisfaction and lagged changes in the remaining traits did not influence changes in life satisfaction. These results suggest that neuroticism is the only Big Five personality trait that has a prospective influence on life satisfaction. The influence of lagged changes in neuroticism on changes in life satisfaction was partly mediated by negative affect. However, further research is needed to better understand what drives personality change and subsequently how to successfully foster healthy personality change.
CHAPTER 7

7.0 Discussion

7.1 Overview

The overarching aim of this thesis was to improve understanding of individual-level predictors of health and well-being, through integrating and advancing literatures across the social sciences. This thesis illustrates how economic and public health research on individual-level predictors of health and well-being can be advanced by incorporating research findings and measures from the psychological literature and how psychological research may be advanced by using large-scale economic datasets to better understand change in psychological measures such as personality traits and how this change relates to well-being. Specifically, this thesis contributed to the economic and public health literature on the importance of relative deprivation on health and well-being outcomes by identifying an exact psychological pathway through which income relates to health and well-being. Furthermore, the relative contribution of a psychological predictor (personality) to an economic predictor (income) to well-being outcomes was explored. This thesis also contributed to the psychological literature on personality change by showing that an individual’s personality traits changes as much as their income and that these changes are more strongly linked to well-being than changes in income. In addition to that, this thesis examined the nature of the association between personality trait change and well-being and found that the association between personality and well-being is in line with theoretical predictions. This final chapter will summarise the key findings of this thesis, discuss the theoretical, methodological and policy implications of these findings for health and well-
being research, and consider the limitations and future directions of research in this area. The key conclusion of the findings of this thesis is detailed.

### 7.2 Chapter Summary

The literature review presented in Chapter 1 indicated that much of the research contrasting the material and psychosocial effects of income on health and well-being used the Yitzhaki Index, a function of the aggregate income shortfall of an individual’s income relative to those with higher incomes in their reference group, to model the psychosocial effect of income. Though evolutionary studies and cognitive findings have indicated that rank of income (rather than alternative specifications of relative income) relates to health, there have been only a handful of studies that have examined the influence of social position on health using a measure of income rank as a proxy of social position and additionally controlling for absolute income. Moreover, there has been a lack of studies assessing the influence of income rank on health and well-being outcomes for a midlife sample and a lack of studies directly contrasting the influences of income rank and the Yitzhaki Index. Chapter 3 therefore examined the association between income/wealth rank and depressive symptoms in a midlife sample and found that income and wealth rank significantly predicted depressive symptoms, both before and after controlling for absolute income and wealth. This finding suggested that the association between income or wealth and depressive symptoms is better explained by psychosocial processes than material factors. Although this study additionally controlled for distance from the individual’s income/wealth relative to the mean income/wealth of their reference group as an alternative measure of relative deprivation, it was not clear if the influence of income/wealth rank on health may be attributed to the Yitzhaki Index. Chapter 4 provided the first direct test contrasting the influences of income rank and the Yitzhaki Index in an
adult sample. Income rank was found to be a stronger predictor of both a subjective (self-rated health) and objective (high-risk allostatic load) health than the Yitzhaki Index for two culturally different adult populations; models predicting health from income rank (plus covariates) alone provided a better fit on the data than models predicting health from absolute income or models predicting health from the Yitzhaki Index. Furthermore, adding the Yitzhaki Index or absolute income to the model predicting health from rank alone did not improve prediction, suggesting that income rank also predicted health better than any combination of income-related predictors. This study indicated that psychosocial factors, specifically an individual’s rank within a reference group rather than the magnitude of the difference between an individual’s income and those with higher incomes in their reference group, relate to health more closely than material factors. Chapters 3 and 4 highlight the benefits of applying psychological theories to answer existing research questions within the fields of economics and public health, which can in turn improve health and well-being.

Chapter 5 further demonstrated the advantages of using psychological measures in well-being research. In Chapter 5, an individual’s personality traits were found to change as much as variable socioeconomic indices and personality change scores were found to explain a larger amount of variance in well-being than socioeconomic indices. Chapter 5 therefore suggested that personality measures may have an applied value in economic research as markers of well-being. Chapter 5 also advanced the personality psychology literature by demonstrating how much an individual’s personality changes and that personality change scores are more closely linked to change in psychological rather than hedonic well-being. This finding suggests that personality change is particularly important for an individual’s strive towards fulfilment and provides an intrinsic indicator of an
individual’s well-being. Finally, Chapter 6 proceeded to examine the nature of the associations between personality trait measures and well-being. Chapter 6 provided evidence to support a true (unconfounded) and possibly causal influence of neuroticism on life satisfaction, suggesting that improvements in life satisfaction scores may be achieved through targeting change in neuroticism. However, there was lack of evidence to support a prospective influence of changes in personality traits on life satisfaction after accounting for measurement error and person-specific factors, suggesting that the changes in these traits do not drive changes in life satisfaction but rather share common causal influences with life satisfaction change. Together the empirical chapters suggest that psychological factors such as social comparisons (represented by income rank) and personality traits more precisely predict health and well-being outcomes than income and other socioeconomic factors, although it is not conclusive whether such associations are causal.

7.3 Limitations

The limitations specific to each empirical investigation are discussed in their corresponding chapters. This section presents the overarching limitations of the thesis and considers some limitations that have not been discussed within the empirical chapters. The limitations that relate to the sample and measures used are first discussed, followed by a discussion of the limitations that relate to the methodological approaches adopted in this thesis.

7.3.1 Sample.

The data used in this thesis were selected due to their sample size and the availability of income and personality measures at multiple time points. Apart from Chapter 6 which includes data from a broad age-group, the studies in this thesis mainly use data from nationally representative samples of individuals at midlife. These individuals
were therefore within the last decade of their working lives, approaching retirement or already retired. It is likely that the importance of income and social comparisons for this age group will be different to that of a younger individual who, for example, is in the early years of their career. Similarly, it can be argued that individuals in their midlife will be more motivated or encouraged to achieve authenticity and strive to exist in the world as their true selves. For these reasons, it is difficult to generalise our findings from Chapters 3, 4 and 5 to a younger sample. Furthermore, the Wisconsin Longitudinal Study (which was used in Chapters 3 and 5) was slightly under-representative of African-Americans and Hispanic individuals (Herd et al., 2014), thus further reducing generalizability of the results.

7.3.2 Measures.

Throughout this thesis, self-report measures of well-being and personality are used. Although such measures are well-established and demonstrated high validity and reliability in our analytic samples, such measures are vulnerable to response bias (Stone et al., 2000). Respondent bias is particularly problematic for studies assessing change in self-report measures over time. More objective measures are needed to ensure that any apparent changes in such measures over time are not illusionary. It can be argued that behavioural observations within a natural setting may be used (in addition to self-report measures) to provide more accurate measures of an individual’s personality and well-being (Specht et al., 2014). However, data on behavioural observations is not commonly available in large scale studies due to the high costs and ethical considerations associated with collecting such data (McDonald, 2008). Another disadvantage in using self-report measures in studies of personality and well-being change is that self-report measures are vulnerable to measurement error (Chmielewski & Watson, 2009), thus making it difficult to determine
how much of the observed change in a self-report measure is due to true change rather than
noise. However, Chapter 6 addresses measurement error by using a structural equation
model which allows true change in psychological constructs to be isolated from random
measurement error. Chapter 6 indicated that 74-82% of change in personality traits and 71-
75% of change in well-being was due to true change rather than measurement error.

Another measure-related limitation of the thesis is that we derive income rank
values by ranking respondent income within a comparison group. This method has the
advantage that it provides an objective measure of an individual’s ordinal position within a
reference group and as such is not susceptible to self-report bias. However, it is not entirely
clear how strongly such an objective measure of rank relates to an individual’s perception
of their income rank. Since it is an individual’s perception of their income rank rather than
their objective income rank that should relate more closely to health (Adler, Epel,
Castellazzo, & Ickovics, 2000), it is possible that our regression coefficients may be
slightly biased if our objective measure income rank is not perfectly correlated with
subjective income rank. For example, an individual A who is identified as having the
highest objective income rank may in fact have slightly worse self-rated health (after
controlling for health behaviours) than an individual B who is identified as having slightly
lower objective income rank if individual A makes more social comparisons or does not
perceive themselves as having higher rank than individual B. Subjective measures of
income rank may provide a more accurate indication of the influence of income rank on
health as these measures take into account an individual’s feelings and emotional responses
to income inequality as well as their satisfaction with income (Miething, 2013).

Finally, different transformations of income have been used for different empirical
chapters; Chapter 3 assesses the effect of non-equivalised CRRA-transformed income on
health, Chapter 4 assesses the effect of equivalised CRRA-transformed income on health and Chapter 5 uses log-transformed non-equivalised income. This is because the transformation of income was selected partly to suit the convention and readership of the target journal. For example, log-transformed income was used in Chapter 5 as the readership would be more familiar with the logarithmic transformation than the CRRA transformation and the main purpose of the study in Chapter 5 was to compare the predictive value of personality change and socioeconomic changes for well-being change (rather than demonstrate that CRRA more adequately accounts for non-linearity in the association between income and health). Equivalised income rather than non-equivalised income was used in Chapter 4 since previous papers published in Social Science and Medicine that have assessed the effect of income on health have used equivalised income.

7.3.3 Methodological limitations.

As highlighted in the individual chapters, the analytic procedures used in this thesis are predictive models and do not allow us to make strong causal inferences about the association between outcome and independent variables. Methods such as fixed-effect models and structural equation models (including latent change score models) provide strong evidence for a relation between variables because they control for time-invariant person-specific omitted variables that may confound the association between a dependent variable and predictor. However, these models are only approximations of the true model (Tomarken & Waller, 2005) and are susceptible to omitted variable bias. Specifically, these models often are not able to control for all time-varying variables that may explain the association between the variables of interest. Recent advances in structural equation models such as latent change score models allows the researcher to assess if prior changes in one construct influence subsequent changes in another construct, which can offer some
support for a possible causal association. However, a limitation of structural equation models, (as with any statistical method) is that it is not possible to prove that a specified model is the true model since alternative models may fit the data equally well (Tomarken & Waller, 2005).

7.4 Theoretical Implications

7.4.1 The mechanism underlying the association between income/wealth and health and well-being.

The studies in this thesis make a number of theoretical advances on the association between psychological factors and health and well-being. The first two empirical chapters advance the debate on the importance of psycho-social factors on the income-health relationship by demonstrating that a psychosocial explanation of the influence of income or wealth on health is consistently supported when a measure of income rank is used to represent the psychosocial effect of income. The second empirical study provides direct evidence that the income rank hypothesis can be distinguished from the relative income hypothesis (as represented by the Yitzhaki Index) and suggests that individuals more likely compare how their income ranks in comparison to that of others (Stewart et al., 2006) than the magnitude of the difference between an individual’s income and the incomes of all individuals within their reference group that have higher incomes, possibly as the former is less cognitively demanding than the latter. Chapter 4 advances the operationalization of relative deprivation and concludes that the previous studies that have failed to find a psychosocial effect of income may be due to the use of the Yitzhaki Index or alternative measure which does not adequately operationalize relative deprivation. Additionally, the results of Chapter 4 suggests that previous studies finding an influence of income rank on, for example, economic satisfaction (Brown et al., 2008; Clark et al., 2008), mental health
(Hounkpatin, Wood, et al., in press; Wood, Boyce, et al., 2012), health behaviours (Maltby et al., 2012; Wood, Brown, & Maltby, 2012), psychological well-being (Wood et al., 2011), and physical health (Daly et al., 2015) are not confounded by alternative measures of relative deprivation.

7.4.2 Mechanisms underlying personality change.

This thesis extends previous studies (for example Specht et al., 2013) that suggest life satisfaction contributes to personality maturation by finding that the association between (changes in) life satisfaction and changes in at least three personality traits (agreeableness, openness and conscientiousness) is not causal but likely occur due to shared causal processes. Comparing the associations between personality change and different measures of well-being indicated that personality change explained considerably more variation in changes in psychological well-being than changes in subjective well-being or changes in depressive symptoms. Such a finding may provide insight into the drivers of personality change since psychological well-being is concerned with an individual’s psychological needs and positive functioning (Samman, 2007) whereas subjective well-being relates to hedonic experience. That personality change is a better predictor of psychological than subjective well-being supports theories such as the existential-humanistic theories (Wong, 2006), self-regulatory theories (Denissen et al., 2013) and paradoxical theories (Caspi & Moffitt, 1993) of personality change that suggest that personality change occurs because individuals value and desire personality change. Personality change, therefore, may occur as a result of effortful self-regulated changes and not merely due to unconscious, biological maturation processes. Such self-regulated changes will likely also result in changes in life satisfaction, which may explain why changes in life satisfaction co-occur with changes in personality traits.
This thesis provides evidence to suggest a reciprocal association between changes in life satisfaction and neuroticism which is mediated by negative affect. Thus, changes in life satisfaction may contribute to subsequent changes in neuroticism; An individual who experiences increases to their life satisfaction will also experience less negative affect since negative affect and life satisfaction have been structurally linked (Busseri, 2015; Schimmack, Diener, et al., 2002; Schimmack, Radhakrishnan, et al., 2002). Changes in negative affect may subsequently lead to decreases in neuroticism since neuroticism comprises negative affect (Augustine & Larsen, 2015). However, further research is needed to assess whether the association between changes in neuroticism and life satisfaction are not due to omitted time-variant variables.

7.4.3 Do personality traits predict life satisfaction?

The lack of a causal association between changes in life satisfaction and changes in at least three of the Big Five personality traits contribute to the wider literature of the association between personality and life satisfaction. This literature, which spans three decades, has suggested that personality traits and life satisfaction are closely related, although it had not been determined whether the association was causal. This thesis provides evidence to suggest that life satisfaction and personality traits (except for neuroticism) are not causally related; the well-established associations between life satisfaction and personality traits (except for neuroticism) are likely due to omitted third variables. Omitted third variables which may have confounded the association between personality traits and life satisfaction may include time-invariant person-specific factors such as genetic composition or time-variant factors such as life experiences (Boyce et al., 2015) or self-regulatory processes (Denissen et al., 2013) which have been associated with both personality and life satisfaction. Neuroticism may be causally associated to life
satisfaction since neuroticism is composed of negative affect (Augustine & Larsen, 2015) which may be causally associated with life satisfaction (Busseri, 2015; Schimmack, Radhakrishnan, et al., 2002).

7.5 Methodological Implications

The studies in this thesis make two methodological advances to the study of the influence of income on health and well-being. It has been noted that the relationship between income and health variables are highly curvilinear (Backlund et al., 1996; Mellor & Milyo, 2002; Wolfson, Kaplan, Lynch, Ross, & Backlund, 1999) and that the curvilinearity of the association between income and health depends on the health variable (Der, Macintyre, Ford, Hunt, & West, 1999) and population (Mackenbach et al., 2005) being studied. While the logarithm of income has commonly been used to model the diminishing rate of benefits to health with increasing income, it is unlikely that this transformation adequately accounts for the curvilinear association between income and all measures of health. Chapter 3 demonstrates that a better representation of the income-health relationship may be achieved using the Constant Relative Risk Aversion (CRRA) specification. The CRRA function contains a parameter $\rho$ which can be varied to estimate the exact shape of the association between income and a specific health or well-being outcome for a specific population. It is particularly important to use the CRRA function instead of the logarithmic transformation to model the effect of income on health/well-being when comparing the direct and indirect relative effects of income or when studying interaction effects, to ensure that any significant coefficients on the relative income specification or interaction term are not due to additional non-linearity in the income-health relationship that is not fully captured by the logarithmic transformation. Use of the
CRRA function to represent the direct effect of income therefore provides a more stringent test for an independent psychosocial effect on health and well-being.

Chapters 3 and 4 also suggest using goodness of fit tests to compare the fit of the competing models on the data. The fact that absolute income measures (representing material hypothesis) and relative income measures (representing psychosocial hypothesis) are highly co-linear makes it difficult to isolate the unique effects of each through joint regressions. Goodness of fit tests allow the researcher to assess which of the hypotheses better explains the association between income and health and well-being when there is evidence of co-linearity in models regressing health or well-being jointly on absolute and relative income measures.

7.6 Practice and Policy Implications

The overarching practice and policy implication of this thesis is that well-being research can be improved by continuing to adopt an inter-disciplinary approach to the study of individual-level predictors of health and well-being. An interdisciplinary approach will also be beneficial for the individual academic disciplines. Disciplines such as public health and economics can benefit from the use of psychological measures as predictors of health and well-being, whereas psychology can benefit from the use of large survey datasets and complex analytical models more commonly used in public health and economic research. The following two subsections consider the specific practice and policy implications of this thesis.

7.6.1 Psychological interventions to improve health and well-being.

The findings of the thesis indicated that the psychosocial effects of income (specifically rank comparisons) are more closely related to health outcomes than the direct material effects of income, suggesting efforts to reduce income-related health inequalities
should address the underlying psychosocial mechanism through which income relates to health. Psychosocial interventions are more likely to reduce health inequalities than strategies that aim to increase incomes of those with lower incomes (for example, income redistribution). One possibility would be to tackle negative cognitions associated with being of low social rank through psychological interventions. For example, cognitive behavioural therapies (CBT) may be used to reduce perceptions of defeat and entrapment in individuals who are, or perceive themselves as being of low rank. This may be achieved by changing the way an individual interprets their situation, themselves and the world around them (Johnson, Gooding, Taylor, & Tarrier, 2008; Taylor et al., 2011). Therapies which foster self-belief and self-efficacy in transforming their circumstances may help individuals recover from and even become resilient to the negative cognitions associated with being of low rank (Wood, Boyce, et al., 2012). Such therapies may have the ability to prevent further disorders or suicide attempts from occurring (Johnson, Wood, Gooding, Taylor, & Tarrier, 2011; Wood, Boyce, et al., 2012). Emotion-regulation skills training may be also integrated into CBT programs to help reduce anxiety and distress and facilitate implementation of self-belief and coping strategies (Berking et al., 2008). Such programs may require participants to set and record long and short term goals, make a detailed plan to achieve their goals and monitor their progress in achieving these goals. Support and advice on overcoming barriers can be provided to participants to help increase self-regulation skills (Annesi & Gorjala, 2010). Increasing individuals’ self-regulation skills can directly influence changes in health and well-being (Annesi & Gorjala, 2010) and may also foster favourable personality changes (Denissen et al., 2013) such as decreases in neuroticism, which in turn may result in subsequent increases in well-being. However, multiple randomised controlled trials are needed to assess the effectiveness of such
therapies at reducing negative effects of being of low rank and/or encouraging healthy personality change.

### 7.6.2 Personality change as markers of change in well-being.

The findings from Chapter 6 indicate that there is increasing room for the use of personality measures as well-being indicators since personality change measures explained at least 6 times as much variation in within-person psychological well-being and 2-3 times as much within-person variation in depressive symptoms, hostility and life satisfaction than socioeconomic indicators. The fact that personality measures were shown to change over time and that these changes predicted changes in well-being further suggests that personality change scores can be used as markers of well-being, and as such should be included in models assessing well-being change over time. Personality change measures may be most useful as indicators of whether an individual is living a self-directed meaningful life and whether they feel they have experienced personal growth and fulfilment. The use of personality measures in this way is advantageous since changes in socioeconomic indicators commonly used in well-being research do not relate to changes in psychological well-being (as shown in Chapter 5).

### 7.7 Proposals for Future Research

The findings of this thesis have prompted new questions regarding the nature of the association between health/well-being and income rank and personality traits. As a result, there are a number of research projects that could directly follow on from and extend this research. Recommendations for future research have been made in the discussion sections of each empirical chapter. However, this section outlines specific research proposals that can build on the evidence produced in this thesis.
7.7.1 Using self-defined reference groups and perceived rank measures to better understand impact of relative deprivation.

Future research should use survey data or questionnaires which specifically ask participants to whom they compare their income to, whether they are satisfied with their income and whether they feel frustrated (or ashamed) about earning less than their peers. In addition to that, participants should be asked to rank their income position within their comparison group. This additional information will provide a more accurate measure of the effect of income rank on health also highlight whether the association between health and subjective income rank differs from the association between health and objective income rank. Furthermore, asking people who they compare their income to will help provide a clearer understanding of which reference groups to use when analysing the role of income-related predictors on health. This is particularly important as the effect of income-related predictors on health may vary with reference groups.

7.7.2 Instrumentation study to determine causal association between income rank, personality traits and health and well-being.

The research presented here can be advanced by assessing whether income and psychological measures such as neuroticism and negative affect are causally related to health and well-being. This may be achieved by instrumenting for income and personality. Instrumentation will not only determine whether there is a causal association between two variables but also account for measurement error and indicate the true (unconfounded) effect size of the association (Powdthavee, 2010; Wooldridge, 2003). The effect size obtained from regression models such as fixed-effects or linear regression model will often be biased since other variables which may confound the association between two variables have not been controlled. The instrumentation technique uses a variable that is strongly
correlated with the variable of interest (i.e., income or personality trait) and does not relate to the outcome variable (i.e., depressive symptoms) beyond its effect on the variable of interest, to determine the true causal effect of the variable of interest on the outcome variable. A handful of studies have now examined the effect of income on health and well-being using an instrumentation approach (for example Powdthavee, 2010), but no study, to the best of my knowledge, has used this approach to assess the effect of a personality trait on health and well-being\(^4\). This is unsurprising as it is difficult to find a variable that is strongly correlated with neuroticism but does not relate to health or well-being other than through its association with neuroticism.

A study may be conducted using a measure such as time preference as an instrument for personality. A measure of time preference would serve as suitable instrument of personality as both measures have been found to be closely related to the Big Five personality traits (for example, Heckman, 2011; Daly, Delaney, & Harmon, 2009) and should not relate to an individual’s well-being in any way other than through being related to personality. The design of the study would be experimental in nature; Individuals may be recruited to the study using university-wide email invitation and informed consent obtained from individuals willing to participate in the study. Participants can be shown a fixed set of binary choices ranging from small immediate monetary rewards to large

\(^4\) An exception is a study by Jewell & Kambhampati (2012) which predicted happiness from a set of predictors in a youth sample and extracted the unobserved person-specific effect from this model. The unobserved person-specific effect was then used as an instrumental variable for the effect of personality on adult life satisfaction. However, this approach may be biased since a person-specific effect of happiness can be expected to be associated with life satisfaction even after controlling for personality traits.
delayed monetary rewards and asked to select which reward they would prefer. Each participant’s selection can then be converted to a time preference measure by subtracting the value of the immediate reward from the value of the delayed reward and dividing the difference by the magnitude of the delay (as has been done in Kirby et al., 1999 and Daly, Delaney, & Harmon, 2009). Participants should additionally be asked to complete questionnaires which contain items of the Big Five personality traits and questions on socio-demographic data.

In the first stage of the instrumental variable approach, the correlation between the instrument (i.e., time preference) and variable of interest (i.e., personality trait neuroticism) should be assessed. To do this, the specified personality trait can be predicted from the instrumental variable (i.e., time preference) plus covariates. In the second stage of the instrumental variable approach, the dependent variable (i.e., well-being) is predicted from the instrumental variable (i.e., time preference) plus covariates. The parameter estimate on the time preference variable from the second stage estimation indicates the causal effect of personality traits on well-being. It must be noted that an instrumental variable should not be correlated with person-specific determinants of the dependent variable (Angrist & Pischke, 2008). However, it is likely that time preference will be correlated with person-specific variables such as gender (Borghans, Golsteyn, Heckman, & Meijers, 2009). In order to satisfy the requirement that the instrumental variable is not correlated with person-specific determinants of well-being, any available person-specific variables should be controlled for in the analytic model or alternatively, a fixed-effects model can be used as fixed-effects models control for person-specific variables.

Time preference measures are commonly used in economic research. The use of a time preference measure as an instrument variable for personality traits further
demonstrates the benefits of drawing on concepts across the social sciences to improve health and well-being research.

7.7.3 Using a ‘simplex’ and ‘SIMEX’ approach to isolate measurement error from psychological measures.

This thesis uses self-report measures of personality traits and well-being. Self-report measures will inevitably be measured with some error. Therefore, it can be difficult to determine how much change in self-report measures is due to true change rather than measurement error and to what extent the association between self-report variables is affected by measurement error. Future studies assessing associations between self-report measures should use appropriate techniques to adjust for measurement error associated with these measures. In addition to latent change score models adopted in Chapter 6, there are alternative structural equation models that can be used to isolate true changes in personality traits and well-being from measurement error in panel data containing repeated measures of personality and also improve understanding of how an individual’s personality traits change over time. For example, an autoregressive quasi-simplex model (Jöreskog, 1970) can be used to assess the pattern of change in an individual’s personality over time. In the simplex model, an individual’s personality is considered to change gradually over time, although the rate and direction of change will vary across individuals (Marsh, 1993). According to this model, an individual’s true personality score at any measurement occasion is assumed to be equal to the score of its immediate predecessor plus any random disturbance due to true change and measurement error.

The simplex model can be used to estimate the reliability in self-report measures and the measurement error associated with each self-report measure. The simplex model requires that personality traits and well-being are measured at three separate occasions. At
each measurement occasion, the observed self-report measure (i.e., the observed personality trait score) is specified to load onto a latent factor variable representing the true personality score. The loadings of the personality score on each latent variable are constrained to be equal to 1. Next, the degree of measurement error (error variances) in the observed scores is constrained to be equal across time. Constraining the loadings to ‘1’ and constraining the error variances to be equal across time ensures that the true variance in each self-report measure score is isolated from variance due the measurement error (Jöreskog, 1970), so that any changes in the latent factors (LP) represent true changes in personality traits rather than changes in the measurement of traits over time. Three types of variances are estimated from a simplex model: variance between subjects over time (i.e. ‘between-subjects’ variance), the variance within a subject over time (i.e. ‘within-subjects’ variance) and the error variance associated with measurement error. The reliability of each self-report measure can be estimated by dividing the ‘between-subjects’ variance by the sum of the of the ‘between-subjects’ and ‘within-subjects’ variance (Biemer, Christ, & Wiesen, 2009).

The estimated measurement error variance obtained from the simplex model can then be used to correct for measurement bias in the parameter estimates of the association between personality change and well-being. First, the association between observed change in an individual’s personality traits score and observed change in their well-being score is estimated using a fixed-effects model. The same fixed-effects model is simulated 100 times and the average of the 100 estimates is taken as an estimate (Lederer & Kuchenhoff, 2006) of the effect of an individual’s personality on their well-being when measurement error is ignored. The fixed-effects model is then estimated using a range of additional measurement error (corresponding to the measurement error variance multiplied by a
factor of $1 + \lambda$, where $\lambda \geq 0$ and is the additional amount of measurement error added to the model (Hardin, Schmiediche, & Carroll, 2003; Lederer & Kuchenhoff, 2006). The trend of measurement error is estimated and then used to extrapolate back to the true measure of the variable. The true measure of the variable (i.e. the value when there is no measurement error) is achieved when $\lambda$ is equal to -1 (Lederer & Kuchenhoff, 2006). This re-sampling procedure is known as the Simulation extrapolation (SIMEX) (Cook & Stefanski, 1994; Stefanski & Cook, 1995) method. Bootstrapping procedures can be used to obtain the standard error of the extrapolated estimate. The results of the SIMEX estimate of the true effect of personality on well-being can then be compared to the parameter estimates produced from the analysis on the observed variables (without accounting from measurement error) in order to determine the extent of measurement error bias.

**7.7.4 Determining the nature of the association between personality change and change in psychological well-being.**

Chapter 6 found that (changes in) four of the Big Five personality traits were not prospectively related to (changes in) life satisfaction after accounting for measurement errors and omitted variables. It was not possible to examine whether changes in personality related to changes in psychological well-being after accounting for measurement error and omitted variables due to lack of availability of measures of psychological well-being in the dataset utilised. However, it would be interesting and informative to study the association between changes in personality traits and changes in psychological well-being since personality change may be more closely related to changes in psychological well-being than life satisfaction, as indicated by the findings in Chapter 5. Future research using large scale archived datasets containing measures of personality and psychological well-being (taken at three or more separate occasions) may investigate if changes in any of the
personality traits lead to subsequent changes in psychological well-being. The study would use four bivariate latent change score (LCS) models (as described in Chapter 6) to assess the association between changes in each personality trait and each psychological well-being subscale. Each LCS model would consist of a measurement component (which models the association between observed scores or personality traits and psychological well-being and their true unconfounded [or latent] values) and a structural component (which estimates the association between latent personality change scores and latent psychological well-being change scores). The first LCS model (Model 1) would not include any associations between change scores, thus assuming that changes in personality traits do not influence changes in psychological well-being and changes in psychological well-being do not influence changes in personality traits. The second LCS model (Model 2) would assume that changes in personality traits precede changes in psychological well-being. Therefore, Model 2 would include a path to allow subsequent change scores in psychological well-being to be influenced by change scores for personality. The third LCS model (Model 3) would include a path to allow the subsequent change scores in personality to be influenced by change scores for psychological well-being. Model 3 therefore assumes that changes in psychological well-being precede changes in personality traits. The fourth LCS model (Model 4) would include a path to allow the subsequent change scores in personality to be influenced by change scores for psychological well-being and another path to allow the subsequent change score in psychological well-being to be influenced by change scores for personality. Model 4 assumes a reciprocal association whereby changes in personality influence subsequent changes in psychological well-being and changes in psychological well-being influence subsequent changes in personality. The fit of Models 1-
4 can then be compared goodness-of-fit indices to determine the direction of the association between changes in personality traits and changes in psychological well-being.

7.8 Final Conclusions

The aim of this thesis was to improve understanding of individual-level predictors of health and well-being, through integrating and advancing literatures across the social sciences. This aim has been achieved. This thesis provides cross-sectional and longitudinal evidence that an individual’s income relates to their health due to a psychological pathway (represented by income rank). The thesis has contributed to the literature on the association between individual-level income and individual-level health and well-being by extending the role of income rank to a midlife sample, providing an explanation for earlier inconsistent support for a psychosocial influence of income on health, and identifying the precise mechanism through which income relates to health. The thesis has also made important advances in the field of personality research by providing evidence to suggest that personality changes as much as variable economic factors and that personality change is more closely linked to psychological well-being than subjective well-being, thus suggesting personality change is particularly important for existentialism. Furthermore, the thesis introduces new analytical method into personality psychology that allows stronger inferences regarding a causal association between personality traits to be made.
References


Little, J. K. (1958). *A state-wide inquiry into decisions of youth about education beyond high school- follow up studies*. Madison, WI: University of Wisconsin, School of Education.


*Social Science and Medicine, 128*, 316-326.


StataCorp. (2009). Stata Statistical Software: Release 11. College Station, TX: StataCorp LP.


Appendix I: Fit Statistics Comparing Contemporaneous and Lagged Models of the Association between Income-Related Predictors and Health

<table>
<thead>
<tr>
<th></th>
<th>Contemporaneous model</th>
<th>Lagged model</th>
<th>Contemporaneous + Lagged model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BIC</td>
<td>AIC</td>
<td>BIC</td>
</tr>
<tr>
<td><strong>ELSA</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Self-rated health</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual income</td>
<td>32279.26</td>
<td>32056.07</td>
<td>32258</td>
</tr>
<tr>
<td>Yitzhaki Index (age)</td>
<td>32292.48</td>
<td>32069.29</td>
<td>32266.96</td>
</tr>
<tr>
<td>Rank (age)</td>
<td>32283.77</td>
<td>32060.58</td>
<td>32241.31</td>
</tr>
<tr>
<td><strong>Allostatic load</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual income</td>
<td>29340.00</td>
<td>29121.62</td>
<td>29331.74</td>
</tr>
<tr>
<td>Yitzhaki Index (age)</td>
<td>29339.81</td>
<td>29121.42</td>
<td>29331.68</td>
</tr>
<tr>
<td>Rank (age)</td>
<td>29337.89</td>
<td>29119.51</td>
<td>29324.38</td>
</tr>
<tr>
<td><strong>LISS</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Self-rated health</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Actual income</td>
<td>66906.82</td>
<td>66699.74</td>
<td>66911.54</td>
</tr>
<tr>
<td>Yitzhaki Index (age)</td>
<td>66898.19</td>
<td>66691.11</td>
<td>66912.01</td>
</tr>
<tr>
<td>Rank (age)</td>
<td>66864.07</td>
<td>66657.00</td>
<td>66872.05</td>
</tr>
</tbody>
</table>

Note. For each health outcome, the fit of contemporaneous models of the association between each income-related predictor and health and the fit of lagged models of the association between each income-related predictor and health is compared to models predicting health from contemporaneous and lagged actual income-related predictor simultaneously. The best fitting parameter within each model is indicated in bold. N = 12,576 for models of self-rated health in ELSA, N= 10,717 for models of allostatic load in ELSA and N = 29,234 for models of self-rated health in LISS.
Appendix II: Fit Statistics for Competing Models of the Association between Income-Related Predictors and Self-rated Health and Allostatic Load

<table>
<thead>
<tr>
<th></th>
<th>Rank + Actual Income</th>
<th>Rank + Yitzhaki</th>
<th>Rank + Actual Income + Yitzhaki</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BIC</td>
<td>AIC</td>
<td>BIC</td>
</tr>
<tr>
<td><strong>ELSA, self-rated health</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>32194.01</td>
<td>31963.39</td>
<td>32195.89</td>
</tr>
<tr>
<td><strong>ELSA, allostatic load</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>29328.46</td>
<td>29102.79</td>
<td>29346.32</td>
</tr>
<tr>
<td><strong>LISS, self-rated health</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>66864.41</td>
<td>66649.05</td>
<td>66880.46</td>
</tr>
</tbody>
</table>

*Note.* For each health outcome, the fit of the rank model is compared to models predicting health (1) jointly from rank and actual income (2) jointly from Rank and Yitzhaki Index and (3) jointly from rank + actual income + Yitzhaki Index. N = 12,576 for models of self-rated health in ELSA, N = 10,717 for models of allostatic load in ELSA and N = 29,234 for models of self-rated health in LISS. The best fitting of the combinations of the income parameters are indicated in bold.