

**Childhood Psychological Predictors of Unemployment:  
Evidence from Four Cohort Studies**

**by**

**Mark Egan**

Thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy in Behavioural Science

University of Stirling, Department of Economics

October 2016

## **Acknowledgements**

I am extremely grateful to my wife Yukyung for her love and support during the writing of this thesis. It would not have been started without her, let alone completed. I am also very grateful to my supervisors Michael Daly and Liam Delaney for their guidance and intellectual probity over the last three years, to the members of the Stirling Behavioural Science Centre for creating a vibrant and friendly work atmosphere, and to the Economic and Social Research Council and Skills Development Scotland for their generous funding. Lastly, I thank the staff, past and present, of the Centre for Longitudinal Studies and the National Longitudinal Study for providing and curating the data-sets used in this thesis. They are the unsung heroes of social science. This thesis is dedicated to my daughter Esther.

### Note on Inclusion of Published Work

Chapter 1 has been accepted for publication as a chapter in a forthcoming textbook. It will appear as:

Egan, M., Daly, M., & Delaney, L. (forthcoming). Childhood psychological predictors of lifelong economic outcomes. In R. Ranyard (Ed.), *Economic Psychology: The Science of Economic Mental Life and Behaviour*. Wiley/Blackwell.

Chapters 3, 4, 5 and 6 have been published or accepted for publication during the period of the PhD registration. Copyright of these papers resides with the publishers, but under the terms of the copyright they have been reproduced as chapters in this thesis. The published papers are:

Chapter 3: Daly, M., Delaney, L., Egan, M., & Baumeister, R. (2015). Childhood self-control and unemployment throughout the life span: Evidence from two British cohort studies. *Psychological Science*, 26, 709-723. doi:10.1177/0956797615569001

Chapter 4: Egan, M., Daly, M., Delaney, L., Boyce, C., & Wood, A. (accepted for publication). Adolescent conscientiousness predicts lower lifetime unemployment. *Journal of Applied Psychology*.

Chapter 5: Egan, M., Daly, M., & Delaney, L. (2015). Childhood psychological distress and youth unemployment: Evidence from two British cohort studies. *Social Science & Medicine*, 124, 11-17. doi:10.1016/j.socscimed.2014.11.023

Chapter 6: Egan, M., Daly, M., & Delaney, L. (2016). Adolescent psychological distress, unemployment, and the Great Recession: Evidence from the National Longitudinal Study of Youth 1997. *Social Science & Medicine*, 156, 98-105. doi:10.1016/j.socscimed.2016.03.013

## Abstract

Recent research in economics and psychology has examined the childhood noncognitive skills which predict future economic success. However, there has been relatively little research on whether these skills predict future unemployment. This thesis uses data from four cohort studies (total N = 47,328) from Great Britain and the United States to examine how lifetime trajectories of unemployment are affected by childhood differences in self-control (chapter 3), conscientiousness (4), and mental health (5-6). These are some of the first studies to examine how pre-labor market measures of these psychological characteristics prospectively predict future unemployment. Chapters 3, 5 and 6 are the first studies to examine how early psychological characteristics interact with recessions to produce differential unemployment outcomes.

After adjusting for cognitive ability and key sociodemographic indicators (e.g. gender, SES), all three of these psychological characteristics are found to predict future unemployment. The effects are statistically significant and economically meaningful, comparable in magnitude to the effects of intelligence. Chapter 3 shows that childhood with poor self-control were disproportionately more likely than their more self-controlled peers to become unemployed during the 1980s UK recession, and chapters 5 and 6 find a similar effect for children with high psychological distress compared to their less distressed peers during the 1980s UK recession and 2007 US recession.

These studies demonstrate the value of using psychological research to examine economic outcomes. The chief policy implication is that interventions which improve childhood levels of self-control, conscientiousness and mental health may be an effective way to reduce future population unemployment levels. In the short term, remediation programs which take into account individual psychological differences may improve the efficacy of

unemployment interventions, particularly during recessions when certain groups are more likely than others to become unemployed.

## Table of Contents

<b>1. Childhood Psychological Predictors of Lifelong Economic Outcomes .....</b>	<b>1</b>
1.1 Introduction .....	1
1.2 Literature Review .....	3
1.2.1 Overview .....	3
1.2.2 Cognitive Skills.....	4
1.2.3 Noncognitive Skills.....	7
1.3 Lifecourse Perspectives .....	15
1.4 Methodological Challenges .....	18
1.5 Policy Implications.....	21
1.6 Concluding Remarks .....	23
<b>2. Overview of Thesis, Datasets and Methodology.....</b>	<b>24</b>
2.1 Thesis .....	24
2.2 Datasets .....	29
2.3 Methodology .....	32
<b>3. Childhood Self-Control and Unemployment Throughout the Life Span: Evidence From Two British Cohort Studies .....</b>	<b>36</b>
3.1 Abstract .....	36
3.2 Introduction .....	37
3.3 Study 1 Method .....	40
3.4 Study 1 Results.....	48
3.5 Study 2 Method .....	53
3.6 Study 2 Results .....	61
3.7 Discussion .....	70
3.8 Appendix .....	75
<b>4. Adolescent Conscientiousness Predicts Lower Lifetime Unemployment .....</b>	<b>99</b>
4.1 Abstract .....	99
4.2 Introduction .....	100
4.3 Data and Method .....	104
4.4 Results .....	111
4.5 Discussion .....	122
4.6 Appendix .....	126
<b>5. Childhood Psychological Distress and Youth Unemployment: Evidence from Two British Cohort Studies .....</b>	<b>134</b>

5.1 Abstract .....	134
5.2 Introduction .....	135
5.3 Study 1 Method .....	136
5.4 Study 1 Results .....	140
5.5 Study 2 Method .....	143
5.6 Study 2 Results .....	147
5.7 Discussion .....	152
5.8 Appendix .....	155
<b>6. Adolescent Psychological Distress, Unemployment, and the Great Recession: Evidence from the National Longitudinal Study of Youth 1997 .....</b>	<b>179</b>
6.1 Abstract .....	179
6.2 Introduction .....	180
6.3 Data and Method .....	183
6.4 Results .....	190
6.5 Discussion .....	198
6.6 Appendix .....	203
<b>7. Discussion.....</b>	<b>223</b>
7.1 Summary .....	223
7.2 Strengths and Limitations.....	225
7.3 Policy Implications.....	230
7.4 Future Research.....	236
<b>8. References.....</b>	<b>241</b>

## List of Tables

3.1. Descriptive statistics for Study 1 (British Cohort Study): Characteristics of participants at each assessment wave and of participants with lifetime unemployment data.....	45
3.2. Regression results from Study 1 (British Cohort Study): Predicting probability of unemployment at each assessment wave and duration of lifetime unemployment.....	50
3.3. Descriptive statistics for Study 2 (National Child Development Study): Characteristics of participants at each assessment wave and of participants with lifetime unemployment data..	58
3.4. Regression results from Study 2 (National Child Development Study): Predicting probability of unemployment at each assessment wave and duration of lifetime unemployment.....	63
3.5. Regression results from Study 2 (National Child Development Study): The effect of childhood self-control on the probability of unemployment before and after the 1980s recession.....	67
S3.1. Correlation matrix comparing the self-control scales used in Study 1 and Study 2 to the Brief Self-Control Scale (BSCS), the Domain-Specific Impulsivity Scale (DSIS) and Peer and Emotional Problems subscales of the Strengths & Difficulties Questionnaire (SDQ)....	86
S3.2. Conduct problems and hyperactivity in Study 1 and Study 2.....	88
S3.3. Unemployment regressions in Study 1 controlling for childhood conduct problems and hyperactivity.....	90
S3.4. Unemployment regressions in Study 2 controlling for childhood conduct problems and hyperactivity.....	92
S3.5. Unemployment regressions in Study 2 controlling for an extended range of childhood background characteristics.....	95
S3.6. Unemployment regressions for the British Cohort Study (Study 1) and National Child Development Study (Study 2), controlling for prior unemployment.....	98
4.1. Descriptive statistics and correlation matrix for key variables.....	113
4.2. Probit regressions predicting average probability of unemployment from January 1986 to April 2009.....	117
4.3. OLS Regressions Predicting the Effect of Conscientiousness on Academic Motivation and Educational Attainment.....	120
4.4. Decomposition of total effect of conscientiousness on unemployment through academic motivation and education.....	121
S4.1. Probit regression predicting the average probability of unemployment from 1986 to 2008, controlling for childhood self-control.....	127
S4.2. Probit Regression predicting the average probability of unemployment from 1986 to 2008 using different levels of imputation.....	128
S4.3. Negative Binomial regression predicting the total months of unemployment from 1986 to 2008.....	131
S4.4. Negative Binomial regression predicting the number of spells of unemployment from 1986 to 2008.....	132
S4.5. Negative Binomial regression predicting the length of unemployment spells among those who experienced at least one spell of unemployment from 1986 to 2008.....	133



5.1. Regression of unemployment between ages 16 and 21 on childhood psychological distress in the LSYPE sample (N=10,232) .....	141
5.2. Regression of unemployment between ages 16 and 23 on childhood psychological distress in the NCDS sample (N=8,985).....	149
S5.1. Descriptive statistics in the LSYPE by levels of childhood distress.....	161
S5.2. Descriptive statistics in the NCDS sample by levels of childhood distress.....	162
S5.3. Regression of unemployment on standardized childhood psychological distress between ages 16 and 21 in the LSYPE sample (N=10,232).....	164
S5.4. Regression of unemployment on standardized childhood psychological distress between ages 16 and 23 in the NCDS sample (N=8,985).....	165
S5.5. Regression of unemployment between ages 16 to 21 on childhood psychological distress in the LSYPE sample with extended controls (N=10,232).....	166
S5.6. Regression of unemployment on childhood psychological distress between ages 16 and 23 in the NCDS sample with extended controls (N=8,985).....	171
S5.7. Regression of unemployment (excluding those of inactive status in cols. 1-4, including inactives in col. 5) on childhood psychological distress between ages 16 and 21 in the LSYPE sample .....	175
S5.8. Regression of unemployment on childhood psychological distress interacting with the 1980 economic recession in the NCDS sample (N=8,985).....	177
6.1. Descriptive statistics of the National Longitudinal Study of Youth 1997 .....	191
S6.1. List of Mental Health Inventory item scores measured in 2000 (N = 7,125).....	204
S6.2. Regressions examining the association between mental health in 2000 and three labor market outcomes over 2000-11 (i) probability of unemployment (ii) probability of unemployment + being out of the labor force (UOLF) (iii) total number of weeks unemployed.....	212
S6.3. Regressions restricted to the sibling sample examining the association between mental health in 2000 and three labor market outcomes over 2000-11 (i) probability of unemployment (ii) probability of unemployment + being out of the labor force (UOLF) (iii) total number of weeks unemployed.....	214
S6.4. Difference-in-difference estimates describing the probability of unemployment and UOLF in 2006-08 (pre-recession) and 2009-11 (post-recession) by levels of distress as measured in 2000.....	216
S6.5. Regressions stratified by gender examining the association between mental health in 2000 and three labor market outcomes over 2000-11 (i) probability of unemployment (ii) probability of unemployment + being out of the labor force (UOLF) (iii) total number of weeks unemployed.....	219
S6.6a. Regressions stratified by educational attainment examining the association between having mental health in 2000 and probability of unemployment over 2000-11.....	220

S6.6b. Regressions stratified by educational attainment examining the association between having mental health in 2000 and probability of unemployment + being out of the labor force (UOLF) over 2000-11.....	221
S6.6c. Regressions stratified by educational attainment examining the association between having mental health in 2000 and total number of weeks unemployed over 2000-11.....	222

## List of Figures

3.1: Results from Study 1: (a) predicted probability of unemployment at each wave as a function of childhood self-control and (b) predicted marginal total number of months of unemployment as a function of childhood self-control.....	52
3.2: Results from Study 2 (National Child Development Study): (a) predicted probability of unemployment at each wave as a function of childhood self-control and (b) predicted marginal total number of months of unemployment as a function of childhood self-control..	65
3.3: Descriptive unemployment statistics from Study 2 (National Child Development Study).....	68
3.4: Results from Study 2 (National Child Development Study): predicted marginal probability of unemployment before and after the 1980 recession, for participants at three levels of childhood self-control.....	69
4.1. Unemployment over time by levels of adolescent conscientiousness.....	114
5.1: Predictive margins with 95% CIs showing (A) predicted probability of unemployment across all months surveyed (B) predicted total number of months unemployed, for different levels of childhood distress in the Longitudinal Study of Young People in England (Study 1) and National Child Development Study (Study 2).....	142
5.2: Descriptive statistics describing unemployment in the NCDS from August 1974 – November 1981 by levels of childhood distress.....	151
S5.1: Distribution of GHQ12 scores in Study 1 and the codings used to generate the categorical distress variable used in the main analysis.....	157
S5.2: Distribution of distress scores in Study 2 and the codings used to generate the categorical distress variable used in the main regression analysis.....	159
S5.3: Predictive margins with 95% CIs examining the probability of unemployment in Study 2 for different levels of distress in the pre- (June 1974 – December 1979) and post-recession (January 1980 – February 1982) period.....	178
6.1. Descriptive statistics (unweighted) showing the labor force status of the cohort members over 2000-11 (N = 7125) by the level of psychological distress measured in 2000.....	193
6.2. Predicted effects with 95% confidence intervals of high distress, 1 standard deviation (SD) decrease in intelligence, and physical health problems (Phys. health) on the (a) probability of unemployment (b) probability of being unemployed or out of the labor force (UOLF), and (c) the number of weeks spent unemployed.....	195
6.3. Predicted probabilities with 95% confidence intervals of (a) unemployment and (b) unemployment or out of the labor force (UOLF) by levels of psychological distress.....	197

## CHAPTER 1

### Childhood Psychological Predictors of Lifelong Economic Outcomes

#### 1.1 Introduction

Which psychological characteristics help children become economically successful adults? This is a question of interest to parents, governments and academics all over the world. Parents invest time, energy and money into raising their children, partly with the goal of fostering qualities which will help them succeed in life. Governments structure health and education policies to help children maximize their potential, and academics study the factors in childhood which lead to success in school and the labour market.

In this chapter we summarize the results of a large body of research from economics and psychology examining childhood psychological predictors of adult economic outcomes. We follow recent economics literature by classifying these predictors into cognitive and noncognitive skills<sup>1</sup> and we focus on the two broad domains of school and work since these encompass the principal individual-level indicators of economic success (e.g. employment, earnings, educational attainment). The principal studies we draw on are based on longitudinal studies which use information on people's childhood psychological characteristics to prospectively predict their later educational and labour market outcomes. Where possible we cite literature reviews and meta-analyses which provide the strongest available evidence by aggregating the results of many studies.

---

<sup>1</sup> We use the term 'noncognitive skills' to maintain consistency with prior literature. However, there is considerable debate about whether this term is appropriate for categorizing such a diverse collection of psychological differences, or even whether these differences reflect deeper underlying preferences rather than skills per se.

Economists have long recognized the importance of cognitive ability as a determinant of economic success. Since the turn of the millennium however, researchers in economics and psychology have become increasingly interested in the role of noncognitive skills in shaping economic outcomes. Noncognitive skills, also called soft skills, socioemotional skills and character, refer to relatively stable individual differences in psychological characteristics which are not captured by conventional tests of cognitive ability but which contribute to economic success. They include personality traits, attitudes and abilities, such as self-control, interpersonal skills, motivation, conscientiousness, agreeableness, locus of control, and many others. Growing evidence linking these psychological differences to educational and labour market success has led some economists to consider noncognitive skills to be as important as cognitive skills in predicting economic outcomes, if not more so (e.g. Heckman, Stixrud, & Urzua, 2006).

The rest of this chapter is structured as follows. Using the framework of cognitive and noncognitive skills, we summarize the empirical evidence on some of the main childhood psychological differences which predict success in school and work. We examine how this evidence has been incorporated into an economic model of lifespan development and review the main methodological challenges of the field. Finally we discuss the policy implications of this stream of research and make concluding remarks.

## 1.2 Literature Review

### 1.2.1 Overview

Two major methodological developments in the 20<sup>th</sup> century laid the foundations for the scientific study of childhood psychological differences and adult outcomes. The first was the development of reliable psychometric tools to quantify individual psychological differences, beginning with the creation of the modern IQ test in 1905. Hundreds of more sophisticated intelligence tests were later developed, notably the Stanford-Binet scale, the Wechsler Adult Intelligence Scale and Raven's Progressive Matrices. As theories of personality and psychometric measurement developed throughout the century, psychologists produced a diverse array of scales to measure psychological differences not captured by intelligence tests, including the International Personality Item Pool, NEO Five-Factor Inventory, Brief Self-Control Scale, Rotter Locus of Control Scale and General Health Questionnaire. The second methodological development was the establishment, principally in Britain and the United States, of prospective longitudinal studies following hundreds or thousands of participants over the course of their lives<sup>2</sup>. Many of these studies have followed their participants from birth and include information on their background and childhood psychological characteristics as well as later educational and labour market outcomes.

Because of these methodological advances, modern researchers can draw on a rich set of measurement tools across many different studies to examine how individual psychological differences in childhood predict economic outcomes occurring years or even decades later.

---

<sup>2</sup> The UK Data Service website (<http://ukdataservice.ac.uk/>) contains examples of such studies. It hosts, among others, the National Child Development Study (cohort members born 1958), the British Cohort Study (1970), the Longitudinal Study of Young People in England (1989/90) and the Millennium Cohort Study (2000).

Using the framework of cognitive and noncognitive skills, we now examine the predictive power of some of these differences in forecasting future economic success.

### ***1.2.2 Cognitive skills***

Cognitive skills refer to the subcomponents of intelligence, which is “*a very general capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience. It is not merely book learning, a narrow academic skill, or test-taking smarts. Rather, it reflects a broader and deeper capability for comprehending our surroundings—‘catching on’, ‘making sense’ of things, or ‘figuring out’ what to do.*” (Gottfredson, 1997, p. 13). One influential model of intelligence, based on an analysis of over 400 data-sets of cognitive ability test scores, conceives of a three-stratum hierarchy that includes general intelligence (also known as ‘g’) at the top, broad domains at the second level such as processing speed, fluid and crystallized intelligence, general memory and learning, and narrow specific abilities at the bottom level such as mathematical and lexical knowledge, reading speed and comprehension, listening and communication ability, working memory capacity and many others (Carroll, 1993).

Intelligence has been a lauded trait in human society since antiquity and has obvious implications for economic success. Individuals with better reasoning skills, memory and decision-making capabilities are more likely to perform well in school, gain entry into more competitive universities, and enter cognitively demanding professions which typically provide higher remuneration. Furthermore, a robust finding from many studies is that intelligence is relatively stable over time. Children who score highly on intelligence tests (termed their IQ scores) tend to score highly as adults; an illustrative example is a study of 106 Scottish adults which found that their intelligence scores at age 11 correlated moderately

high ( $r = 0.54$ , rising to  $0.67$  when correcting for range restriction) with their scores on the same test at age 90 (Deary, Pattie, & Starr, 2013). Highly intelligent children are therefore likely to become intelligent adults and continue to benefit from their greater mental faculties over time.

Although history contains many examples of child prodigies whose remarkable cognitive abilities attracted much attention, the effects of high childhood intelligence on later life outcomes were not systematically studied until the 1920s, when the American psychologist Lewis Terman began to track the life outcomes of 1,528 high-IQ children in California (Terman, 1925). Terman found that by mid-life the study participants were earning twice as much as the average white-collar worker, were substantially more educated than the average American and, contrary to contemporary expectations that high intelligence would be compensated for by a deficiency in other areas (e.g. by having poor health or limited social skills), were on average as healthy and well-adjusted as the general population (Terman, 1959).

More recent studies have examined the predictive power of childhood intelligence using larger and more representative samples. A study of 70,000 English children found that higher intelligence at age 11 predicted better performance at age 16 on national examination tests in all 25 subjects examined. For those scoring a standard deviation above (below) the mean intelligence score, 91% (16%) achieved the criterion of five or more GSCEs<sup>3</sup> at grades A-C (Deary, Strand, Smith, & Fernandes, 2007). Upon leaving education and entering the labour market, high IQ children have also been found to be more likely to avoid unemployment (Caspi, Wright, Moffitt, & Silva, 1998), become managers as opposed to

---

<sup>3</sup> GSCE stands for General Certificate of Secondary Education. GSCE qualifications are awarded to British adolescents who complete examinations at the end of their compulsory period of education.



employees (Daly, Egan, & O'Reilly, 2015), advance more quickly in their careers (Cheng & Furnham, 2012) and experience more positive social mobility (Deary et al., 2005). Lastly, a meta-analysis of studies comparing intelligence scores elicited before age 19 with socioeconomic success after age 29 found that, on average, higher cognitive ability correlated positively with better educational attainment ( $r = 0.56$ ,  $N = 20$  studies), occupational status ( $r = 0.45$ ,  $N = 21$ ) and income ( $r = 0.23$ ,  $N = 15$ ) (Strenze, 2007).

In summary, there is strong evidence that higher cognitive ability in childhood contributes substantially to later educational attainment and success in the labour force. However, while intelligence is advantageous in these areas, it is not a guarantee of success. As noted by Heckman and Rubinstein (2001), "*numerous instances can be cited of people with high IQs who fail to achieve success in life because they lacked self-discipline and of people with low IQs who succeeded by virtue of persistence, reliability and self-discipline*" (p. 145). Kuhn and Weinberger (2005) cite practical evidence of the demand for skills other than cognitive ability in the labour market; a nationwide survey of American employers found that their five most valued qualities in employees were, in descending order of importance, communication skills, motivation/initiative, teamwork skills, leadership and academic achievement. The first four of these are noncognitive skills, suggesting these abilities play an important role in determining labour market success. Finally, empirical evidence suggesting a relative parity of importance of noncognitive and cognitive skills comes from two analyses of Swedish data which used skill measures elicited during mandatory military enlistment at age 18-19 to predict future earnings. Lindqvist and Vestman's (2011) analysis of almost 15,000 men found that a 1 standard deviation increase in cognitive and noncognitive skills predicted 8.9% and 6.9% higher earnings respectively; Lundborg, Nilsson, and Rooth's (2014) analysis of over 275,000 male siblings found respective increases of 11% and 7.7%.

### ***1.2.3. Noncognitive skills***

While there is disagreement on the definition of noncognitive skills, the term is generally used “*to contrast a variety of behaviours, personality characteristics, and attitudes with academic skills, aptitudes, and attainment*” (Gutman & Schoon, 2013, p. 7). Noncognitive skills encompass a much broader spectrum of psychological differences than cognitive skills. They include relatively stable personality traits (i.e. one’s characteristic patterns of thoughts, feelings, and behaviors) such as conscientiousness and self-control, more flexible constructs such as motivation and expectations, metacognitive strategies such as setting goals and being aware of one’s strengths and weaknesses, and socioemotional skills such as social awareness and empathy. The importance of these abilities may seem unsurprising: a person who is thorough, hard-working, goal-oriented, motivated and has high expectations of what they can achieve should perform better in school and work than someone of equal cognitive ability who lacks these traits. However, the empirical evidence on their predictive power for socioeconomic outcomes has been neglected in the economics literature until relatively recently.

The economist James Heckman has produced an influential set of studies analysing the long-run effects of the Michigan-based Perry Preschool Program which demonstrate the importance of noncognitive skills in childhood for future labour market success. Heckman, Moon, Pinto, Savelyev, and Yavitz (2010) found that disadvantaged young children who were randomly assigned to receive daily preschool achieved higher rates of high school graduation, higher earnings and greater rates of home ownership in adulthood than a comparable group of children who did not attend the preschool program. These effects operated through an improvement in academic motivation and a reduction in externalizing behaviour (Heckman, Pinto, & Savelyev, 2013). An important caveat of this study is that it used a small sample and had an unusually large effect size, making its scalability unclear.

Moreover, the short-run impact of such interventions is more mixed; a meta-analysis of 84 American pre-school programs spanning five decades found that their average effect on cognitive and achievement scores, as measured at the end of the intervention period, varied substantially and that larger studies tended to have smaller effect sizes (Duncan & Magnuson, 2013)<sup>4</sup>.

We now describe the childhood noncognitive skills which are most predictive of educational and labour market outcomes<sup>5</sup>. Adapting the classification schemes of recent literature reviews on the predictive power of childhood noncognitive skills by Gutman and Schoon (2013) and Goodman, Joshi, Nasim, and Tyler (2015), we focus on six areas, some of which overlap with each other: 1. Self-control, 2. Self-perception, 3. Socioemotional skills, 4. Motivation, 5. Mental health, and 6. Metacognitive strategies.

### *Self-control*

Self-control, also known as willpower, self-discipline and self-regulation, refers to an individual's "*capacity for altering one's own responses, especially to bring them into line with standards such as ideals, values, morals, and social expectations, and to support the pursuit of long-term goals*" (Baumeister, Vohs, & Tice, 2007, p. 351). The ability to resist

---

<sup>4</sup> That meta-analysis also found that average effect sizes have declined over time; programs beginning before 1980 had effect sizes twice as large as those that began afterwards. The authors suggest that one plausible explanation for this is that counterfactual conditions in the past were of a lower quality (i.e. children in control groups in the 1960s and '70s may have lived in relatively more deprived circumstances, so the effects of older interventions would have been relatively larger).

<sup>5</sup> Due to space limitations, our review is not exhaustive; for example we omit evidence on achievement striving, grit, and creativity. See Table 1 of Heckman & Kautz (2013) for a complete list of noncognitive skills, categorized using the taxonomy of the Big Five personality traits.

impulsive desires in favour of higher order goals has potentially wide-ranging benefits: a recent meta-analysis of the literature argued that “*high self-control is relevant to nearly all forms of behavior conducive to a successful and healthy life. Conversely, low self-control is assumed to be at the heart of many societal problems, including obesity, substance abuse, criminality, impulsive buying, and procrastination*” (de Ridder, Lensvelt-Mulders, Finkenauer, Stok, & Baumeister, 2012, p. 76).

The value of self-control in children was demonstrated by Walter Mischel and colleagues in the early 1970s in a series of seminal delay-of-gratification experiments collectively known as the “Marshmallow Tests”. Four-year-old children were offered a single marshmallow immediately or two marshmallows if they could wait fifteen minutes. Children who were able to wait longer had higher SAT<sup>6</sup> scores a decade later (Shoda, Mischel, & Peake, 1990) and were less impulsive on behavioural tasks 40 years later (Casey et al., 2011). A later longitudinal study of 140 American high school students by Duckworth and Seligman (2005) supported the idea that self-control matters for academic achievement, finding that an aggregated measure of several self-control indicators outperformed IQ in predicting end-of-year grades. Larger studies using parent- and teacher-rated self-control measures drawn from nationally representative samples from New Zealand and Great Britain have also found striking long-run benefits of good self-control in childhood, including higher income, better financial planfulness and socioeconomic status (Moffitt et al., 2011) and lower unemployment (Daly, Delaney, Egan, & Baumeister, 2015). Notably, the predictive strength of self-control was comparable to cognitive ability in both these studies. Lastly, self-control is thought to be a key antecedent of the personality trait conscientiousness (Eisenberg, Duckworth, Spinrad, & Valiente, 2014), which is the tendency to be organized, responsible

---

<sup>6</sup> SAT stands for the Scholastic Aptitude Test, a standardized test used for college admissions in the United States.

and hardworking. Of the ‘Big Five’ personality traits (openness, conscientiousness, extraversion, agreeableness, neuroticism), a recent overview of the personality literature concluded that conscientiousness is the trait most predictive of positive outcomes in a wide variety of domains including educational attainment, job performance and earnings (Almlund, Duckworth, Heckman, & Kautz, 2011).

A related concept to low self-control in economics is ‘impatience’, used to denote individuals who prefer rewards sooner rather than later in time preference questions (e.g. preferring £100 now rather than £300 in one year)<sup>7</sup>. While only a small number of studies have examined childhood impatience and later economic outcomes, their results accord with the self-control literature in psychology. For example, a Swedish longitudinal study of almost twelve thousand individuals found that more impatient choices on a time preference measure at age 13 predicted worse school performance, lower labour supply and reduced lifetime income (Golsteyn, Grönqvist, & Lindahl, 2014). Taken together, these results suggest that children who are self-controlled, conscientious and future oriented are much more likely to perform well in school and the labour market.

### *Self-Perception*

A child’s beliefs about the effect of their actions, operationalised in this section by locus of control and self-efficacy, are potentially very important in that they may become

---

<sup>7</sup> The relationship between “impatience” in economics and low “self-control” in psychology is often misunderstood. An individual who chose £100 now might be classified by economists as being impatient or having a high discount rate. This choice would not necessarily be indicative of poor self-control if it reflected the respondent’s preferences; it would however be a self-control failure if the individual wanted the higher, more temporally distant sum but contravened this higher order goal by succumbing to the temptation of receiving the immediate sum.

self-fulfilling. For example, a student who believes there are no returns to studying is unlikely to study very hard.

Locus of control is the extent to which individuals believe that they can control events around them. A person who believes in their own ability to effect change is characterised as having an 'internal' locus of control, as opposed to someone with an 'external' locus of control who believes that luck or fate play a larger role in determining their life outcomes. An example is a child with an external locus of control who attributes their poor test scores to the difficulty of the test rather than their own efforts. Self-efficacy measures the strength of an individual's belief in their own ability to complete tasks and meet their goals. Research examining self-efficacy in children has typically focused on academic achievement as an outcome. Self-efficacy in this context can include both a student's belief in their innate ability to perform well in a given subject, as well as their ability to organize their own learning activities and goals in order to maximize their academic performance.

A meta-analysis of 98 studies involving students from primary to university level found that, on average, greater internal locus of control correlated modestly with better academic performance ( $r = 0.18$ ), and this effect was stronger for adolescents than children (Findley & Cooper, 1983). Similarly, there is strong evidence linking high self-efficacy to better academic outcomes: a meta-analysis of studies published between 1977 and 1988 found that higher self-efficacy correlated with greater persistence on academic tasks ( $r = 0.34$ ,  $N = 18$  studies) and better academic performance ( $r = 0.38$ ,  $N = 38$ ) (Multon, Brown, & Lent, 1991).

### *Socioemotional skills*

Although the term socioemotional skills is sometimes used interchangeably with noncognitive skills, it specifically refers to the ability to understand and manage emotions, set

and achieve goals, feel and show empathy for others, hold positive relationships and make responsible decisions (CASEL, 2015). Aside from promoting greater wellbeing for the child, these skills should provide a better foundation for academic engagement by improving classroom behaviour, reducing conduct problems and increasing the motivation to learn.

Durlak, Weissberg, Dymnicki, Taylor, and Schellinger (2011) conducted a meta-analysis of 213 school-based socio-emotional learning (SEL) programs covering 270,034 students ranging from age 5 to 18. Compared to children in control groups who did not receive such training, SEL program participants had significantly more positive attitudes, fewer conduct problems and better emotional wellbeing, effects which persisted even among the 33 studies with follow up periods longer than 6 months. The SEL programs were effective when delivered by teachers or non-school personnel, across elementary, middle and high schools and in urban, suburban and rural environments. These improvements in psychological functioning also translated into an 11 percentile-point improvement in academic performance among the 35 studies which measured this outcome. While these effects represent impressive evidence of the value of SEL training, to date there remains much less evidence on whether such programs also improve children's future labour market performance.

### *Motivation*

Different levels of motivation are a plausible explanation for differences in performance since motivation may act as a spur to increased focus and effort. Although there are many theories of motivation (Eccles & Wigfield, 2002), we focus here on intrinsic motivation. A person who is intrinsically motivated performs an activity because they enjoy it for its own sake rather than for instrumental reasons, such as the prospect of a reward. Intrinsic motivation in students is typically measured by asking them to rate to what extent

they agree with statements such as “I experience pleasure and satisfaction while learning new things”. A meta-analysis of 10 studies including over 4,000 students by Taylor et al. (2014) found that children who were more intrinsically motivated performed better in school. The authors also conducted a longitudinal study of 319 Canadian high school students which found that higher intrinsic motivation predicted better grades one year later even after taking into account baseline grades.

One gap in this literature identified by Goodman et al. (2015) is that there are no studies examining whether childhood intrinsic motivation predicts long-term economic outcomes in adulthood. Instead, Goodman et al. (2015) review studies showing that participants in both the British Cohort Study and National Child Development Study who were more academically motivated at age 16 (measured by items such as “I feel that school is largely a waste of time”<sup>8</sup>) were more likely to stay in education longer and have better qualifications by age 42.

### *Mental health*

Although mental health does not fit neatly under the heading of noncognitive ‘skills’, it is an important psychological characteristic which varies across individuals and has a large impact on socioeconomic prospects. Children and adolescents who experience severe anxiety and depression have been found to be substantially more likely to perform worse in school, experience higher rates of youth unemployment and have 28% lower family incomes by age 50 (Fletcher, 2010; Goodman, Joyce, & Smith, 2011; Egan, Daly, & Delaney, 2015). Additionally, Smith and Smith (2010) used data from the American Panel Study of Income Dynamics (PSID) to show that siblings who recalled as adults having had childhood

---

<sup>8</sup> Higher ratings on this question would measure greater amotivation. In order to measure greater academic motivation this item would be reverse scored.



psychological problems had worse educational attainment and 20% lower family incomes than their siblings who did not recall such problems. Based on those data, the authors estimated the lifetime economic costs of childhood distress to be over \$2 trillion in the United States alone.

Perhaps surprisingly, given the relatively greater attention given to physical health compared to mental health in most Western societies, a recent literature review concluded that poor mental health in early life has a far larger negative impact than poor physical health on long-run economic outcomes (Delaney & Smith, 2012). These large but hitherto relatively neglected effects have led the noted labour economist Richard Layard to dub mental health a “new frontier for labour economics”, one requiring greater study and attention from policymakers (Layard, 2013). One area requiring further study is the need to identify the relative economic penalties of the range of possible mental health conditions, such as depression and anxiety, ADHD, conduct and personality disorders, alcoholism and drug dependence (Currie & Stabile, 2009; Lundborg, Nilsson, & Rooth, 2014).

### *Metacognitive strategies*

Metacognitive strategies are goal-oriented efforts to influence one’s own learning behaviours and processes by focusing awareness on thinking and selecting, monitoring, and planning strategies that are most conducive to learning. In other words, these strategies encourage “thinking about thinking”. Teaching these skills to children encourages them to proactively understand the processes that help them learn, rather than being passive agents waiting to receive information. The tools used to teach these strategies in the classroom can include checklists which encourage self-monitoring on tasks, reserving class time for thinking aloud approaches to problems, and after completing a task, evaluating the learning experience and identifying ways to improve.

Gutman and Schoon (2013) cite four meta-analyses covering 148 studies examining the efficacy of school-based interventions which teach metacognitive strategies. Those meta-analyses unanimously conclude that teaching children these strategies improves academic performance in a meaningful way across a wide variety of subjects, from elementary school to university level. However, it is still unclear to what extent these improvements persist in the long-term, and whether they transfer to non-academic domains such as the labour market.

### **1.3 Lifecourse Perspective**

The previous section summarizes research showing that childhood cognitive and noncognitive skills matter for educational and labour market success. One challenge for researchers is the need to synthesize this body of research in order to address the deeper questions arising from this literature. Why do children have different levels of cognitive and noncognitive abilities in the first place? Which factors encourage or inhibit the development of these skills over time? How malleable are these skills during childhood and adolescence?

The main framework in Economics to examine the development of economically-relevant psychological differences has been developed by Heckman and colleagues over the last decade. Cunha and Heckman (2007) describe a lifecourse model of skill development which presents a framework for understanding how cognitive and noncognitive skills develop in children. The model posits that children are born with a set of traits determined by their inherited genes and the prenatal environment. Throughout childhood and into adolescence, their development is influenced by their parents, schools, the broader environment, their health and their own efforts. Parents who are more nurturing, attentive and effective supervisors of their children will causally affect their child's skills in a positive way, as will schools which provide a safe and enriching learning environment. Children with good physical and mental health will miss fewer school days, and children with good self-control

and who are academically motivated will learn more in school. Thus the model predicts that important life outcomes will be shaped by the combined influence of a child's cognitive and noncognitive skills as well as their broader environment.

Two important characteristics of this model are self-productivity and dynamic complementarity. Self-productivity means that the process of skill formation at one stage (e.g. adolescence) depends on the skills acquired at a previous stage (e.g. childhood). For example, a child with high levels of concentration, motivation and well developed socioemotional skills will be more likely to engage productively with their school environment, and this engagement should help them grow into an adolescent with good cognitive and noncognitive ability. Cognitive and noncognitive skills may therefore dynamically interact to shape subsequent skill development; a concept summarized with the phrase "skills beget skills". Dynamic complementarity means that skills produced at one stage raise the productivity of future investments. Imagine an intervention which successfully improves the academic motivation and socioemotional skills of a group of five year olds. Suppose these gains compound over time by improving the children's engagement with their schooling and increasing their ambition to attend university. By age 18 the children have developed a larger stock of cognitive and noncognitive skills. Subsequent interventions which encourage school-leavers to proceed to tertiary education (e.g. via grants or access programs) may now be more effective than if they had targeted less able and motivated young people who did not benefit from the original intervention. As is suggested by this example, an implied feature of dynamic complementarity is that early investments should be followed up with later investments in order for the initial investment to be maximally productive.

The dynamic nature of skill development is constrained by the existence of sensitive and critical periods for investment. Investments are relatively more productive during sensitive periods. Critical periods refer to timeframes within which investments must be

made if they are to be successful; during any other period, they will not be effective.

Heckman (2008) cites the examples that “*if a second language is learned before age 12, the child speaks it without an accent (sensitive period)... a child born with a cataract on the eye will be blind for life if the cataract is not removed within the first year of life (critical period)*” (p. 17). The existence of sensitive and critical periods for skill development is borne out by extensive research demonstrating greater plasticity in early life for the development of social skills in humans and animals, followed by decreasing plasticity with age (see Knudsen, Heckman, Cameron, & Shonkoff, 2006).

There is some evidence suggesting that a critical period for the development of cognitive skills is before the age of 3. One notable study by O'Connor, Rutter, Beckett, Keaveney & Kreppner (2000) examined Romanian infants raised in extremely deprived orphanage environments who were adopted by families in the United Kingdom. Children raised in these environments had severely impaired social and cognitive development and high sensitivity to stress. Because many of the 165 children examined were adopted at different ages, they experienced different amounts of exposure to the orphanage environment. On average, children who spent more time in the orphanage before being adopted had worse cognitive performance than children who were adopted before the age of six months. Similarly, the Abecedarian Project in North Carolina provided intensive preschool and parental support to a selected number of 111 disadvantaged children. The effects of the intervention were similar to the Perry Preschool Program; the children who attended the preschool performed better in school, and had higher rates of high school and college graduation (Campbell et al., 2002). Unlike the Perry Preschool Program, the children who received the treatment from a very early age (4 months) had lasting IQ improvements. However, both these results must be interpreted with the proviso that they used relatively

small samples, and the evidence-base supporting the malleability of early-life IQ is still relatively limited.

Noncognitive skills appear to be much more malleable than cognitive skills. This is suggested by comparisons of test-retest rank-order stability estimates, which show that while IQ reaches terminal stability at age six to eight, personality does not reach comparable stability until at least age 50 (Almlund, Duckworth, Heckman, & Kautz, 2011), and by Heckman and Kautz's (2013) review of 25 interventions targeted from pre-school age to young adulthood which finds that many improve long-run outcomes by improving noncognitive skills, whereas only very early interventions improve IQ in a lasting way. As children grow into adolescents and become more entrenched in their habits and preferences, it becomes relatively more difficult to improve noncognitive skills and there is less potential for self-productivity (e.g. improving academic motivation at age 18 does not have the same potential for positive knock-on effects as intervening at age 5). This pattern of evidence suggests a decreasing gradient of sensitivity for investment as children grow older, implying that interventions to improve noncognitive skills should begin very early in life in order to be maximally effective.

#### **1.4 Methodological Challenges**

The main strength of this field has been its use of randomized trials and observational longitudinal studies to link childhood psychological differences with socioeconomic outcomes occurring years or decades later. Using variables elicited in childhood to predict future outcomes also allows researchers to avoid issues of reverse causality, which may occur when examining psychological measures and economic outcomes elicited simultaneously in adulthood (e.g. does unemployment cause poor mental health, vice versa, or do they mutually influence each other?). However, there remain significant methodological challenges for

future researchers to address, some of which are inseparable from the use of these longitudinal studies.

Firstly, the research cited in this chapter overwhelmingly relies on data from Great Britain and the United States. This reflects the reality that very few countries invest in and make high-quality longitudinal data-sets available to researchers. Nonetheless it exacerbates a problem common across the social sciences of relying on samples from “Western, educated, industrialized, rich, democratic countries” (called the ‘WEIRD’ problem by Henrich, Heine, & Norenzayan, 2010). Given that identifying the skills which help children grow into economically successful adults is a research topic with global relevance, it is essential to develop a wider evidence base in order to expand the relevance of these findings to different countries and cultures.

The second issue is measurement error. Because noncognitive skills are usually elicited via self- or observer-report, they are typically considered to be more prone to measurement error than IQ tests. Consider a question designed to measure the personality trait conscientiousness which asks a person to rate how hard-working they are on a scale of 1 to 7. Respondents may prefer not to describe themselves negatively and thus overstate how hard-working they are. Alternatively, respondents may have different benchmarks of what constitutes hard-work and thus provide scores which are not comparable. This problem of subjective interpretation of response scales can make it difficult to make meaningful comparisons across different groups. In extreme cases, subjective ratings seem to directly contradict objective evidence: for example among OECD countries South Korea ranks first in annual hours worked but second last in self-reported conscientiousness scores (Heckman & Kautz, 2013). Measurement error of noncognitive skills may also arise from the fact that researchers are often obliged to work with older secondary data. This may mean using psychological measures which seem out-of-date or not designed for purpose. For example,

many childhood psychological measures in the National Child Development Study were elicited in the 1960s. Modern researchers using these measures to answer contemporary research questions therefore rely on questionnaires which are over 50 years old (for an example of how researchers may address this issue by validating such measures against modern scales, see Daly, Delaney, Egan, & Baumeister, 2015).

Although the problems involved with measuring noncognitive skills are well-known, even cognitive skills may be inaccurately measured if IQ tests capture factors other than intelligence. A recent meta-analysis of 2,008 individuals found that providing incentives such as candy or money increased IQ scores by an average of 0.64 standard deviations, suggesting that motivation plays an important role in determining scores in low-stakes IQ tests (Duckworth et al., 2011). Relatedly, highly neurotic individuals may perform poorly on IQ tests due to test-anxiety (Moutafi, Furnham, & Tsaousis, 2006). Personality can therefore have a direct effect on IQ scores (for a full discussion of measurement error in this area see Borghans, Golsteyn, Heckman, & Humphries, 2011), suggesting that the predictive power of cognitive ability for economic outcomes may be overstated if personality is not taken into account.

The third issue, arguably the most important of the three highlighted here, is causal inference. While many studies show that a certain childhood noncognitive skill predicts a later socioeconomic outcome, considerably fewer studies use research designs which can demonstrate a causal relationship (as might be obtained by randomizing participants into treatment and control groups). Instead researchers typically rely on observational data and attempt to isolate the contributing role of a skill on an outcome by including an array of statistical control variables (e.g. examining whether academic motivation predicts future employment while taking into account gender and socioeconomic status). A limitation of this method is that there may be background variables not present in the data which influence

both the skill and outcome being examined (e.g. perhaps cognitive ability in early life causes later motivation and employment levels). Failing to control for these confounding variables can produce misleading results and potentially lead to misguided interventions. The issue is exacerbated by the fact that different researchers in different disciplines do not consistently examine the same noncognitive skills or outcomes, or control for the same background factors. This problem is likely to persist until the field adopts a cohesive theoretical framework which provides guidance on which noncognitive skills and outcomes researchers should prioritize.

### **1.5 Policy Implications**

Given that early life cognitive and noncognitive skills are strong predictors of future economic success, governments may wish to implement policies which promote these skills, thereby creating more economically productive populations and bringing greater wellbeing and prosperity to society. The theoretical case for prioritizing investment in children rather than adults is that the economic return is likely to be higher due to the mechanisms of self-productivity and dynamic complementarity (Cunha & Heckman, 2007). The results of interventions such as the Perry Preschool Program and Abecedarian Project, discussed elsewhere in this chapter, and a meta-analysis of 30 interventions from 23 countries across Europe, Asia, Africa, Central and South America (Nores & Barnett, 2010) suggest that early childhood interventions can improve cognitive and noncognitive skills in a lasting way. However, two important distinctions between these skill types emerge from the literature. Firstly, early intervention programs lead more consistently to improvements in noncognitive skills than cognitive skills. Secondly, while better cognitive skills are a robust predictor of better performance in school and work, there is no comparable single noncognitive skill with the same predictive power. Instead, as noted by Gutman and Schoon (2013), “*there are many*



*[noncognitive] skills that are inter-linked and the enhancement of one of these skills without improvement of the others is unlikely to lead to lasting changes” (p. 43).*

Investing in cognitive and noncognitive skills in early life may be an effective way to address social inequality. Gaps in test scores open up early in life across socioeconomic groups and are stable by age 8 to 9, suggesting the education children receive after this age is not effective at closing these gaps (Heckman, 2006). For this reason, Heckman and Kautz (2013) argue that “*waiting until kindergarten to address these gaps is too late. It creates achievement gaps for disadvantaged children that are costly to close*” (p. 7). Interventions might therefore be designed to address the portion of these gaps which is attributable to variation in the quality of family life in the child’s early years. Such interventions might include pre- and postnatal nutritional supplementation programs (e.g. iron, iodine), home visitations which teach parenting skills and/or high-quality early preschool programs which promote cognitive and socioemotional development, and school-based programs extending into adolescence in order to take advantage of dynamic complementarities.

The practical implementation of such interventions would ideally adhere to certain best practices in order to identify the cognitive and noncognitive pathways to economic success while addressing the limitations of prior literature. Broadly speaking, the ideal intervention would: (i) target a large, representative sample to ensure that the findings were relevant to the broader population and provide sufficient power for statistical analyses, (ii) implement a randomized design with low rates of attrition over time to demonstrate causality, (iii) use established strategies (where available) to improve cognitive and noncognitive skills which take into account their changing malleability over the lifespan, (iv) assess cognitive and noncognitive skills via a multi-method approach to minimize measurement error (e.g. combining scores on individual tests and behavioural tasks with self-, informant- and

observer-ratings) and (v) examine a wide set of outcome variables in order to evaluate the full range of effects of the program.

## **1.6 Concluding Remarks**

We began this chapter by asking which psychological characteristics help children become economically successful adults. A large body of research in economics and psychology confirms that early-life cognitive and noncognitive skills play a substantial role in shaping outcomes in education and the labour market. Indeed, by focusing only on the domains of school and work in this chapter, we have omitted considerable evidence showing that greater childhood cognitive and noncognitive skills also predict better outcomes in areas such as health, criminality and wellbeing.

Future research in this area should move towards identifying the noncognitive skills which are causal determinants of later socioeconomic success, rather than merely predictors of it. It would also be useful to broaden the outcomes examined beyond academic achievement and extend the follow-up periods of interventions; knowing whether, for example, improvements in early life socioemotional skills also lead to consistently better labour market outcomes could substantially change the cost-benefit evaluations of early interventions. Lastly, while there is consensus on the importance of early childhood interventions, there is no gold standard intervention template which delineates which specific skills and outcomes should be targeted and the optimum duration and intensity for programmes to produce the greatest economic return.

## CHAPTER 2

### Overview of Thesis, Datasets and Methodology

Chapter 1 reviewed the importance of childhood cognitive and noncognitive skills in shaping future labour market success. This chapter situates the central research question of this thesis with respect to that literature. This chapter also provides an overview of the datasets and methodology used in the empirical studies in chapters 3-6. Chapter 7 concludes the thesis by discussing the contribution of the research, its strengths and limitations, and directions for future research.

#### *2.1 Thesis*

To what extent can differences in childhood noncognitive skills explain differences in adult unemployment levels? This is the central question examined in this thesis, which proposes that individual differences in pre-labour market measures of self-control (chapter 3), conscientiousness (chapter 4), and mental health (chapters 5 and 6) can explain meaningful differences in future unemployment trajectories.

This thesis addresses this question using a cross-disciplinary approach which draws on concepts from psychology and economics. A key benefit of this approach is that it highlights important, hitherto relatively neglected, psychological determinants of this important economic outcome. This is because, broadly speaking, economists have traditionally been more interested in cognitive (rather than noncognitive) skills as a determinant of labour market outcomes. Psychologists have conducted a considerable amount of research on the various psychological differences that fall under the term ‘noncognitive skills’, but have rarely examined unemployment as an outcome, preferring instead to focus on

occupational status or broader measures of employment. As a result, there are relatively few studies in either discipline examining childhood noncognitive predictors of unemployment.

This thesis addresses this gap in both literatures by drawing on a rich psychology literature on self-control, conscientiousness and mental health to examine the predictive power of these characteristics for future unemployment. Each of the four empirical chapters provides a unique contribution to the literature. Chapter 3 is the first study to examine the relationship between childhood self-control and unemployment. Chapter 4 is the first to examine pre-labour market conscientiousness and this outcome. Chapter 5 is the first to examine how childhood psychological distress prospectively predicts unemployment in the first decade of working life, and chapter 6 is the first to examine this relationship while comparing the outcomes of siblings.

Before discussing the importance of studying unemployment, it is worth highlighting two benefits of using psychological variables elicited in childhood rather than later in life. Firstly, using childhood measures avoids the econometric issue of endogeneity, which often exists as a limitation in studies eliciting psychological differences and economic outcomes contemporaneously. For example, cross-sectional studies which show an association between poor mental health and current unemployment are typically unable to demonstrate whether poor mental health caused the individual to become unemployed, whether unemployment worsened mental health, or whether unemployment and mental health dynamically affect each other. By using longitudinal data containing psychological measures elicited years before the possibility of unemployment even arises, the empirical studies in chapters 3-6 clarify the direction of influence as running from the psychological variable to unemployment. The second benefit of using childhood variables to predict future labour market states is that such studies may have greater potential policy implications than studies using adult measures. Cunha and Heckman's (2007) model of lifelong skill development, discussed in chapter 1,

emphasizes the importance of early skills as a foundation for later economic success. That model also notes the greater malleability of noncognitive skills in childhood compared to adulthood, and the relatively higher return of interventions which improve noncognitive skills in childhood compared to programs designed to remediate skill deficits in adulthood. Therefore, studies which demonstrate large future returns to high levels of childhood noncognitive skills add greater weight to the argument that policy interventions should prioritize prevention, rather than remediation, of poor economic outcomes by directing resources towards improving individuals' skills early in life.

Unemployment merits specific study because it is a global concern with dramatic negative consequences for individuals and society. There were over 201 million unemployed people around the world in 2014. In the United Kingdom and the United States, the countries whose labour markets are examined in this thesis, the number of unemployed was over 10 million in 2015.<sup>9</sup> The economic and noneconomic costs of unemployment are substantial; to society in the form of reduced amounts of goods and services, increased welfare payments, higher rates of alcoholism (Mossakowski, 2008), suicide (Milner, Page & LaMontagne, 2013) and early mortality (Roelfs, Shor, Davidson & Schwartz, 2011), and to the individual in the form of forgone income, missed opportunities for career development, deleterious effects on physical and mental health (McKee-Ryan, Song, Wanberg, & Kinicki, 2005; Paul & Moser, 2009), and 'scarring effects' on future well-being and earnings (Gregg & Tominey, 2005;

---

<sup>9</sup> The global unemployment figure (201 million) is from the International Labour Organization ([http://www.ilo.org/wcmsp5/groups/public/---dgreports/---dcomm/---publ/documents/publication/wcms\\_368640.pdf](http://www.ilo.org/wcmsp5/groups/public/---dgreports/---dcomm/---publ/documents/publication/wcms_368640.pdf)); the UK figure (1.9 million) is from the Office of National Statistics (<http://ons.gov.uk/ons/taxonomy/index.html?nscl=Unemployment+Rates#tab-data-tables>); the US figure (8.3 million) is from the Bureau of Labor Statistics (<http://www.bls.gov/news.release/empsit.nr0.htm>). All figures retrieved in September 2015.

Daly & Delaney, 2013). Identifying the psychological characteristics that help people to avoid unemployment can therefore guide interventions towards fostering these qualities.

There are two main reasons to believe that childhood measures of self-control, conscientiousness and mental health will be among the most important psychological characteristics for predicting future unemployment. The first is the weight of existing empirical evidence, noted in chapter 1, showing that these characteristics are strongly predictive of better socioeconomic outcomes in areas such as educational attainment, earnings, labour force participation and wellbeing. One caveat of the existing studies which have examined labour market outcomes is that they have tended to examine more general outcomes of labour supply, such as the number of hours worked per week, rather than unemployment. This approach typically contrasts those who are in employment with everyone else in the sample. Among ‘everyone else’, it does not adequately distinguish between those who are unemployed (those not currently employed but available for work) versus out of the labor force entirely (such as homemakers, those in education, the retired, those not seeking work). It is essential to separate these two subgroups in order to make precise comparisons between the employed and unemployed.

The second reason to expect that childhood self-control, conscientiousness and mental health will influence future unemployment trajectories is the theoretical predictions derived from the economics and psychology literatures. The broad explanation of how these characteristics, measured in childhood and adolescence, might influence future labor market outcomes is motivated by Cunha and Heckman’s (2007) lifecourse model of skill development. That model, discussed in chapter 1, emphasizes the importance of early skills as a foundation for later skill development. More specifically, chapters 3-6 discuss how self-control, conscientiousness and mental health are likely to affect entry into employment through three broad areas; through different levels of academic motivation and educational

attainment in early life, through different levels of job search effectiveness, and through different levels of job performance. For example, children who are more self-controlled and conscientiousness are more likely to resist distractions and concentrate on their studies (Duckworth & Seligman, 2005; Tangney, Baumeister, & Boone, 2004). When these individuals enter the job market, reserves of persistence and a tendency towards organization and hard-work should help them to navigate the potentially arduous process of job-searching (Ent, Baumeister, & Tice, 2015; Kanfer, Wanberg, & Kantrowitz, 2001). When employed, highly self-controlled and conscientiousness workers are more likely to perform well due to their hardworking and responsible tendencies (Barrick & Mount, 1991; Judge, Higgins, Thoresen, & Barrick, 1999). During recessions, when unemployment tends to spike dramatically, these same benefits should assist these workers in minimizing their experience of unemployment. Conversely, poor mental health is likely to negatively impact performance in all of these areas. High levels of psychological distress have been linked with lower academic motivation and reduced educational attainment (Currie & Stabile, 2009; Fletcher, 2010), which may limit future employment opportunities. During periods of job search, more depressed and anxious individuals may become discouraged and be less likely to find employment (Caplan et al., 1989). The experience of unemployment itself may also worsen existing distress, which may lead to a downward spiral of mental health (Daly and Delaney, 2013) and further limit job search effectiveness. Within the workforce, psychological distress may directly impair job performance (Lerner & Henke, 2008) and work attendance (Lagerveld et al., 2010; Störmer & Fahr, 2013). During recessions, these factors may all pose additional challenges preventing distressed individuals from returning to employment.

## **2.2 Data**

Chapters 3-6 examine empirically whether certain psychological differences measured in childhood / adolescence predict future unemployment. This type of research question is best answered using longitudinal data which tracks the same individuals over time. Ideally, the data would contain a sufficiently large number of people to ensure sufficient power for statistical analyses, and be representative of the broader national population so that the findings had greater real-world relevance. The empirical studies in this thesis therefore draw on four large, nationally-representative longitudinal studies which meet these criteria: (i) the National Child Development Study (NCDS; participants born 1958), (ii) the British Cohort Study (BCS; 1970), (iii) the Longitudinal Study of Young People in England (LSYPE; 1989/90), (iv) the National Longitudinal Study of Youth 1997 (NLSY97; 1980-84). The first three studies are from Great Britain and are available online from the UK Data Service website (UK Data Service, 2015). The last study is from the United States and is hosted by the National Longitudinal Surveys website (National Longitudinal Surveys, 2015). Together the four cohort studies contain data on around 60,000 individuals; after accounting for attrition, the empirical studies in this thesis use a total sample of 47,328.

The cohort studies used in this thesis have two notable limitations. The first is that cohort studies are typically only capable of describing correlational relationships rather than causal ones. This reflects the fact that cohort data are observational; unlike in randomized controlled trials, the gold-standard methodology for isolating causal relationships, cohort study participants are not randomized into treatment and control groups. For example, chapter 3 uses the BCS and NCDS data to show that children with better self-control are more likely to avoid unemployment as adults. Given the observational nature of the data, one obvious critique of this finding is that better self-control is likely to be correlated with other background characteristics which are also important for avoiding unemployment. Indeed, that



chapter includes controls for socioeconomic status and intelligence which both positive correlate with self-control and are themselves predictors of unemployment. More concerning is the possibility of unobserved factors not present in the data which may partially or entirely explain the relationship between self-control and unemployment. That chapter attempts to address the issue of unobserved confounding through rigorous supplemental analyses which add controls for an extensive set of background characteristics. While this approach does not entirely rule out the possibility of unobserved confounding, it does make it less likely. Chapter 6 goes further in its attempt to rule out unobserved confounding by conducting analysis on a sub-sample of siblings in the NLSY97 data. By implementing sibling fixed-effects models which partial out stable, unobserved family background characteristics, that chapter argues that this method produces causal estimates of the relationship between mental health and unemployment.

The second limitation of cohort data is the age-period-cohort (APC) problem. The APC problem refers to the impossibility of simultaneously separating age effects, period effects and cohort effects in statistical modelling. Consider the cohort members of the NCDS. These 18,000 individuals were born in a single week in Britain in 1958 (the cohort). In 1980 (the period), when they were 22 years old (the age), Britain entered a major recession and the unemployment rate of the sample rose dramatically. Note that there are three possible effects which might explain the dramatic rise in unemployment. The first is a cohort effect; perhaps people born in 1958 in Britain grew up in an environment which caused them to have an unusually poor work ethic. The second is a period effect; perhaps the overwhelming effect of the 1980 recession was the main cause of the rise in unemployment. The third is an age effect; perhaps 22 year olds tend to fare particularly poorly in the British labour market in general. This example is somewhat exaggerated given that the onset of the recession does seem to be the most plausible explanation of the sudden rise in unemployment, which occurred more or

less in lock-step with the onset of the economic downturn. However it does highlight the inseparability of the age-period-cohort effects. Age is simply the time period minus the cohort birth date: this mathematical confounding means that all three terms cannot be simultaneously entered into regression analysis due to their perfect collinearity. The implication of the APC problem in the context of this thesis is that the observed relationships between childhood psychological characteristics and later unemployment may be reflective of any one of these three effects, thus limiting their generalizability to other contexts and time periods.

This thesis takes an indirect approach to addressing the APC problem by examining four different cohort studies covering different ages, birth cohorts and time periods. For example, chapters 3 and 4 show that the conceptually similar concepts of self-control and conscientiousness predict unemployment in both the NCDS and BCS cohorts from the 1970s to late 2000s. Chapters 5 and 6 demonstrate a link between mental health and unemployment in the first decade of working life in the LSYPE, NCDS and NLSY97 cohorts. These cohort members are all subject to different age, period and cohort effects. For example, the NCDS and LSYPE cohort members experienced major recessions during their first years in the labour market (the 1980 and 2008 recessions respectively), while the BCS cohort members completed the first two decades of their careers in the relatively booming 1990s and 2000s British economy. Like the LSYPE cohort members, the participants in the NLSY97 study entered the labour market during the 2008 recession, but with two key differences: they were up to a decade older than the LSYPE cohort members when the recession began, and entered the American rather than British labour market. In summary, despite the many contextual differences across the studies, chapters 3 and 4 find similar results for the effects of self-control and conscientiousness, as do chapters 5 and 6 for mental health. This suggests

that the ACP problem does not limit the generalizability of the results of this thesis in a major way, at least in the context of the British and American labour markets.

### ***2.3 Methodology***

Chapters 3-6 use a similar methodology to examine the psychological determinants of unemployment. This methodology is described below.

#### *Outcome Variables*

Unemployment is the outcome variable in chapters 3-6. It follows the conventional definition of being available to work but not currently in employment, a categorization which excludes people who are outside the labour force such as homemakers and students. Most of the chapters use two measures of unemployment, which are constructed via retrospective self-reported employment histories elicited over multiple interviews. They are (i) a binary measure of unemployment (coded as 0 = employed, 1 = unemployed) at each time point the cohort member was interviewed and (ii) a summed total across the total period observed (i.e. the number of months of unemployment experienced from age 16 through 50, or the total weeks of unemployment from the year 2000 to 2010). The first outcome delineates unemployment trends over time. The second shows the aggregated effect of a psychological characteristic on unemployment over the lifespan.

#### *Main Independent Variables*

The main independent variables are teacher-rated measures of self-control (chapter 3), self-reported conscientiousness (4) and self-reported mental health (5-6). The measures in chapters 3-5 were elicited between the ages of 7 to 17, before the cohort members entered the labour market. As noted, this clarifies the direction of influence as flowing from the psychological characteristic to the labour market outcome rather than the other way around.

That direction is less clear-cut in chapter 6, where the mental health measure was elicited when the cohort members were aged 16 to 20. That chapter therefore includes sensitivity tests which show that excluding the cohort members who experienced unemployment before the measure was elicited (i.e. the 20 year old cohort members who experienced unemployment when they were 18 or 19, which may have worsened their mental health) does not substantially affect the main results.

The main limitation of these psychological measures, discussed in chapter 1 as one of the main methodological challenges in this field, is measurement error. The issue is more apparent in the chapters which use older scales. For example, chapter 3 uses teacher-rated measures of self-control elicited in 1965, 1969 and 1980. Chapter 4 uses measures of Big Five personality which are derived from a small set of questions about the respondents' behaviours in 1986 rather than questions from a longer, validated personality scale. Chapter 5 uses measures of teacher-rated depression elicited in 1965 and 1969. These measures are not what a modern researcher would ideally choose to represent the psychological constructs in question. Consequently, they all contain varying degrees of measurement error. The two principal sources of error are the presence of anachronistic items (e.g. one measure of self-control in chapter 3 asks teachers to rate to what extent the child is "slapdash") or the relatively small number of available items (e.g. the 3-item personality scales in chapter 4) used to construct the scale in question.

This limitation is addressed in two ways. The first is to check the convergent and discriminant validity of the scale in question against other items present in the data. Convergent validity in this context means that a scale which purports to measure a psychological construct should be highly positively correlated with another scale measuring the same concept. Discriminant validity means that the same scale should also not measure dissimilar concepts. For example, chapter 3 compares the self-control measure in the British

Cohort Study against an alternative measure of self-control and finds a high positive correlation, indicating good convergent validity. That same scale exhibits modest negative correlations with the dissimilar concepts of neuroticism and introversion, indicating good discriminant validity. The second tool used to address measurement error is validation studies comparing scores on the older scales to scores on contemporary scales measuring the same psychological construct. For example, chapter 3 includes details of an online validation study of 100 parents which asked them to rate their children's self-control using the older self-control measures in the British Cohort Study and National Child Development Study and the most modern self-control scales used in psychology. These scores exhibit relatively high positive correlations, indicating that they are measuring the same underlying constructs. Similarly, chapter 4 describes the results of a study of 389 adults which found acceptable correlations between the Big Five personality measures in the British Cohort Study and a modern personality scale. Taken together, the validation tests described in these chapters suggests that the level of measurement error in the psychological scales is acceptable.

### *Main Covariates*

Selection of covariates was motivated by the decades of empirical literature, described in chapter 1, examining the determinants of labour market outcomes. The main models in chapters 3-6 control for gender, childhood intelligence, a measure of socioeconomic status derived from parental occupation / education, age (if the cohort members are not the same age), and a time trend (such as month or year) in longitudinal regressions to account for naturally fluctuating background economic conditions which may affect the probability of unemployment.

These base models therefore have relatively few covariates, although those included (e.g. intelligence, childhood SES) are established, powerful predictors of future

socioeconomic success. A potential problem with using only a small set of control variables is the potential for omitted variable bias, i.e. an unobserved third variable that may be the ultimate cause of a statistically significant, but causally spurious, relationship between independent and dependent variables (e.g. such as cognitive ability being the true cause of a statistically significant relationship between academic motivation and academic performance). The chapters therefore include additional analyses in an attempt to rule out this confounding explanation. Chapters 3 and 5 include supplemental regressions controlling for an extensive set of background characteristics such as childhood health and socio-demographic background characteristics. Chapter 6 uses sibling fixed-effects models to implicitly control for shared unobserved family characteristics which might affect the relationship between mental health and unemployment, such as shared genetic propensities or exposure to an unsafe environment in childhood.

### *Statistical Methods*

Chapters 3-6 specify Probit models to predict the probability of unemployment when examining the binary unemployment outcome (0 = employed, 1 = unemployed). In order to present the results more intuitively, average marginal effects with covariates held at their observed values are calculated after the Probit regressions (Long & Freese, 2014). These produce percentage point changes in the probability of unemployment for unit changes in the independent variables. Negative binomial and OLS models are used when examining the continuous measures of unemployment (such as the total weeks or months of unemployment). Negative binomial models are appropriate for over-dispersed count data (Sturman, 1999); this is the case in chapters 3, 4 and 5 where the majority of cohort members report 0 months of unemployment and the mean total number of months of unemployment is much lower than the variance.

## CHAPTER 3

### Childhood Self-Control and Unemployment Throughout the Lifespan:

#### Evidence From two British Cohort Studies.

#### 3.1 Abstract

The capacity for self-control may underlie successful labor-force entry and job retention, particularly in times of economic uncertainty. Analyzing unemployment data from two nationally representative British cohorts ( $N = 16,780$ ), we found that low self-control in childhood was associated with the emergence and persistence of unemployment across four decades. On average, a 1-*SD* increase in self-control was associated with a reduction in the probability of unemployment of 1.4 percentage points after adjustment for intelligence, social class and gender. From labor-market entry to middle age, individuals with low self-control experienced 1.6 times as many months of unemployment as those with high self-control. Analysis of monthly unemployment data before and during the 1980s recession showed that individuals with low self-control experienced the greatest increases in unemployment during the recession. Our results underscore the critical role of self-control in shaping life-span trajectories of occupational success and in affecting how macroeconomic conditions affect unemployment levels in the population.

### 3.2 Introduction

Self-control is one of the most useful human capabilities and has important implications for career success. Challenging work environments require employees to successfully inhibit their impulses and control their emotional expression in order to meet deadlines and avoid potential conflicts with customers and colleagues. Self-control may also enable workers to resist conflicting but desirable activities (e.g., leisure activities or sleep), minimize distractions, and form adaptive routines, thus facilitating the completion of demanding tasks and management of substantial workloads (de Ridder, Lensvelt-Mulders, Finkenauer, Stok, & Baumeister, 2012; Ent, Baumeister, & Tice, 2015; Hofmann, Vohs, & Baumeister, 2012; Schmidt, Hupke, & Diestel, 2012). Indeed, hard work is almost synonymous with self-control, as workers need to exert effort today to achieve valuable future benefits in the form of paychecks, bonuses, and promotions (Kaur, Kremer, & Mullainathan, 2010).

The research we report here builds on an emerging psychological literature demonstrating a close relationship between self-control and work performance and other work-related outcomes, including income and occupational prestige (de Ridder et al., 2012; Moffitt et al., 2011; Schmidt et al., 2012). Given these findings, it is somewhat surprising that self-control has not yet been linked to unemployment, a substantial global problem with vast consequences for people's welfare. Using longitudinal data from two ongoing studies of British cohorts, we examined the extent to which self-control during childhood predicts spells of unemployment and the total amount of time people are unemployed throughout their working lives. To test whether adverse economic conditions may amplify the influence of self-control, we tracked unemployment outcomes as the United Kingdom entered the early-1980s recession.



## Childhood Self-Control

Individual differences in temperament emerge in the first decade of life and can have a large effect on a diverse range of adult life outcomes, including labor-market success (Caspi, Wright, Moffitt, & Silva, 1998; Heckman, Stixrud, & Urzua, 2006). Although temperament has been conceptualized in numerous ways, there is a degree of commonality across existing theoretical models. In particular, young children show enduring behavioral tendencies in their activity levels, their sensitivity to sensory stimuli, the degree to which they express positive (e.g., eagerness, joy) and negative (e.g., fear, irritability) emotions, and their capacity for self-control (Zentner & Bates, 2008). We focus on self-control, a basic component of temperament that is often indexed by observer ratings of a child's ability to pay attention, persist on tasks, and suppress inappropriate behaviors (Zentner & Bates, 2008).

The effortful self-governance that typifies self-control has been described in a broad set of interrelated ways across subfields of psychology. For instance, in temperament research, the terms *effortful control* and *self-control* are often used synonymously to indicate the ability to suppress a dominant response in order to allow a subdominant response to be performed. Effortful control is thought to emerge from the developmental improvements in attentional control over the first several years of life (Rothbart, Ellis, Rueda, & Posner, 2003). In neuropsychology, *inhibitory control* captures both response inhibition and interference control, or the capacity to control attention, ignore distracting stimuli, and inhibit unwanted thoughts and emotions (Diamond, 2013). In personality research, *self-regulation* overlaps considerably with inhibitory control but also captures the capacity to maintain optimal levels of arousal (Diamond, 2013). Inhibitory control is also considered to underlie effective self-control, enabling children to resist or ignore tempting or distracting stimuli and inhibit impulsive behavior.

The benefits of self-control in a work-related context are readily apparent. Self-control helps people to ignore distractions and to persevere on and complete demanding tasks (Diestel & Schmidt, 2012; Ent et al., 2015). Furthermore, self-control is thought to underlie the emergence of conscientiousness, which is the personality trait most closely linked to school and career success (Eisenberg, Duckworth, Spinrad, & Valiente, 2014; Roberts, Kuncel, Shiner, Caspi, & Goldberg, 2007). Emerging evidence suggests that the benefits of self-control begin to accrue early in childhood and persist into adult life. Using data from a cohort of more than 1,000 children from New Zealand, Moffitt et al. (2011) demonstrated that measures of childhood self-control taken at ages 3 through 11 were closely related to adult outcomes in areas as diverse as physical health, income, substance abuse, and criminal behavior. Although suggestive evidence exists, no research has directly examined whether childhood self-control fosters successful entry into the labor force and assists workers in avoiding unemployment throughout adulthood.

### **Childhood Self-Control and Unemployment**

Self-control seems to be a highly plausible mechanism for attaining and retaining employment. Academic success has already been linked to good self-control, presumably because it facilitates concentration on studies and resistance to distracting temptations (Duckworth & Seligman, 2005; Tangney, Baumeister, & Boone, 2004). Self-control is also potentially valuable during the job-search process, which can be arduous and time-consuming. Individuals with lower self-control may be more likely to succumb to tempting or distracting alternatives and disengage from their search sooner (Ent et al., 2015; Kanfer, Wanberg, & Kantrowitz, 2001). Finally, a person with high self-control who is already employed may draw on these reserves to meet deadlines, arrive punctually, tolerate difficult customers, and so on (Schmidt et al., 2012). In school and the workplace, the advantage will

lie with people who are better able to inhibit a preference for leisure, concentrate on their work, and regulate their emotions in favor of their education or career goals.

We hypothesized that the importance of self-control for successful entry into employment and for job retention is particularly pronounced in times of economic recession. During such periods, the returns to self-control are potentially highest, as the effort that needs to be devoted to job search increases. Employers may place a greater emphasis on self-control through processes such as internships, which make it possible to explicitly assess key skills like time management, persistence, and task completion. Also, when managers need to select staff for dismissal during adverse economic conditions, it is likely that the most self-controlled staff who invest heavily in their work life will be retained.

In summary, we hypothesized that children with low self-control will be much more likely than others to experience unemployment throughout their adult life, particularly when macroeconomic conditions are unfavorable. To test this idea, we capitalized on two British studies that have collected comprehensive measures of childhood characteristics and labor-force participation during adulthood.

### **3.3 Study 1**

#### ***Method***

#### ***Participants and Procedure***

We first examined data from the nationally representative British Cohort Study (BCS), a study of children born in Britain in a single week in 1970. We estimated the probability of unemployment at individual waves when the cohort members were ages 21, 26, 30, 34, 38, and 42; sample sizes ranged from 759 (a 10% random sample was conducted at age 21 because of funding issues) to 5,377 cohort members. Detailed data on total months duration of unemployment were available from 1986 through 2008, when the cohort

members were ages 16 to 38 (sample size of 6,675). All sample sizes were determined by retaining all participants for whom data on the outcome variables and independent variables were available. All unemployment data that were analyzed have been reported in the current study

## ***Measures***

### ***Childhood self-control***

Self-control scores were derived from nine items of the Disorganised Activity subscale of the Child Developmental Behaviors questionnaire, which was administered when the children were 10 years old. This scale was designed for the BCS and consists of items drawn chiefly from the Conners Teachers Hyperactivity Rating Scale (Conners, 1969) and the Rutter Teacher Behavioral Scale B (Rutter, 1967). Each child's teacher rated the degree to which each item represented the child using a visual analogue scale ranging from *not at all* to *a great deal*. The questions centrally gauged attentional control (e.g., "cannot concentrate on a particular task," "pays attention in class," and "easily distracted") and perseverance ("shows perseverance," "completes tasks," and "fails to finish tasks"; for a complete list of the items, see Section 1.2 in the Supplemental Material available online). The control of attention is a fundamental, perhaps even defining, component of self-control and one of the most common ways in which self-control is measured in laboratory settings (e.g., Hagger, Wood, Stiff, & Chatzisarantis, 2010). Similarly, the degree to which participants exhibit perseverance on experimental tasks (e.g., read-aloud tasks, unsolvable tracing or anagram tasks) is frequently used as a measure of self-control (Hagger et al., 2010). We reverse-scored ratings as appropriate so that higher scores always meant better self-control and then created a composite self-control variable by averaging the ratings for these nine questions ( $M = 31.09$ ,  $SD = 10.22$ ; range: 1.44–47; Cronbach's  $\alpha = .92$ ). We then standardized this variable to have a mean of 0 and standard deviation of 1.

We tested the convergent and discriminant validity of this self-control measure in two ways: (a) using available measures in the BCS data and (b) using contemporary data collected specifically for this purpose. To construct an alternative measure of self-control in the BCS, we identified six teacher-rated items gauging persistence (e.g., “Does the child show perseverance?” and “percentage of time interested in other tasks”) and attentional control (e.g., “How well does the child concentrate?” and “percentage of time daydreaming”). The observed internal reliability coefficient for this measure was .83. This scale demonstrated strong convergent validity with our main self-control measure derived from the Child Developmental Behaviors questionnaire ( $r = .86, p < .01$ ). Furthermore, in additional analyses, we found that the strength of the association between childhood self-control and our unemployment outcome measures did not differ when this alternative measure was used instead of our main measure.

To test discriminant validity using alternative BCS measures, we examined correlations between our main self-control measure and the Neuroticism (e.g., “worried and anxious” and “behaves nervously”) and Introversion (e.g., “rather solitary” and “introverted”) subscales of the Child Developmental Behaviors questionnaire. Both subscales demonstrated satisfactory levels of internal consistency (Neuroticism: Cronbach’s  $\alpha = .85$ ; Introversion: Cronbach’s  $\alpha = .67$ ). Our main self-control measure was moderately correlated with these commonly assessed basic personality dimensions: neuroticism:  $r = -.38, p < .01$ ; introversion:  $r = -.44, p < .01$ . The percentage of variance the main and alternative self-control measures had in common was 4 to 5 times the percentage of variance our main self-control measure had in common with the measure of either neuroticism or introversion. Details of these personality measures are provided in Section 2 of the Supplemental Material.

To collect new data to test the convergent and discriminant validity of our main self-control measure, we conducted an online study of 100 American parents of children ages 5

through 12. These parents, who were recruited through Amazon Mechanical Turk, rated the temperament and behavior of their children on the Disorganised Activity scale used in this study and two contemporary self-control measures: the Brief Self-Control Scale (BSCS; Tangney et al., 2004) and the Domain-Specific Impulsivity Scale (DSIS; Tsukayama, Duckworth, & Kim, 2013). All three scales demonstrated high reliability, Cronbach's  $\alpha$ s = .83–.89. Scores on the nine-item Disorganised Activity scale (Cronbach's  $\alpha$  = .88) correlated strongly with scores on the BSCS ( $r = .75, p < .01$ ) and DSIS ( $r = .75, p < .01$ ). Thus, this online study provided support for convergent validity of our main measure and commonly used measures of childhood self-control.

To gauge discriminant validity of our main measure of self-control with contemporary data, we wanted to use measures similar to those we used in our test with BCS data. Our online study therefore included items commonly used to measure childhood emotional and peer problems, which are likely to correspond broadly with neuroticism and extraversion-introversion; these items were taken from the Strengths and Difficulties Questionnaire (SDQ; Goodman, 1997). The self-control measure exhibited a significantly weaker correlation with emotional problems ( $r = -.35, p < .01$ ) and peer problems ( $r = -.40, p < .01$ ) than with contemporary measures of self-control. Thus, this test also provided evidence for discriminant validity. The common variance between our main self-control measure and the contemporary measures of self-control was 4 times the common variance between our main self-control measure and these measures of peer and emotional problems. Taken together, these analyses suggest a strong degree of convergent and discriminant validity for our main measure of self-control. Our analysis of the validation data is described in full in Section 3 of the Supplemental Material.

### ***Childhood covariates***

Intelligence has previously been shown to predict labor-market outcomes, including unemployment (e.g., Caspi et al., 1998), and was positively correlated with self-control in this study ( $r = .41, p < .01$ ). Consequently, we included intelligence as a covariate to rule out the possibility that self-control may predict unemployment because individuals with better self-control tend to be more intelligent. Intelligence was measured at age 10 using the British Ability Scales, which was made up of two verbal subscales (Word Definitions and Word Similarities) and two nonverbal subscales (Digit-Span and Matrices; Elliott, Murray, & Pearson, 1978). Intelligence scores were standardized to a mean of 0 and standard deviation of 1. Parental social class was derived from the father's occupation in 1970; scores ranged from I, for higher administration, to V, for unskilled workers. Child gender was also included as a covariate. As a test of robustness, we adjusted for measures of childhood conduct problems (e.g., "often disobedient" and "has tantrums") and hyperactivity (e.g., "restless" and "can't settle"); these items are described in full in Section 4 of the Supplemental Material.

### ***Unemployment***

Our outcome variables were (a) unemployment at ages 21, 26, 30, 34, 38, and 42 and (b) total months of unemployment from 1986 through 2008. At each wave, being in any kind of employment was coded as 0, and being unemployed was coded as 1. Unemployment rates in the sample ranged from a maximum of 10.8% in 1991, when the cohort members were age 21, to a minimum of 2.1% in 2004, when the participants were age 34 (see Table 2.1). The total number of months of unemployment was calculated from data collected across multiple waves, from the age-16 to the age-38 assessment. This variable was highly clustered at the left end of the scale—76% of cohort members never reported being unemployed, 14% reported being unemployed for a total of 1 to 12 months, and the remaining 10% reported being unemployed for anywhere from 13 to 269 months.

- 1 Table 3.1. Descriptive Statistics For Study 1 (British Cohort Study): Characteristics of Participants at Each Assessment Wave and of Participants  
 2 With Lifetime Unemployment Data

Characteristic	Assessment wave						Lifetime-
	Age 21 ( <i>n</i> = 759)	Age 26 ( <i>n</i> = 4,339)	Age 30 ( <i>n</i> = 5,377)	Age 34 ( <i>n</i> = 4,700)	Age 38 ( <i>n</i> = 4,405)	Age 42 ( <i>n</i> = 4,824)	unemployment sample ( <i>n</i> = 6,675)
Unemployment <sup>a</sup>	10.8%	4.9%	3.4%	2.1%	2.3%	2.4%	5.3 months
Self-control <sup>b</sup> (mean)	31.17 (10.00)	32.69 (9.74)	31.79 (10.00)	32.01 (9.85)	32.33 (9.85)	32.12 (9.87)	31.66 (9.99)
Intelligence <sup>c</sup> (mean)	76.16 (13.13)	78.93 (13.61)	77.94 (13.86)	78.24 (13.77)	78.75 (13.51)	78.43 (13.69)	77.31 (13.94)
Female (%)	50.6	51.1	45.7	46.6	48.3	48.9	50.6
Social class <sup>d</sup> (%)							
I	5.7	7.7	7.2	7.2	7.8	7.3	6.8
II	21.1	26.3	25.2	25.5	26.1	25.5	24.0
III	57.3	52.6	53.4	53.1	52.2	53.0	54.1



IV	12.0	10.8	11.1	11.2	11.2	11.4	11.8
V	3.9	2.6	3.1	3.0	2.7	2.8	3.3

---

3 Note: Standard deviations are given in parentheses. *Lifetime unemployment* refers to unemployment from age 16 through age 38.

4 <sup>a</sup>The table shows the percentage of participants who were unemployed at each wave and the total number of months of unemployment for  
5 participants in the lifetime-unemployment sample. <sup>b</sup>Unstandardized self-control scores ranged from 1.44 to 47.0; higher scores indicate better  
6 self-control. <sup>c</sup>Unstandardized intelligence scores ranged from 23 to 125; higher scores indicate higher intelligence. <sup>d</sup>Social class was derived  
7 from the father's occupation: I = higher administration, II = managerial or technical occupations, III = skilled workers, IV = semiskilled workers,  
8 and V = unskilled workers.

## 9 *Statistical Methods*

10 We specified Probit regressions to determine the probability of unemployment at ages  
 11 21, 26, 30, 34, 38, and 42 and computed marginal effects to estimate percentage-point  
 12 changes in the probability of unemployment at each age (Long & Freese, 2014). We also  
 13 specified a negative binomial model to estimate the total number of months of unemployment  
 14 from age 16 through age 38 and estimated the predicted number of months of unemployment  
 15 by levels of self-control (Low = those with scores 1 *SD* below the mean, Medium = Mean  
 16 scores, High = those with scores 1 *SD* above the mean) to represent these differences more  
 17 intuitively (Long & Freese, 2014). A negative binomial model is appropriate for  
 18 overdispersed count data; in our sample, the mean total number of months of unemployment  
 19 was much lower than the variance, and a significant number of cohort members reported 0  
 20 months of unemployment, so this was an appropriate analytic method (see Sturman, 1999, for  
 21 a discussion of the merits of this model compared with others when analyzing count data).  
 22 This model also controlled for the number of months of employment data available for each  
 23 cohort member to account for the possibility that those with lower self-control may have  
 24 more likely to disengage with the survey over time. The formal specifications of the models  
 25 were as follows:

26

27 Model 1: unemployment at age (21/26/30/34/38/42) $_i = \beta_0 + \beta_1$  childhood self-control $_i + \beta_2$   
 28 gender $_i + \beta_3$  childhood intelligence $_i + \beta_4$  social class $_i + \varepsilon_i$

29 Model 2: total months of unemployment at ages 16–38 $_i = \beta_0 + \beta_1$  childhood self-control $_i + \beta_2$   
 30 gender $_i + \beta_3$  childhood intelligence $_i + \beta_4$  social class $_i + \beta_5$  months of employment data  
 31 recorded $_i + \varepsilon_i$

32

33

### 34 3.4 Results

#### 35 *Descriptive statistics*

36 Table 3.1 presents descriptive statistics for this study. On average, males had lower  
37 self-control scores ( $M = 29.54$ ) than females ( $M = 33.63$ ),  $t(6703) = -17.1$ ,  $p < .0001$ ,  
38 supporting the rationale for controlling for gender in our models. Better self-control  
39 correlated with higher intelligence ( $r = .41$ ,  $p < .01$ ) and to a lesser extent with higher social  
40 class ( $r = .14$ ,  $p < .01$ ); these results are in line with previous research (Moffitt et al., 2011).  
41 To examine the relationship between total unemployment from age 16 to age 38 and level of  
42 self-control, we divided participants into three groups: participants with low self-control  
43 (those with scores 1 *SD* below the mean and lower; 17% of the sample), participants with  
44 high self-control (those with scores 1 *SD* above the mean and higher; 19% of the sample),  
45 and participants with medium self-control (all others). We found that participants with low-  
46 self-control accumulated 2.8 times as many months of unemployment as those with high self-  
47 control over the 22-year period examined (low self-control:  $M = 9.36$  months,  $SD = 27.30$ ;  
48 medium self-control:  $M = 4.86$  months,  $SD = 17.51$ ; high self-control:  $M = 3.35$  months,  $SD$   
49  $= 12.71$ ).

#### 50 *Regressions*

51 Table 3.2 and Figure 3.1 present our main results. Controlling for gender, intelligence,  
52 and parental social class, we found that a 1-*SD* increase in childhood self-control was  
53 associated with the following reductions in the probability of unemployment in adulthood:  
54 4.2 percentage points at age 21, 1.2 percentage points at age 26, 1.3 percentage points at age  
55 30, and 0.6 percentage points at age 42. Self-control did not significantly predict  
56 unemployment at age 34 or age 38, when average unemployment rates were at their lowest.  
57 These results are shown graphically in Figure 3.1a. Across all six waves, a 1-*SD* increase in  
58 childhood self-control decreased the probability of unemployment by 1.3 percentage points

59 on average; this was double the magnitude of the average effect of a 1-*SD* increase in  
60 intelligence (0.65 percentage points).

61 Higher self-control was also significantly associated with less accumulated time spent  
62 unemployed from age 16 to age 38 ( $b = -0.247$ ,  $SE = 0.055$ ,  $p < .01$ ). As shown in Figure  
63 3.1b, the predicted number of months of unemployment was 6.34 (95% confidence interval,  
64  $CI = [5.46, 7.22]$ ), for participants with low self-control (1 *SD* below the mean), 4.99 (95%  
65  $CI = [4.49, 5.47]$ ) for those with mean self-control, and 3.91 (95%  $CI = [3.32, 4.51]$ ) for those  
66 with high self-control (1 *SD* above the mean). Thus, our analyses indicated that from youth to  
67 age 38, participants with low self-control experienced 1.6 times as many months of  
68 unemployment as those with high self-control.

69 Table 3.2. Regression Results From Study 1 (British Cohort Study): Predicting Probability of Unemployment at Each Assessment Wave and  
 70 Duration of Lifetime Unemployment

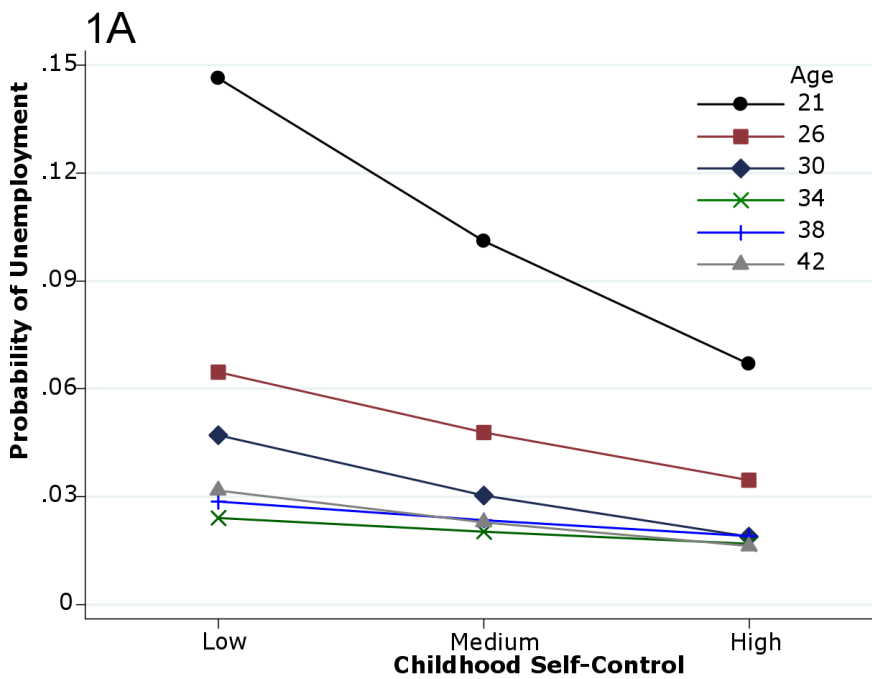
Predictor	Probability of unemployment						
	Age 21 ( <i>n</i> = 759)	Age 26 ( <i>n</i> = 4,339)	Age 30 ( <i>n</i> = 5,377)	Age 34 ( <i>n</i> = 4,700)	Age 38 ( <i>n</i> = 4,405)	Age 42 ( <i>n</i> = 4,824)	Lifetime unemployment ( <i>n</i> =6,675)
Self-control	-0.042** (0.012)	-0.012** (0.004)	-0.013** (0.003)	-0.002 (0.002)	-0.004 (0.002)	-0.006* (0.002)	-0.247** (0.055)
Intelligence	-0.003 (0.013)	-0.008* (0.004)	-0.007* (0.003)	-0.006* (0.002)	-0.007* (0.003)	-0.008** (0.003)	-0.200** (0.052)
Female gender	0.054* (0.023)	-0.033** (0.007)	-0.011* (0.005)	-0.005 (0.004)	-0.008 (0.005)	-0.013** (0.005)	-0.550** (0.099)
Social class							
II	-0.110* (0.055)	-0.005 (0.014)	-0.001 (0.011)	-0.017 (0.010)	-0.004 (0.010)	-0.001 (0.009)	-0.055 (0.205)
III	-0.019	0.000	0.004	-0.008	0.001	0.008	0.141

	(0.056)	(0.014)	(0.010)	(0.010)	(0.009)	(0.009)	(0.194)
IV	-0.017	-0.002	0.009	-0.003	0.009	0.001	0.229
	(0.064)	(0.016)	(0.012)	(0.012)	(0.012)	(0.010)	(0.231)
V	0.071	0.026	0.016	0.010	-0.016	0.034	0.812*
	(0.092)	(0.027)	(0.018)	(0.019)	(0.011)	(0.020)	(0.326)

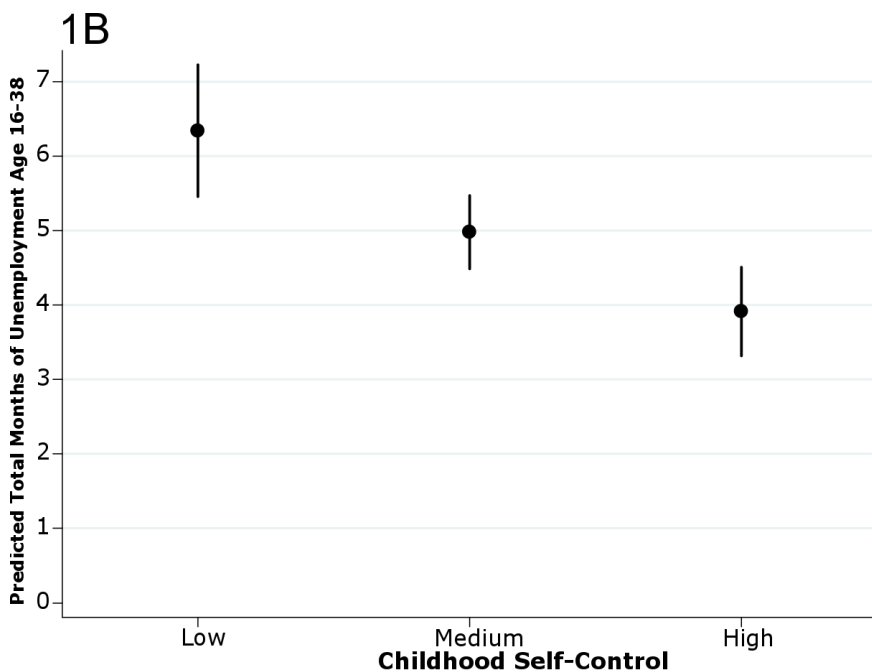
71 Note: Standard errors are given in parentheses. *Lifetime unemployment* refers to unemployment from age 16 through age 38. For the probability  
72 of unemployment, the table presents marginal effects coefficients from Probit regressions. For the duration of lifetime unemployment, the table  
73 presents coefficients from a negative binomial model that controlled for length of activity data. Self-control and intelligence were standardized.  
74 Social class was derived from the father's occupation: I = higher administration, II = managerial or technical occupations, III = skilled workers,  
75 IV = semiskilled workers, and V = unskilled workers. Social class I was the reference group.

76 \* $p < .05$ . \*\* $p < .01$ .

77 Figure 3.1. Results from Study 1: (a) predicted probability of unemployment at each  
 78 assessment wave as a function of childhood self-control and (b) predicted marginal total  
 79 number of months of unemployment as a function of childhood self-control. The error bars in  
 80 (b) represent 95% confidence intervals. Low self-control = 1 standard deviation below the  
 81 mean; medium self-control = mean scores; high self-control = 1 standard deviation above the  
 82 mean.



83



84

85           We conducted a robustness test of the association between self-control and  
86 unemployment by including control variables for mother-rated conduct problems and  
87 hyperactivity in our analyses. Given that these constructs overlap conceptually with self-  
88 control (e.g., Barkley, 1997) and that childhood traits such as aggressiveness have been  
89 shown to predict unemployment (e.g., Kokko, Bergman, & Pulkkinen, 2003), including  
90 conduct problem and hyperactivity was an attempt to stringently isolate the specific  
91 contribution of the self-control measure. Including these controls reduced the coefficients for  
92 self-control as a predictor of the probability of unemployment by an average of 13% across  
93 the individual time points and reduced the coefficient for self-control as a predictor of the  
94 duration of unemployment by 1% without affecting the significance levels of those  
95 coefficients. These results are detailed in full in Section 4 of the Supplemental Material.

96

## 97 **3.5 Study 2**

### 98 **Method**

99           Having demonstrated a link between childhood self-control and unemployment in  
100 Study 1, we used data from the British National Child Development Study (NCDS) to test the  
101 robustness of this association from 1974 through 2008. The NCDS contains extremely rich  
102 information on childhood characteristics, and thus allowed us to markedly extend the set of  
103 potentially confounding variables we considered in Study 1. Additionally, the monthly data  
104 recorded on labor-force status from age 16 through age 23 in the NCDS allowed us to test  
105 whether the potential impact of self-control on unemployment was amplified during the early  
106 1980s, when the United Kingdom experienced an economic recession.

107

108

109



## 110 *Participants and procedure*

111           The NCDS is an ongoing longitudinal study following an initial cohort of 17,638  
112 people born in Britain from March 3 through March 9, 1958. Extensive measures of  
113 participants' early childhood environments were elicited through parental questionnaires,  
114 along with comprehensive measures of childhood characteristics elicited through teacher- and  
115 child-completed measures. To date, there have been eight follow-up waves (three in  
116 childhood, at ages 7, 11, and 16, and five in adulthood, at ages 23, 33, 42, 46, and 50). The  
117 attrition rate has been low: 12,316 cohort members responded in the latest wave (in 2008).  
118 Hawkes and Plewis (2006) showed that those who have left the survey do not differ from the  
119 remaining participants in observable socioeconomic characteristics, which reduces the risk  
120 that participants with an elevated probability of unemployment are absent from our analyses.  
121 We examined unemployment using one wave from each decade of participants' working  
122 lives. The final sample sizes in our analyses estimating the probability of unemployment at  
123 ages 23, 33, 42, and 50 ranged from 6,251 to 7,616 cohort members, and data on the total  
124 duration of unemployment from age 16 through age 50 were available for 10,107  
125 participants. All sample sizes were determined by retaining all participants for whom data on  
126 the outcome variables and independent variables were available.

## 127 *Measures*

### 128 *Childhood self-control*

129           Childhood self-control was gauged at the first and second NCDS follow-ups, when  
130 participants were ages 7 and 11. At both of these waves, teachers rated the children's  
131 behavior using the Bristol Social Adjustment Guide (Stott, 1969), which included a 13-item  
132 scale related to behavior considered "impulsive acting out without regard for consequences."  
133 Research from this period found that children with low scores on this measure demonstrated

134 poor educational performance (Chazan, 1968). Today, a wide array of measures are available  
135 for gauging individual differences in temperament early in life (Zentner & Bates, 2008).  
136 However, in 1965, when the NCDS participants were 7 years old, the evidence base  
137 supporting the measurement of individual differences in temperament in children was much  
138 less well developed (Kubzansky, Martin, & Buka, 2009).

139         Nonetheless, the self-control measure we used contains items comparable to those  
140 included in modern scales (e.g., Tsukayama et al., 2013), capturing individual differences in  
141 attentional control (e.g., “cannot attend or concentrate for long” and “too restless to  
142 remember for long”), persistence (“does not know what to do with himself, can never stick at  
143 anything long”), and impulsive behavior (“constantly needs petty correction”; for a complete  
144 list of the items, see Section 1.2 in the Supplemental Material). Teachers were asked to  
145 underline the phrases that they thought described the children’s behavior; each underlined  
146 item was scored as 1 point, and the maximum possible score was 13. We took the average of  
147 these scores at ages 7 and 11 to create a composite self-control measure ( $M = 11.61$ ,  $SD =$   
148  $1.67$ ), coded so that a higher score was indicative of higher self-control. This variable was  
149 then standardized to have a mean of 0 and standard deviation of 1.

150         We built evidence for the validity of this measure using the data available in the  
151 NCDS and data we collected ourselves (including the contemporary self-control measures  
152 reported in Study 1). Although we could not estimate the convergent validity of the self-  
153 control measure in the NCDS data as we did in Study 1, we examined discriminant validity  
154 using a set of other measures also taken from the Bristol Social Adjustment Guide (Stott,  
155 1969). To gauge emotional functioning, we used an 18-item Depression scale, and to assess  
156 introversion, we combined scores on the 13-item Withdrawal scale (e.g., “quite cut off from  
157 people . . .” and “distant, shuns others’ company”) and the 18-item Unforthcomingness scale  
158 (e.g., “too shy to ask teacher’s help” and “says very little . . .”) (Details of these measures are

159 provided in Section 2 of the Supplemental Material.) Our analyses supported discriminant  
160 validity of our self-control measure: It had a moderate negative association with depression ( $r$   
161  $= -.44, p < .01$ ) and a weak negative correlation with introversion ( $r = -.15, p < .01$ ).

162 To test the convergent and discriminant validity of the main self-control measure  
163 using contemporary measures, we examined data collected in our online study of 100 parents  
164 of children ages 5 through 12 (see Study 1; also see Section 3 of the Supplemental Material).  
165 The 13-item scale that was our main self-control measure in Study 2 showed a high level of  
166 reliability (Cronbach's  $\alpha = .87$ ), and scores on this scale correlated strongly with scores on  
167 the BSCS (Tangney et al., 2004),  $r = .74, p < .01$ , and DSIS (Tsukayama et al., 2013),  $r = .71,$   
168  $p < .01$ . Furthermore, the Study 2 self-control measure exhibited a weaker correlation with  
169 emotional problems ( $r = -.35, p < .01$ ) and peer problems ( $r = -.38, p < .01$ ) as gauged using  
170 the SDQ (Goodman, 1997), which provided evidence of discriminant validity. The  
171 percentage of common variance between the self-control measure utilized in this study and  
172 the contemporary measures of self-control was more than 4 times the common variance  
173 between the former measure and the SDQ measures of emotional and peer problems. We  
174 interpret the findings of these validation analyses as reasonably strong evidence in support of  
175 the convergent and discriminant validity of the self-control scale used in Study 2.

### 176 ***Childhood covariates***

177 Childhood intelligence was assessed at age 11 using an 80-item general-ability test  
178 developed by the National Foundation for Educational Research in England and Wales  
179 (Pigeon, 1964). Parental social class was derived from the occupation of the father; scores  
180 ranged from I, for higher administrators, to V, for unskilled workers. Child gender was also  
181 included as a covariate. In our extended unemployment regressions, we included extensive  
182 controls for childhood variables that could plausibly have an impact on future employment  
183 trajectories. These variables included detailed measures of childhood health and family

184 difficulties, as well as information on birth weight and region and household size at the time  
185 of the participant’s birth; their inclusion in the regressions did not significantly change the  
186 main results (see Section 5 in the Supplemental Material for further details). By adjusting our  
187 analyses for these factors, we aimed to rule out the possibility that self-control was acting as a  
188 proxy and that adverse experiences, childhood environmental conditions, or early health were  
189 the “true” causes of later unemployment. If including such variables in our regression model  
190 markedly diminished the link between self-control and unemployment, we would consider  
191 the relationship between self-control and unemployment to be affected by confounding.

192         As in Study 1, we also tested whether our results were robust to the inclusion of  
193 mother-rated measures that appeared to capture elements of conduct problems (e.g.,  
194 “disobedient” and “fights other children”) and hyperactivity (“restless” and “squirmy”).  
195 These measures are described in full in Section 4 of the Supplemental Material

### 196 *Unemployment*

197         Our outcome variables were (a) unemployment at ages 23, 33, 42, and 50 and (b) total  
198 number of months of unemployment from 1974 through 2008. For the wave measures of  
199 unemployment, being in any kind of full- or part-time employment was coded as 0, and being  
200 unemployed was coded as 1. Unemployment ranged from a peak of 10.9% at the age-23  
201 wave to a low of 2.4% at the age-42 wave (see Table 2.3). We created a continuous variable  
202 gauging the total time each participant was unemployed by summing the number of months  
203 of unemployment from age 16 through age 50, using data collected across multiple study  
204 waves. As in Study 1, there was significant clustering at the left end of the scale—61% of the  
205 sample never reported any unemployment, 24% reported 1 to 12 months of unemployment,  
206 and the remaining 15% reported 13 to 341 months.

207 Table 3.3. Descriptive Statistics for Study 2 (National Child Development Study):  
 208 Characteristics of Participants at Each Assessment Wave and of Participants With Lifetime  
 209 Unemployment Data

Characteristic	Assessment wave				
	Age 23 ( <i>n</i> = 7,616)	Age 33 ( <i>n</i> = 6,938)	Age 42 ( <i>n</i> = 7,247)	Age 50 ( <i>n</i> = 6,251)	Lifetime unemployment sample ( <i>n</i> = 10,107)
Unemployment <sup>a</sup>	10.9%	4.8%	2.4%	2.8%	8.6 months
Self-control <sup>b</sup>	11.67	11.69	11.75	11.79	11.77
(mean)	(1.63)	(1.59)	(1.56)	(1.53)	(1.62)
Intelligence <sup>c</sup>	44.56	45.03	45.37	46.25	44.06
(mean)	(15.63)	(15.33)	(15.20)	(14.50)	(15.75)
Female (%)	43.4	43	47.1	48.1	50.1
Social class <sup>d</sup> (%)					
I	4.2	4.4	4.3	4.6	4.1
II	14.0	13.9	13.9	14.6	13.2
III	61.2	61.8	61.7	61.6	61.6
IV	12.1	11.8	11.9	11.6	12.1
V	8.5	8.1	8.2	7.6	9.0

210 Note: Standard deviations are given in parentheses. *Lifetime unemployment* refers to  
 211 unemployment from age 16 to age 50.

212 <sup>a</sup>The table shows the percentage of participants who were unemployed at each wave and the  
 213 total number of months of unemployment for participants in the lifetime-unemployment  
 214 sample. <sup>b</sup>Unstandardized self-control scores ranged from 0 to 10.5; higher scores indicate  
 215 better self-control. <sup>c</sup>Unstandardized intelligence scores ranged from 0 to 80; higher scores

216 indicate higher intelligence. <sup>d</sup>Social class was derived from the father's occupation: I = higher  
 217 administration, II = managerial or technical occupations, III = skilled workers, IV =  
 218 semiskilled workers, and V = unskilled workers.

### 219 *Statistical Methods*

220 We specified Probit regressions to estimate the probability of unemployment at ages  
 221 23, 33, 42, and 50 (Model 3) and a negative binomial model to estimate overall duration of  
 222 unemployment from age 16 through age 50 (Model 4). (As in Study 1, a negative binomial  
 223 model was appropriate because the mean total number of months of unemployment was  
 224 much lower than the variance, and a significant number of cohort members reported no  
 225 unemployment.) As in Study 1, we complemented the latter analysis with estimates of the  
 226 predicted number of months of unemployment by levels of self-control. We included controls  
 227 for gender, intelligence, and parental social class in all regressions. For the model examining  
 228 accumulated duration of unemployment (Model 4), we also included a continuous variable  
 229 measuring the length of activity data. The formal specifications of the models were as  
 230 follows:

231 Model 3: unemployment at age (23/33/42/50)<sub>*i*</sub> =  $\beta_0 + \beta_1$  childhood self-control<sub>*i*</sub> +  $\beta_2$  gender<sub>*i*</sub> +  
 232  $\beta_3$  childhood intelligence<sub>*i*</sub> +  $\beta_4$  social class<sub>*i*</sub> +  $\varepsilon_i$

233 Model 4: total months of unemployment at ages 16–50<sub>*i*</sub> =  $\beta_0 + \beta_1$  childhood self-control<sub>*i*</sub> +  $\beta_2$   
 234 gender<sub>*i*</sub> +  $\beta_3$  childhood intelligence<sub>*i*</sub> +  $\beta_4$  social class<sub>*i*</sub> +  $\beta_5$  months of employment data  
 235 recorded<sub>*i*</sub> +  $\varepsilon_i$

236 As already noted, to test the robustness of our results, we repeated all analyses  
 237 examining the association between self-control and unemployment adjusting for an additional  
 238 array of childhood covariates (see Section 5 in the Supplemental Material). As in Study 1, we  
 239 also tested the robustness of our findings to adjustment for conduct and emotional problems  
 240 (see Section 4 in the Supplemental Material).

241           If self-control-related differences in the unemployment rate were amplified as a result  
 242 of economic recession, this would have implications for future investigative strategies, and  
 243 possibly also for public policy. To test the effect of recession on the association between self-  
 244 control and unemployment, we used monthly employment data collected on each participant  
 245 from 1974 through 1982. The United Kingdom entered a recession in January 1980 (Jenkins,  
 246 2010), and the effect of this downturn on the labor market was dramatic; more than 619,000  
 247 jobs were lost, and the unemployment rate did not return to its prerecession level for 8 years.  
 248 We created a recession variable that was coded as follows: 0 = June 1974–December 1979  
 249 (when cohort members were ages 16–21) and 1 = January 1980–February 1982 (ages 21–23).  
 250 Using a Probit difference-in-difference model (Model 5) with clustered standard errors to  
 251 account for nonindependence in repeated observations on the same individuals, we then  
 252 estimated the average predicted probability of unemployment for individuals at different  
 253 levels of self-control before and after the recession, using the “margins” command in Stata  
 254 (Long & Freese, 2014). This model tested whether the average difference in unemployment  
 255 level between participants with low and high self-control grew in the postrecession period.  
 256 We entered the self-control and recession variables simultaneously with the Self-Control ×  
 257 Recession interaction term, in line with recommended practice (Aiken & West, 1991). The  
 258 formal specification of the model is described below, where the  $t$  subscript refers to time:  
 259 Model 5: monthly unemployment at ages 16–23 $_{it} = \beta_{0i} + \beta_1$  childhood self-control $_i + \beta_2$   
 260 gender $_i + \beta_3$  childhood intelligence $_i + \beta_4$  social class $_i + \beta_5$  month $_t + \beta_6$  recession $_t + \beta_7$   
 261 childhood self-control $_i * recession_t + \varepsilon_{it}$

262

263

264

265

## 266 3.6 Results

### 267 *Descriptives*

268 Table 3.3 presents descriptive statistics for this study. As in Study 1, males had lower  
 269 self-control scores ( $M = 11.23$ ) on average than females ( $M = 12.09$ ),  $t(10105) = -27.7$ ,  $p <$   
 270  $.0001$ , and better self-control correlated with higher intelligence ( $r = .39$ ,  $p < .01$ ) and to a  
 271 lesser extent with higher parental social class ( $r = .13$ ,  $p < .01$ ). Also as in Study 1, we  
 272 divided participants into three self-control groups: participants with low self-control (those  
 273 with scores 1  $SD$  below the mean and lower; 13% of the sample), participants with high self-  
 274 control (those scoring the maximum value of 0.83  $SD$  above the mean; 28% of the sample),  
 275 and participants with medium self-control (all others). We found that participants with low  
 276 self-control accumulated around 3.3 times as many months of unemployment as those with  
 277 high self-control (low self-control:  $M = 17.70$  months,  $SD = 39.19$ ; medium self-control:  $M =$   
 278  $8.13$  months,  $SD = 24.54$ ; high self-control:  $M = 5.42$  months,  $SD = 16.95$ ).

### 279 *Regressions*

280 Table 3.4 and Figure 3.2 describe our results. After controlling for gender,  
 281 intelligence, and parental social class, we found that a 1- $SD$  increase in childhood self-control  
 282 predicted the following decreases in the probability of unemployment in adulthood: 2.6  
 283 percentage points at age 23, 1.2 percentage points at age 33, 0.9 percentage points at age 42  
 284 and 0.8 percentage points at age 50. These results are shown graphically in Figure 3.2a. On  
 285 average, across the four waves examined, a 1- $SD$  increase in self-control was associated with  
 286 a reduction of 1.4 percentage points in the probability of unemployment.

287 Our analysis of the total cumulative duration of unemployment showed that more self-  
 288 controlled children went on to spend less time unemployed over their working lives ( $b =$   
 289  $-0.261$ ,  $SE = 0.034$ ,  $p < .01$ ). As shown in Figure 3.2b, the predicted number of months of  
 290 unemployment was 10.30 (95% CI = [9.43, 11.16]) for participants with low self-control (1



291 *SD* below the mean), 7.93 (95% CI = [7.46, 8.41]) for those with mean self-control scores,  
292 and 6.39 (95% CI = [5.84, 6.94]) for those with high self-control (0.83 *SD* above the mean).  
293 As in Study 1, our analyses showed that from adolescence to midlife, participants with low  
294 self-control experienced 1.6 times as many months of unemployment as those with high self-  
295 control.

296 Table 3.4. Regression Results From Study 2 (National Child Development Study): Predicting  
 297 Probability of Unemployment at Each Assessment Wave and Duration of Lifetime  
 298 Unemployment

Predictor	Probability of unemployment				Lifetime
	Age 23 ( <i>n</i> = 7,616)	Age 33 ( <i>n</i> = 6,938)	Age 42 ( <i>n</i> = 7,247)	Age 50 ( <i>n</i> = 6,251)	unemployment ( <i>n</i> = 10,107)
Self-control	-0.026** (0.004)	-0.012** (0.002)	-0.009** (0.002)	-0.008** (0.002)	-0.261** (0.034)
Intelligence	-0.028** (0.004)	-0.021** (0.003)	-0.005** (0.002)	-0.013** (0.002)	-0.250** (0.030)
Female gender	0.002 (0.008)	-0.019** (0.006)	-0.003 (0.004)	-0.009* (0.004)	-0.388** (0.059)
Social class					
II	-0.032 (0.021)	-0.011 (0.016)	0.003 (0.009)	-0.003 (0.013)	-0.142 (0.158)
III	-0.016 (0.020)	-0.006 (0.014)	0.010 (0.008)	-0.005 (0.012)	-0.047 (0.144)
IV	-0.007 (0.022)	-0.013 (0.016)	0.008 (0.009)	-0.010 (0.013)	0.051 (0.162)
V	0.042 (0.024)	0.025 (0.018)	0.024* (0.011)	-0.003 (0.014)	0.356* (0.169)

299 Note: Standard errors are given in parentheses. *Lifetime unemployment* refers to  
 300 unemployment from age 16 to age 50. For the probability of unemployment, the table  
 301 presents marginal effects coefficients from Probit regressions. For the duration of lifetime  
 302 unemployment, the table presents coefficients from a negative binomial model that controlled

303 for length of work data. Self-control and intelligence were standardized. Social class was  
304 derived from the father's occupation: I = higher administration, II = managerial or technical  
305 occupations, III = skilled workers, IV = semiskilled workers, and V = unskilled workers.

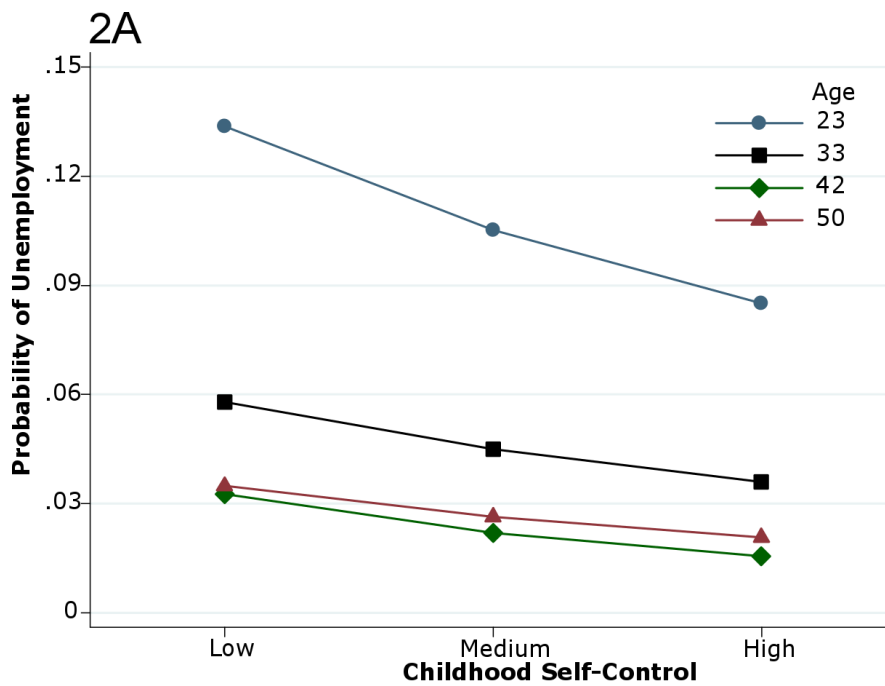
306 Social Class I was the reference group.

307 \* $p < .05$ . \*\* $p < .01$ .

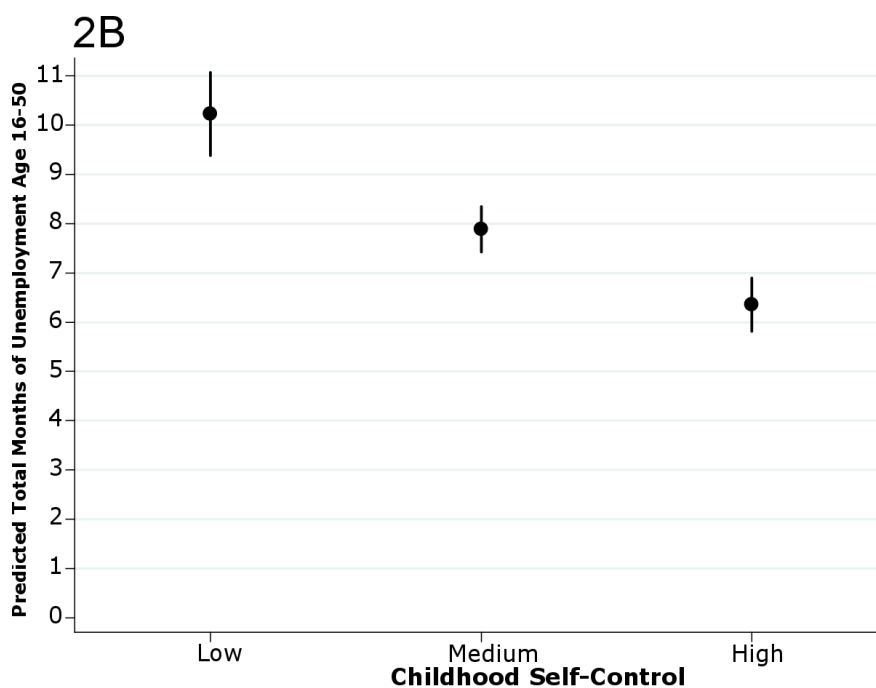
308

309

310 Figure 3.2: Results from Study 2 (National Child Development Study): (a) predicted  
 311 probability of unemployment at each wave as a function of childhood self-control and (b)  
 312 predicted marginal total number of months of unemployment as a function of childhood self-  
 313 control. The error bars in (b) represent 95% confidence intervals. Low self-control = 1  
 314 standard deviation below the mean; medium self-control = mean scores; high self-control =  
 315 0.83 standard deviations above the mean.



316



317

318 In our analysis including the extended range of important early-life controls (see  
319 Table S5 in the Supplemental Material), we found that the self-control coefficients remained  
320 significant at all time points except for age 50. Thus, we can say that the association between  
321 self-control measured at ages 7 and 11 and unemployment throughout adulthood appears to  
322 be independent of key potentially confounding variables concerning childhood physical and  
323 mental health, region of birth, ethnicity, and family structure.

324 As in Study 1, we conducted a robustness check by using mother-rated measures  
325 assessing elements of conduct problems and hyperactivity. The inclusion of these variables  
326 reduced the self-control coefficients by 7.6 per cent on average for the individual time points  
327 and led to a 7 per cent increase in the self-control coefficient for predicting lifetime  
328 unemployment, without altering the significance levels of the self-control coefficients. These  
329 measures and results are described in the Supplementary Materials, Section 3.4.

330

### 331 *Self-control and unemployment pre- and post-recession*

332 Unemployment levels rose sharply among participants with low self-control (1 *SD*  
333 below the mean) in the aftermath of the 1980 recession (see Fig. 3.3 for descriptive  
334 unemployment rates for participants with low, medium, and high self-control, see Fig. 3.4 for  
335 predicted unemployment probabilities in the pre- and post-recession periods). From 1974  
336 through 1979, the average predicted probability of unemployment for this group was 6.1%,  
337 compared with 4.1% for participants with high self-control (0.83 *SD* above the mean, the  
338 highest level of self-control reported). These figures rose to 9.2% and 5.8%, respectively, in  
339 the 1980–1982 period. The difference in the average unemployment level between the  
340 participants with low and high self-control therefore rose by 1.4 percentage points; from a 2-  
341 point gap to a 3.4-point gap after controlling for covariates, as shown in Figure 3.4 (also see  
342 Table 3.5 for a summary of these analyses). Thus, the difference-in-difference analysis

343 indicated that participants in the low-self-control group were disproportionately more likely  
 344 to become unemployed after the onset of the recession. There was a similar gap between the  
 345 low- and medium-self-control (those with mean self-control scores) groups, but it was  
 346 smaller in magnitude (0.9 percentage points).

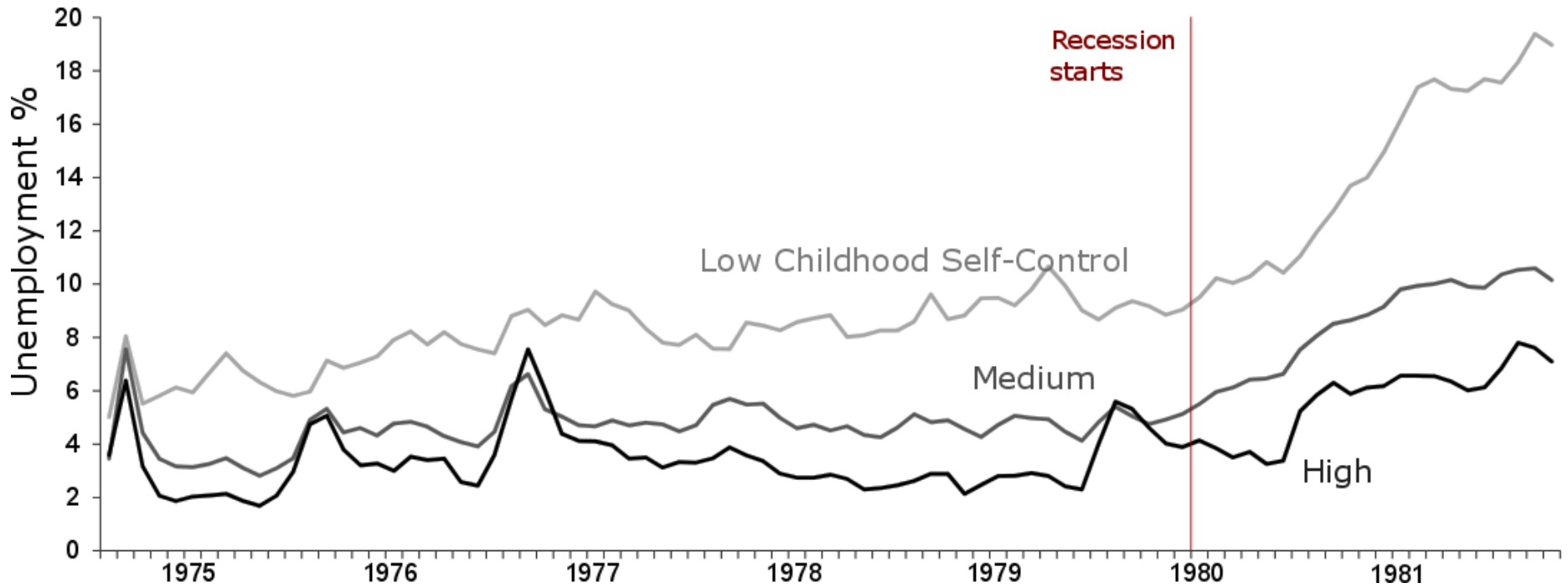
347

348 Table 3.5. Regression Results From Study 2 (National Child Development Study): The Effect  
 349 of Childhood Self-Control on the Probability of Unemployment Before and After the 1980s  
 350 Recession (Observations = 597,858)

	1974–1979 (prerecession)	1980–1982 (postrecession)	Difference (postrecession - prerecession)	Difference-in-Difference (Medium - Low, High - Low)
<i>Self-Control</i>				
Low	0.061 (0.002)	0.092 (0.003)	0.031 (0.003)	
Medium	0.050 (0.001)	0.072 (0.002)	0.022 (0.002)	0.009 (0.002)***
High	0.041 (0.002)	0.072 (0.002)	0.017 (0.003)	0.014 (0.003)***

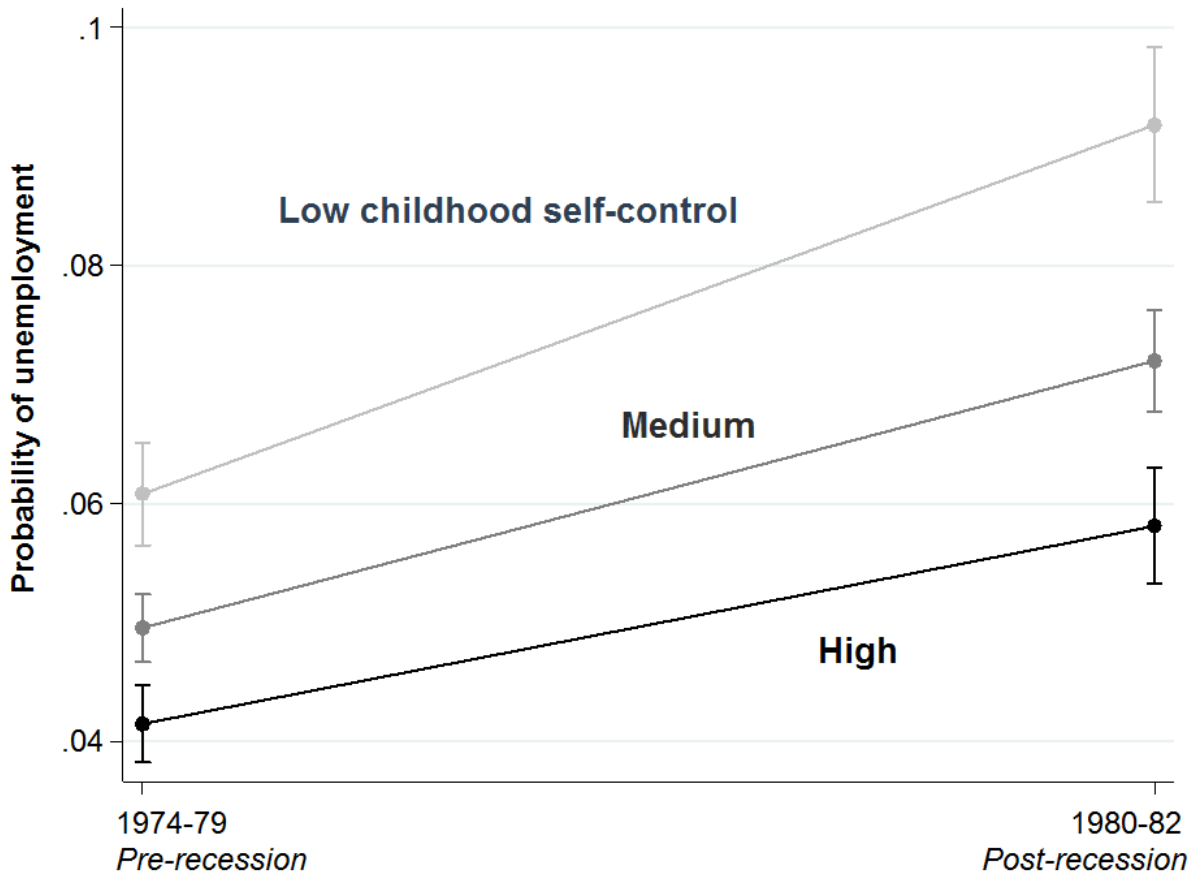
351 Note: Gender, intelligence, social class, and a time trend were included in the analysis, but  
 352 results for these predictors are not shown. Robust standard errors are given in parentheses.  
 353 The table presents predicted probabilities calculated after a Probit regression clustered by ID  
 354 to account for nonindependence of repeated observations. Low self-control was defined as  
 355 scoring 1 standard deviation below the mean on the standardized self-control measure,  
 356 medium self-control was defined as scoring at the mean on this measure, and high self-  
 357 control was defined as scoring at the maximum of 0.83 standard deviations above the mean.  
 358 Difference in difference coefficients and standard errors were calculated using the lincom  
 359 command in Stata.

360 Figure 3.3: Descriptive unemployment statistics from Study 2 (National Child Development Study). Monthly data for August 1974 through  
361 October 1981 are shown for participants at three levels of childhood self-control (low = 1 *SD* below the mean and lower; high = 0.83 *SD* above  
362 the mean and higher; medium = all others). The year above the cohort members' age indicates March of that year, the month when the cohort  
363 members were born.



364

365 Figure 3.4: Results from Study 2 (National Child Development Study): predicted marginal  
366 probability of unemployment before and after the 1980 recession, for participants at three  
367 levels of childhood self-control (low = 1 *SD* below the mean; medium = mean; high = 0.83  
368 *SD* above the mean).



369



### 3.7 Discussion

Our findings link childhood self-control to unemployment across adulthood. We utilized two large-scale prospective birth-cohort studies with detailed measurements of childhood psychological characteristics and comprehensive unemployment data gathered over four decades. Low childhood self-control predicted unemployment in adulthood, even decades later at age 50. The predictive strength of differences in childhood self-control was equal to or greater than that of intelligence, and childhood self-control was still a significant predictor after we controlled for variation in intelligence, social class, and an extensive range of family and health factors.

In Study 1, we found that children with lower self-control at age 10 experienced a higher cumulative duration of unemployment by age 38 and were more likely to be unemployed at ages 21, 26, 30, and 42 years. In Study 2, self-control was rated at ages 7 and 11, and lower scores predicted a greater duration of accumulated unemployment by age 50 and higher unemployment at ages 23, 33, 42, and 50. The link between self-control and unemployment peaked in magnitude when participants were in their early 20s. At that time, a 1-*SD* increase in self-control predicted an increase of more than 3 percentage points in the probability of unemployment across the two studies. However, even in the fourth and fifth decades of life, when unemployment rates in the cohorts were low (i.e., 2.4–2.8%), a 1-*SD* increase in self-control was associated with a large and statistically significant decrease in unemployment levels (~ 1 percentage point).

These findings contribute to a growing body of work suggesting that poor self-control is often a stable aspect of personality—and one that brings a host of long-run disadvantages (e.g., Moffitt et al., 2011; Slutske, Moffitt, Poulton, & Caspi, 2012). In Study 1, teachers rated children on whether they paid attention or were easily distracted and on whether they completed or gave up on tasks; in Study 2, teachers rated children on carelessness, the

tidiness of their work, level of concentration, restlessness, posture, reliability, and rule breaking. It is perhaps understandable that adults who break rules, fail to complete tasks, lack concentration, and are careless and sloppy find fewer employment opportunities than their counterparts who follow rules, complete tasks, pay attention, and are careful workers. But the fact that these traits are sufficiently evident in young children to predict large, statistically significant and meaningful differences in employment among middle-aged adults indicates a remarkable degree of stability.

Although the contribution of self-control to unemployment showed substantial consistency over time in both cohorts, we hypothesized that this effect would become more pronounced in exceptionally poor macroeconomic circumstances, such as during a major recession. To test this idea, we examined monthly unemployment data for the NCDS cohort, who were tracked before and throughout the 1980s recession. We found a rapid growth in unemployment among participants with low self-control as the economy worsened in 1980 (see Figs. 3 and 4). The employment prospects of workers low in self-control appeared to be particularly vulnerable to macroeconomic fluctuations, which suggests that in difficult economic times, when employers need to scale back, many people with poor self-control either lose jobs or fail to get new ones.

The delayed consequences of such a potential differential impact remain to be examined in further research, but it is not safe to assume that people with poor self-control go back to work as soon as the macroeconomic picture brightens. Temporary career interruptions can have lasting, even permanent consequences, such as if one moves off the path of advancement, if one's skills become obsolete, or if one eventually settles in at a lower-quality job (e.g., Arulampalam, 2001). Periods of unemployment also increase opportunities for abandoning healthy habits of regular sleep schedules, nutritious eating, good hygiene, and sobriety (and such opportunities may especially attract people lacking self-

control); unemployment may also increase vulnerability to stress. As a result, the unemployed may become even less likely to reenter employment (e.g., Daly & Delaney, 2013; Digdon & Howell, 2008; Henkel, 2011; Krueger & Mueller, 2012).

The current research is limited in several respects. Although we adjusted for an extensive array of variables, it is possible that unobserved factors, such as unmeasured aspects of the family environment or genetic differences, predispose children to both poor self-control and later unemployment. Future studies comparing the impact of differences in self-control between siblings or twins would assist in ruling out these factors as explanations of the association between low self-control and unemployment (e.g., Delaney & Smith, 2012; Moffitt et al., 2011). An additional limitation is that the self-control measures used in Studies 1 and 2 were not originally designed for that purpose, which raises the possibility of measurement error that could have attenuated the relationship between self-control and unemployment. However, we gathered data that provided empirical support for the validity of the scales used as measures of self-control: Both scales we used correlated above .7 with modern self-control scales (BSCS: Tangney et al., 2004; DSIS: Tsukayama et al., 2013). Incorporating observational and parent- and self-report measures would help ensure that future studies precisely identify the role of self-control. Although this was not possible in the current study, our extended regressions show that self-control is unlikely to have acted as a proxy for other childhood characteristics (e.g., cognitive ability, family background, physical and mental health).

However, despite these adjustments, it remains difficult to determine how precisely we isolated the relationship between self-control and unemployment. For instance, by controlling for a detailed index of cognitive ability, we may have underestimated the contribution of self-control, given that aspects of cognitive ability, particularly working memory capacity, have been proposed to overlap with and facilitate self-control. Working

memory capacity may promote effective self-control by protecting against attentional capture by tempting or distracting stimuli and by enabling important goals and standards to be kept in mind or protected from interference (Hofmann, Schmeichel, & Baddeley, 2012). Conversely, by failing to adjust for potentially important constructs, such as “grit” (i.e., perseverance and passion for long-term goals), that overlap with self-control (Duckworth & Gross, 2014), we may have overestimated the contribution of self-control.

Although we observed an enhanced contribution of self-control during a recession, it is unclear whether these striking findings are generalizable to other time periods and countries. The NCDS cohort’s early labor-market experience (at the end of the 1970s) occurred during a period of economic and industrial upheaval in the United Kingdom. Identifying whether an enhanced risk of unemployment among the less self-disciplined has occurred in other cohorts, such as those entering the labor market during the recent 2008 recession, will provide a new lens for understanding the effects of business-cycle fluctuations on both short- and long-run outcomes.

In summary, the present investigation provides robust evidence that poorer trait self-control is associated with higher unemployment across the life span. Teachers’ ratings of differences in self-control among children as young as 7 predicted unemployment more than four decades later. The policy implications are considerable: Improving children’s self-control could yield lifelong benefits to these individuals themselves, by raising their standard of living and reducing their danger of being unemployed, and also to broader society, by increasing employment and productivity. Emerging evidence suggests that the capacity for self-control is, to a certain degree, malleable and may be enhanced through training and sustained practice. Self-control and closely related traits have been shown to be enhanced by preschool programs, elementary-school interventions, and activities such as yoga or martial arts, computerized training games, and walking meditation exercises (Alan & Ertac, 2014;

Diamond, 2012; Diamond & Lee, 2011; Heckman, Pinto, & Savelyev, 2013; Posner, Rothbart, & Tang, 2013). The present findings demonstrate the long-range power of self-control in predicting success in life and single out self-control as a key target for early intervention programs. Being able to regulate one's behavior to comply with rules and systems during childhood appears to be a highly adaptive trait for engaging successfully in working life as an adult in a complex modern society.

#### Author Contributions

All authors contributed to the study concept. M. Daly, M. Egan, and L. Delaney conceived the analytic strategy, which was executed by M. Egan under the supervision of M. Daly and L. Delaney. All authors contributed to drafting the manuscript and approved the final version of the manuscript for submission.

#### Acknowledgments

We are grateful to The Centre for Longitudinal Studies, Institute of Education, for their management of these data and to the UK Data Archive for making them available. However, these organizations bear no responsibility for the analysis or interpretation of the data.

#### Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

#### Funding

We gratefully acknowledge funding support from the Economic and Social Research Council (ES/L010437/1, ESRC Future Leaders grant to M. Daly), from Skills Development Scotland (Ph.D. scholarship funding M. Egan), and from the European Commission Marie Curie Initiative (Grant Agreement PCIG10-GA-2011-303833, grant to L. Delaney).

## **Appendix**

**Section 1:** Details of data-sets & self-control measurements used in Study 1 and Study 2.

**Section 2:** Convergent and discriminant validity in Study 1 and Study 2.

**Section 3:** Details of validation data and analyses comparing self-control scales in Study 1 and Study 2 with contemporary self-control scales.

**Section 4:** Unemployment regressions controlling for conduct problems and hyperactivity in Study 1 and Study 2.

**Section 5:** Unemployment regressions using extended controls in Study 2.

**Section 6:** Unemployment regressions controlling for prior unemployment in Study 1 and Study 2.

**Section 1: Details of data-sets & self-control measurements used in Study 1 and Study 2.****Data-Sets Used****British Cohort Study (Study 1) (accessed October 4<sup>th</sup> 2014)**

1. Activity Histories, 1986-2000 (BCS 6943).
2. Ten-Year Follow-up, 1980 (BCS 3723).
3. Sixteen-Year Follow-up, 1986 (BCS 3535).
4. Twenty-One Year Sample-survey, 1992 (BCS 4715).
5. Twenty-Six Year Follow-up, 1996 (BCS 3833).
6. Thirty Year Follow-up, 2000 (BCS 5558)
7. Thirty-Four Year Follow-up, 2004-05 (BCS 5585).
8. Thirty-Eight Year Follow-up, 2008-09 (BCS 6557).
9. Forty-Two Year Follow-up, 2012-2013 (BCS 7473).

**National Childhood Development Study (Study 2) (accessed October 4<sup>th</sup> 2014)**

1. NCDS Activity Histories, 1974-2008 (NCDS 6942).
2. NCDS Childhood Data, Sweeps 0-3, 1958-1974 (NCDS 5565).
3. NCDS Sweep 4 data (NCDS 5566).
4. NCDS5 Cohort Member Interview and booklets data (NCDS 5567).
5. NCDS Sweep 6 data (NCDS 5578).
6. NCDS8 data labels library for SAS version (NCDS 6137).

All data-sets were downloaded from the UK Data Service:

<http://discover.ukdataservice.ac.uk/series/?sn=2000032>

## Details of Self-Control Measurements

### British Cohort Study (Study 1)

Self-control scores were derived from teacher ratings of the 11-item ‘inattentive’ subscale of the 53-item Child Developmental Behaviors questionnaire, taken when the child was 10 years old. This measure was designed for the British Cohort Study and consists of items drawn chiefly from the Conners Teachers Hyperactivity Rating Scale (Conners, 1969) and the Rutter Teacher Behavioral Scale B (Rutter, 1967). We omitted two items due to poor face validity (“Confused or hesitant”, “Shows lethargic/listless behaviour”). Dropping these two items reduces the reliability of the scale from 0.93 to 0.92 and has essentially no effect on the self-control coefficient in the regressions. The questions used are listed below:

1. Child is daydreaming. **R**
2. Cannot concentrate on particular task. **R**
3. Becomes bored during class. **R**
4. Shows perseverance.
5. Easily distracted. **R**
6. Pays attention in class.
7. Forget on complex tasks. **R**
8. Completes tasks.
9. Fails to finish tasks. **R**

**R** means the scale was reverse coded. All these scores were then summed and averaged to create a composite self-control score, which was then standardized to have a mean of 0 and standard deviation of 1.



## National Childhood Development Study (Study 2)

Childhood self-control was gauged as part of the first and second NCDS follow-ups at ages 7 and 11. At both of these ages teachers rated the child's behaviour using the British Social Adjustment Guide (Stott, 1969) which included a 13-item scale related to behaviour considered "impulsive acting out without regard for consequences". Teachers were asked to underline the phrases which applied to the child. The questions used are listed below:

1. Sometimes eager, sometimes doesn't bother (answering questions).
2. Constantly needs petty correction (classroom behaviour).
3. Too restless to remember for long (effect of correction).
4. Cannot attend or concentrate for long (cannot sit still when read to or during broadcasts, plays with things under desk) (attentiveness).
5. Rough and ready, slapdash (standard) (manual).
6. In informal play starts off others in scrapping and rough play.
7. Does not know what to do with himself, can never stick at anything long (free activity).
8. Misbehaves when teacher is out of room (liking the limelight).
9. Careless, untidy, often loses or forgets books, pen (belongings).
10. Gets very dirty during day (care for appearance).
11. Slumps, lolls about (posture).
12. Foolish pranks when with a gang (nuisance).
13. Follower in mischief (nuisance)

The NCDS does not contain an individual score breakdowns for these questions - instead there is only an aggregate score. We took the average of these two scores to create a composite self-control score where a higher score meant worse self-control. Scores ranged

from 0-10.5 out of a possible maximum of 13. We then inverted these scores so that a higher score meant better self-control and standardized the variable to a mean of 0 and standard deviation of 1. Due to clustering on the scale, the maximum value of the standardized variable was 0.83 SD above the mean.

**Section 2:** Convergent and discriminant validity in Study 1 and Study 2.

### **S2.1 Details of Convergent and Discriminant Validity Scales**

#### **British Cohort Study (Study 1)**

##### *Convergent Validity*

To test convergent validity with our self-control scale we used alternative teacher-rated measures which gauged persistence and attentional control. The children's scores on the below questions were coded so that a higher score always meant better self-control. Each of the six individual items was then standardized and the six items were summed. The summed variable itself was then standardized to create the Convergent Validity scale (Cronbach's  $\alpha = 0.82$ ).

1. How well does the child concentrate (score range 1-47)
2. Percentage of time concentrating (0-100)
3. Percentage of time fidgeting (0-95)
4. Does the child show perseverance (0-100)
5. Percentage of time interested in other tasks (0-100)
6. Percentage of time daydreaming (0-100)

This scale demonstrated strong convergent validity with our main self-control measure derived ( $r = 0.85, p < 0.01$ ).

### *Discriminant Validity*

To test discriminant validity we constructed scales of Neuroticism and Extraversion-Introversion. As above, all questions were coded so that a higher score meant more neurotic introverted. The scales were created by standardizing each variable individually, summing them and then standardizing the resultant variable. The neuroticism questions were:

1. Afraid of new things / situations (all scored 1-47)
2. Behaves 'nervously'
3. Fussy or over-particular
4. Worried and anxious
5. Anxious, worried

This scale demonstrated high internal consistency (Cronbach's  $\alpha = 0.85$ ) and displayed moderate correlation with our main self-control measure ( $r = -0.44$ ,  $p < 0.01$ ).

The questions measuring introversion were:

1. Rather solitary (all scored 1-47)
2. Listless or lethargic
3. Sullen or sulky
4. Introverted

This scale demonstrated moderate-high internal consistency (Cronbach's  $\alpha = 0.68$ ) and displayed moderate correlation with our main self-control measure ( $r = -0.50$ ,  $p < 0.01$ ).

## **National Child Development Study (Study 2)**

### ***Discriminant Validity***

The NCDS data does not contain appropriate measures to estimate convergent validity. Instead we estimate discriminant validity using (i) an 18-item 'Depression' scale assessing emotional functioning, measured at 7 and 11 years and (ii) a 'Extraversion-Introversion' scale created using a combination of a 13-item 'Withdrawal' scale and 18-item 'Unforthcomingness' scale, both measured at 7 and 11 years. The discriminant validity scales were created by standardizing the constituent variables, summing them and then standardizing the resultant variable. For example to create our Extraversion-Introversion scale we standardized Unforthcomingness at 7 years, Unforthcomingness at 11 years, Introversion at 7 years and Introversion at 11 years. We then summed these variables and standardized the result to create the Extraversion-Introversion scale.

The questions measuring 'Depression' are:

1. Depends on how he feels (asking teacher's help).
2. Varies noticeably from day to day (persistence in class work).
3. Sometimes alert, sometimes lethargic in team games.
4. In free activity sometimes lacks interest.
5. Persistence in manual tasks varies greatly.
6. Impatient, loses temper with job (persistence - manual tasks).
7. Flies into a temper if provoked (physical prowess).
8. Can work alone but has no energy (persistence in class work).
9. Lacks physical energy (persistence manual tasks).
10. Has no life in him (class room behaviour).
11. Apathetic (just sits) (attentiveness).

12. Shuffles restlessly (posture).
13. In asking teacher's help too apathetic to bother.
14. Dull listless eyes.
15. Always sluggish, lethargic in team games.
16. Sometimes wanders off alone (companionship).
17. Speech is thick, mumbling, inaudible.
18. Expression is miserable, depressed (under the weather) seldom smiles.

Our self-control measure demonstrated a moderate negative association with the depression scale ( $r = -0.44$ ,  $p < 0.01$ ).

The questions used to measure 'Unforthcomingness' are:

1. Chats only when alone with teacher.
2. Bursts into tears (attitude to correction).
3. Never offers to help teacher with jobs by pleased when asked.
4. Submissive, takes less wanted position, a ball fetcher (team games).
5. Too timid to be naughty (class room behaviour).
6. Lies from timidity (truthfulness).
7. Likes sympathy but reluctant to ask.
8. Never brings flowers, gifts, although classmates often do.
9. Never brings objects he has found, drawings, models, etc, to show teacher although classmates often do.
10. Associates only with one other child and mostly ignores the rest.
11. Waits to be noticed before greeting teacher.
12. Never makes first approach (talking to teacher).
13. Too shy to ask teacher's help.

14. When answering questions, gets nervous, blushes, cries when questioned
15. Shrinks from active play in informal play.
16. Mumbles shyly, awkwardly in response to greeting.
17. Can't get a word out of child (talking to teacher).
18. Says very little when talking to teacher.

The questions used to measure 'Withdrawal' are:

1. Absolutely never greets teacher.
2. Does not answer when greeted.
3. Makes no friendly or eager response (general manner with teacher).
4. Avoids talking to teacher (distant, deep).
5. Dreamy and distracted (lives in another world) (attentiveness).
6. Distant and uninterested (persistence in manual tasks).
7. Dreamy, uninterested in team games.
8. Distant, shuns others' company.
9. Keeps clear of adults even when hurt or wronged (liking for sympathy).
10. Quite cut off from people, you can't get near him as a person (general with teacher).
11. Unresponsive eyes.
12. Speech is an incoherent rumbling chatter.
13. In contacts with teacher, is like a suspicious animal

The withdrawn and introversion scales were combined to create an extraversion-introversion scale. Our self-control variable displayed a weak negative correlation with this extraversion-introversion scale ( $r = -0.13$ ,  $p < 0.01$ ).

**Section 3:** Details of validation data and analyses comparing self-control scales in Study 1 and Study 2 with contemporary self-control scales.

In order to test the validity of the main measurements used in Study 1 and 2, we conducted an online study to examine their correlation with 3 modern self-control scales. We recruited a sample of 100 American parents of children aged 5-12 via the website Amazon Mechanical Turk. Our survey was advertised as a “Adult and child personality study”. The survey routed participants to complete a set of self-control scales if they reported having a child aged 5-12 or a set of adult personality scales (not described here) if they reported not having a child in that age range. If a parent had more than one child in the 5-12 age range, they were asked to complete the survey with respect to the oldest child (e.g. if they had a 10 year old and an 8 year old , they were instructed to complete the survey about the 10 year old).

Since participants received compensation for their participation regardless of which task they completed (rating their own or their child’s personality), this design minimized the risk that participants may claim to have a child in order to receive payment for completing the survey. There was no obvious pattern of deceit in the answers of either group; the participants took several minutes to complete the survey, indicating that they weren’t just answering as quickly as possible, there was no clustering of answers at particular points on the scale (e.g. participants may have just mindlessly clicked the right-most answer every time) and in line with the general findings of the literature, female children were reported to have better self-control than boys on average on all five self-control scales.

The sample of parents rated their child’s temperament and behaviour on the below five scales:

*Cohort studies*

- (i) The 11-item scale in the British Cohort Study (BCS).
- (ii) The 13-item ‘Inconsequential Behaviour’ scale from the National Child Development Study (NCDS).

*Modern scales*

- (iii) 10-items gauging peer and emotional problems drawn from the Strengths & Difficulties Questionnaire (Goodman, 1997)
- (iv) The 13-item ‘Brief Self-Control Scale’ (Tangney et al., 2004)
- (v) The 7-item Domain-Specific Impulsivity Scale (Tsukayama et al., 2013)

To test the convergent validity of the scales used to measure self-control in Study 1 and 2, we examined their correlation with contemporary self-control scales (iv) and (v). The Brief Self-Control Scale (BSCS) is one of the most used modern self-control scales and has been used extensively to gauge self-control in school-aged children (e.g. Duckworth & Seligman, 2005; Duckworth & Seligman, 2006). The Domain-Specific Impulsivity Scale (DSIS) is was developed to gauge self-control and has been validated against existing measures including the BSCS (Duckworth, Tsukayama, & Kirby, 2013; Tsukayama, Duckworth, & Kim, 2013). To test the discriminant validity of the scales used in Study 1 and Study 2 we used 10 items from (v) the Strengths & Difficulties Questionnaire (SDQ) covering two facets; peer and emotional problems. If better self-control did not correlate strongly with more peer problems and emotional problems, this would be evidence of discriminant validity given that these represent different constructs.

In our sample of 100 parents, all self-control scales demonstrated high reliability with Cronbach’s alpha scores ranging from 0.83 to 0.89. In addition to the full 11-item and 13-item measures used in the British Cohort Study and National Child Development Study respectively, we tested reduced versions of these scales: (i) a 9-item version of the scale used in the BCS which removed 2 items due to poor face validity (“lethargic/listless” and “hesitant”) (ii) a 7-item version of the scale used in the NCDS which removed 6 items due to weak face validity (e.g. “rough and ready, slapdash”, “follower in mischief”). Removing



these items did not substantially alter the reliability scores of the scales nor the magnitude of the correlations with the modern self-control measures.

*Correlations between old and new self-control scales*

Table S3.1 shows the correlation results from the validation study. The 9-item self-control scale in Study 1 correlated with better self-control on the BSCS ( $r=0.75$ ,  $p<0.01$ ) and DSIS ( $r=0.75$ ,  $p<0.01$ ), indicating a strong level of convergent validity, and a much lesser extent with emotional ( $r= -0.35$ ,  $p<0.01$ ) and peer problems ( $r= -0.40$ ,  $p<0.01$ ) as measured by the SDQ, indicating evidence of discriminant validity. Similarly, the 13-item scale from Study 2 also correlated strongly with better self-control on the BSCS ( $r=0.74$ ,  $p<0.01$ ) and DSIS ( $r=0.71$ ,  $p<0.01$ ) and exhibited a weaker correlation with emotional ( $r= -0.35$ ,  $p<0.01$ ) and peer problems ( $r= -0.40$ ,  $p<0.01$ ).

Table S3.1. Correlation matrix comparing the self-control scales used in Study 1 and Study 2 to the Brief Self-Control Scale (BSCS), the Domain-Specific Impulsivity Scale (DSIS) and Peer and Emotional Problems subscales of the Strengths & Difficulties Questionnaire (SDQ).

	<b>Study 1<sup>a</sup></b>	<b>Study 2<sup>b</sup></b>	<b>BSCS<sup>c</sup></b>	<b>DSIS<sup>d</sup></b>	<b>SDQ: Peer problems<sup>e</sup></b>
<b>Study 2<sup>b</sup></b>	0.74	1			
<b>BSCS<sup>c</sup></b>	0.75	0.74	1		
<b>DSIS<sup>d</sup></b>	0.75	0.71	0.61	1	
<b>SDQ: Peer problems<sup>e</sup></b>	-0.40	-0.38	-0.32	-0.32	1
<b>SDQ: Emotional Problems<sup>e</sup></b>	-0.35	-0.35	-0.38	-0.28	0.48

<sup>a</sup> Self-control scale from the British Cohort Study (Study 1). <sup>b</sup> Self-control scale from the National Child Development Study (Study 2). <sup>c</sup> Brief Self-Control Scale. <sup>d</sup> Domain-Specific Impulsivity Scale. <sup>e</sup> Subscale of the Strengths & Difficulties Questionnaire. All correlations are significant at  $p < 0.01$

We interpret the findings of this validation study as reasonably strong evidence for the convergent and discriminant validity of the self-control scales used in Study 1 and 2. The two scales used in Study 1 and Study 2 show high levels of reliability with values approaching Cronbach's alpha of 0.9 and they are not sensitive to the removal of specific items or sets of items in terms of substantially reduced reliability nor in terms of convergent validity with the contemporary self-control scales. We identify similar levels of convergent validity with contemporary self-control measures as identified in the recent literature during the development of self-control measures (Tsukayama et al., 2013). Furthermore, we show that the two measures of self-control correlate strongly together and not with other commonly measured constructs such as peer and emotional problems, providing evidence of discriminant validity: the percentage of variance in common between the self-control measures in Study 1 and 2 and the modern self-control measures was 4 times greater than the common variance between the self-control measures in Study 1 and 2 and the measures of peer and emotional problems.

We acknowledge two main limitations of the validation study. Firstly, the sample used in the validation study was a group of American parents rather than British teachers. Secondly, the former group rated these measures in 2014 whereas the latter rated them between 1965 and 1980. These changes introduce the potential for measurement bias, potentially due to changing perceptions of question meaning or different cultural standards to judge children against in terms of what constitutes 'normal' behaviour. Despite these issues, which cannot be avoided when comparing older scales against modern measures, we consider

the evidence to on balance favor the use of the scales in Study 1 and 2 as good indicators of childhood self-control.

**Section 4:** Unemployment regressions controlling for conduct problems and hyperactivity.

This section details the mother-rated measures we identified in Study 1 and 2 as capturing elements of conduct problems and hyperactivity. Given that both these constructs are conceptually similar to self-control (Barkley, 1997), including these measures as control variables in our unemployment regressions represent a stringent attempt to isolate the contributing effects of self-control.

Table S3.2 describes the items used in both studies. Our selection of these measures was guided by attempting to match the items available in the data with those from the ‘conduct problems’ and ‘hyperactivity’ sections in the well-validated Strengths and Difficulties Questionnaire. The composite ‘conduct problems’ and ‘hyperactivity’ variables were created by taking the average of their component measures.

Table S3.2. Conduct problems and hyperactivity in Study 1 and Study 2.

Variable	N	Mean	SD	Min	Max	$\alpha$
<i>Study 1 (age 10)</i>						
Often disobedient		25.87	25.15	0	100	
Fights other children		17.73	20.09	0	100	
Bullies other children		13.79	14.36	0	99	
Often tells lies		18.86	20.32	0	100	
Takes others’ belongings		12.87	14.72	0	100	
Has tantrums		17.74	14.72	0	100	
Destroys belongings		13.16	15.21	0	100	

<b>Conduct problems</b>	8,022	17.31	13.46	0	96.71	0.76
Restless		34.54	31.00	0	100	
Squirmy		27.97	28.36	0	100	
Can't settle		23.39	25.70	0	100	
Easily distracted		33.18	30.33	0	100	
Fails to finish things		27.80	27.36	0	100	
<b>Hyperactivity</b>	8,376	29.30	20.81	0	100	0.78
<i>Study 2 (age 7 and 11)</i>						
Disobedient		1.17	0.90	0	4	
Fights other children		1.19	0.95	0	4	
Generally destructive		0.26	0.62	0	4	
<b>Conduct problems</b>	10,065	0.87	0.61	0	4	0.56
Restless		0.47	0.88	0	4	
Squirmy		1.05	1.14	0	4	
Can't settle		0.81	1.03	0	4	
<b>Hyperactivity</b>	10,171	0.78	0.74	0	4	0.55

---

Better self-control correlated with fewer conduct problems in Study 1 ( $r = -0.25$ ,  $p < 0.01$ ) and Study 2 ( $r = -0.32$ ,  $p < 0.01$ ) and with less hyperactivity in Study 1 ( $r = -0.35$ ,  $p < 0.01$ ) and Study 2 ( $r = -0.48$ ,  $p < 0.01$ ).

Table S3.3 describe the results of including these variables in our unemployment regressions in Study 1. Exhibiting more conduct problems in childhood was associated with a higher probability of unemployment at age 26, 30 and 38. Conduct problems were also associated with a greater lifetime duration of unemployment. Hyperactivity displayed no significant relationship with later unemployment at any time-point. The inclusion of these two variables reduced the self-control coefficients by an average of 23 per cent for the individual timepoints and 1 per cent for predicting lifetime unemployment.

Table S3.3. Unemployment regressions in Study 1 controlling for childhood conduct problems and hyperactivity.

Outcome	Age 21 <sup>a</sup>	Age 21 <sup>a</sup>	Age 26 <sup>a</sup>	Age 26 <sup>a</sup>	Age 30 <sup>a</sup>	Age 30 <sup>a</sup>	Age 34 <sup>a</sup>	Age 34 <sup>a</sup>
Observations	779	698	4,432	4,075	5,484	5,030	4,792	4,419
Self-control <sup>c</sup>	-0.040***	-0.037***	-0.015***	-0.010***	-0.015***	-0.015***	-0.004	-0.003
	(0.012)	(0.011)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Conduct problems <sup>c</sup>		0.012		0.010***		0.005*		0.005**
		(0.012)		(0.003)		(0.003)		(0.002)
Hyperactivity <sup>c</sup>		-0.012		0.006*		-0.005*		-0.003
		(0.012)		(0.003)		(0.003)		(0.002)
Outcome	Age 38 <sup>a</sup>	Age 38 <sup>a</sup>	Age 42 <sup>a</sup>	Age 42 <sup>a</sup>	Age 16-38 <sup>b</sup>	Age 16-38 <sup>b</sup>	--	--
Observations	4,497	4,136	4,921	4,526	6,879	6,290	--	--
Self-control <sup>c</sup>	-0.005**	-0.002	-0.008***	-0.007***	-0.275***	-0.271***		
	(0.002)	(0.002)	(0.002)	(0.002)	(0.054)	(0.059)		
Conduct problems <sup>c</sup>		0.006**		0.001		0.170***		
		(0.002)		(0.002)		(0.063)		
Hyperactivity <sup>c</sup>		0.004		0.003		-0.043		

(0.002)

(0.002)

(0.061)

---

<sup>a</sup> Regressions contain Probit marginal effects coefficients. <sup>b</sup> Regressions contain negative binomial coefficients. <sup>c</sup> Self-control, conduct problems and hyperactivity are standardized. Controlling for childhood intelligence, gender and parental social class. Standard errors in parentheses \*\*\* p<0.01, \*\* p<0.05

Table S3.4 describes the results of including these variables in our unemployment regressions in Study 2. Conduct problems were associated with a higher probability of unemployment at age 26 and 33 and a greater lifetime duration of unemployment. Hyperactivity was associated with a reduced probability of unemployment at age 23 and a reduced lifetime duration of unemployment. The inclusion of these variables reduced the self-control coefficients by 7.6 per cent on average for the individual timepoints and led to a 7 per cent increase in the self-control coefficient for predicting lifetime unemployment.

We interpret these regressions as evidence that the self-control measurement is robust to controls for childhood hyperactivity and conduct problems in both studies.

Table S3.4. Unemployment regressions in Study 2 controlling for childhood conduct problems and hyperactivity.

Observations	7,616	6,568	6,938	5,979	7,247	6,265
Outcome	Age 23 <sup>a</sup>	Age 23 <sup>a</sup>	Age 33 <sup>a</sup>	Age 33 <sup>a</sup>	Age 42 <sup>a</sup>	Age 42 <sup>a</sup>
Self-control <sup>c</sup>	-0.027*** (0.003)	-0.028*** (0.003)	-0.012*** (0.002)	-0.011*** (0.002)	-0.009*** (0.002)	-0.011*** (0.002)
Conduct problems <sup>c</sup>		0.019*** (0.003)		0.012*** (0.003)		0.003 (0.002)
Hyperactivity <sup>c</sup>		-0.014*** (0.003)		-0.005* (0.003)		-0.004* (0.002)
Observations	6,251	5,407	10,107	8,650	--	--
Outcome	Age 50 <sup>a</sup>	Age 50 <sup>a</sup>	Age 16-50 <sup>b</sup>	Age 16-50 <sup>b</sup>	--	--
Self-control <sup>c</sup>	-0.008*** (0.002)	-0.006*** (0.002)	-0.261*** (0.034)	-0.279*** (0.039)		
Conduct problems <sup>c</sup>		0.003 (0.002)		0.118*** (0.035)		
Hyperactivity <sup>c</sup>		0.001 (0.002)		-0.104*** (0.037)		

<sup>a</sup> Regressions contain Probit marginal effects coefficients. <sup>b</sup> Regressions contain negative binomial coefficients. <sup>c</sup> Self-control, conduct problems and hyperactivity are standardized. Controlling for childhood intelligence, gender and parental social class. Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05

**Section 5: Unemployment regressions using extended controls in Study 2.**

As a robustness check of our analysis of the association between childhood self-control and later unemployment, we included extensive childhood controls that could plausibly have affected future employment trajectories. Firstly we considered adverse childhood experiences and mental health. We created dummy variables for whether the childhood home had housing difficulties, financial difficulties, domestic tension, alcoholism, physical handicap, unemployment or sickness, mental illness or ‘mental subnormality’ and other serious difficulties. These 9 variables were then summed into a ‘Family Difficulties’ scale ranging from 0-6 where a higher score meant more difficulties. For health controls we included dummies for whether the child had ‘mental retardation’ at age 7, low birth weight (less than 88 ounces), whether the child received psychiatric treatment by age 11 and/or was recorded as being emotionally maladjusted at age 7, and whether the child suffered frequent headaches, migraines or epilepsy at age 7. The rationale for controlling for these kinds of early childhood trauma and mental health conditions was that such early events can have significant impacts on adult socioeconomic outcomes, with research suggesting a negative impact on employment, education and earnings resulting from childhood abuse (Currie & Widom 2010), early mental-health disorders (Kawakami et al. 2012, Goodman, Joyce, & Smith, 2011) and other adverse childhood experiences (Liu et al. 2013).

Secondly we included demographic and regional controls. We created dummies for the 11 different regions of birth represented in the NCDS, a continuous variable for the husband’s age at the time of the child’s birth and for household size (continuous from 0-7 and 8+ thereafter). We created a dummy variable for race but since the vast majority of respondents identified as Euro-Caucasian (almost 96 per cent of those for whom data is available), we coded this as 0 and everything else as 1. There is data on the mother’s marital



status at the time of the child's birth, but since over 99 per cent of the sample reported being married or in a stable union, we did not use this measure.

Table S3.5 describes our unemployment regressions with extended control variables. Self-control remains a significant predictor of unemployment at ages 23, 42 and 50, although the coefficient sizes are reduced. Other notable results include: (1) there are also significant regional differences in predicting lifetime unemployment, with the East and South-East, South and South-West regions reporting much lower averages than the North for this measure; (2) Non-whites have a significantly higher chance of being unemployed at ages 23 and 50; (3) Children who received psychiatric treatment have a significantly higher probability of being unemployed at several time points and have higher lifetime unemployment. This is in keeping with recent research demonstrating the "long shadow" of childhood psychiatric problems on adult income and well-being (Goodman et al., 2011).

Table S3.5. Unemployment regressions in Study 2 controlling for an extended range of childhood background characteristics.

Unemployment	Age 23 <sup>a</sup>	Age 33 <sup>a</sup>	Age 42 <sup>a</sup>	Age 50 <sup>a</sup>	Lifetime <sup>b</sup>
N	4,207	3,840	4,030	3,547	5,383
Self-Control <sup>c</sup>	-0.023*** (0.005)	-0.012*** (0.003)	-0.007*** (0.002)	-0.003 (0.002)	-0.172*** (0.050)
Intelligence <sup>c</sup>	-0.012** (0.005)	-0.010*** (0.004)	-0.004 (0.003)	-0.005* (0.003)	-0.126*** (0.046)
Female	0.004 (0.009)	-0.017** (0.007)	-0.005 (0.005)	-0.012** (0.005)	-0.449*** (0.082)
<i>Social class (base=I) <sup>d</sup></i>					
Social class II	0.004 (0.024)	-0.038** (0.018)	0.006 (0.008)	-0.004 (0.013)	-0.204 (0.203)
Social class III	0.004 (0.022)	-0.009 (0.015)	0.011 (0.007)	-0.000 (0.012)	-0.067 (0.188)
Social class IV	-0.003 (0.025)	-0.012 (0.017)	0.012 (0.009)	-0.007 (0.013)	0.130 (0.217)
Social class V	0.038 (0.028)	0.015 (0.018)	0.028** (0.013)	-0.003 (0.014)	0.310 (0.236)
<i>Childhood Experiences</i>					
Family Difficulties Scale	0.003 (0.009)	-0.002 (0.006)	-0.001 (0.004)	0.007* (0.004)	0.098 (0.077)
Low birth weight	0.011 (0.021)	0.011 (0.015)	-0.002 (0.011)	0.014 (0.009)	0.029 (0.190)
Psychiatric problems	0.065***	0.027	0.000	0.021**	0.430*

	(0.023)	(0.016)	(0.012)	(0.011)	(0.249)
Headaches or Epilepsy	0.030**	0.003	0.001	0.002	0.263*
	(0.014)	(0.011)	(0.007)	(0.008)	(0.139)
Mental Retardation	0.029	0.035	0.018	0.015	0.405
	(0.031)	(0.022)	(0.014)	(0.015)	(0.341)
<i>Region of birth (base=North)</i>					
North West	-0.020	0.009	0.008	0.012	0.168
	(0.022)	(0.013)	(0.011)	(0.013)	(0.172)
East-West Riding	-0.045*	0.006	-0.009	-0.020**	0.020
	(0.024)	(0.014)	(0.010)	(0.010)	(0.190)
North Middle	-0.077***	-0.006	-0.008	0.002	-0.280
	(0.021)	(0.015)	(0.010)	(0.013)	(0.189)
Middle	-0.031	-0.000	-0.001	-0.000	0.232
	(0.023)	(0.014)	(0.010)	(0.012)	(0.179)
East	-0.080***	-0.033*	-0.006	-0.001	-0.307
	(0.021)	(0.018)	(0.010)	(0.012)	(0.191)
South East	-0.073***	-0.011	0.002	-0.006	-0.210
	(0.020)	(0.013)	(0.010)	(0.010)	(0.165)
South	-0.079***	-0.039*	-0.012	-0.009	-0.535**
	(0.023)	(0.021)	(0.010)	(0.012)	(0.209)
South West	-0.062***	-0.016	-0.017**	-0.020**	-0.164
	(0.023)	(0.017)	(0.009)	(0.010)	(0.200)
Wales	0.013	0.003	-0.005	-0.009	0.049
	(0.028)	(0.016)	(0.011)	(0.012)	(0.209)
Scotland	0.006	-0.010	0.005	-0.008	0.118

	(0.023)	(0.014)	(0.010)	(0.010)	(0.171)
<i>Demographics</i>					
Husband age at birth	-0.000	0.001*	0.000	0.000	0.007
	(0.001)	(0.001)	(0.000)	(0.000)	(0.006)
Household Size	0.009***	0.005**	0.001	0.001	0.116***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.031)
Race	0.105**	0.013	-0.004	0.038**	-0.334
	(0.042)	(0.027)	(0.023)	(0.017)	(0.435)
Length of activity history					0.003***
					(0.000)

---

<sup>a</sup> Regressions contain Probit marginal effect coefficients. <sup>b</sup> Regression contains negative binomial coefficients. <sup>c</sup> Self-Control and intelligence are standardized. <sup>d</sup> Social class is derived from the father's occupation where I = Higher admin, II = Managerial or technical occupations, III = skilled workers, IV = semi-skilled workers and V = Unskilled workers. Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

### **Section 6:** Unemployment regressions controlling for prior unemployment in Study 1 and 2.

The regressions in Table S3.6 control for employment status at the previously observed time-point. In Study 1 this means we predicted the probability of unemployment at age 30, 34, 38 and 42 while controlling for unemployment at the previous time-point. In Study 2 we predicted the probability of unemployment at age 33, 42 and 50 while controlling for prior unemployment. In both studies better self-control predicts a reduced probability of unemployment even after controlling for prior unemployment, although the coefficients decrease by 45% on average. Nonetheless the coefficients remain significant at p<0.01, indicating that poor childhood self-control has a strong association with later unemployment

above and beyond the contributing effects of intermediating unemployment.

Table S3.6. Unemployment regressions for the British Cohort Study (Study 1) and National Child Development Study (Study 2), controlling for prior unemployment.

Observations	19,768	15,391	20,436	16,398
Study	1	1	2	2
Self-Control	-0.008*** (0.001)	-0.004*** (0.001)	-0.010*** (0.002)	-0.006*** (0.001)
Unemployment (t-1)		0.060*** (0.004)		0.051*** (0.004)

All columns report Probit marginal effects coefficients controlling for childhood intelligence, gender, social class and a time trend. Robust standard errors in parentheses. \*\*\* p<0.01

## CHAPTER 4

### Adolescent Conscientiousness Predicts Lower Lifetime Unemployment

#### 4.1 Abstract

Existing research on Big Five personality and unemployment has relied on personality measures elicited after the respondents had already spent years in the labor market, an experience which could change personality. We clarify the direction of influence by using the British Cohort Study ( $N = 4,206$ ) to examine whether conscientiousness and other Big Five personality traits at age 16-17 predict unemployment over age 16-42. Our hypothesis that higher conscientiousness in adolescence would predict lower unemployment was supported. In analyses controlling for intelligence, gender, and parental socioeconomic status, the less conscientious ( $-1SD$ ) had a predicted probability of unemployment twice as high (3.4% vs 1.7%) as the highly conscientious ( $+1SD$ ), an effect size comparable to intelligence. Mediation analysis revealed that academic motivation and educational attainment explained only 8.9% of this association. Fostering conscientiousness in early-life may be an effective way to reduce unemployment throughout adulthood.

## 4.2 Introduction

Unemployment profoundly affects human welfare (McKee-Ryan, Song, Wanberg, & Kinicki, 2005), has long-term scarring effects on well-being and wages (Gregg & Tominey, 2005; Daly & Delaney, 2013) and incurs large economic costs to society via increased welfare payments and reduced productivity. Unemployment is often viewed as directly resulting from economic factors including the business cycle, economic recessions, and a mismatch between the skills sought by employers and the qualifications of those available for work (Hogan, Chamorro-Premuzic, & Kaiser, 2013). Whilst these factors are undoubtedly important, it is also likely that unemployment depends, at least partially, on psychological characteristics. Organizational research has identified the role of dispositional variables in shaping job performance and career success but has been less successful in pinpointing the traits that contribute to finding and retaining a job (Hogan et al., 2013; Ones, Dilchert, Viswesvaran, & Judge, 2007). Identifying the psychological characteristics that help people find and retain employment could help direct resources towards fostering these characteristics (Heckman & Kautz, 2013).

Personality traits, often indexed by the Big Five framework of conscientiousness, neuroticism, extraversion, openness and agreeableness (Costa & McCrae, 1985) are among the most important psychological characteristics given their predictive power for many consequential labor market outcomes (Borghans, Duckworth, Heckman & ter Weel, 2008). Of the Big Five, conscientiousness has the strongest links with career performance and occupational status (Almlund, Duckworth, Heckman & Kautz, 2011). Conscientious individuals are organized, responsible, hardworking, and ambitious, all quintessentially desirable habits in employees. Decades of organizational research has provided empirical evidence that conscientious employees thrive in the workplace (Barrick, Mount, & Judge, 2001; Judge, Higgins, Thoresen, & Barrick, 1999), are highly motivated to learn (Colquitt,

LePine, & Noe, 2000), set high work goals (Judge & Ilies, 2002), tend to avoid procrastination and other counterproductive behaviors (Berry, Ones, & Sackett, 2007; Steel, 2007), show superior individual and team performance (Judge, Rodell, Klinger, Simon, & Crawford, 2013; Peeters, Van Tuijl, Rutte, & Reymen, 2006), and go on to emerge as leaders (Judge, Bono, Ilies, & Gerhardt, 2002).

Despite the established importance of conscientiousness in the work domain, it is not clear whether conscientiousness shapes employment prospects. Results from Germany, America and Finland are mixed, with some studies showing that high levels of conscientiousness are associated with lower unemployment (Uysal & Pohlmeier, 2011; Fletcher, 2013b) and others finding null effects (Specht, Egloff, & Schmukle, 2011; Viinikainen & Kokko, 2012; Boyce, Wood, Daly, & Sedikides, 2015). This is despite evidence that the conscientious are more effective at the job search process, which helps them re-enter employment more quickly (Kanfer, Wanberg, & Kantrowitz, 2001). Furthermore, they also appear to experience greater drops in well-being following unemployment and gain greater satisfaction from their jobs and higher income, suggesting they may be particularly motivated to achieve productive employment (Boyce, Wood, & Brown, 2010; Boyce & Wood, 2011; Judge, Heller, & Mount, 2002).

However, a key limitation of prior studies examining the link between conscientiousness and unemployment is their use of personality measures elicited several years after the respondent entered the labor market. Given that unemployment can change personality (Boyce, Wood, Daly, & Sedikides, 2015), these studies cannot rule out the possibility that personality was at least partly determined by unemployment, thus explaining why the two variables are related – indeed one test of reverse causality in Viinikainen and Kokko (2012) could not rule out that unemployment in early life may have affected personality by middle age. Some studies have clarified the direction of influence by



examining traits measured before the respondents accumulated substantial labor market experience; for example Daly, Delaney, Egan, and Baumeister (2015) showed that more self-controlled children tend to experience less unemployment as adults. Self-controlled children are thought to better internalize and comply with standards and norms for behavior in order to become more conscientious adolescents (Eisenberg, Duckworth, Spinrad, & Valiente, 2014). Conscientiousness captures more than the continuity of childhood self-control into adolescence and adulthood; it encapsulates work-promoting tendencies such as being responsible and punctual, being orderly and organized and persevering to achieve important goals. Additionally, prior studies have been limited by the use of small samples or have neglected to control for important early-life predictors of future employment success (such as cognitive ability and social class at birth) which are known to correlate with personality (e.g. see Daly, Delaney, Egan, & Baumeister, 2015).

We seek to address this gap in the literature and avoid the limitations of prior studies. We therefore examine the hypothesis that higher conscientiousness in adolescence will predict lower future unemployment. We examine this relationship over three decades in a large sample of British adults while controlling for cognitive ability and social class. Because the personality measures we employ were elicited before the cohort members accumulated substantial experience in the labor market, this design limits the possibility of unemployment influencing personality. Since this is the first paper we are aware of which uses pre-labor market measures of Big Five personality to examine this outcome, our results may help to settle previously mixed findings in this literature.

*Hypothesis 1:* More conscientious adolescents will be less likely to experience unemployment as adults.

Theoretical research by Cunha and Heckman (2007) on lifecourse skill development, emphasizing the compounding benefits over time of high levels of early noncognitive skills (a term which includes personality traits), suggests that higher conscientiousness in early-life could lead to better labor market outcomes through education. Highly conscientious young people perform better academically and gain more advanced educational qualifications (Almlund et al., 2011). Meta-analytic evidence indicates that the consistent positive association between conscientiousness and academic performance ( $d = .46$ ) may even be comparable in magnitude to that of cognitive ability ( $d = .52$ ) (Poropat, 2009). More years of education are in turn linked with better labor market prospects in the form of higher earnings and employment rates (Card, 1999; Lundborg, Nilsson, & Rooth, 2014). Unemployment rates also differ markedly as a function of educational attainment: unemployment rates among the OECD countries in 2012 were 5.4% for those with a tertiary education, 8.3% for those with an upper secondary education and 13.5% for those without an upper secondary education (figures taken from Table A5.2a in OECD, 2014).

The close link between conscientiousness and educational attainment partially reflects the tendency of conscientious students to be highly academically motivated (De Feyter, Caers, Vigna, & Berings, 2012; Steel, 2007). They value education, enjoy learning, and are interested in mastering new and challenging tasks (Gottfried, 1990; Komarraju, Karau, & Schmeck, 2009). The benefits of a preference for active learning could extend beyond the school and college years into the workplace where employees need to engage with professional development training, master course materials, and accumulate career relevant knowledge to improve their work competencies and enhance their career success (Bakker, Demerouti, & ten Brummelhuis, 2012).

Given the established link between conscientiousness and greater academic motivation and educational attainment, we therefore examine whether these serve as intervening variables explaining the conscientiousness-unemployment link.

*Hypothesis 2:* The relationship between conscientiousness and unemployment will be partially mediated by differences in academic motivation and educational attainment.

### 4.3. Data and Method

#### Participants and Procedure

We examined data from the British Cohort Study (BCS) to test the relationship between adolescent personality and adult unemployment (all data-sets used are described in the Supplementary Materials, Section 1). The BCS<sup>10</sup>, a nationally-representative study of 17,000 children born in Britain in a single week in 1970, contains self-reported personality measures at age 16-17 and month-by-month employment data spanning January 1986 to April 2009. Although the age 16-17 sweep recorded data from 11,622 cohort members, many did not report personality data due to teacher strikes preventing them from receiving questionnaires in school. The survey design was altered so that questionnaires were sent directly to cohort members' homes, but this process had relatively high rates of non-response: only 4,947 cohort members reported complete data for all four personality measures used in our analysis. Those reporting personality data differed on important observable background characteristics from the rest of the sample: They were more likely to be female (57% female for those with personality data vs. 43% for those without), have a father from the two highest socioeconomic classes (21% vs. 14%) and have higher scores on an intelligence test at age 10 (79.8 vs. 73.9,  $t(10,907) = -20.6, p < .0001$ ). After retaining data for those with complete data

---

<sup>10</sup> For an overview of the British Cohort Study see <http://www.cls.ioe.ac.uk/page.aspx?&sitesectionid=795&sitesectiontitle=Welcome+to+the+1970+British+Cohort+Study>. For a list of publications using this data see <http://www.cls.ioe.ac.uk/Bibliography.aspx?sitesectionid=647&sitesectiontitle=Bibliography&d=1&yf=&yt=&a=&s=BCS70&o=&j=>.

for all four personality items, imputing values for intelligence, and matching with adult unemployment data, we used a sample size of 4,206 (835,454 observations) for our main regressions. To account for the over-representation of females and higher SES groups in our sample, we applied weights to all of our regression analyses so that these variables tracked the nationally-representative distribution present in the first wave of the BCS. Our results do not substantially differ in the weighted versus unweighted analyses (latter available upon request).

## Measures

**Adolescent Personality.** Four personality measures were derived from 12 individual items, elicited via self-report when the cohort members were aged 16-17 as part of a set of questionnaires concerning attitudes. In order to select the questions which best captured elements of personality as indexed by the Big Five, we followed the factor analysis Lenton (2014) conducted using the BCS, whereby three questions for each personality trait were used. We created variables for four of the Big Five personality traits using Lenton's recommended items. Although we were unable to find suitable items to construct Openness, we did control for intelligence which typically correlates positively with openness (Zeidner & Matthews, 2000). From the 'Knowing Myself' questionnaire, we used 10 statements which appeared to capture elements of Conscientiousness ("I am punctual / reliable / responsible"), Extraversion ("I am quiet / shy / popular"), Agreeableness ("I am friendly / helpful / obedient") and Neuroticism ("I am nervous"). These statements were rated on a scale of (1) "Does not apply", (2) "Applies somewhat", (3) "Applies very much". We used two statements from the 'How I Feel' questionnaire for the Neuroticism measure ("Felt constantly under strain", "Been losing confidence in myself"). These two questions were rated on a scale of (1) "Not at all", (2) "No more than usual", (3) "Rather more than usual", (4) "Much more than usual". We recoded these latter two variables to combine categories (3) and (4) to maintain

consistency with the previous questions, such that all responses ranged in value from 1 to 3. After reverse scoring the appropriate items, we summed 3 questions per trait to create variables for Conscientiousness, Extraversion, Agreeableness and Neuroticism. We then standardized these four personality variables to have a mean of 0 and standard deviation of 1.

In order to determine the validity of the BCS personality measures, we examined the extent to which they correlated with a standard contemporary personality scale. Specifically, we collected a sample of 389 Americans ranging in age from 18 to 75 ( $M = 31.7$ ,  $SD = 11.5$ ) via the website Amazon Mechanical Turk and asked them to rate their personality using the 12 items from the present study and the 50-item version of the International Personality Item Pool (IPIP) (Goldberg, 1992). We used AMOS 19 to examine factor covariances for each personality trait as gauged using the BCS measures and the IPIP. The four personality domains from the present study all exhibited high correlations with their counterparts in the IPIP ( $r = .78$  on average), indicating a good degree of convergent validity. The correlations for the Conscientiousness ( $r = .67$ ), Extraversion ( $r = .93$ ), Agreeableness ( $r = .70$ ) and Neuroticism measures ( $r = .83$ ) were significant at  $p < .01$ . The size of the convergence is in keeping with personality validation studies (Muck, Hell & Gosling, 2007; Rammstedt & John, 2007) which found similar levels of correspondence between short personality scales and a Big Five Inventory, as well as a similar pattern of higher convergent validity for short measures of Extraversion (average  $r = .72$  across those two validation studies) and lower convergent validity for short measures of Agreeableness ( $r = .55$ ).

**Unemployment.** We created binary variables (0 = “Employed”, 1 = “Unemployed”) tracking whether the cohort member was unemployed on a month-by-month basis from January 1986 to April 2009. This variable followed the conventional coding by excluding people outside the labor force, such as students or homemakers. The average cohort member reported 198 months of data ( $SD = 58.4$ ) and the average (unweighted) unemployment rate

was 2.2% among the 4,206 cohort members in our sample (18,264 out of 835,454 observations). Unemployment statistics from the Labor Force Survey over 1992 to 2008 among people of a similar age to our sample members are around 7% in the population compared to around 2-3% in our sample (“A05 NSA,” 2016). The low rate of unemployment in our sample reflects the fact that those who provided personality data were more likely to be female and be from a higher SES background, both groups less likely to experience unemployment

**Childhood Factors.** We included childhood intelligence, gender and initial socioeconomic status as control variables as these are all established predictors of adult socioeconomic outcomes. Intelligence was measured at age 10 using the British Ability Scales which was made up of two verbal (word definitions, word similarities) and two non-verbal (digit-span, matrices) subscales (Elliot et al., 1978). Intelligence scores were standardized to have a mean of 0 and standard deviation of 1 to allow direct comparison with the standardized personality variables. We included the child’s gender and a measure of socioeconomic status (SES) derived from the father’s occupation in 1970. The five main categories for this measure were: I = “Professional occupations”; II = “Managerial or technical occupations”; III = “Skilled occupations”; IV = “Semi-skilled occupations”; V = “Unskilled occupations”). In order to maximize sample size we also included two additional categories “Other status” and “Missing data”; these categories represented 191 out of 3,280 observations for this variable. Because self-control and conscientiousness are conceptually related, and because childhood self-control has been shown to be an important future predictor of unemployment (Daly, Delaney, Egan, & Baumeister, 2015), we also conducted a robustness check by rerunning our main analyses while controlling for a 9-item self-control measure elicited when the cohort members were aged 10 (see Supplementary Materials, Section 2). This scale, described in detail in Daly, Delaney, Egan, and Baumeister (2015),

was based on teacher-scored items which gauged attentional control (e.g. “cannot concentrate on a particular task”) and perseverance (e.g. “shows perseverance”). If the inclusion of the self-control variable in our robustness check did not markedly diminish the relationship between adolescent conscientiousness and later unemployment, then we would consider the latter relationship not to be strongly affected by confounding.

**Pathways between Conscientiousness and Unemployment.** We included two educational variables which we considered plausible pathways between adolescent conscientiousness and future unemployment. Academic motivation was measured at age 16 by having students rate their level of agreement with eight statements (e.g. “school is largely a waste of time”, “never take work seriously”) on a 3-point Likert scale. While we would prefer a measure of academic motivation measured at a separate time-point to conscientiousness, the collinearity between these two variables ( $r = .26, p < .01$ ) is not sufficiently large as to markedly attenuate the unique variance available to explain our outcome, unemployment. Higher scores on this scale have been found to predict better adult occupational status and educational attainment after controlling for intelligence and initial socioeconomic status in the British Cohort Study and National Child Development Study (Ritchie & Bates, 2013; Schoon, 2008). In our data this scale demonstrated good internal consistency (Cronbach’s alpha = .76 for a sample of 2,997 reporting data on this measure). After coding individual item scores so that a higher score always meant more academic motivation, we summed scores for the eight items and standardized the resulting variable to have a mean of 0 and standard deviation of 1. We also included a measure of educational attainment assessed at ages 26 and 30. Although this variable was elicited several years after the cohort members entered the labor market, we consider it reasonable to treat it as an intermediate step between conscientiousness and unemployment because very few cohort members experienced unemployment prior to leaving education: almost 97% completed their

full-time education by age 23, and by that same age 89% had experienced 3 months or less of unemployment (figures refer to a sample size of 3,788 individuals reporting both unemployment histories and information on when they completed full-time education). Omitting from the sample the cohort members who experienced more than 3 months of unemployment before completing their education by age 23 does not substantially change our mediation results. The education variable was indexed using National Vocational Qualifications (NVQ). There were six categories ranging from 0 = No qualification to 5 = NVQ 5 indicating higher degrees. We first used data from the age 30 measure; if this was unavailable we used the age 26 measure.

**Missing Data.** Of the cohort members reporting data on the four personality measures, gender, the SES variable and the outcome variable ( $N = 4,206$ ), only 3,204 reported intelligence data. Analysis of the pattern of missing data found that this variable was not missing completely at random (MCAR), indicating that intelligence values could be estimated using observed values for the other variables. We therefore applied Rubin's multiple imputation method (Rubin, 1987) to impute missing intelligence values using multiple imputation chained equations (MICE), a technique which carries out a series of sequential regressions for each of the multiple imputations (White, Royston, & White, 2011). We used predictive mean matching to limit the imputed intelligence values to within the possible score range and created five imputed values. These imputed values were then pooled to produce the final estimates. Using this method instead of listwise deletion did not substantially alter the regression results, nor did supplemental analyses using both imputed intelligence and imputed personality values (see Supplementary Materials, Section 3).



## Statistical Methods

We specified a longitudinal Probit model to estimate the association between adolescent personality and the average probability of being unemployed from age 16 to 38 (*Model 1*) and calculated marginal effects to estimate percentage point changes in the probability of unemployment for unit changes in the independent variables (Long & Freese, 2014). We also included a time variable (ranging from the year 1986 to 2009) to account for the decreasing unemployment rate as the cohort members entered middle age (a trend evident in Figure 1), and clustered observations by ID to account for repeated observations on the same individual. The formal specification of this model was:

*Model 1:* Unemployment from age 16 to 38<sub>it</sub> =  $\beta_0 + \beta_1$  adolescent personality<sub>i</sub> +  $\sum \beta_2$  childhood factors<sub>i</sub> +  $\beta_3$  year<sub>t</sub> +  $\epsilon_{it}$

Our examination of explanatory pathways added our intermediary variables to this model (*Model 2*). Because our examination of the mediating role of education in isolation (omitting academic motivation) found no indirect pathway from conscientiousness to unemployment, it was not possible to conduct sequential path analysis. For this reason we used parallel path analysis. Our mediation analysis was implemented using the *khb* procedure in Stata (Kohler, Bernt Karlson, & Holm, 2011), which adjusts for the rescaling issues which occur when attempting cross-model comparisons of non-linear models and can provide an unbiased decomposition of the total effect of conscientiousness on unemployment into direct and indirect (mediation) effects. The *khb* method calculates the mediation effect by comparing the results from a full model, which includes the mediating variables, to the results from a reduced model, which includes the residuals of the mediating variables (calculated separately by regressing the mediating variables on the model covariates). This method standardizes the scale between the two equations. The difference between the main

coefficients in the two analyses can then be interpreted as the mediation effect. The *khb* procedure assumes a normal distribution of the indirect effect, an assumption shown to be valid in large samples such as the one we use in this study (MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002). Including academic motivation and educational attainment in the regression model, and omitting imputed intelligence values which are not supported in the *khb* procedure, reduced the number of cohort members in the mediation analysis from 4,206 to 2,933. The formal specification of this model was:

*Model 2:* Unemployment from age 16 to 38<sub>it</sub> =  $\beta_0 + \beta_1$  adolescent personality<sub>i</sub> +  $\sum \beta_2$  childhood factors<sub>i</sub> +  $\beta_3$  year<sub>t</sub> +  $\beta_4$  academic motivation<sub>i</sub> +  $\beta_5$  education<sub>i</sub> +  $\epsilon_{it}$

Lastly, we conducted analyses testing three alternative unemployment outcomes used in Viinikainen and Kokko (2012). These were the total duration of unemployment in months, the number of spells of unemployment, and length of unemployment spells among those who experienced at least one spell (see Supplementary Materials, Section 4).

## 4.4. Results

### Descriptives

Table 4.1 contains descriptive statistics and correlations among key variables respectively. The average unweighted unemployment rate across all time periods was 2.2%, ranging from a high of 7.7% at age 16 to a low of 0.9% at age 35. The average total number of months of unemployment was 4.3 ( $SD = 16.9$ ) and the median was 0. Although the sample differed on observable covariates from the cohort members who did not report personality data, there was not substantial attrition over time on the basis of childhood intelligence, personality, gender or SES, diminishing the risk that certain cohort members (e.g. the less conscientious) may have been less likely to engage with the survey over time. Conscientiousness correlated positively with academic motivation ( $r = .26, p < .01$ ) and

educational attainment ( $r = .08, p < .01$ ) and negatively with months of unemployment ( $r = -.07, p < .01$ ). More months of unemployment also correlated with worse academic motivation ( $r = -.08, p < .01$ ) and lower educational attainment ( $r = -.11, p < .01$ ), supporting our rationale for including these variables as potential pathways between conscientiousness and unemployment.

Unemployment rates varied considerably by level of conscientiousness (see Figure 4.1). From age 16 to 38, the average unweighted unemployment rate for the highly conscientious (those scoring 1 *SD* and above the mean conscientious score) was 1.5%, compared to 3% for those with low conscientiousness scores (those scoring 1 *SD* and below the mean conscientiousness score) and the less conscientious reported an average of 5.8 months of unemployment ( $SD = 19.7$ ) compared to 3.0 months ( $SD = 13.1$ ) for the highly conscientious.

Table 4.1. Descriptive Statistics and Correlation Matrix for Key Variables.

	Mean (SD) / % [range]	U	F	C	E	A	N	IQ	SES	M	E
Months unemployed	4.3 (16.8) [0-267]	1									
Female	58.1%	<b>-0.08</b>	1								
Conscientiousness	7.5 (1.3) [3-9]	<b>-0.07</b>	<b>0.07</b>	1							
Extraversion	6.6 (1.4) [3-9]	-0.02	<b>0.05</b>	0.03	1						
Agreeableness	7.0 (1.1) [3-9]	-0.03	<b>0.11</b>	<b>0.47</b>	<b>0.09</b>	1					
Neuroticism	5.2 (1.6) [3-9]	-0.00	<b>0.13</b>	-0.04	<b>-0.30</b>	-0.04	1				
Intelligence	80.3 (13.3) [31-123]	<b>-0.08</b>	<b>-0.07</b>	0.01	-0.01	<b>-0.06</b>	<b>0.05</b>	<b>1</b>			
SES at birth	2.9 (0.8) [1-5]	<b>0.10</b>	0.00	0.01	0.00	0.00	<b>-0.07</b>	<b>-0.27</b>	1		
Academic motivation	18.0 (3.1) [7-24]	<b>-0.08</b>	<b>0.07</b>	<b>0.26</b>	<b>-0.10</b>	<b>0.26</b>	-0.02	<b>0.15</b>	<b>-0.10</b>	1	
Education	2.9 (1.4) [0-5]	<b>-0.11</b>	<b>-0.06</b>	<b>0.07</b>	-0.04	0.03	<b>0.09</b>	<b>0.43</b>	<b>-0.26</b>	<b>0.30</b>	1

*Note.* Months of unemployment covers ages 16 to 38. SES excludes the categories “other” and “missing data”, and higher scores indicate lower SES. Bolded correlations are statistically significant at the 1% level. Data are unweighted. SES. Bolded correlations are statistically significant at the 1% level. Data are unweighted.



Figure 4.1. Unemployment over time by levels of adolescent conscientiousness ( $N = 4,206$ ; Observations = 834,530). “Low conscientiousness” refers to the 25.4% of cohort members scoring 1 SD and below the mean conscientious score; “Medium” is the 46.1% of cohort members scoring between 1 SD below and 1 SD above the average; “High” is the 28.5% of cohort members scoring 1 SD and above the average. Data are unweighted and omit the year 2009 due to small sample size.

## Regressions

Table 4.2 describes our regression results. After controlling for intelligence, gender and SES, and computing marginal effects, a 1 *SD* increase in conscientiousness was associated with a 0.8 percentage point (95% confidence intervals (CI) = [-0.5, -1.2]) ( $p < .001$ ) lower average probability of unemployment from age 16 to 38. In percentage terms this was equivalent to a 34% reduced likelihood of unemployment. Stated differently, the less conscientious (-1 *SD*) had a predicted unemployment rate twice as high as the highly conscientious (+1 *SD*): 3.4% (95% CI = [2.7%, 4.0%]) vs. 1.7% (95% CI = [1.4%, 2.0%]). The effect of higher conscientiousness was similar to the effect of a 1 *SD* increase in intelligence (-0.6 percentage points; 95% CI = [-0.1, -1.1]), and larger than the effects of extraversion, agreeableness or neuroticism, none of which were significantly associated with unemployment.

Additional regressions, not presented here, did not find substantive gender differences in the association between any personality trait and unemployment. Because self-control is considered to be a lower-order facet of conscientiousness (Roberts, Chernyshenko, Stark, & Goldberg, 2005) and is an established predictor of unemployment (Daly, Delaney, Egan, & Baumeister, 2015), we tested whether conscientiousness was associated with unemployment independently of the effects of self-control. That robustness test found that controlling for childhood self-control reduced the conscientiousness coefficient slightly without altering its significance level (see Table S1). Conscientiousness predicted unemployment in analyses when using both imputed intelligence and personality scores (see Table S4.2), and when using alternative specifications of the outcome variable (Tables S4.3-4.5). In the latter, higher conscientiousness predicted fewer total months of unemployment ( $b = -0.27$ ,  $SE = 0.06$ ,  $p$

< .001) and fewer spells of unemployment ( $b = -0.19$ ,  $SE = 0.04$ ,  $p < .001$ ) but not significantly shorter unemployment spell durations ( $b = 0.81$ ,  $SE = 0.38$ ,  $p = 0.06$ ).

Table 4.2. Probit Regressions Predicting Average Probability of Unemployment from January 1986 to April 2009.

Outcome: Unemployment				
	Model 1		Model 2	
	Probit marginal effects		Probit marginal effects	
Independent variables	Coef.	SE	Coef.	SE
Conscientiousness	-0.008***	(0.002)	-0.006***	(0.002)
Extraversion	-0.002	(0.002)	-0.002	(0.002)
Agreeableness	0.004	(0.002)	0.004*	(0.002)
Neuroticism	0.002	(0.001)	0.001	(0.001)
Intelligence	-0.006*	(0.002)	-0.004	(0.003)
Female	-0.014***	(0.003)	-0.014***	(0.003)
<i>SES</i>				
I (highest)	-	-	-	-
II	0.004	(0.005)	0.002	(0.005)
III	-0.001	(0.003)	-0.004	(0.004)
IV	0.011*	(0.005)	0.006	(0.005)
V (lowest)	0.052**	(0.017)	0.039	(0.016)*
Other	0.015	(0.008)	0.014	(0.008)
Missing	0.011	(0.007)	0.006	(0.007)
Year	-0.002***	(0.000)	-0.002***	(0.000)
Academic motivation			-0.004*	(0.002)
Education			-0.002	(0.002)



Sample size	4,206	3,848
Observations	835,454	763,937

---

*Note.* Personality measures, intelligence and academic motivation are standardized ( $M = 0$ ,  $SD = 1$ ). The comparison category for SES is 'I'. Year ranges from 1986 to 2009; this variable captures the trend of declining unemployment over time. Education ranges from 0 (No qualification) to 5 (NVQ 5). Estimates are weighted by gender and SES, and include imputed intelligence values. Standard errors clustered by ID.

\*\*\* Significant at the 0.1% level. \*\* Significant at the 1% level. \* Significant at the 5% level.

Higher conscientiousness was predictive of higher academic motivation ( $b = 0.53$ ,  $SE = 0.06$ ,  $p < .001$ ) and greater educational attainment ( $b = 0.10$ ,  $SE = 0.03$ ,  $p < .001$ ) in OLS regressions (see Table 4.3), providing initial support for our prediction that these variables might partly explain the long-run association between conscientiousness and unemployment. Adjusting for the two mediation variables decreased the effect of higher conscientiousness on unemployment by 0.2 percentage points (see Model 2 in Table 4.2): of the two mediators, higher academic motivation predicted a 0.4 point lower probability of unemployment ( $p < .05$ ), whereas more educational attainment had no statistically significant impact on unemployment.

Formal mediation analysis, produced using the *khb* procedure (see Table 4.4), found similar results; the association between conscientiousness and unemployment (total effect:  $b = -0.15$ ,  $SE = 0.04$ ,  $p < .001$ ) was partially mediated by differences in academic motivation and educational attainment but their combined effect was not statistically significant (indirect effect:  $b = -0.01$ ,  $SE = 0.01$ ,  $p = .06$ ). Separating their effects revealed a significant mediation effect for academic motivation ( $b = -0.01$ ,  $SE = 0.00$ ,  $p < .05$ ) and a non-significant mediation effect for educational attainment ( $b = -0.00$ ,  $SE = 0.00$ ,  $p = .73$ ), but differences in academic motivation still only explained 8.9% of the association between conscientiousness and unemployment. In other words, the vast majority of the association between conscientiousness and unemployment was not explained by our mediating variables.

Table 4.3. OLS Regressions Predicting the Effect of Conscientiousness on Academic Motivation and Educational Attainment.

Outcome	Academic motivation		Education	
	OLS coefficients		OLS coefficients	
Independent variable	Coef.	SE	Coef.	SE
Conscientiousness	0.531***	(0.057)	0.097***	(0.025)
Extraversion	-0.447***	(0.053)	-0.020	(0.023)
Agreeableness	0.600***	(0.062)	0.040	(0.025)
Neuroticism	-0.200***	(0.052)	0.109***	(0.023)
Intelligence	0.349***	(0.063)	0.429***	(0.031)
Female	0.374***	(0.100)	-0.143***	(0.044)
<i>SES</i>				
I (highest)	-	-	-	-
II	-0.589***	(0.199)	-0.460***	(0.081)
III	-0.819***	(0.171)	-0.779***	(0.071)
IV	-1.171***	(0.222)	-0.879***	(0.090)
V (lowest)	-1.063***	(0.358)	-1.137***	(0.142)
Other	-0.907***	(0.250)	-0.786***	(0.115)
Missing	-0.787***	(0.262)	-0.659***	(0.158)
Sample size	3,947		4,091	

*Note.* Academic motivation is unstandardized and ranges from 7 to 24. Education ranges from 0 (No qualification) to 5 (NVQ 5). Personality measures and intelligence are standardized ( $M = 0$ ,  $SD = 1$ ). The comparison category for SES is 'I'. Estimates are weighted by gender and SES, and include imputed intelligence values.

\*\*\* Significant at the 0.1% level. \*\* Significant at the 1% level. \* Significant at the 5% level.

Table 4.4. Decomposition of Total Effect of Conscientiousness on Unemployment through Academic Motivation and Education.

Outcome: Unemployment		
Model 2		
Probit coefficients		
	Coef.	SE
Effect of conscientiousness on unemployment		
Total effect	-0.152***	0.036
Direct effect	-0.139***	0.035
Indirect effect (mediation effect)	-0.014	0.007
<i>via</i> Academic motivation	-0.013*	0.007
<i>via</i> Education	0.000	0.004
Sample size	2,933	
Observations	583,591	

*Note.* Estimates are weighted by gender and SES and control for all the covariates in *Model 2*.

Standard errors clustered by ID. Sample size is smaller than that shown in Table 2, Model 2 because the mediation analysis does not use imputed intelligence values as these are not supported in the *khb* procedure.

\*\*\* Significant at the 0.1% level. \*\* Significant at the 1% level. \* Significant at the 5% level.

#### 4.5 Discussion

Our results showed that conscientiousness at age 16-17 predicted unemployment across two decades. The long reach of conscientiousness could not be attributed to either childhood socioeconomic status, intelligence, or other personality traits. The effect of conscientiousness was comparable to intelligence, traditionally the strongest predictor of occupational outcomes (e.g. Roberts, Kuncel, Shiner, Caspi, & Goldberg, 2007). Previous research examining how Big Five personality predicts unemployment has used personality measures elicited after the study participants had entered the labor market. Since unemployment can itself influence personality (Boyce, Wood, Daly, & Sedikides, 2015), this may partly explain the hitherto mixed results in this literature. A key benefit of the data used in the study is that personality was measured before the cohort members had accumulated much labor market experience, clarifying the direction of influence as flowing from personality to unemployment.

Our findings suggest that conscientiousness contributes to sustained employment and that its influence is meaningful and not conditional on life-stage. Our results also contribute to the growing research in organizational psychology looking at the determinants of employability (Hogan et al., 2013) by providing empirical evidence that conscientiousness is valued by employers. Whilst reliable, responsible adolescents went on to experience little unemployment in adulthood, we found no effects for neuroticism, agreeableness or extraversion. Given that neuroticism and distress have been shown to predict unemployment (Egan, Daly, & Delaney, 2016; Fletcher, 2013b; Uysal & Pohlmeier, 2011), particularly during periods of economic turbulence (Egan, Daly, & Delaney, 2015; Egan, Daly, & Delaney, 2016), it is possible that the absence of a link in this study may be because the labor market experience of this cohort mostly coincided with a period of relatively low unemployment in Britain throughout the 1990s and early 2000s.

Early identification of the personality traits that influence who becomes unemployed may better guide the targets of interventions, such as school and work programs designed to foster the development of particular psychological characteristics (Heckman & Kautz, 2013). For instance, school programs which promote attentional control, patience and forward-looking behavior (Diamond & Lee, 2011) may be effective ways of producing lasting changes in conscientiousness (Eisenberg et al., 2014). This may in turn reduce later unemployment levels, although there is not yet strong evidence that such programs improve long-run labor market outcomes. Given the large economic and welfare costs of unemployment, the potential returns to such interventions may be high.

In addition to inducing dispositional changes, interventions could target the intermediary processes which connect conscientiousness and later labor market success. We found that conscientious adolescents were more academically motivated than their peers, and went on to experience less unemployment. Those who are motivated to devote time and effort to their schoolwork will likely carry this work ethic into their adult occupations, become valued employees and find more employment opportunities. Given that educational attainment had little additional explanatory power for predicting unemployment after adjusting for academic motivation, this suggests that investing in motivational interventions in early life may yield positive returns. However, despite the explanatory power of the pathways we examined, over 90% of the association between conscientiousness and unemployment remained unexplained, suggesting a potential role for mediating factors outside the domain of education.

Industrial-organizational research points to additional pathways through which conscientiousness may confer resilience to unemployment. Conscientiousness forms an established dispositional basis for organizational citizenship behaviors, performance motivation and workplace performance (e.g. Judge & Ilies, 2002; Chiaburu, Oh, Berry, Li, &

Gardner, 2011). The strong inclination of the conscientious to set goals, work hard, and go beyond their role requirements may explain, at least in part, why they tend to experience lower unemployment. Conversely, periods of unemployment experienced by the less conscientious could have long-lasting effects on their subsequent career prospects (Arulampalam, 2001), a negative cycle that could be compounded by the difficulties in the job-search process experienced by this group (Kanfer et al., 2001). However, the results of our supplemental analyses (Tables S3-5), which found that less conscientiousness individuals were more likely to experience a greater number of unemployment spells, but that these spells were not significantly longer than those experienced by the highly conscientious, suggests that low conscientiousness may be a greater concern for retaining a job rather than finding one.

We note three limitations. First, although we applied weights to our analyses to enable generalizability of our findings to the broader British population, the weighted unemployment rate in our sample was still lower than the population rate. Adding a greater array of background variables (e.g. region of birth) to generate more precise weights might allay this problem, but this would reduce the sample size as many cohort members do not report data on these variables. Additionally, we cannot weigh for unobserved variables which may have affected the probability of the cohort members appearing in our sample, which we would not have been able to weigh for. For example, our sample may have been biased in terms of personality (e.g. more conscientious people may have been more likely to respond to the personality survey), although we were not able to directly test for this. However, we did find that self-control scores (a conceptually related trait to conscientiousness) were 0.4 SD higher among those who reported personality data compared to those who did not, suggesting that the more conscientious may also have been more likely to respond. The fact that we identify a relatively large effect of conscientiousness on unemployment despite the possible

restriction in range of the conscientiousness variable suggests that our finding is robust. Secondly, we use not fully validated scales. Such trade-offs are near inevitable when using historical data and are, we believe, offset by the benefits of using a large panel sample, particularly when it was essential to measure personality prior to labor force entry. We mitigated this limitation by showing reasonably sized correlations with a fully validated Big Five questionnaire in a contemporary sample. A comprehensive assessment of the construct of conscientiousness, which coupled self-reports with observer ratings, informant reports, and behavioral measures, would reduce measurement error and provide a more precise estimate of the success of this trait in forecasting unemployment (Roberts, Lejuez, Krueger, & Hill, 2014). Thirdly, our use of observational data means that we are unable to categorically rule out potential third factors as being the ultimate cause of both personality scores and labor market outcomes. Since our analysis does not demonstrate causality, the policy implications of our results remain necessarily tentative. Future researchers may attempt to isolate the causal association using study designs such as sibling fixed-effects models, which can implicitly adjust for a greater range of family background characteristics than was possible in the present data.

In conclusion, this study underscores the importance of conscientiousness in shaping unemployment levels across working life, highlights the advantages of using adolescent personality measures to clarify the direction of influence, and identifies academic motivation as a mechanism linking adolescent conscientiousness and subsequent unemployment.



## Appendix

**Section 1:** List of data-sets used.

**Section 2:** Estimates of the association between conscientiousness and unemployment, before and after adjusting for childhood self-control.

**Section 3:** Estimates of the association between personality and unemployment using different levels of multiple imputation.

**Section 4:** Analyses using three alternative unemployment outcomes.

**Section 1:** List of data-sets used.

The British Cohort Study is managed by the Centre for Longitudinal Studies and is available to UK based researchers via the UK Data Archive

(<http://discover.ukdataservice.ac.uk/series/?sn=200001>). The datasets used in this study are:

Birth and 22-Month Subsample, 1970-1972 [SN2666], Ten-Year Follow-Up, 1980 [SN3723],

Sixteen-Year Follow-Up, 1986 [SN3535], Twenty-Six Year Follow-Up, 1996 [SN3833],

Thirty Year Follow-Up, 2000 [SN5558], Thirty-Four Year Follow-Up, 2004 [SN5585],

Thirty-Eight Year Follow-Up, 2008 [SN6557], Activity Histories, 1986-2008 [SN 6943].

**Section 2:** Estimates of the association between conscientiousness and unemployment, before and after adjusting for childhood self-control.

Table S4.1. Probit Regression Predicting the Average Probability of Unemployment from 1986 to 2008, Controlling for Childhood Self-Control.

Outcome variable: Unemployment				
	Model 1		Model 2	
	Probit marginal effects		Probit marginal effects	
Independent variables	Coef.	SE	Coef.	SE
Conscientiousness	-0.009***	(0.002)	-0.008***	(0.002)
Self-control			-0.006**	(0.002)
Sample size	2,876		2,876	
Observations	637,353		637,353	

*Note.* Conscientiousness and self-control are standardized ( $M = 0$ ,  $SD = 1$ ). Estimates are weighted by gender and SES, include imputed intelligence values and control for SES at birth, extraversion, agreeableness, neuroticism, intelligence, gender, and year of observation. Standard errors clustered by ID.

\*\*\* Significant at the 0.1% level. \*\* Significant at the 1% level. \* Significant at the 5% level.

**Section 3:** Estimates of the association between personality and unemployment using different levels of multiple imputation.

Table S4.2. Probit Regression Predicting the Average Probability of Unemployment from 1986 to 2008 Using Different Levels of Imputation.

	Model 1		Model 2		Model 3	
	Probit marginal effects		Probit marginal effects		Probit marginal effects	
	Coef.	SE	Coef.	SE	Coef.	SE
Conscientiousness	-0.010***	(0.002)	-0.008***	(0.002)	-0.010***	(0.003)
Extraversion	-0.000	(0.002)	-0.002	(0.002)	-0.004***	(0.001)
Agreeableness	0.004	(0.002)	0.004	(0.002)	0.003	(0.002)
Neuroticism	0.002	(0.002)	0.002	(0.001)	0.001	(0.002)
Intelligence	-0.006*	(0.003)	-0.006*	(0.002)	-0.012***	(0.001)
Female	-0.012**	(0.004)	-0.014***	(0.003)	-0.016***	(0.002)
<i>SES</i>						
I (highest)	-	-	-	-	-	-
II	-0.001	(0.005)	0.004	(0.005)	-0.003	(0.005)
III	-0.004	(0.004)	-0.001	(0.003)	-0.003	(0.004)
IV	0.006	(0.006)	0.011*	(0.005)	0.004	(0.005)
V (lowest)	0.048*	(0.019)	0.052**	(0.017)	0.038***	(0.008)
Other	0.018	(0.010)	0.015	(0.008)	0.010	(0.006)
Missing	0.024	(0.039)	0.011	(0.007)	0.005	(0.007)
Year	-0.002***	(0.000)	-0.002***	(0.000)	-0.002***	(0.000)
Imputed variables	None		Intelligence		Intelligence, Personality	
Sample size	3,204		4,206		11,372	

Observations	638,251	835,454	2,239,024
Weighted unemployment rate	2.5%	2.5%	3.2%

---

*Note.* Personality measures and intelligence are standardized ( $M = 0$ ,  $SD = 1$ ). Year ranges from 1986 to 2009. Standard errors clustered by ID.

\*\*\* Significant at the 0.1% level. \*\* Significant at the 1% level. \* Significant at the 5% level.

**Section 4:** Analyses using three alternative unemployment outcomes.

In order to provide further insight on the nature of the relationship between personality and unemployment, we conducted analyses using three alternative unemployment outcome measures modelled on those used in previous research (Viinikainen & Kokko, 2012). We examined (i) the total months of unemployment experienced from age 16 to 38 ( $M = 4.34$ ,  $SD = 16.9$ , Range = 0-267), (ii) the number of spells of unemployment experienced from age 16 to 38 ( $M = 0.34$ ,  $SD = 0.75$ , Range = 0-9), where a spell was defined as being unemployed in month T after being employed in month T-1, and (iii) unemployment spell length in months among those reporting at least one spell of unemployment from age 16 to 38 ( $M = 12.9$ ,  $SD = 23.0$ , Range = 1-267). We specified negative binomial models to examine these three outcomes, a suitable analytic method for over-dispersed (i.e. where the variance is greater than the mean) count data.

Our results are described in Tables S3-5. Higher conscientiousness predicted fewer total months of unemployment ( $b = -0.27$ ,  $SE = 0.06$ ,  $p < .001$ ) and fewer spells of unemployment ( $b = -0.19$ ,  $SE = 0.04$ ,  $p < .001$ ) but not significantly shorter unemployment spell durations ( $b = 0.81$ ,  $SE = 0.38$ ,  $p = 0.06$ ). Calculating the marginal effects of these analyses to present the results more intuitively, a 1 standard deviation increase in conscientiousness predicted 1.4 fewer month of unemployment ( $b = -1.37$ ,  $SE = 0.31$ ,  $p < 0.001$ ), 0.7 fewer spells of unemployment ( $b = -0.70$ ,  $SE = 0.15$ ,  $p < 0.001$ ), and a non-significant 1 month shorter average unemployment spell duration ( $b = -1.05$ ,  $SE = 0.63$ ,  $p = 0.10$ ).

Table S4.3. Negative Binomial Regression Predicting the Total Months of Unemployment from 1986 to 2008.

	Total months of unemployment	
	Coef.	SE
Conscientiousness	-0.274***	(0.057)
Extraversion	-0.091	(0.054)
Agreeableness	0.073	(0.056)
Neuroticism	0.034	(0.058)
Intelligence	-0.225***	(0.063)
Female	-0.631***	(0.113)
<i>SES</i>		
I (highest)	-	-
II	0.266	(0.233)
III	0.113	(0.174)
IV	0.550*	(0.214)
V (lowest)	1.415***	(0.283)
Other	0.660**	(0.254)
Missing	0.620*	(0.296)
Sample size	4,206	

*Note.* Personality measures and intelligence are standardized ( $M = 0$ ,  $SD = 1$ ). Estimates are weighted by gender and SES, control for SES at birth and include imputed intelligence values. Constant omitted.

\*\*\* Significant at the 0.1% level. \*\* Significant at the 1% level. \* Significant at the 5% level.

Table S4.4. Negative Binomial Regression Predicting the Number of Spells of Unemployment from 1986 to 2008.

	Spells of Unemployment	
	Coef.	SE
Conscientiousness	-0.192***	(0.040)
Extraversion	-0.123***	(0.036)
Agreeableness	0.035	(0.044)
Neuroticism	0.019	(0.036)
Intelligence	0.016	(0.043)
Female	-0.528***	(0.071)
<i>SES</i>		
I (highest)	-	-
II	-0.149	(0.153)
III	-0.178	(0.131)
IV	-0.046	(0.156)
V (lowest)	0.418*	(0.203)
Other	0.021	(0.204)
Missing	-0.252	(0.174)
Sample size	4,206	

*Note.* Personality measures and intelligence are standardized ( $M = 0$ ,  $SD = 1$ ). Estimates are weighted by gender and SES, control for SES at birth and include imputed intelligence values. Constant omitted.

\*\*\* Significant at the 0.1% level. \*\* Significant at the 1% level. \* Significant at the 5% level.

Table S4.5. Negative Binomial Regression Predicting the Length of Unemployment Spells Among Those Who Experienced at Least One Spell of Unemployment from 1986 to 2008.

	Length of Unemployment Spell	
	Coef.	SE
Conscientiousness	-0.081	(0.048)
Extraversion	0.034	(0.047)
Agreeableness	0.012	(0.049)
Neuroticism	0.027	(0.049)
Intelligence	-0.211***	(0.059)
Female	-0.115	(0.098)
<i>SES</i>		
I (highest)	-	-
II	0.499*	(0.200)
III	0.296*	(0.130)
IV	0.569**	(0.172)
V (lowest)	0.977***	(0.249)
Other	0.723**	(0.223)
Missing	0.829***	(0.229)
Sample size	959	
Observations	1,151	

*Note.* Personality measures and intelligence are standardized ( $M = 0$ ,  $SD = 1$ ). Estimates are weighted by gender and SES, and include imputed intelligence values. Constant omitted.

Standard errors clustered by ID.

\*\*\* Significant at the 0.1% level. \*\* Significant at the 1% level. \* Significant at the 5% level.



## CHAPTER 5

### **Childhood Psychological Distress and Youth Unemployment:**

#### **Evidence from Two British Cohort Studies**

##### **5.1 Abstract**

The effect of childhood mental health on later unemployment has not yet been established. In this article we assess whether childhood psychological distress places young people at high risk of subsequent unemployment and whether the presence of economic recession strengthens this relationship. This study was based on 19,217 individuals drawn from two nationally-representative British prospective cohort studies; the Longitudinal Study of Young People in England (LSYPE) and the National Child Development Study (NCDS). Both cohorts contain rich contemporaneous information detailing the participants' early life socioeconomic background, household characteristics, and physical health. In adjusted analyses in the LSYPE sample (N = 10,232) those who reported high levels of distress at age 14 were 2 percentage points more likely than those with low distress to be unemployed between ages 16 and 21. In adjusted analyses of the NCDS sample (N = 8,985) children rated as having high distress levels by their teachers at age 7 and 11 were 3 percentage points more likely than those with low distress to be unemployed between ages 16 and 23. Our examination of the 1980 UK recession in the NCDS cohort found the difference in average unemployment level between those with high versus low distress rose from 2.6 pct points in the pre-recession period to 3.9 points in the post-recession period. These findings point to a previously neglected contribution of childhood mental health to youth unemployment, which may be particularly pronounced during times of economic recession. Our findings also suggest a further economic benefit to enhancing the provision of mental health services early in life.

## 5.2 Introduction

Understanding how childhood mental health can shape economic outcomes over the lifespan is a key question that cuts across health, education, and employment policy. Depression and mental health problems in childhood have been shown to detrimentally affect family income (Goodman, Joyce & Smith, 2011; Smith & Smith, 2010), labor supply (Goodman, Joyce & Smith et al., 2011), educational attainment (Fletcher, 2008, Cornaglia, Crivellaro & McNally 2015), and earnings in adulthood (Fletcher, 2013a). A recent review of this literature concluded that the influence of early mental health problems on later socioeconomic success (e.g. education, earnings) appears to be more pronounced and pervasive than that of childhood physical health conditions (Delaney & Smith, 2012). In this paper we extend existing research by estimating the association between childhood psychological distress and unemployment in the formative early stages of working life.

Numerous studies of adults have documented a range of affective and mental health problems amongst the unemployed (McKee-Ryan, Song, Wanberg & Kinicki, 2005; Paul & Moser, 2009). This link has been attributed to both the ‘scarring’ effects of unemployment on subsequent mental health (Clark, Georgellis & Sanfey, 2001; Daly & Delaney, 2013) and the effect of poor mental health on subsequent unemployment (Butterworth, Leach, Pirkis & Kelaher, 2012). However, firmly establishing the direction of causality of the link between unemployment and mental health in adult samples is difficult due to the bidirectional and mutually reinforcing nature of this relationship. By examining how psychological distress prior to labor market entry affects subsequent unemployment we avoid such econometric problems in the current study.

Specifically, we use data from two cohort studies to test whether measures of psychological distress taken in childhood are associated with unemployment between the

ages of 16 and 21 (Study 1) and 16 and 23 (Study 2). We also examine whether the role of distress in conditioning employment prospects may be amplified during the difficult labor market of a major economic recession (Study 2). Recent research examining repeated cross-sectional samples of European citizens has shown those with poor mental health experienced a more marked increase in unemployment than others in the period from before to after the 2008 recession (Evans-Lacko, Knapp, McCrone, Thornicroft, & Mojtabai, 2013). Prospectively examining whether distress measured prior to the onset of unfavourable macroeconomic conditions leads to substantially higher unemployment levels is crucial in order to understand the causes of unemployment and to adapt mental health policy in the context of economic downturns.

### **5.3 Study 1: Methods**

#### *Study Population*

Participants were drawn from the Longitudinal Study of Young People in England (LSYPE), a nationally representative cohort of around 15,500 English residents born in 1989/90. We examined the relationship between distress measured at age 14 and the likelihood that a participant is unemployed over the 2006-10 period. The LSYPE high frequency monthly labor force data combines the unemployed and inactive and classifies this group as not in education, employment or training (NEET). Because we are interested in the unemployed only we removed the majority of inactive participants from the NEET group by excluding 194 female participants who reported giving birth as of October 2010 and henceforth refer to those retained in this group as “unemployed”. After deleting observations which did not contain data on our main covariates we used a sample of 404,556 monthly employment status observations for 10,232 cohort members. Table S5.1 contains descriptive statistics for the sample. In supplementary analyses we estimated the association between

distress levels and unemployment in four yearly waves of data where it was possible to exclude all inactive participants from the analysis.

### *Measures*

#### *Childhood psychological distress*

Psychological distress was assessed at age 14 using the 12-item General Health Questionnaire (GHQ-12). The GHQ-12 is a short screening tool for gauging non-specific psychiatric morbidity in the general population (Goldberg & Williams, 1988) by asking to what extent the respondent has been unable to carry out normal functions (“Lost much sleep over worry”) and whether they have been feeling distressed (“Been thinking of yourself as a worthless person”). It has been employed extensively in youth populations and validated in adolescents (Banks, 1983; French & Tait, 2004). The typical cut-off for GHQ ‘caseness’ is 2/3 (Goldberg & Williams, 1988) with 3/4 considered a more stringent cut-off that has been shown to demonstrate high levels of sensitivity and specificity in several samples (Makowska, Merez, Moscicka & Kolasa, 2002; Yusoff, Rahim & Yaacob, 2010). The cohort members were given a score of 1 for each item if they reported more or much more negative feelings than usual and a score of 0 if they reported no more negative feelings than usual or none at all. These scores were then summed to produce a score range of 0-12. We employed the 3/4 cut-off as an indicator of significant distress and potential ‘caseness’. Specifically, we created a categorical variable coded as 0 for GHQ scores of 0 (labelled ‘Low Distress’, representing 50 per cent of the sample), 1 for GHQ scores between 1 and 3 (‘Medium Distress’, 32 per cent) and 2 for scores between 4 and 12 (‘High Distress’, 18 per cent). The average score on the GHQ measure was 1.69 (SD = 2.50) with females reporting more psychological distress, as is typical (Males = 1.21, Females = 2.18;  $t = 20.08$ ,  $p < 0.001$ ) (see Figure S1 for variable distribution).

### *Unemployment*

The LSYPE contains monthly employment activity data covering 2006-10 (approximately age 16 to 21), constructed from self-reports elicited in waves 4-7. We used these data to generate two outcome variables: (i) a variable tracking monthly employment status, coded as 0 for anyone in education, training or employment and coded as 1 for the unemployed and (ii) a continuous variable measuring the total months of unemployment. Twenty nine per cent of the sample experienced at least one month of unemployment between 2006-10 (Mean = 3.17 months, SD = 6.93). In total, 19 per cent of the sample reported 1-12 months unemployment and 10 per cent reported 13-45 months. Although the employment activity data spans the period from September 2006 to May 2010, it is not possible to separate the effects of school-leaving and the 2008 recession on subsequent unemployment because both events occurred concurrently.

### *Covariates*

The main covariates are gender, the main parent's socioeconomic status (SES) derived from their occupation (from I = Higher managerial, administrative and professional occupations, to VIII = long-term unemployed) and a monthly time variable to track changing macro-economic conditions. We also included extended controls that might plausibly affect labor market entry. These controls, described in Supplementary Materials, Section 5.3b, can broadly be grouped into (i) childhood environmental factors such as the number of siblings in the childhood home and whether English was the main language, (ii) demographic measures such as race and region of birth, and (iii) childhood physical health as gauged by the child's disability status.

### *Statistical analysis*

We specified a Probit model (*Model 1*) to estimate the probability of being unemployed on a monthly basis from ages 16 to 21, controlling for gender, parental SES and a monthly time trend. Standard errors were clustered by individual to account for repeated observations of the same person and we estimated marginal effects after the Probit regression to calculate percentage point changes in unemployment probability (Long & Freese, 2014). We specified a negative binomial model (*Model 2*) to estimate accumulated months of unemployment. A negative binomial model is appropriate for over-dispersed count data: in both Study 1 and 2 there is significant clustering at zero months of accumulated unemployment and the mean number of unemployed months is much lower than the variance (see Sturman, 1999 for the merits of using the negative binomial model versus other models when analyzing count data). The formal specification of each of the analytic models is detailed below:

Model 1: Monthly unemployment status (age 16 to 21) $_{it} = b_0 + b_1\text{GHQ-12 category}_i + b_2\text{Gender}_i + b_3\text{Parental SES}_i + b_4\text{Monthly index}_t + \varepsilon_{it}$

Model 2: Total months of unemployment (age 16 to 21) $_i = b_0 + b_1\text{GHQ12 category}_i + b_2\text{Gender}_i + b_3\text{Parental SES}_i + \varepsilon_i$

We also estimated models with: (i) a standardized rather than categorical GHQ measure (ii) an extended set of additional control variables and (iii) a dependent variable excluding the inactive population and estimating only unemployment versus those in education, employment or training.

## 5.4 Study 1: Results

Between ages 16 and 21 those classified as highly distressed experienced unemployment levels that were on average 2.0 percentage points higher than their low distress peers ( $b = 0.020$ ,  $SE = 0.005$ ,  $p < 0.01$ ), as detailed in Table 5.1 and illustrated in Figure 5.1a. Negative binomial analysis confirmed that the high distressed group experienced significantly more accumulated months unemployed ( $b = 0.265$ ,  $SE = 0.086$ ,  $p < 0.01$ ) compared to the low distress group, as shown in Table 5.1. In order to represent this difference more intuitively, we also estimated the average number of months unemployed using the margins command in Stata after estimating Model 2 (for a full description of ‘margins’ see Long & Freese, 2014). The high distress group experienced 3.86 months of unemployment (95% CI, 3.29-4.43) compared to 2.96 months for the low distress group (95% CI, 2.71-3.22), shown in Figure 5.1a.

The use of a standardized distress measure did not change the main findings (see Table S5.3), nor did the inclusion of an extended set of demographic, childhood environment, and health controls, as summarized in columns 2 and 4 of Table 5.1 and detailed in full in Table S5.5. Examining the association between distress levels and unemployment excluding those of inactive status for each wave yielded similar results on average as the main analyses, described in Table S5.7.

Table 5.1. Regression of unemployment between ages 16 and 21 on childhood psychological distress in the LSYPE sample (N=10,232).

Outcome variable	Monthly unemployment status <sup>a</sup>	Monthly unemployment status fully adjusted <sup>a</sup>	Total months of unemployment <sup>b</sup>	Total months of unemployment fully adjusted <sup>b</sup>
Observations	404,556	394,197	10,232	9,964
Medium distress <sup>c</sup>	0.005 (0.004)	0.006 (0.004)	0.065 (0.070)	0.087 (0.070)
High distress <sup>c</sup>	0.020*** (0.005)	0.022*** (0.005)	0.265*** (0.086)	0.287*** (0.087)

Included in analyses but not shown are: gender, parental socioeconomic status (all columns), and month of observation (col. 1 & 2). Fully adjusted models add further controls for race, childhood disability, family structure, region, and parental education levels (all columns).

<sup>a</sup> Regressions contain Probit marginal effects coefficients, clustered by id.

<sup>b</sup> Regressions contain negative binomial coefficients.

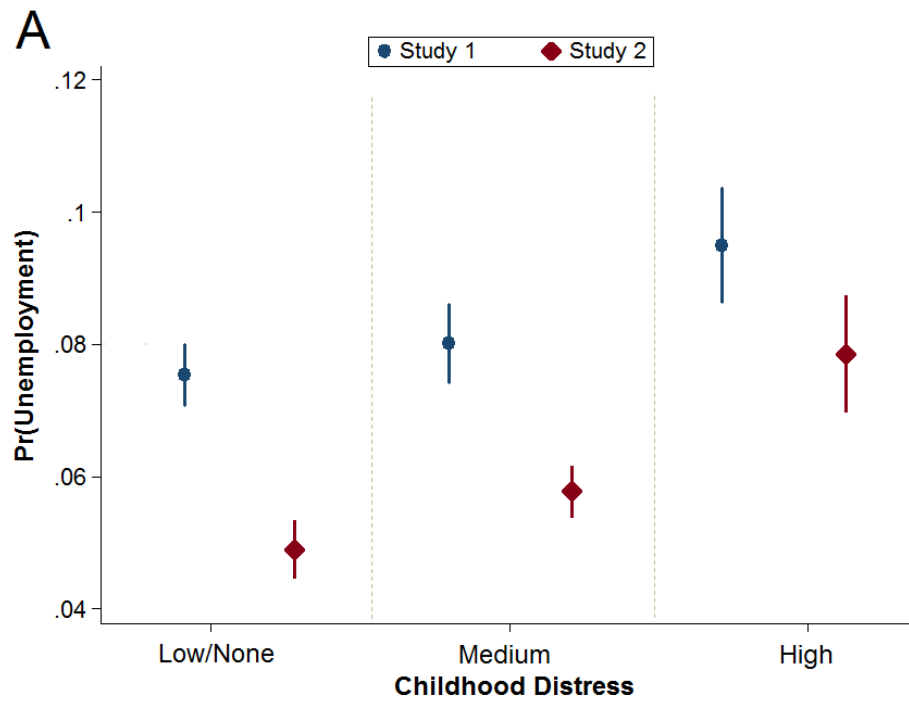
<sup>c</sup> Base category is Low distress = a GHQ score of 0; Medium distress = GHQ scores 1-3; High distress = 4+.

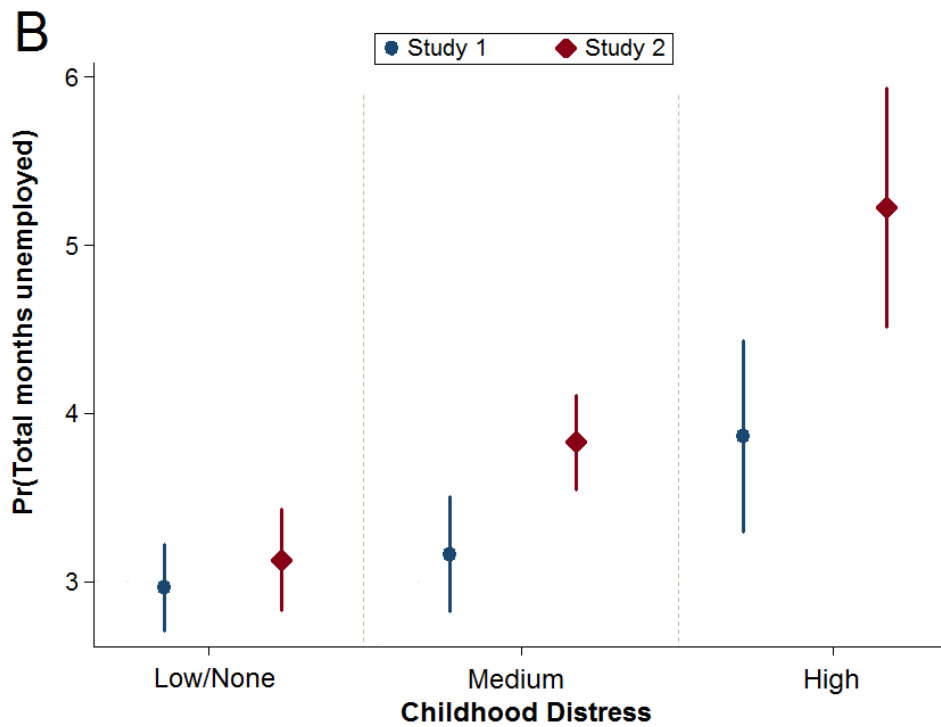
Robust standard errors in parentheses.

\*\*\* p<0.01



Figure 5.1: Predictive margins with 95% CIs showing (A) predicted probability of unemployment across all months surveyed (B) predicted total number of months unemployed, for different levels of childhood distress in the Longitudinal Study of Young People in England (Study 1) and National Child Development Study (Study 2).





### 5.5 Study 2: Methods

Having demonstrated a link between childhood distress and greater difficulty entering the labor market in Study 1, we next tested the robustness of this relationship using data including additional detail on participants' childhood cognitive ability, temperament and early childhood environment. The data in Study 2 also allowed us to test whether childhood distress was associated with particularly high levels of unemployment after the onset of the early 1980s recession in the United Kingdom.

#### *Study population*

Participants were from the British National Child Development Study (NCDS), a longitudinal study following a cohort of 17,638 people born in Britain in a single week in March 1958. The NCDS contains rich information on the cohort members' childhood characteristics as well as monthly employment activity data from ages 16 to 23. We used employment data from wave 4, which elicited responses from 68 per cent of all-time

participants at age 23. After matching childhood data from birth, age 7, and age 11 waves with employment data gathered at age 23 and deleting observations which did not contain data for the main covariates, we constructed a sample of 597,858 monthly unemployment status observations for 8,985 cohort members. Although some degree of attrition was observed, Hawkes and Plewis (2006) show that those who left the survey did not differ significantly from the rest of the sample on the basis of observable socioeconomic characteristics. Table S5.2 contains descriptive statistics for the sample.

### *Measures*

#### *Childhood psychological distress*

At ages 7 and 11 the cohort members were assigned a ‘depression’ score by their teacher based on questions from the depression subscale of the British Social Adjustment Guide. This measure asked teachers to rate children on their depression (“Expression is miserable, depressed”), apathy (“In asking teacher's help too apathetic to bother”, “Apathetic (just sits)”), and lethargy levels (“Lacks physical energy”, “Has no life in him”). We constructed a measure of childhood distress by averaging age 7 and 11 scores on this measure. This new variable ranges from 0-9 where high scores indicate greater distress. We then created a three-category distress variable by grouping those with scores of 0 (‘Low Distress’, 36 per cent of the sample), 0.5-2 (‘Medium Distress’, 49 per cent) and those scoring greater than 2 (‘High Distress’, 15 per cent). The average score on the distress measure was 0.95 (SD = 1.18) with males rated as having more psychological distress (Males = 1.10, Females = 0.79;  $t = 12.79$ ,  $p < 0.001$ ) (see Figure S5.2 for variable distribution and Supplementary Materials, Section 5.1 for an item list).

### *Unemployment*

When the cohort members were aged 24 they were asked to recall their monthly employment history from age 16 to 23, spanning the period June 1974 to February 1982. We used these data to generate two outcome variables: (i) a variable tracking monthly employment status for the 1974-82 period where being in full-time employment is coded as 0 and being unemployed is coded as 1 and (ii) a continuous variable for summed total months of youth unemployment. This latter variable ranged from 0-87 months (Mean = 3.91 months, SD = 8.95) with over 57 percent of the sample reporting 0 months of unemployment, over 33 percent reporting between 1-12 months and the remaining 9.4 per cent accounting for 13-87 months.

### *Covariates*

The main controls were gender, the father's socioeconomic status (from I = Higher administrative occupations, to V = Unskilled workers) which we used as an SES proxy for the child and cognitive ability at age 11 as assessed by an 80-item general ability test (Pigeon, 1964). Given that lower childhood cognitive ability is associated with higher adult distress (Gale, Hatch, Batty & Deary, 2009) and unemployment (Caspi, Wright, Moffitt & Silva, 1998), this may reduce potential confounding of the main effect of distress. We also controlled for childhood self-control given that this is associated with unemployment over the lifespan (Daly et al., 2015) and a monthly time variable to take into account changing macro-economic conditions. As a robustness check to determine whether childhood distress predicted youth unemployment above and beyond distress later in life, we also included a measure of adult distress elicited at age 23 using the 9-item Malaise Inventory (Rutter, Tizard & Whitemore, 1970) (see Supplementary Materials, Section 5.1 for an item list).

As in Study 1, we included extended childhood controls that might influence employment trajectories. These controls, available in the Supplementary Materials, Section 5.3b, can be grouped into (i) adverse childhood experiences such as domestic tension, parental unemployment or sickness and housing or financial difficulties (ii) physical health such as low birth weight or neurological problems (e.g. epilepsy, intellectual disability) and (iii) demographics such as region of birth and race.

### *Statistical analysis*

We specified a Probit model (*Model 3*) to estimate the impact of childhood psychological distress on later unemployment on a monthly basis from ages 16 to 23. As in Study 1, standard errors were clustered to account for repeated observations on individuals and we estimated marginal effects. Next, we estimated a negative binomial model (*Model 4*) to gauge the association between distress and accumulated months of unemployment. Across both sets of analyses the main control variables were gender, childhood cognitive ability and self-control, and socioeconomic status. Model 3 also included a monthly time variable. We also estimated extended models with a comprehensive range of further control variables. The formal specification of each of the core hierarchical analytic models is detailed below:

Model 3: Monthly unemployment status (age 16 to 23)<sub>it</sub> =  $b_0 + b_1$ Childhood distress category<sub>i</sub> +  $b_2$ Gender<sub>i</sub> +  $b_3$ Childhood cognitive ability<sub>i</sub> +  $b_4$ Childhood self-control<sub>i</sub> +  $b_5$ Parental SES<sub>i</sub> +  $b_6$ Monthly index<sub>t</sub> +  $\varepsilon_{it}$

Model 4: Total months of unemployment (age 16 to 23)<sub>i</sub> =  $b_0 + b_1$ Childhood distress category<sub>i</sub> +  $b_2$ Gender<sub>i</sub> +  $b_3$ Childhood cognitive ability<sub>i</sub> +  $b_4$ Childhood self-control<sub>i</sub> +  $b_5$ Parental SES<sub>i</sub> +  $\varepsilon_i$

Lastly, we specified a Probit model (*Model 5*) to conceptualize the interaction of distress and the onset of the 1980s UK recession, dated as starting in January 1980 (Jenkins, 2010). We created a binary variable for the recession where 0 = June 1974 – December 1979 (participants aged 16 to 21) and 1 = January 1980 – February 1982 (participants aged 21 to 23). We then interacted this variable with the distress measure to determine whether the more distressed were more likely to become unemployed after the recession began. Specifically, after running a Probit regression we estimated the average predicted probability of unemployment for different distress levels before and after the recession using the margins command in Stata (Long & Freese, 2014). We entered this interaction variable and its constituent parts simultaneously in the regression in line with recommended practice (Aiken & West, 1991).

Model 5: Monthly unemployment status (16-23yrs) $_{it} = b_0 + b_1$ Childhood distress category $_i + b_2$ Gender $_i + b_3$ Childhood cognitive ability $_i + b_4$ Childhood self-control $_i + b_5$ Parental SES $_i + b_6$ Monthly index $_t + b_7$ Recession $_t + b_8$ Childhood distress category $_i *$ Recession $_t + \varepsilon_{it}$

As in Study 1, we also estimated models with: (i) a standardized rather than categorical distress measure and (ii) an extended set of additional control variables.

## 5.6 Study 2: Results

### *Unemployment regressions*

High and medium distress significantly predicted 3 (High:  $b = 0.030$ ,  $SE = 0.005$ ,  $p < 0.01$ ) and 0.9 (Medium:  $b = 0.009$ ,  $SE = 0.003$ ,  $p < 0.01$ ) percentage points higher unemployment between ages 16 and 23 compared to the low distress group, as detailed in Table 5.2 and illustrated in Figure 5.1b. Negative binomial analysis finds that both these groups accumulated significantly more months of unemployment compared to the low

distress group (Medium:  $b = 0.205$ ,  $SE = 0.056$ ,  $p < 0.01$ ; High:  $b = 0.513$ ,  $SE = 0.086$ ,  $p < 0.01$ ).

As in Study 1, we also estimated the average number of total months of unemployment by level of distress by using the margins command after estimating Model 4. The high distress group experienced 5.21 months of unemployment (95% CI, 4.53-5.90) compared to 3.83 months for the medium distress group (95% CI, 3.57-4.10) and 3.13 months for the low distress group (95% CI, 2.83-3.41).

As in Study 1, the use of a standardized distress measure did not change the main findings (see Table S5.4), nor did the inclusion of an extended set of demographic, childhood environment, and health controls, as summarized in columns 2 and 4 of Table 5.2 and detailed in full in Table S5.6. Lastly, while adult distress had a large and significant association with youth unemployment in terms of probability of monthly unemployment ( $b = 0.044$ ,  $SE = 0.007$ ,  $p < 0.01$ ) and total duration of months unemployed ( $b = 0.453$ ,  $SE = 0.016$ ,  $p < 0.01$ ), including it as a covariate in Model 3 did not substantially affect the coefficient for childhood distress. This indicates that childhood distress incurs a cumulative disadvantage on later employment outcomes above and beyond adult distress.

Table 5.2. Regression of unemployment between ages 16 and 23 on childhood psychological distress in the NCDS sample (N=8,985).

Outcome variable	Monthly unemployment status <sup>a</sup>	Monthly unemployment status fully adjusted <sup>a</sup>	Total months of unemployment <sup>b</sup>	Total months of unemployment fully adjusted <sup>b</sup>
Observations	597,858	321,950	8,985	4,925
Medium distress <sup>c</sup>	0.009*** (0.003)	0.009*** (0.003)	0.205*** (0.056)	0.229*** (0.075)
High distress <sup>c</sup>	0.030*** (0.005)	0.027*** (0.006)	0.513*** (0.086)	0.568*** (0.119)

Included in analyses but not shown are: gender, parental socioeconomic status, childhood intelligence and self-control (all columns), and month of observation (col. 1 & 2). Fully adjusted models add further controls for extensive set of demographic characteristics, adverse childhood experiences, and physical health variables.

<sup>a</sup> Regressions contain Probit marginal effects coefficients, clustered by id.

<sup>b</sup> Regressions contain negative binomial coefficients.

<sup>c</sup> Base category is Low distress = a score of 0; Medium distress = Distress scores 0.5-2; High distress = 2.5-9.

Robust standard errors in parentheses

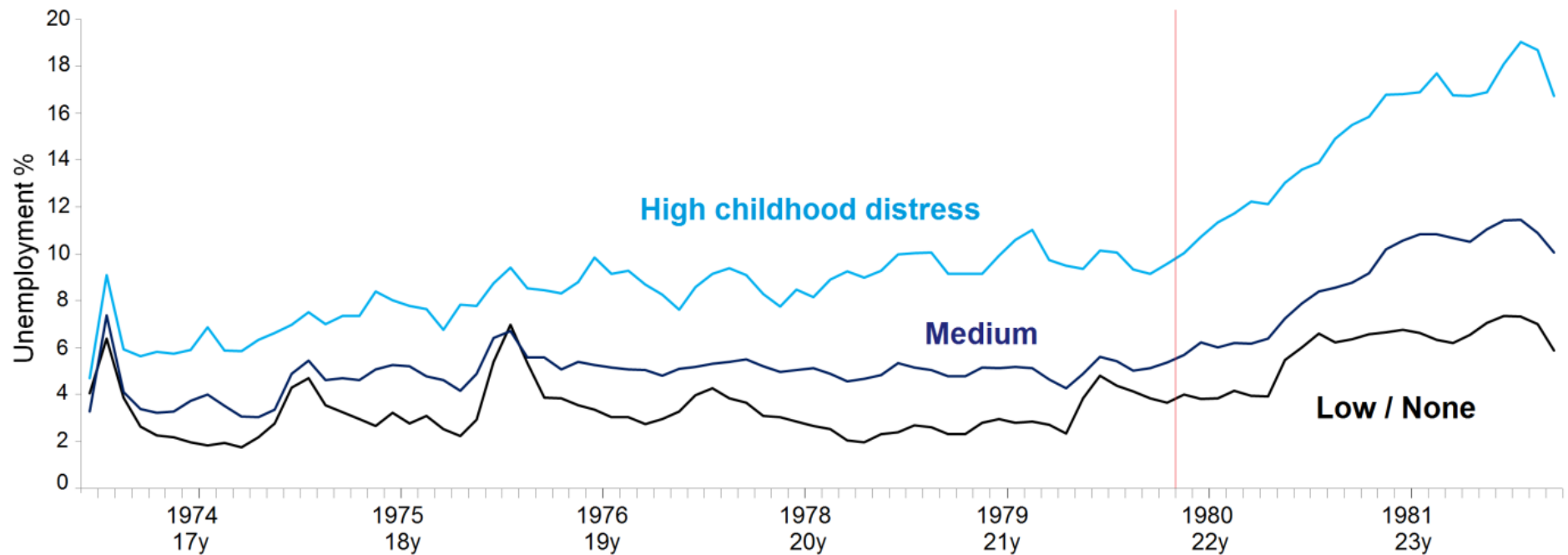
\*\*\* p<0.01.



*Differential response to recession*

We first estimated an OLS regression using the form described in Model 5 and identified a significant interaction between medium distress levels and the presence of the economic recession ( $b = 0.013$ ,  $SE = 0.004$ ,  $p < 0.01$ ) and between high distress levels and the recession dummy ( $b = 0.036$ ,  $SE = 0.008$ ,  $p < 0.01$ ). These coefficients indicated that the association between distress and unemployment was stronger during the recession, particularly amongst the highly distressed. We next examined the predicted probability of unemployment for different distress groups before and after the recession. Prior to the recession the average predicted probability of unemployment for the low distress group was 4.3% and 6.9% for the high distress group. In the post-recession period the probability of unemployment rose to 6.2% for the low distress group and 10.1% for the highly distressed. Contrasting the pre- and post-recession periods, the difference in unemployment level between the high and low distress groups therefore increased by 50 per cent (from a 2.6 point gap to a 3.9 point gap) after controlling for covariates. Taken together these analyses suggest that the high distress group were disproportionately more likely to be unemployed after the recession began. This trend is shown graphically in Figure 5.2 and Figure S5.3, and detailed in Table S5.8.

Figure 5.2: Descriptive statistics describing unemployment in the NCDS from August 1974 – November 1981 by levels of childhood distress. The year above the cohort members' age refers to March of that year, the month when the cohort members were born. The red line denotes the onset of the U.K. recession in January 1980. Five months at the beginning and end of the data-range are omitted due to small sample sizes.



## 5.7 Discussion

In this study we found that differences in psychological distress are evident in childhood and appear to shape early career labor market prospects. Using data from two nationally representative longitudinal datasets we showed, for the first time, that highly distressed children experience youth unemployment levels higher than their less distressed peers. Given that distress is measured in childhood, years before the cohort members first entered the labor market, our methodology also eliminates potential econometric issues of endogeneity between experienced unemployment and psychological distress. These sizeable effects (2 to 3 percentage points) were robust to the inclusion of a broad set of potential confounding variables and were consistent across estimates derived from self-reported distress levels (Study 1) and teacher-rated distress levels (Study 2). The link between childhood distress and unemployment was not markedly affected by adjustment for adult distress in Study 2, suggesting that childhood distress may set in motion a broad set of effects (e.g. social, educational, health) that act to influence later employment, above and beyond the effects of adult distress.

Furthermore, we found in Study 2 that the impact of the economic shock of the 1980 UK recession appeared to be much greater amongst the highly distressed. This was most evident in the difference in unemployment levels between the low and high distress groups which grew by 50 per cent in the pre- to post-recession period. This finding has clear contemporary relevance given the marked rise in youth unemployment in much of Europe and the US following the 2007 recession. Whether those with poor initial mental health were more vulnerable to exclusion from the labor force during the most recent economic crisis requires investigation, particularly given the potential mutually reinforcing relationship between mental health problems and unemployment (Clark et al., 2001, Butterworth et al., 2012, Evans-Lacko et al., 2013).

These findings also suggest several plausible pathways from childhood distress to later unemployment that require further investigation. Early psychological distress might lead to youth unemployment by adversely affecting job performance and increasing absenteeism (Lerner & Henke, 2008, Lagerveld et al., 2010). Distress could also act to impair job search intensity (McKee-Ryan et al., 2005, Kanfer, Wanberg & Kantrowitz, 2001) and reduce investment in further training and human capital accumulation (Fletcher, 2008, Berndt et al., 2000). Finally, employers may discriminate against job applicants with potential mental health issues or be unwilling to accommodate existing employees with mental health issues, particularly in competitive labor markets (Evans-Lacko et al., 2013; Chatterji, Alegria, & Takeuchi, 2011; Callard, 2012).

There are three main limitations of this study. Firstly, there may be unobserved confounding variables which affect both childhood distress and youth unemployment, such as genetic factors or childhood environmental characteristics not fully captured by the data. Secondly, while we use a well-validated measure of childhood distress in Study 1, such a measure was not available in Study 2. However, this latter teacher-rated measure appears to gauge distress by assessing apathy, depression and lethargy. Lastly, although we found that the highly distressed were more likely to become unemployed after the 1980s recession, the generalizability of this finding is unclear – this association may be specific to the time period, the country or the nature of that particular recession.

In summary, our findings add to the growing literature which suggests that mental health, like cognitive abilities and socio-emotional skills, can be considered as an important factor involved in the production of economic success (Goodman et al., 2011, Smith & Smith, 2010, Delaney & Smith, 2012, Cunha, Heckman & Schennach, 2010). Layard (2013) has described mental health as a frontier of labor economics and called for more recognition of its influence on economic outcomes and greater mental health promotion. Our findings support

these arguments and suggest that reduced unemployment may be an additional benefit of intervention programs targeting childhood mental health. Given that our findings demonstrate an association between childhood psychological distress and unemployment but not a precise mechanism linking the two, additional policy implications are necessarily speculative. Enhanced labor market activation programs for those with mental health problems (see Caplan, Vinokur, Price & Van Ryn, 1989 and Vinokur, Schul, Vuori & Price, 2000) and increased efforts to reduce stigma and eliminate discriminatory work practices may help attenuate the link between psychological distress and unemployment (Rüsch, Angermeyer, & Corrigan, 2005; Stuart, 2006). Future research should examine whether our central finding of childhood distress robustly predicting unemployment replicates in other datasets and whether the distressed are consistently more likely to become unemployed during recessions. If so, our findings could point to hitherto neglected economic benefits of childhood mental health interventions and a strong need to consider mental health as a core component in the design of job search programs.

## **Appendix**

**Section 1:** Details of data-sets & distress measurements.

**Section 2:** Descriptive statistics.

**Section 3:** Supplementary regressions:

3a: Regressions using standardized distress variables in Study 1 and 2.

3b: Regressions using extended control variables in Study 1 and 2.

3c: Regressions excluding all inactive participants in Study 1.

**Section 4:** Extended analysis of the interaction between psychological distress and the 1980s

UK recession in Study 2.

**Section 1:** Details of data-sets & distress measurements.**Data-Sets Used**

*National Childhood Development Study (accessed October 12<sup>th</sup> 2013)*

7. NCDS Activity Histories, 1974-2008 (NCDS 6942).
8. NCDS Childhood Data, Sweeps 0-3, 1958-1974 (NCDS 5565).
9. NCDS Sweep 4 data (NCDS 5566).

*Longitudinal Study of Young People in England (accessed October 15<sup>th</sup> 2013)*

1. Wave Two LSYPE Family Background File.
2. Wave Two LSYPE Young Person File.
3. LSYPE Main Activity Waves 4-7.

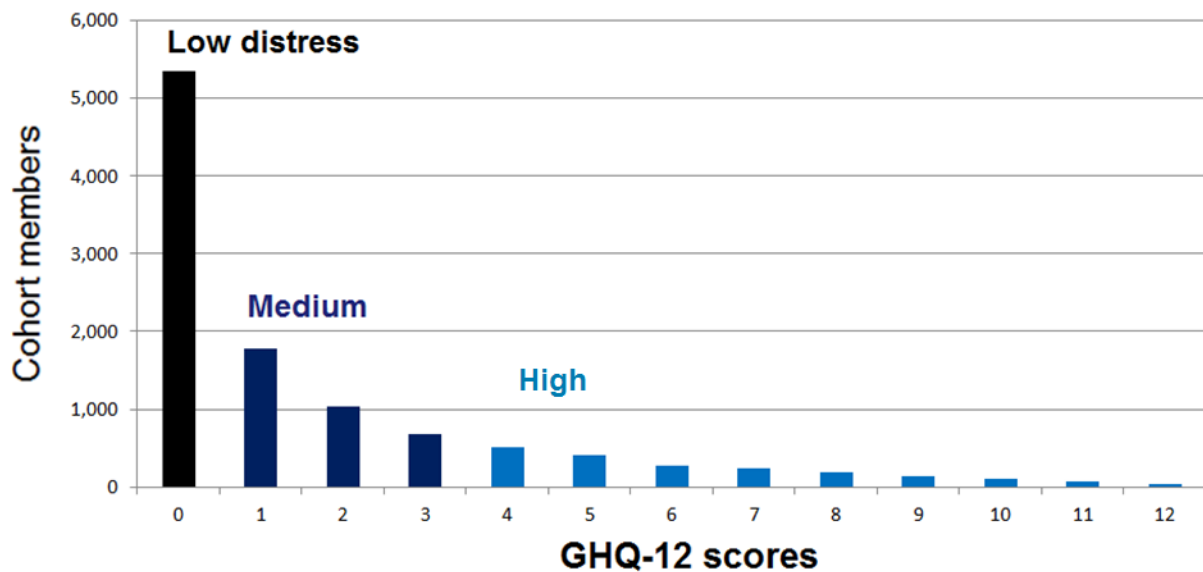
All data-sets were downloaded from the UK Data Service:

<http://discover.ukdataservice.ac.uk/>

**Details of Distress Measurements*****Longitudinal Study of Young People in England (Study 1)***

The cohort members in the LSYPE completed the 12-item version of the General Health Questionnaire (Goldberg & Williams, 1988) when they were 14 years old. We do not list the GHQ items here because they are copyrighted. The four possible responses to each question were scored in the LSYPE in the form 0-0-1-1 for a maximum score of 12 where a higher score means worse mental health. Figure S1 describes the distribution of scores for this variable in the sample of 10,232 cohort members (Mean=1.69, SD=2.51).

Figure S5.1: Distribution of GHQ12 scores in Study 1 and the codings used to generate the categorical distress variable used in the main analysis.



### *National Child Development Study (Study 2)*

#### *Childhood Distress*

At ages 7 and 11 the cohort members were assigned a ‘depression’ score by their teacher based on questions from the depression subscale of the British Social Adjustment Guide. The teachers were given the list of phrases below and asked to underline the items they thought described the child’s behaviour or attitude. The underlined phrases were then summed to create the aggregate depression score.

1. Depends on how he feels (asking teacher's help).
2. Varies noticeably from day to day (persistence in class work).
3. Sometimes alert, sometimes lethargic in team games.
4. In free activity sometimes lacks interest.
5. Persistence in manual tasks varies greatly.
6. Impatient, loses temper with job (persistence - manual tasks).

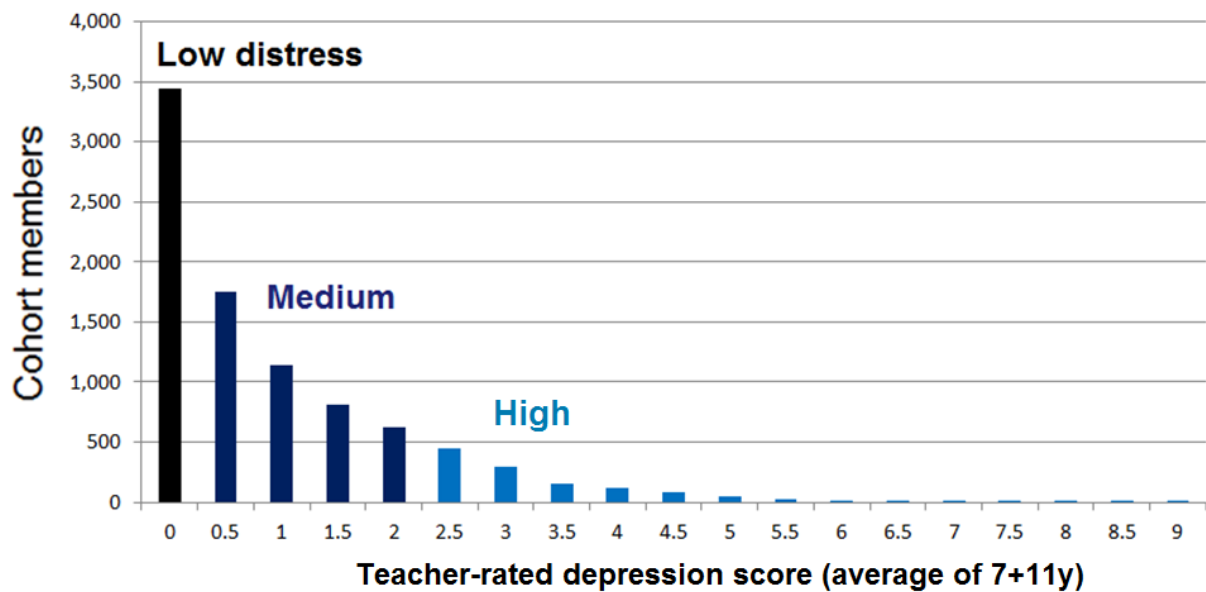


7. Flies into a temper if provoked (physical prowess).
8. Can work alone but has no energy (persistence in class work).
9. Lacks physical energy (persistence manual tasks).
10. Has no life in him (class room behaviour).
11. Apathetic (just sits) (attentiveness).
12. Shuffles restlessly (posture).
13. In asking teacher's help too apathetic to bother.
14. Dull listless eyes.
15. Always sluggish, lethargic in team games.
16. Sometimes wanders off alone (companionship).
17. Speech is thick, mumbling, inaudible.
18. Expression is miserable, depressed (under the weather) seldom smiles.

To create our distress variable, we took the average of the two 'depression' scores.

Although the maximum score possible is 18, we observe scores ranging from 0 to 9 in our working sample of 8,985 cohort members. Figure S2 describes the distribution of our composite variable (Mean=0.94, SD=1.18).

Figure S5.2: Distribution of distress scores in Study 2 and the codings used to generate the categorical distress variable used in the main regression analysis.



### *Adult Distress*

At age 23 the NCDS cohort members were asked to complete the Malaise Inventory, comprised of 24 ‘yes-no’ questions covering emotional disturbance and related physical symptoms (Rutter, Tizard & Whitmore, 1970). We focused on the 9 questions related to psychological functioning to create the adult distress variable (Cronbach’s alpha = 0.70). Each ‘yes’ answer was given a score of 1 for a possible score range of 0-9 where a higher score indicated more psychological distress (M=1.24, SD=1.58)

### **Malaise Inventory**

1. Feel tired most of the time
2. Often miserable or depressed
3. Often get worried about things
4. Often get into violent rage
5. Often suddenly become scared

6. Easily upset or irritated
7. Constantly keyed-up + jittery
8. Things get on your nerves
9. Heart often races like mad

**Section 2:** Descriptive statistics.

Table S5.1. Descriptive statistics in the LSYPE sample by levels of childhood distress.

Distress	Low / None	Medium	High	All
N	5,100	3,301	1,831	10,232
<b>Socio-demographics</b>				
Female	41.8%	49.6%	66.3%	48.7%
<i>Parental SES</i>				
I (highest)	5.6%	6.3%	5.2%	5.7%
II	25.7%	27.8%	26.9%	26.6%
III	13.0%	14.1%	14.7%	13.7%
IV	6.1%	5.4%	4.8%	5.6%
V	8.7%	9.5%	8.0%	8.8%
VI	20.0%	18.2%	18.6%	19.2%
VII	11.1%	10.5%	12.0%	11.0%
VIII (lowest)	9.8%	8.2%	9.8%	9.4%
<b>Employment activity</b>				
Months of data	39.30 (10.65)	39.75 (10.22)	39.84 (10.08)	39.54 (10.41)
Months unemployed	3.05 (6.83)	3.14 (6.93)	3.57 (7.19)	3.17 (6.93)

Table S5.2. Descriptive statistics in the NCDS sample by levels of childhood distress.

Distress	Low / None	Medium	High	All
N	3,441	4,337	1,207	8,985
<b>Socio-demographics</b>				
Intelligence (0-79)	50.37 (13.65)	42.32 (15.14)	32.70 (14.98)	44.11 (15.69)
Female	59.0%	45.9%	39.4%	50.0%
Self-Control (0-10.5)	10.00 (0.83)	8.91 (1.64)	7.94 (1.90)	9.20 (1.60)
<i>SES</i>				
I (highest)	5.1%	3.9%	1.7%	4.1%
II	15.9%	12.3%	8.8%	13.2%
III	61.4%	62.1%	60.6%	61.6%
IV	10.9%	12.5%	15.3%	12.3%
V (lowest)	6.7%	9.2%	13.6%	8.8%
<b>Employment activity</b>				
Months of data	61.9 (26.38)	68.26 (24.63)	73.47 (21.89)	66.54 (25.29)
Months unemployed	2.5 (5.82)	4.08 (8.97)	7.35 (13.87)	3.91 (8.95)
<b>% months unemployed</b>				
1974-79 (Pre-recession)	5.8%	6.3%	9.2%	6.5%
1980-82 (Post-recession)	7.6%	10.8%	16.4%	10.3%

**Section 3: Supplementary regressions:*****3a. Regressions using standardized distress variables.****LSYPE (Study 1)*

In the main text we created a categorical distress variable derived from GHQ scores ranging from 0-12. Here we present analysis using a standardized variable derived from the same GHQ scores. Although this method does not account for the large differences in unemployment outcomes between those with Medium and High distress, the central finding of distress predicting unemployment remains robust, as described in Table S3.3. A 1 SD increase in distress significantly predicts an average 0.7 percentage point increase in unemployment during the 2006-10 period ( $b = 0.007$ ,  $SE = 0.002$ ,  $p < 0.01$ ) and significantly higher total months unemployed ( $b = 0.092$ ,  $SE = 0.031$ ,  $p < 0.01$ ).

Table S5.3. Regression of unemployment on standardized childhood psychological distress between ages 16 and 21 in the LSYPE sample (N=10,232).

Outcome variable	Monthly unemployment status <sup>a</sup>	Total months of unemployment <sup>b</sup>
Observations	404,556	10,232
Distress	0.007*** (0.002)	0.092*** (0.031)

Included in analyses but not shown are: gender, parental socioeconomic status (both columns) and month of observation (col. 1).

<sup>a</sup>Regressions contain Probit Marginal Effects coefficients, clustered by id.

<sup>b</sup>Regressions contain negative binomial coefficients.

Robust standard errors in parentheses.

\*\*\*  $p < 0.01$

#### *NCDS (Study 2)*

Our test of the relationship between a continuous measure of distress and unemployment in Study 2 is described in Table S4. A 1 SD increase in distress significantly predicts a 1 percentage point increase in unemployment during the 1974-82 period ( $b = 0.010$ ,  $SE = 0.002$ ,  $p < 0.01$ ) and significantly higher total months unemployed ( $b = 0.181$ ,  $SE = 0.029$ ,  $p < 0.01$ ).

Table S5.4. Regression of unemployment on standardized childhood psychological distress between ages 16 and 23 in the NCDS sample (N=8,985).

Outcome variable	Monthly unemployment status <sup>a</sup>	Total months of unemployment <sup>b</sup>
Observations	597,858	8,985
Distress <sup>c</sup>	0.010*** (0.002)	0.181*** (0.029)

Included in analyses but not shown are: gender, parental socioeconomic status, childhood intelligence and self-control (both columns), and month of observation (col. 1).

<sup>a</sup> Regressions contain Probit marginal effects coefficients, clustered by id.

<sup>b</sup> Regressions contain negative binomial coefficients.

Robust standard errors in parentheses.

\*\*\*  $p < 0.01$

### ***3b. Regressions using extended control variables.***

#### *LSYPE (Study 1)*

Table S5.5 describes our extended LSYPE regressions using a range of childhood controls that may affect employment trajectories. These controls can broadly be grouped into (i) childhood environmental factors such as the number of siblings in the childhood home, whether English was the main language, parental marital status and whether the child had a disability and (ii) demographic measures such as race and region of birth. The distress coefficients do not substantially change following the addition of these controls.



Table S5.5. Regression of unemployment between ages 16 to 21 on childhood psychological distress in the LSYPE sample with extended controls (N=10,232).

Variable	Monthly unemployment status <sup>a</sup>	Monthly unemployment status fully adjusted <sup>a</sup>	Total months of unemployment <sup>b</sup>	Total months of unemployment fully adjusted <sup>b</sup>
Observations	404,556	394,197	10,232	9,964
Med. Distress <sup>c</sup>	0.005 (0.004)	0.006 (0.004)	0.065 (0.070)	0.087 (0.070)
High Distress <sup>c</sup>	0.020*** (0.005)	0.022*** (0.005)	0.265*** (0.086)	0.287*** (0.087)
Female	-0.030*** (0.003)	-0.029*** (0.003)	-0.346*** (0.063)	-0.341*** (0.064)
<i>Parental SES (base=I)</i>				
II <sup>d</sup>	0.007 (0.005)	0.003 (0.007)	0.112 (0.143)	0.058 (0.145)
III <sup>d</sup>	0.015** (0.006)	0.005 (0.007)	0.217 (0.154)	0.039 (0.161)
IV <sup>d</sup>	0.024*** (0.008)	0.011 (0.009)	0.353* (0.183)	0.114 (0.190)
V <sup>d</sup>	0.051*** (0.008)	0.034*** (0.009)	0.631*** (0.166)	0.404** (0.175)
VI <sup>d</sup>	0.036*** (0.006)	0.016** (0.007)	0.468*** (0.147)	0.198 (0.158)

VII <sup>d</sup>	0.069*** (0.008)	0.035*** (0.009)	0.774*** (0.159)	0.370** (0.172)
VIII <sup>d</sup>	0.086*** (0.009)	0.048*** (0.011)	0.910*** (0.164)	0.474** (0.187)
Time <sup>e</sup>	0.002*** (0.000)	0.002*** (0.000)	N/A N/A	N/A N/A
<i>Parents Education</i>				
<i>(base=Degree)</i>				
Higher ed. below degree		-0.001 (0.005)		-0.058 (0.109)
GCSE A-C / lower quals.		0.016*** (0.005)		0.161 (0.112)
No qualifications.		0.046*** (0.007)		0.415*** (0.132)
<i>Race (base=white)</i>				
Mixed		-0.007 (0.008)		-0.099 (0.150)
Indian		-0.044*** (0.006)		-0.661*** (0.141)
Pakistani		-0.014* (0.008)		-0.074 (0.173)
Bangladeshi		-0.032*** (0.009)		-0.309 (0.201)
Black Caribbean		-0.008 (0.010)		-0.088 (0.191)

Black African	-0.044***	-0.668***
	(0.009)	(0.211)
Other	-0.038***	-0.403*
	(0.010)	(0.231)
<i>Childhood Home</i>		
<i>(base # siblings = 0)</i>		
1 Sibling	0.001	-0.005
	(0.005)	(0.097)
2 Siblings	0.010*	0.129
	(0.005)	(0.106)
3 Siblings	0.039***	0.446***
	(0.007)	(0.130)
4+ Siblings	0.041***	0.517***
	(0.009)	(0.159)
English not main language	-0.013*	-0.142
	(0.008)	(0.140)
<i>Region (base=N. East)</i>		
North West	-0.012	-0.096
	(0.010)	(0.163)
Yorkshire & Humber	-0.009	-0.078
	(0.010)	(0.171)
East Midlands	-0.015	-0.161
	(0.010)	(0.177)
West Midlands	-0.004	-0.002

	(0.010)	(0.169)
East England	-0.019*	-0.169
	(0.010)	(0.171)
London	-0.023**	-0.206
	(0.010)	(0.169)
South East	-0.023**	-0.217
	(0.009)	(0.164)
South West	-0.028***	-0.338*
	(0.010)	(0.178)
<i>Parents' marital status</i>		
<i>(base =married)</i>		
Cohabiting	0.036***	0.443***
	(0.007)	(0.122)
Lone father	0.030**	0.229
	(0.015)	(0.255)
Lone mother	0.047***	0.456***
	(0.005)	(0.082)
No parents	0.087***	0.763**
	(0.023)	(0.352)
<i>Childhood disability</i>		
<i>(base=none)</i>		
Mild	-0.013**	-0.094
	(0.005)	(0.120)
Severe	0.065***	0.626***
	(0.010)	(0.136)

---

<sup>a</sup> Regressions contain Probit marginal effects coefficients, clustered by id.

<sup>b</sup> Regressions contain negative binomial coefficients.

<sup>c</sup> Base category is Low Distress = a GHQ score of 0; Medium Distress = GHQ scores 1-3; High Distress = 4+.

<sup>d</sup> SES is derived from main parent's occupation where I = Higher managerial, administrative and professional occupations, II = Lower managerial, administrative and professional occupations, III = Intermediate occupations, IV = Small employers, V = Lower supervisory occupations, VI = Semi-routine occupations, VII = Routine occupations, VIII = Never worked and long-term unemployed.

<sup>e</sup> Time tracks the 45 months between September 2006-May 2010.

Robust standard errors in parentheses.

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

#### *NCDS (Study 2)*

Table S5.6 describes our extended NCDS regressions using a diverse range of childhood controls that might influence employment trajectories. These controls can broadly be grouped into (i) adverse childhood experiences and mental health such as whether the childhood home had housing or financial difficulties, domestic tension or mental illness (ii) physical health such as low birth weight, headaches, epilepsy or psychiatric problems and (iii) demographics such as region of birth and race. The distress coefficients remain essentially unchanged following the addition of these controls.

Table S5.6. Regression of unemployment on childhood psychological distress between ages 16 and 23 in the NCDS sample with extended controls (N=8,985).

Variable	Monthly unemployment status <sup>a</sup>	Monthly unemployment status fully adjusted <sup>a</sup>	Total months of unemployment <sup>b</sup>	Total months of unemployment fully adjusted <sup>b</sup>
Observations	597,858	321,950	8,985	4,925
Med. Distress <sup>c</sup>	0.009*** (0.003)	0.009*** (0.003)	0.205*** (0.056)	0.229*** (0.075)
High Distress <sup>c</sup>	0.030*** (0.005)	0.027*** (0.006)	0.513*** (0.086)	0.568*** (0.119)
Female	0.011*** (0.003)	0.011*** (0.003)	-0.022 (0.051)	0.060 (0.070)
Intelligence <sup>d</sup>	-0.013*** (0.002)	-0.003 (0.002)	-0.215*** (0.027)	-0.068* (0.040)
Self-Control <sup>d</sup>	-0.010*** (0.001)	-0.006*** (0.002)	-0.178*** (0.031)	-0.147*** (0.045)
<i>Parental SES (base=I)</i>				
II <sup>e</sup>	-0.016** (0.008)	-0.013 (0.010)	-0.168 (0.140)	-0.071 (0.174)
III <sup>e</sup>	-0.010 (0.008)	-0.008 (0.009)	0.062 (0.128)	0.033 (0.160)
IV <sup>e</sup>	-0.000	-0.006	0.243* (0.128)	0.182 (0.160)

	(0.008)	(0.010)	(0.143)	(0.184)
V <sup>e</sup>	0.026***	0.013	0.566***	0.483**
	(0.009)	(0.011)	(0.150)	(0.198)
Time <sup>f</sup>	0.009***	0.008***	N/A	N/A
	(0.000)	(0.001)	N/A	N/A
<i>Region (base=North)</i>				
North West		-0.003		-0.052
		(0.008)		(0.144)
East & West Riding		-0.018**		-0.371**
		(0.008)		(0.160)
North Midlands		-0.029***		-0.503***
		(0.008)		(0.160)
Midlands		-0.017**		-0.203
		(0.008)		(0.152)
East		-0.036***		-0.848***
		(0.007)		(0.162)
South East		-0.036***		-0.753***
		(0.006)		(0.139)
South		-0.040***		-0.795***
		(0.007)		(0.178)
South West		-0.026***		-0.343**
		(0.008)		(0.167)
Wales		0.002		-0.002
		(0.009)		(0.174)
Scotland		0.002		-0.083

	(0.008)	(0.143)
<i>Family difficulties</i>		
<i>(base=0)<sup>g</sup></i>		
1 difficulty	0.005	0.075
	(0.005)	(0.105)
2-6 difficulties	0.015*	0.071
	(0.008)	(0.157)
Household size <sup>h</sup>	0.007***	0.147***
	(0.001)	(0.026)
Father's age in 1958	0.001**	0.013**
(17-72)		
	(0.000)	(0.005)
Non-white race	-0.011	-0.142
	(0.015)	(0.409)
Low birth weight	0.003	0.028
(1= <88oz)		
	(0.007)	(0.160)
Psychiatric problems at	0.037***	0.653***
age 11 (1=yes)		
	(0.010)	(0.211)
Headaches or epilepsy	0.007	0.119
(1=frequent)		
	(0.005)	(0.117)
Mental retardation	0.004	0.055
(1=yes)		



(0.012)

(0.286)

---

<sup>a</sup> Regressions contain Probit marginal effects coefficients, clustered by id.

<sup>b</sup> Regressions contain negative binomial coefficients.

<sup>c</sup> Base category is Low distress = a score of 0; Medium distress = distress scores 0.5-2; High distress = 2.5-9.

<sup>d</sup> Intelligence and Self-Control are standardized. Intelligence was rated by a general ability test at age 10. Self-control was teacher rated at age 7 and 11.

<sup>e</sup> SES is derived from the father's occupation where I = Higher admin, II = Managerial or technical occupations, III = skilled workers, IV = semi-skilled workers and V = Unskilled workers.

<sup>f</sup> Time ranges from 1-93 and refers to the months between June 1974-Feb 1982.

<sup>g</sup> Family Difficulties Scale is a composite measure which sums 9 dummy variables relating to whether the childhood home experienced housing, financial or other difficulties, domestic tension, alcoholism, physical handicap, unemployment, mental illness or the death of a parent.

<sup>h</sup> Household size is coded 0 = 1-3, 1 = 4, 2 = 5, 3 = 6, 4 = 7, 5 = 8+.

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

### ***3c. Regressions excluding all inactive participants in Study 1.***

#### *LSYPE (Study 1)*

Table S5.7 describes regressions in the LSYPE using single wave outcome variables drawn from waves 4-7. These variables, shown in columns 1-4, are coded 0 = in employment, education or training and 1 = unemployment. They therefore exclude completely from the analysis the small number of inactive individuals present in the main regressions (see Table 5.1), which use an unemployment variable derived from the monthly NEET data.

On average, high distress in the four waves (cols. 1-4) is associated with a 2 pct point higher probability of unemployment, which matches the 2 pct points higher probability in the main data (col. 5).

Table S5.7. Regression of unemployment (excluding those of inactive status in cols. 1-4, including inactives in col. 5) on childhood psychological distress between ages 16 and 21 in the LSYPE sample.

Wave	Wave 4 <sup>a</sup>	Wave 5 <sup>a</sup>	Wave 6 <sup>a</sup>	Wave 7 <sup>a</sup>	All waves <sup>a</sup>
Observations	10,109	8,831	7,217	7,217	404,556
Wave	Wave 4	Wave 5	Wave 6	Wave 7	All waves
Med. Distress	-0.001 (0.005)	-0.002 (0.005)	0.005 (0.006)	0.005 (0.006)	0.005 (0.004)
High Distress	0.009 (0.006)	0.016** (0.008)	0.027*** (0.009)	0.027*** (0.009)	0.020*** (0.005)
Inactives	N	N	N	N	Y

Included in analyses but not shown are: gender, parental socioeconomic status (all columns) and month of observation (col. 5). 'Inactives' refer to 194 female participants who reported giving birth as of October 2010.

<sup>a</sup> Regressions contain Probit marginal effects coefficients, clustered by id.

\*\*\* p<0.01, \*\* p<0.05

## SECTION 4

### **Extended analysis of the interaction between psychological distress and the 1980s UK recession in Study 2.**

In the main text, we discuss the interaction of childhood psychological distress and the beginning of the 1980s UK recession in order to investigate whether those with poor mental health were disproportionately more likely to become unemployed during this time. Due to space constraints we omitted some detail which is now provided here.

The NCDS data tracks the monthly employment status of participants for an eight-year period from school-leaving past the onset of the 1980s recession. In contrast to Study 1, the NCDS cohort experienced a recession several years after finishing secondary education so we avoid the problem of separating the effects of school leaving and economic recession on unemployment. In order to determine whether those with high childhood distress were more likely to become unemployed after the recession began, we first examined raw descriptive unemployment statistics before and after the recession began in January 1980. In the pre-recession period (June 1974 – December 1979) the high distress group had an average unemployment rate of 8.3 per cent compared to 4.9 per cent for the medium group and 3.2 per cent for the low distress group. In the post-recession period (January 1980 – February 1982) these rates rose to 15 per cent, 8.9 per cent and 5.9 per cent respectively. This means the unemployment gap between the high and low group increased by 78 per cent after the recession began (from a 5.1 point gap to a 9.1 point gap).

We then specified an OLS regression using the form described in Model 5 and found a significant negative interaction for the high distress variable with our recession dummy ( $b = 0.036$ ,  $SE = 0.008$ ,  $p < 0.01$ ), described in Table S5.8, column 2.

Table S5.8. Regression of unemployment on childhood psychological distress interacting with the 1980 economic recession in the NCDS sample (N=8,985).

Variable	Monthly unemployment status <sup>a</sup>	Monthly unemployment status <sup>a</sup>
Observations	597,858	597,858
Med. Distress <sup>b</sup>	0.006** (0.003)	0.002 (0.003)
High Distress <sup>b</sup>	0.031*** (0.006)	0.022*** (0.005)
Recession <sup>c</sup>		0.015*** (0.003)
Med. Distress*Recession		0.013*** (0.004)
High Distress*Recession		0.036*** (0.008)

Included in analyses but not shown are: gender, parental socioeconomic status, childhood intelligence and self-control and month of observation.

<sup>a</sup> Regressions contain OLS coefficients, clustered by id.

<sup>b</sup> Base category is Low distress = a score of 0; Medium distress = Distress scores 0.5-2; High Distress = 2.5-9.

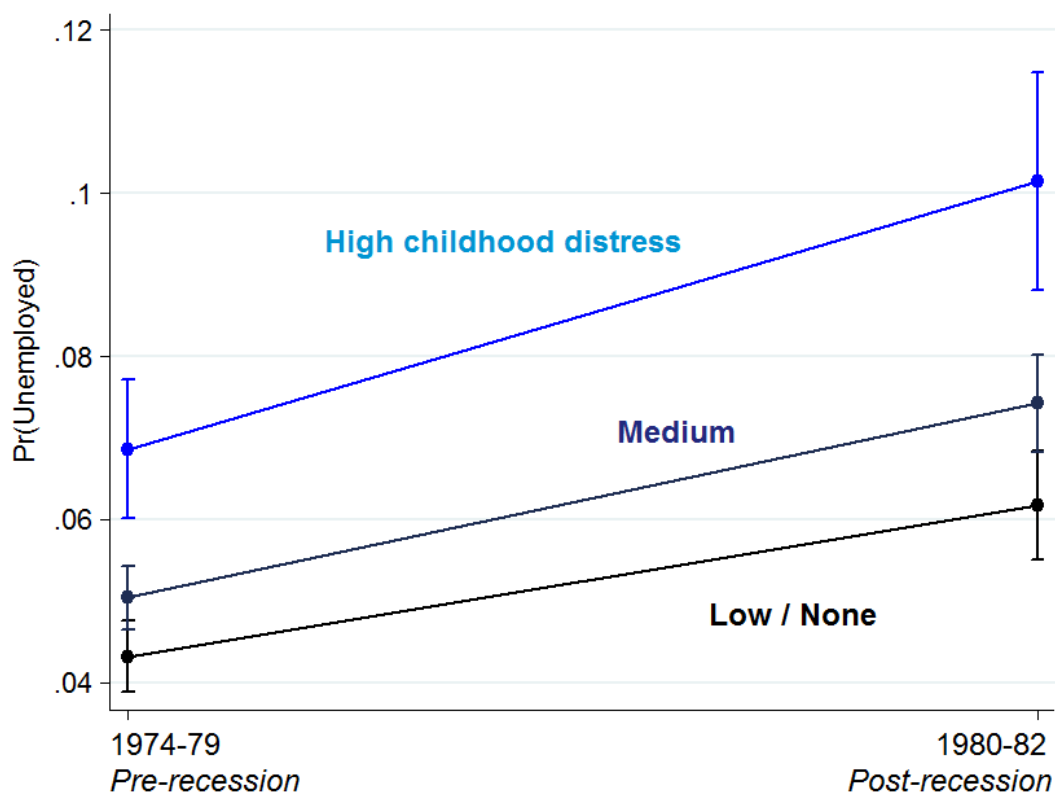
<sup>c</sup> Recession is a dummy where 0 = June 1974 – December 1979 and 1 = January 1980 – February 1982.

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05

Lastly, we examined this interaction using the Probit specification in Model 5, the predictive margins of which are visualized in Figure S5.3. The average predicted probability of unemployment for the low distress group rose from 4.3 per cent in the pre-recession period to 6.2 per cent in the post-recession period, whereas the probability of unemployment for the high group increased from 6.9 per cent to 10.1 per cent. The unemployment gap between the high and low distress groups therefore increased by 50 per cent (from a 2.6 point gap to a 3.9 point gap) after controlling for our covariates, indicating that the high distress group were disproportionately more likely to be unemployed after the recession began.

Figure S5.3: Predictive margins with 95% CIs examining the probability of unemployment in Study 2 for different levels of distress in the pre- (June 1974 – December 1979) and post-recession (January 1980 – February 1982) period. These figures were produced using the margins command after a Probit regression of the specification in Model 5, holding covariates at their specified values.



## CHAPTER 6

### **Adolescent Psychological Distress, Unemployment, and the Great Recession: Evidence from the National Longitudinal Study of Youth 1997.**

#### **6.1 Abstract**

**Rationale:** Several studies have shown a link between psychological distress in early life and subsequent higher unemployment, but none have used sibling models to account for the unobserved family background characteristics which may explain the relationship.

**Objective:** This paper uses the National Longitudinal Study of Youth 1997 data to examine whether adolescent psychological distress in 2000 predicts higher unemployment over 2000–11, whether this relationship changed in the period following the Great Recession, and whether it is robust to adjustment for family effects.

**Methods:** 7125 cohort members (2986 siblings) self-reported their mental health in 2000 and employment activities over 2000–11. This association was examined using Probit and ordinary least squares regressions controlling for intelligence, physical health, other sociodemographic characteristics and family background.

**Results:** After adjustment for covariates and compared to those with low distress, highly distressed adolescents were 2.7 percentage points (32%) more likely to be unemployed, 5.1 points (26%) more likely to be unemployed or out of the labor force and experienced 11 weeks (28%) more unemployment. The impact of high distress was similar to a one standard deviation decrease in intelligence, and double the magnitude of having a serious physical health problem, and these estimates were robust to adjustment for family fixed-effects. The highly distressed were also disproportionately more likely to become unemployed or exit the labor force in the years following the Great Recession.

**Conclusion:** These findings provide strong evidence of the unemployment penalty of early-life psychological distress and suggest that this relationship may be intensified during economic recessions. Investing in mental health in early life may be an effective way to reduce unemployment.

## 6.2 Introduction

The unemployed consistently report worse mental health than the employed (Paul and Moser, 2009). Unemployment has adverse mental health consequences. However, it remains unclear whether pre-adulthood mental health leads to success in avoiding unemployment. Psychological distress, as indexed by low mood, anxiety, neuroticism, depression and psychiatric conditions, has been shown to predict worse employment prospects in longitudinal studies following both adults (Chatterji et al., 2007, Ettner et al., 1997, Layard, 2013 and Uysal and Pohlmeier, 2011) and children and adolescents for several years and even decades (Egan et al., 2015, Fergusson et al., 2007 and Goodman, et al., 2011). While these studies typically adjust for important potential confounding variables such as parental socioeconomic status and intelligence, they have not been able to rule out the possibility that unobserved family background characteristics explain the relationship between mental health and subsequent unemployment.

A smaller set of studies have attempted to isolate the link between early life mental health and labor market outcomes by comparing the outcomes of siblings and twins, an analytic strategy which accounts for a large portion of unobserved heterogeneity by capturing unmeasured factors within the family and/or neighborhood environment. Smith and Smith (2010) showed that siblings who recalled having had childhood psychological problems went on to work seven fewer weeks on average in adulthood than their siblings who did not recall such problems. Currie et al. (2010) found that children diagnosed as having attention deficit hyperactivity disorder (ADHD) or conduct disorders before the age of 18 were 10 percentage points more likely to receive social assistance as adults. Fletcher (2013b) found that differences in depression levels in grades 7–12 predicted 7–8 percentage points lower employment when participants were aged 30 on average, reducing to a non-significant 5 points when controlling for family fixed-effects. Finally, Lundborg et al. (2014) used data on



Swedish males born between 1950 and 1970 to show that mental health conditions at 18–19 years of age strongly predicted within family variation in employment in 2003.

Whilst this literature has examined broad outcomes such as social assistance (Currie et al., 2010) and employment (Fletcher, 2013b; Lundborg et al., 2014; Smith & Smith, 2010), no studies have utilized sibling models to examine unemployment specifically as an outcome. Those studies which have examined employment have derived their outcome measures as a function of earnings (e.g., creating a binary employment variable where 1 = positive earnings) or examined the total number of weeks worked in a year. This approach does not uniquely categorize the unemployed, nor adequately distinguish between those who are unemployed versus out of the labor force, making precise comparisons between the employed and unemployed difficult. Additionally, all four of these studies examined the labor market outcome only at a single point in time and before unemployment rates increased dramatically around the world as the Great Recession began to affect global labor markets in 2008–09.

This paper adds to this literature by using the National Longitudinal Study of Youth 1997 (NLSY97) data from the United States to examine whether adolescent psychological distress in 2000 predicts greater unemployment over 2000–2011 while using sibling fixed-effects analysis to isolate the link between mental health and unemployment. It makes three main contributions. First, it examines unemployment specifically as an outcome. Second, it uses the extremely rich weekly employment history data in the NLSY97 to examine unemployment trends continuously over a 12-year period. Our analytic strategy therefore allows for a precise delineation of the effect of psychological distress during the important transition from education into the labor force. Third, the time period observed (2000–2011) allows for an examination of whether the employment penalty of psychological distress intensified following the Great Recession.

### **6.3 Data & Method**

#### *Participants and Procedure*

Participants were from the NLSY97, a nationally-representative cohort from the United States of 8984 individuals (including 3855 siblings) born in 1980–1984 and interviewed in person or via telephone on an annual basis since 1997. During these interviews the cohort members were asked to describe their recent employment history in detail. These variables were used to examine the relationship between the cohort members' mental health in 2000 and their self-reported weekly employment histories from January 2000 to December 2011. Sibling fixed-effects analysis was used to examine this relationship while accounting for unobserved family background characteristics. Difference-in-difference analyses were used to test whether those with poor mental health were more likely to become unemployed or exit the labor force (UOLF) after the onset of the Great Recession. The main analysis used a maximum sample of 4,002,558 observations for 7125 cohort members and the sibling analysis used a maximum sample of 1,684,984 observations for 2986 cohort members.

#### *Measures*

##### *Mental Health*

Table S6.1 and Figure S6.1 describe the mental health variable used in our analysis (see Supplementary Materials, Section 6.1). The NLSY97 evaluates the cohort members' mental health using the 5-item version of the Mental Health Inventory (MHI-5; Berwick et al., 1991), an established predictor of depression and anxiety disorders (Rumpf, Meyer, Hapke, & John, 2001), which has been validated for use with adolescents (Ostroff, Woolverton, Berry, & Lesko, 1996). When the cohort members were aged 16–20 in 2000, they were asked to rate on a four-point scale from 'none of the time' to 'all of the time' how often they felt

“nervous/calm and peaceful/down or blue/happy/depressed” over the previous month. In order to create the main independent variable, these answers were coded so that a higher score indicated worse mental health, and were then summed (Cronbach's  $\alpha = 0.77$ ) to create a composite mental health variable with a score range of 0–15 (Mean [ $M$ ] = 4.7, standard deviation [ $SD$ ] = 2.5). Because there is not a single validated cut-off score for the MHI-5 (Kelly, Dunstan, Lloyd, & Fone, 2008), our analysis followed the approach of Evans-Lacko et al. (2013) and classified those individuals scoring at least 1  $SD$  above the mean MHI-5 score as experiencing high levels of distress (corresponding to 942 cohort members out of 7125). Henceforth those scoring below this cut-off point are referred to as having ‘low distress’ and those above as having ‘high distress’. The proportion of cohort members defined as having high distress using this cut-off (13%) is similar to recent estimates of the 12-month prevalence of a major depressive episode among American 16–17 year olds (11.4%) and the proportion of 18–25 year olds having any diagnosable mental illness in the past year (19.6%) (National Institute of Mental Health, 2015).

Although the MHI-5 has been administered to the cohort members every two years since 2000, our analysis used only the initial measure as our main independent variable. Our aim is to evaluate the cohort members' mental health before they have accumulated significant experience in the labor market. Using a measure of mental health elicited in adolescence should mean that labor market experiences (such as prolonged unemployment) have not yet substantially affected the mental health of the cohort members. This assumption was tested in sensitivity analyses, described in Section 4 of the Supplementary Materials, which found that our results were not substantially affected by excluding cohort members who had experienced unemployment before the mental health measure was elicited in 2000.

### *Employment Outcomes*

There were three outcome variables. The first was a binary variable tracking employment status over 626 weeks (January 2000–December 2011), coded as 0 if the cohort member was in full- or part-time employment, and coded as 1 if they were unemployed. This variable was used to estimate the average probability of unemployment over the 12 years surveyed. Second, a variable measuring disengagement from employment more broadly was coded as 0 for the employed and coded as 1 if the cohort member was unemployed or out of the labor force (i.e., UOLF), the latter category including those in education, homemakers, the disabled or any other non-employment status. Finally, a continuous variable measuring total weeks of unemployment over 2000–2011, was created by summing the weekly unemployment variables ( $M = 40.6$ ,  $SD = 52.6$ , range = 0–449). For this measure, 54% of cohort members reported 6 months or less of unemployment, 19% reported 6–12 months, 16% reported 12–24 months and 11% reported 24 or more months.

#### *Covariates*

The main covariates were gender, age, socioeconomic status, intelligence, physical health, race, and a time variable. The sample was 49% female and around 1400 cohort members were born in each year of 1980–1984. Age was measured by month of birth (ranging from January 1980 to December 1984). As a proxy for the cohort members' initial socioeconomic status (SES), the resident mother's completed years of education was used. This ranged from first grade to eight or more years of college. If cohort members were missing data for this variable, the resident father's years of education was used in order to maximize sample size. The correlation between the resident mothers' and resident fathers' years of education was 0.66 ( $p < 0.001$ ;  $N = 5704$ ), indicating a reasonable degree of substitutability. Intelligence was measured in 1997 using the computer adaptive Armed Services Vocational Aptitude Battery (ASVAB) which combines math and verbal scores from four key subtests (Mathematical Knowledge, Arithmetic Reasoning, Word Knowledge,

and Paragraph Comprehension); this measure was standardized. Poor physical health in early life is a particularly important control variable since this could plausibly lead to both poor mental health and unemployment. Including this measure also allows for a comparison of the relative employment penalties of poor mental health vs. physical health. This binary measure was coded as 1 if a parent stated in 1997 that the cohort member had any one of 10 serious physical conditions: asthma, a heart condition, anemia, diabetes, cancer, epilepsy, infectious disease, kidney problems, allergies or a category for other conditions (10.9% of the sample had at least one condition). A categorical variable was created for the four racial groups (the sample was 53% White, 26% Black, 20% Hispanic, and 1% Mixed Race). Finally, a yearly time variable was included to take into account changing macro-economic conditions over the 12 years surveyed.

After dropping 1865 cohort members who were missing data on either the mental or physical health variables, the remaining 7125 cohort members had modest amounts of missing data for the SES and intelligence variables (6% and 17%, respectively). Values for these two variables were imputed using a predictive mean matching approach, described in Section 2 of the Supplementary Materials.

#### *Education as a Pathway between Distress and Unemployment*

Given that prior research has demonstrated that poor mental health predicts worse academic performance (Currie and &, 2009; Fletcher, 2010), our analysis tested whether different levels of educational attainment could explain the relationship between mental health and unemployment in the NLSY97 sample. A measure of the cohort members' educational attainment, elicited as of the latest wave, was coded as 0 = No degree (10% of a sample of 7108 reporting education data), 1 = General Educational Development qualification (GED) (12%), 2 = High school (45%), 3 = Junior/Associate College (7%) and 4 = Undergraduate degree or higher (26%). If the inclusion of the education variable in our

regressions markedly diminished the distress coefficients, this would suggest that different levels of educational attainment operated as a pathway between mental health and unemployment.

### *Recession*

The National Bureau of Economic Research dates the Great Recession in the United States as beginning in December 2007 and ending in June 2009 (NBER, 2010). However, this window does not fully capture the lagged post-recession increase in unemployment rates and the persistently high subsequent unemployment rates experienced by young people. In the NLSY97 sample, the unemployment rate only rose significantly at the start of 2009 and remained high until the end of the data-range in December 2011. In order to examine whether the post-recession increase in unemployment disproportionately affected those with poor mental health, difference-in-difference analysis was used to examine average unemployment rates by levels of mental health before and after the sharp increase in unemployment in 2009. Difference-in-difference analyses rely on the assumption of parallel trends between different groups prior to some external shock. In the context of the current study, this methodology is suitable given that there is a relatively consistent difference in unemployment levels of around 3 percentage points between those with low and high distress during 2006–2008, a period when much of the sample was transitioning from education into the labor force or had already completed the transition. Comparing average unemployment rates for these two groups in 2006–08 versus 2009–2011 will show whether the post-recession unemployment increase was disproportionately larger for those with high distress. Our analysis tested this by interacting a binary recession variable (0 = January 2006 – December 2008, 1 = January 2009 – December 2011) with the mental health measure.

### *Siblings*

Despite the presence of the control variables described above, it is possible, even likely, that our models omit important “third” variables which may influence both mental health and unemployment. To address the possibility that unmeasured family background factors may explain the link between adolescent distress and unemployment, our main analyses was complemented with sibling fixed-effects models. The sibling analyses omitted half-siblings since they were more likely to have different family backgrounds for at least part of their childhood, which sibling fixed-effects analysis would not adequately adjust for. The sibling analysis therefore contains only full brothers and sisters. Across sibling models are statistically identical to including a dummy variable for each family. By comparing the outcomes of siblings, these models control for stable, unobserved family-specific characteristics that differ between but not within families. In addition, the portion of genetic variation that is shared between siblings is adjusted for (i.e. 50% common variation shared by full siblings), providing a partial control for genetic endowment. This analysis can clarify whether factors common to the siblings, such as growing up in a high-crime neighborhood, having parents with mental health or substance abuse problems, having negligent parents or a disruptive childhood environment, may have been the ultimate cause of both distress and unemployment, rather than distress leading to unemployment *per se*. If the inclusion of family fixed-effects markedly reduced the distress coefficients in our regressions, this would indicate that the relationship between distress and unemployment was confounded by common unobserved family effects which correlate with both distress and unemployment. The limitations of the sibling fixed-effects approach are described in Section 3 of the Supplementary Materials.

### Statistical Methods

Probit models were specified to estimate the association between high distress in 2000 and the week-by-week probability of unemployment/UOLF over 2000–11 (*Model 1*). Marginal effects were calculated for these models in order to present the results more intuitively (Long & Freese, 2014). Ordinary least squares (OLS) regressions were specified to estimate the total number of weeks unemployed from 2000 to 11 (*Model 2*) and a difference-in-difference Probit model was specified to examine whether highly distressed cohort members were disproportionately more likely to become unemployed/UOLF in the years following the recession (*Model 3*). This latter model used the margins command in Stata (Long & Freese, 2014) to estimate the average predicted probability of the outcome by levels of distress in 2006–2008 (pre-recession) and 2009–11 (post-recession). Standard errors were clustered by individual in Models 1 and 3 to account for repeated observations of the same individual. All models controlled for gender, intelligence, parental education, physical health problems, race and age. For sibling fixed-effects analysis, Models 1 and 2 were re-run with a set of  $(n-1)$  family-specific dummy variables included in the regressions, where  $n$  was the total number of families with complete data on the outcome variable and all covariates. The formal specification of the models is detailed below, where the subscript  $i$  indicates the individual and  $t$  indicates time:

$$\text{Model 1: (Unemployed / UOLF)}_{it} = b_0 + b_1 \text{ Psychological Distress}_i + \sum b_2 \text{ Controls}_i + b_3 \text{ Year}_t + \varepsilon_{it}$$

$$\text{Model 2: Total Weeks Unemployed}_i = b_0 + b_1 \text{ Psychological Distress}_i + \sum b_2 \text{ Controls}_i + \varepsilon_i$$

$$\text{Model 3: (Unemployed / UOLF)}_{it} = b_0 + b_1 \text{ Psychological Distress}_i + \sum b_2 \text{ Controls}_i + b_3 \text{ Recession}_t + b_4 \text{ Psychological Distress}_i * \text{Recession}_t + \varepsilon_{it}$$

$$\text{where } b_4 = [(\hat{Y}_{\text{postrecession, high distress}} - \hat{Y}_{\text{postrecession, low distress}}) -$$

$$(\hat{Y}_{\text{precession, high distress}} - \hat{Y}_{\text{precession, low distress}})]$$



## 6.4 Results

### *Descriptive statistics*

Table 6.1 and Fig. 6.1 show descriptive statistics. Females had worse mental health than males (Females = 5.15, Males = 4.20;  $t = -16.0$ ,  $p < 0.0001$ ), in line with much of the literature. Compared to the low distress group, the highly distressed were more likely to be female (61.7% vs. 47.0%), supporting the rationale for gender controls in our model. The highly distressed also had lower intelligence scores (39.7 vs. 47.3), were more likely to report their parent having fewer than 12 years of education (28.9% vs. 20.5%) and were more likely to report having no high school degree or a GED qualification (30.6% vs. 20.2%). These patterns of lower parental education and intelligence scores among young people with high distress correspond to prior research using American data (Fletcher, 2010; Fletcher, 2013b) and underscore the importance of including both variables as covariates when examining the link between psychological problems and later economic outcomes (Daly, 2011).

Employment statistics also varied considerably as a function of psychological distress. Over 2000–2011 the highly distressed had a higher average unemployment rate than the low distress group (16.0% vs. 10.9%), a higher out-of-labor-force (OLF) rate (30.6% vs. 24.7%), and spent more weeks unemployed (52.8 vs 38.7 weeks). Figure 1 shows graphically that the highly distressed experienced consistently higher rates of unemployment/OLF over 2000–2011 and that these differences were exacerbated in 2009 when the Great Recession began to affect the labor market. From 2008 to 2009, the highly distressed experienced almost twice as large a drop in employment rate as the low distress group (5.8 vs 3.0 percentage points). Finally, the sibling sample did not substantially differ from the general sample on the basis of observed characteristics.

Table 6.1. Descriptive statistics of the National Longitudinal Study of Youth 1997

(unweighted).

Group	Full Sample	Low Distress	High Distress	Sibling Sample
Sample size	7,125	6,183	942	2,986
<i>Socio-demographics</i>				
MHI-5 (0-15) <sup>a</sup>	4.67 (2.53)	3.96 (1.82)	9.28 (1.49)	4.72 (2.54)
Female	48.9%	47.0%	61.7%	48.1%
Intelligence (0-100) <sup>b</sup>	46.3 (29.4)	47.3 (29.3)	39.7 (29.3)	43.9 (29.6)
Physical health prob. <sup>c</sup>	10.9%	10.8%	11.6%	9.7%
Month of birth (1-60) <sup>d</sup>	31.4 (17.1)	31.4 (17.0)	31.4 (17.7)	31.2 (17.2)
<i>Race</i>				
White	52.8%	53.7%	47.1%	51.1%
Black	26.6%	26.2%	29.1%	26.1%
Hispanic	19.7%	19.2%	23.3%	22.0%
Mixed	0.9%	0.9%	0.5%	0.8%
<i>Parental years of education</i>				
1-11	21.6%	20.5%	28.9%	25.4%
12	34.9%	35.3%	32.3%	34.5%
13-20	43.5%	44.2%	38.8%	40.1%

*Degree*<sup>d</sup>

None	9.9%	9.1%	14.4%	11.7%
GED	11.8%	11.1%	16.2%	12.4%
High school	45.3%	45.6%	43.8%	45.1%
Junior college	7.0%	7.1%	6.7%	6.9%
College degree	26.0%	27.1%	18.9%	23.9%

*Employment activity**(2000-11)*<sup>e</sup>

Employment rate	69.7%	70.6%	63.6%	68.7%
Unemployment rate	11.6%	10.9%	16.0%	12.2%
OLF rate	25.5%	24.7%	30.6%	26.6%
Weeks unemployed	40.6 (52.6)	38.7 (51.2)	52.8 (60.0)	41.6 (54.2)

---

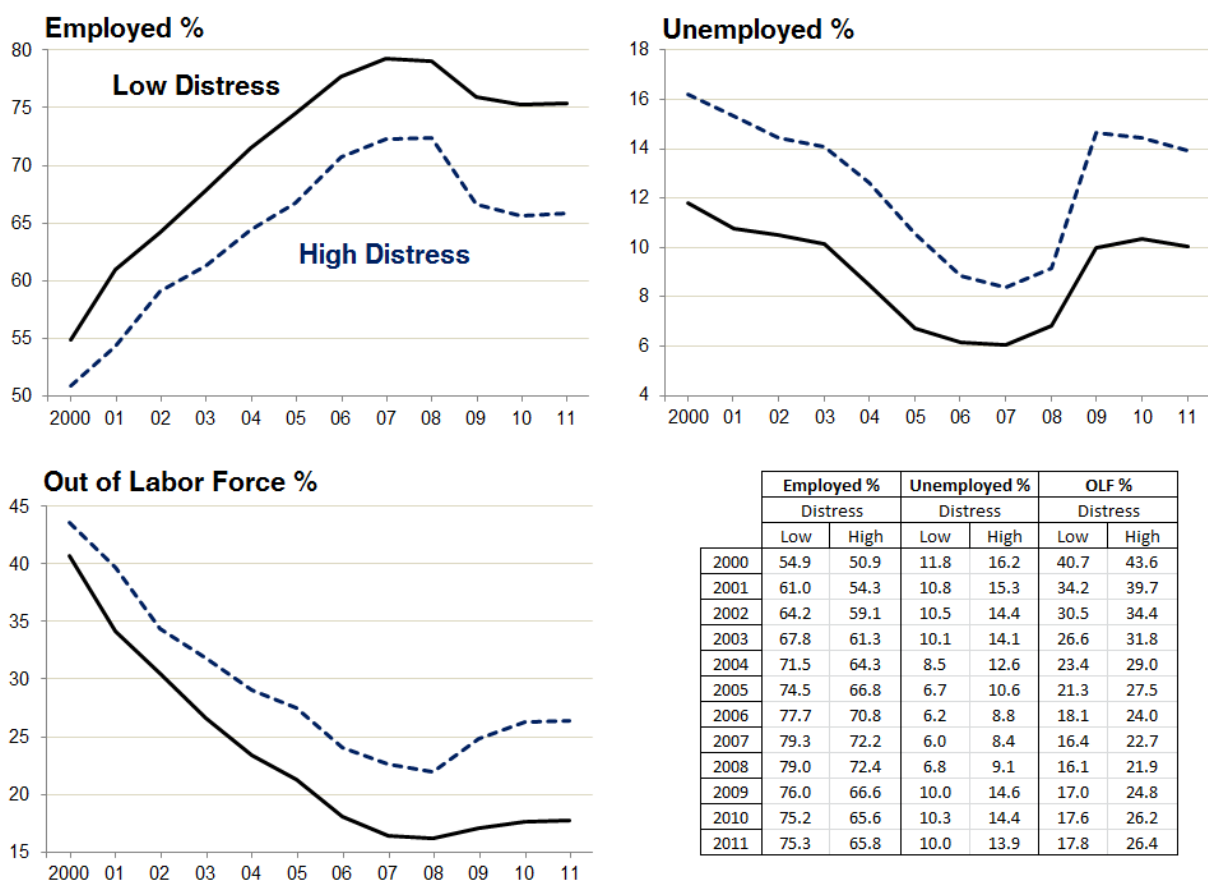
*Note.* Descriptive statistics are Mean (Standard Deviation) or Frequencies (%). The intelligence and parental education variables are missing data for 1193 and 411 out of 7125 cohort members, respectively. Abbr. GED = General Educational Development qualification. MHI-5 = Mental Health Inventory. OLF = Out of the labor force.

<sup>a</sup> A higher MHI-5 score means worse mental health. <sup>b</sup> Unstandardized intelligence scores divided by 1,000. <sup>c</sup> Physical health problems were defined as having any one of ten chronic conditions in 1997, including diabetes, cancer and asthma. <sup>d</sup> Month of birth: 1 = January 1980, 60 = December 1984.

<sup>e</sup> The employment, unemployment and out of the labor force (OLF) rates take the average over 2000-11. Employed is coded as 0 = Unemployed / OLF, 1 = Employed. Unemployed is coded as 0 = Employed, 1 = Unemployed. Out of Labor Force is coded as 0 = Employed, 1 = Out of Labor Force. The number of weeks unemployed ranges from 0-449.

Figure 6.1. Descriptive statistics (unweighted) showing the labor force status of the cohort members over 2000–11 (N = 7125) by the level of psychological distress measured in 2000

(High =  $\geq 1$  standard deviation above the mean score on the mental health measure, 13% of sample vs. Low = remainder of the sample). Employed is coded as 0 = Unemployed/Out of the labor force (OLF), 1 = Employed. Unemployed is coded as 0 = Employed, 1 = Unemployed. OLF is coded as 0 = Employed, 1 = OLF.

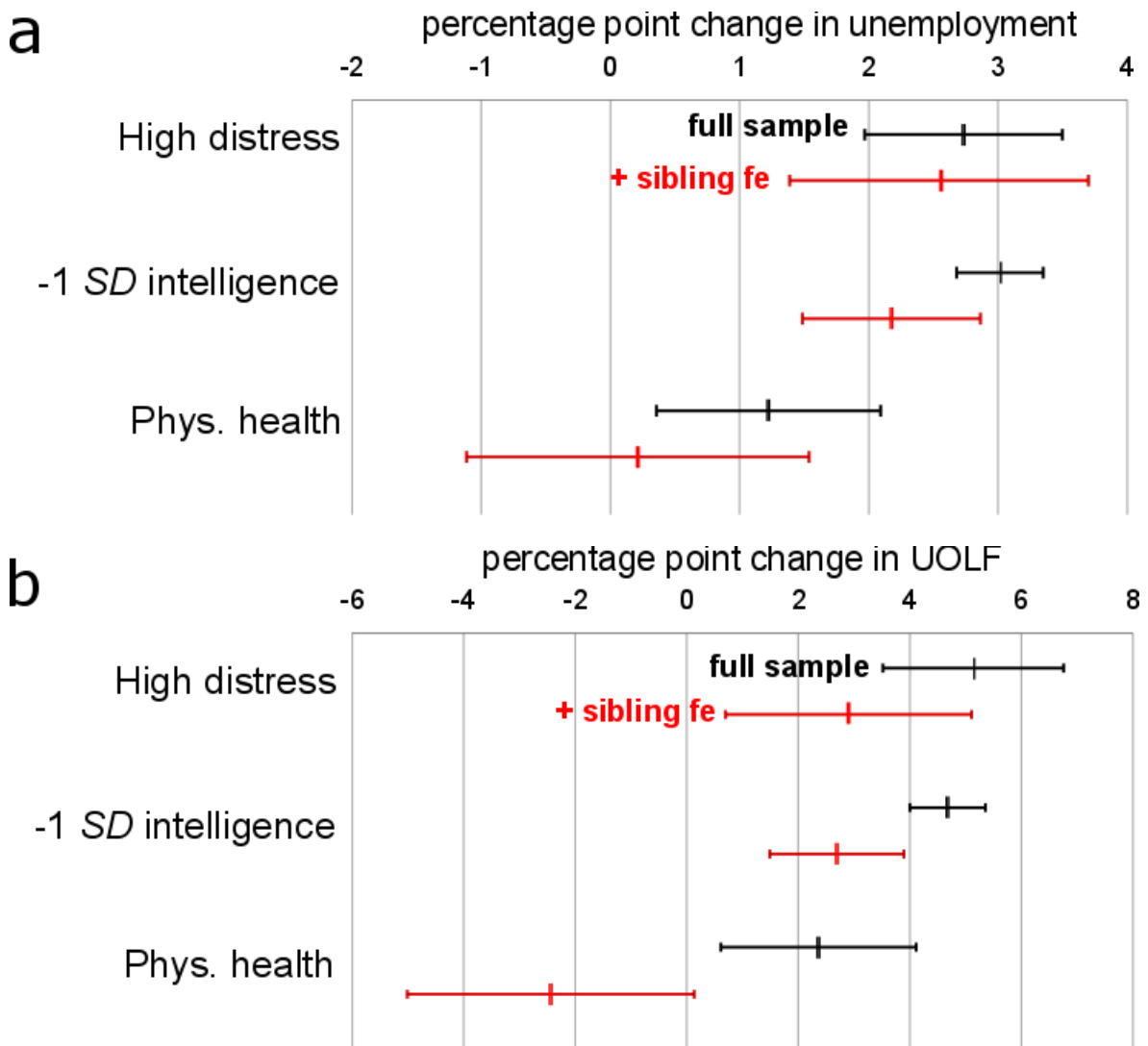


### Regressions

Figure 6.2 summarizes our main results, which are further detailed in Table S6.2 (main regressions) and Table S6.3 (sibling fixed-effects regressions) (see Supplementary Materials, Section 6.5). After adjustment for covariates and compared to those with low distress, high distress in 2000 was associated with a 2.7 percentage point (95% confidence interval [CI] = 2.0 to 3.5 points) higher probability of unemployment over 2000–11, a 5.1 point (95% CI = 3.5 to 6.8) higher probability of UOLF and 11 weeks (95% CI = 9.4 to 12.8) more unemployment. In percentage terms, high distress predicted a 32% higher probability of unemployment, a 28% higher probability of UOLF, and 28% more weeks of unemployment. The effect of high distress on all three outcomes was similar in magnitude to a one *SD* decrease in intelligence and around double the magnitude of having a physical health condition. High distress remained an important predictor of unemployment even after adjusting for family fixed-effects, indicating that the association between distress and unemployment was not confounded by unobserved shared family characteristics (see Fig. 6.2). In other words, when comparing only the outcomes of siblings, a sibling with high distress was predicted to experience substantially more unemployment on average than a sibling with low distress.

Across the three outcomes, adjusting for educational attainment reduced the distress coefficient by 20% without altering significance levels, indicating that different levels of education only partly explained why the highly distressed experienced more unemployment (see Table S6.2). Regressions stratified by gender (Table S6.5) and educational attainment (Tables S6.6a-c) found that high distress predicted higher unemployment for both men and women, and for both university graduates and those with no educational attainment (Supplementary Materials, Section 6.6).

Figure 6.2. Predicted effects with 95% confidence intervals of high distress, 1 standard deviation (SD) decrease in intelligence, and physical health problems (Phys. health) on the (a) probability of unemployment (b) probability of being unemployed or out of the labor force (UOLF), and (c) the number of weeks spent unemployed. Black bars indicate the unadjusted predicted effects; Red bars indicate the predicted effects after adjusting for sibling fixed-effects (+sibling fe).



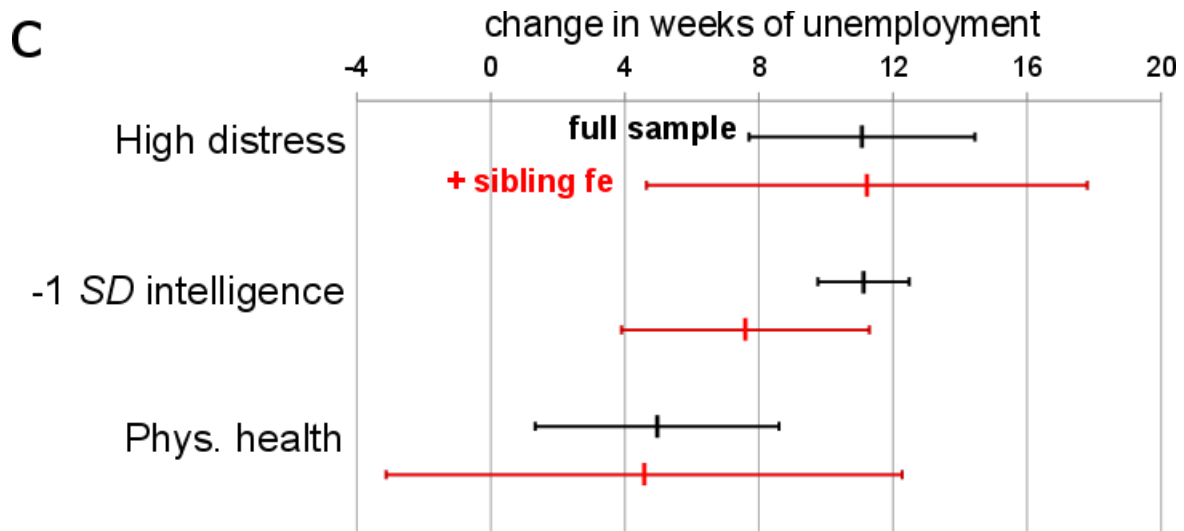
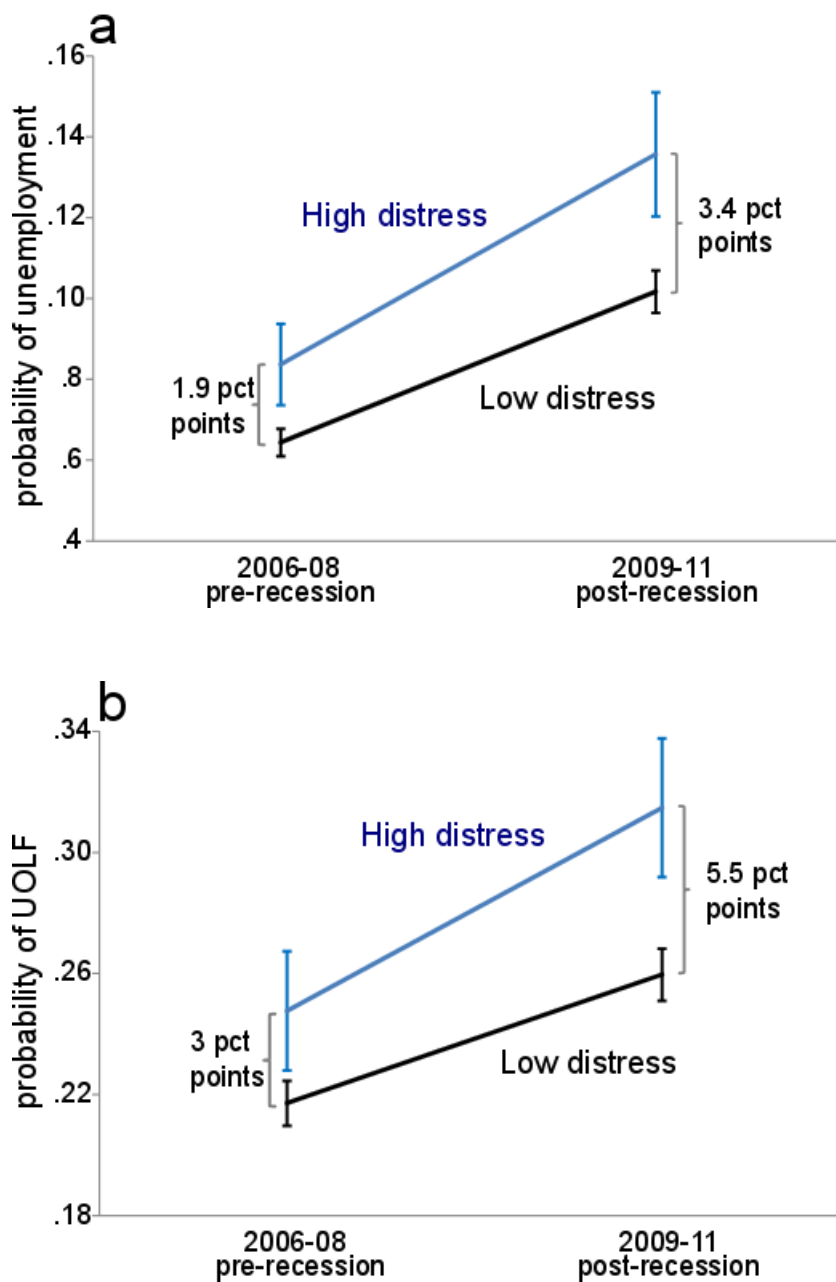


Fig. 6.3 and Table S6.4 show our difference-in-difference results. Comparing 2006–08 to 2009–11, the average probability of unemployment for the group with low distress (high distress) rose from 6.4% to 10.2% (8.4%–13.6%). The difference in average unemployment level between these groups therefore increased by 1.5 percentage points (a 79% increase from a 1.9 to 3.5 point gap) ( $p = 0.07$ ). Over the same periods, the average predicted probability of UOLF for the group with low distress (high distress) rose from 21.7% to 24.8% (26.0%–31.5%). The difference in average UOLF rate between these groups therefore increased by 2.5 percentage points (a 60% increase from a 4.2 to 6.7 point gap) ( $p = 0.02$ ). These effects were partly driven by the least educated cohort members, who had disproportionately high rates of distress, being more likely to exit employment after 2009 (see Table S6.4).

Figure 6.3. Predicted probabilities with 95% confidence intervals of (a) unemployment and (b) unemployment or out of the labor force (UOLF) by levels of psychological distress (High =  $\geq 1$  standard deviation above the mean score on the mental health measure, 13% of sample vs. Low = remainder of the sample) in the pre-recession (2006–08) and post-recession (2009–11) periods. Differences between high and low levels of psychological distress are expressed as percentage (pct) points.





## 6.5 Discussion

This study found that NLSY97 cohort members classified as having high distress in 2000 were significantly more likely to experience unemployment over the subsequent decade; these effects were similar to a one *SD* decrease in intelligence and double the magnitude of having a serious physical health condition. Notably, the unemployment effects were robust to adjustment for family fixed-effects. This ability to exploit sibling clusters to control for family background represents a major strength of this study given that there are many plausible unobserved background characteristics (such as an adverse childhood environment or parental mental health problems) which could be the “true cause” of the association between distress and unemployment. The fact that distress remains an important predictor of unemployment even when comparing the outcomes of siblings, while not conclusively demonstrating causality, does show that the relationship is robust to controlling for a substantial portion of potential omitted-variable bias.

There are several reasons why early psychological distress may lead to lower employment later in life. Persistent distress may lead to less effective engagement during a person's school years, culminating in reduced educational attainment limiting future employment opportunities (Currie & Stabile, 2009; Fletcher, 2010). However, our supplementary analyses showed that controls for educational attainment could only explain a relatively small portion (approximately 20%) of the link between distress and variation in unemployment outcomes. Whilst work performance was not observed in the current study, it remains possible that anxiety and depression could have directly impaired job performance (Lerner & Henke, 2008) and work attendance (Lagerveld et al., 2010; Störmer & Fahr, 2013), leading to less positive evaluations by employers and adversely affecting job retention. Furthermore, entry into employment may also be impaired given that job search, a psychologically demanding process requiring reserves of perseverance, motivation and self-

esteem, may be particularly challenging for highly distressed individuals. Finally, employers may be biased against hiring or accommodating employees with mental health issues (Scheid, 1999). These factors may be intensified by the existence of stigma related to mental health issues, low awareness of available treatments and relatively limited treatment facilities compared to those available for physical health (Layard, 2013).

A test of unemployment trends after the onset of the Great Recession found that the highly distressed were 60% more likely than those with low distress to become unemployed or exit the labor force (i.e., UOLF) in 2009–11 compared to 2006–08. This effect was partly driven by sharply increasing unemployment rates among the least educated cohort members, who also reported the highest rate of distress. This finding expands upon previous work which found that highly distressed children were later disproportionately more likely to become unemployed after the 1980 UK recession (Egan et al., 2015) and suggests that distress may be a risk factor for unemployment during recessions more generally. The rise in the reported frequency of mental health disorders among the unemployed in Europe after the Great Recession (e.g., Evans-Lacko et al., 2013) may therefore be partly due to more distressed individuals having been more likely to become unemployed, rather than unemployment worsening the mental health of previously healthy individuals.

These findings contribute to three literatures. First, while there is abundant evidence that unemployment can worsen mental health (Paul and Moser, 2009), this study provides evidence in the other direction, by using a mental health measure elicited before the cohort members had been exposed to prolonged unemployment. Second, economic downturns are typically accompanied by worsening population-level mental health (Cooper, 2011) such as increases in suicide rates (Chang et al., 2013) and internet searches concerning mental illness (Ayers et al., 2012). Our results suggest that an increased risk of unemployment among the distressed in the aftermath of the Great Recession could have led to further rises in distress in

this group potentially contributing to population-level increases in mental health problems. Finally, there is a literature, reviewed by Suhrcke and Stuckler (2012), which finds that recessions are on aggregate good for health in so far as they promote positive lifestyle habits (e.g., less alcohol consumption, greater leisure time) and reduce a diverse range of cause-specific mortality rates (e.g., alcohol-related deaths and road accidents, although suicide rates are an important exception to this trend). Suhrcke and Stuckler suggest that this population-level improvement likely masks deteriorations in health among those who become unemployed; one question raised by our findings is the extent to which this deterioration is present among the unemployed with a history of distress.

The sizeable effect of distress on unemployment identified here is in keeping with a broader literature showing that poor mental health in early life predicts worse socioeconomic outcomes in areas such as employment, education and earnings, with greater relative penalties than the cost of early physical health problems (Delaney & Smith, 2012). Given that the total lifetime economic costs resulting from childhood psychological problems have been estimated to be over \$2 trillion in the United States (Smith and Smith, 2010), the question naturally arises as to what extent poor mental health can be ameliorated. Interventions which reduce anxiety and depression, particularly if targeted early in life, might have a large economic return if they shift people into a trajectory of more active employment and increased lifetime earnings. Given that the MHI-5 and other short self-report mental health measures have proven to be reliable measures of mental health and robust predictors of future economic outcomes, they could plausibly be embedded in school, work and job search environments in order to identify at risk individuals and direct resources towards improving their mental health. Public awareness campaigns designed to reduce the stigma around mental health and promote the availability of treatments might also be an effective way to reduce the economic penalty of distress. Finally, in line with recent work emphasizing prevention rather

than remediation when addressing human capital deficits (Heckman & Kautz, 2013), interventions which target determinants of child mental health (such as maternal depression; Goodman, Rouse, et al., 2011) and prevent psychological distress from developing could promote later socioeconomic success while maximizing the return on the cost of the intervention.

### *Limitations*

This study has two main limitations. First, although the data contained a mental health measure which is a validated predictor of depression and anxiety in adolescents (the MHI-5), it is more likely to be prone to measurement error than, for example, a clinical assessment of mental health. Second, while our analyses control for cognitive ability, the data do not contain a strong measure of noncognitive skills. Noncognitive skills are increasingly recognised as important predictors of labor market outcomes (Egan et al., 2016; Heckman et al., 2006) and are likely to be correlated with psychological distress. Whilst adjusting for such traits may diminish the contribution of adolescent distress to later unemployment, prior work suggests that this attenuation is unlikely to be substantial: Lundborg et al. (2014) found sizeable effects of distress on labor market outcomes even after controlling for noncognitive skills. Furthermore, re-analysis of the sample in Egan et al. (2015) found that adjusting for the important noncognitive trait of self-control (Daly et al., 2015) led to just a 22% reduction in the distress-unemployment link.

### *Conclusions*

In a national sample, highly distressed adolescents went on to be at higher risk of unemployment as adults, and this elevated risk was accentuated during the Great Recession. Our results lend credence to the potential economic benefits of investment in adolescent mental health services. They also point to the potential value of job activation programs which aim to promote resilience by supporting the unemployed (Caplan et al., 1989) and

which offer fully voluntary access to appropriate mental health services where needed. By reducing the negative impact of job loss and improving mental health, such programs could have the additional benefit of fostering reemployment (Caplan et al., 1989). Further research is needed to understand how psychological distress may hamper the transition from education to work and day-to-day job search behaviours (Wanberg, 2012), and to estimate the economic cost of mental health stigma and low awareness of available treatments. Furthermore, in ongoing research, we are examining the extent to which specific mental health conditions such as depression and schizophrenia condition life-long employment trajectories.

**Appendix**

Section 6.1. Descriptive statistics for the mental health predictor variable.

Section 6.2. Details of the multiple imputation strategy.

Section 6.3. Discussion of the limitations of sibling fixed-effects analysis.

Section 6.4. Sensitivity tests.

Section 6.5. Regression tables detailing the association between mental health and unemployment.

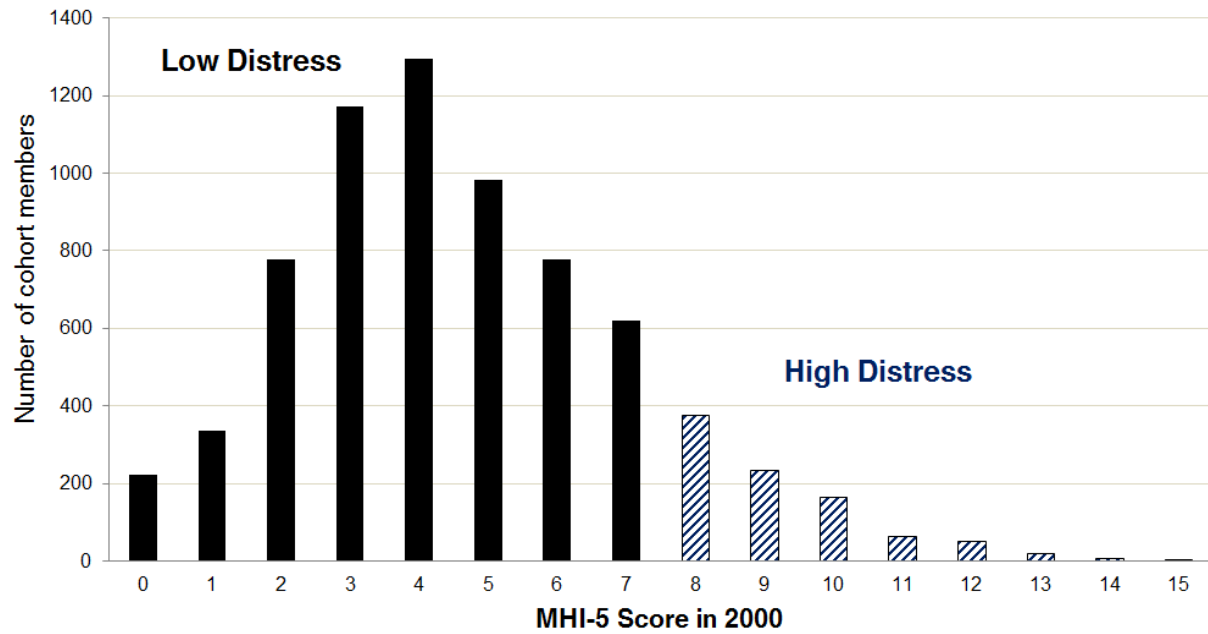
Section 6.6. Supplemental regressions.

### Section 6.1. Descriptive statistics for the mental health predictor variable.

Table S6.1. List of Mental Health Inventory item scores measured in 2000 ( $N = 7,125$ , unweighted).

Variable	Mean	SD	Min	Max	N
<i>How often have you felt...over the previous month?</i>					
<i>(0= None of the time, 3 = All of the time)</i>					
Nervous	0.79	0.71	0	3	7,125
[Not] Calm	1.37	0.72	0	3	7,125
Blue	0.87	0.72	0	3	7,125
[Not] Happy	1.19	0.70	0	3	7,125
Depressed	0.45	0.67	0	3	7,125
<b>Total MHI-5 score</b>	4.67	2.53	0	15	7,125
Low Distress (less than +1 SD)	3.96	1.82	0	7	6,183
High Distress (+1 SD and above)	9.28	1.49	8	15	942

Figure S6.1. Distribution of scores on the Mental Health Inventory in 2000 ( $N = 7,125$ , unweighted).





## **Section 6.2. Details of the multiple imputation strategy.**

After dropping 1,865 cohort members who were missing data on either the mental or physical health variables, we observed modest amounts of missing data for the SES and intelligence variables for the remaining 7,125 cohort members (6% and 17% respectively). Analysis of the pattern of missing data indicated that these variables were not missing completely at random (MCAR); cohort members missing data on these variables were on average less educated and more likely to be black. Given that both these groups reported lower rates of employment, listwise deletion of these observations would lead to biased estimates. Operating under the assumption that these variables were missing at random (MAR) and therefore capable of being estimated from other observed variables, we used Rubin's multiple imputation method (Rubin, 1987) to impute missing values for these variables. Specifically, we used the 'mi' commands in Stata 13 to specify multiple imputation chained equations (MICE), a sequence of univariate imputation methods with fully conditional specification of prediction equations (Stata Corp, 2013). Correct implementation of the multiple imputation procedure produces "asymptotically unbiased estimates and standard errors and is asymptotically efficient" (White et al., 2011). We used a predictive mean matching approach in order to limit the imputed intelligence and SES values to within their possible score ranges and our regression analyses were replicated across five imputed values before combining our results using Rubin's rules to produce our final estimates. Using this method instead of listwise deletion increases the maximum sample size from 5,565 to 7,125 but does not substantially alter the regression results.

### **Section 6.3. Discussion of the limitations of sibling fixed-effects analysis.**

Sibling fixed effects models have several notable limitations. Firstly, between-sibling differences in measurement error can account for more variation in the independent variable in sibling comparisons than in standard OLS models, potentially downward biasing estimates by diminishing the signal to noise ratio (Bound & Solon, 1999; Fletcher, 2013b). In the current study the MHI-5 showed a high level of reliability (Cronbach's  $\alpha = .77$ ) and moderately high correspondence between the measures in 2000 and 2002 ( $r = 0.47$  in a sample of 6,663, with 71% of the sample changing by two points or less on a fifteen point scale), indicating that measurement error is unlikely to produce inconsistent estimates and/or obscure causal effects in this instance. Secondly, siblings tend to show a high degree of overlap in important characteristics, restricting the variation necessary to identify the association of interest. In the current study while relatively few siblings (16% out of 2,986) provided equivalent responses on the MHI-5 in 2000, there was a much higher degree of concordance (80%) between siblings in the two distress categories due to the less granular nature of this binary variable. Given that the sample of siblings with discordant levels of psychological distress will be used to identify an association with subsequent unemployment, it is important to test whether this portion of the sample differs markedly from the remainder of the sibling sample. Our examination of the representativeness of the discordant sibling sample ( $N = 738$ ) revealed some discrepancies with the full sibling sample ( $N = 2,986$ ). In the discordant sample compared to the full sibling sample, the proportion of females was higher (54% vs 46%), intelligence scores were lower (38.5 vs. 45.5), the rate of physical health problems was higher (11.0% vs. 9.3%), a greater proportion reported parental education of less than 12 years (32.6% vs. 23.0%), educational attainment was lower (33.0% reporting no degree or a GED vs. 21.2%), and the average unemployment rate over 2000-11 was higher (15.0% vs. 11.2%). The discordant sample is therefore more disadvantaged, reflecting the

fact that the presence of high distress is a necessary condition for discordance, and the presence of distress in a family is positively correlated with greater socioeconomic disadvantage.

#### **Section 6.4. Sensitivity tests.**

The mental health measure used in our analysis was elicited in 2000. Since the cohort members were born in 1980-84, it is possible that unemployment experienced between 1996 (when the oldest cohort members turned 16) and 2000 may have caused a deterioration in mental health by the time this measure was elicited. Estimates using the mental health measure in 2000 to predict future unemployment might therefore reflect the impact of prior unemployment. To evaluate this possibility we examined the extent of unemployment experienced by the sample prior to the administration of the mental health measure in 2000. From January 1996 to December 2000 the average number of weeks of unemployment in our sample of 7,125 cohort members was relatively low ( $M = 10.7$ ,  $SD = 18.9$ , range = 0-180); 4,995 cohort members (70%) reported 2 months or less of unemployment, 1,170 (16%) had 2-4 months, 605 (8%) had 5-12 months and 355 (5%) had 1 year or more. There is evidence of a gradient of worsening mental health across these groups: the percentage of cohort members in these four groups classified as high distress was 12%, 15%, 16% and 19% respectively. Because we do not have access to a mental health measure before 1996, we cannot test whether this trend is a consequence of psychological distress leading to unemployment, unemployment leading to distress or a combination of these factors. Instead we tested the sensitivity of our results to this issue by conducting additional analysis, not presented here but available upon request, while restricting the sample only to those who had experienced 4 months or less of unemployment prior to 2000 (thus omitting the 14% of 7,125 cohort members who had experienced 5 months or more of unemployment from 1996 to 2000) to examine our unemployment outcomes over 2001-11. Using this more conservative analytic criterion produces slightly smaller distress coefficients but the results are essentially similar to the main analysis.

In an alternative sensitivity test, we examined our regression results while restricting the sample to those born in 1984, a group with minimal labor market experience by 2000 (analyses available upon request). If the distress coefficients for this group were substantially lower than for the whole sample, we would consider this as evidence that unemployment experienced before 2000 for earlier birth cohorts may have biased the distress estimates upwards for predicting employment from 2000 onwards. For those born in 1984 the association between pre-labor market psychological distress and the unemployment outcomes examined were slightly larger on average than for the full NLSY97 sample. Given that the study results are minimally affected by restricting our analyses to those with a limited experience of unemployment or very minimal labor market experience prior to the measurement of mental health, we interpret the results of these two sensitivity tests as suggesting that reverse causality is unlikely to be a major concern in this sample.

### **Section 6.5. Regression tables detailing the association between mental health and unemployment.**

The marginal effects reported in columns 1-4 of the below regression tables can be interpreted as predicted percentage point differences for the unemployment and unemployed / out of the labor force (UOLF) outcomes (where a coefficient of 0.01 = 1 percentage point increase). The OLS coefficients in columns 5-6 for the weeks of unemployment outcome can be interpreted directly (e.g. 9.100 corresponds to 9.1 more predicted weeks of unemployment).

Table S6.2 describes our main regression results. After adjustment for covariates, high distress in 2000 was associated with a 2.7 percentage point (32%) higher probability of unemployment over 2000-11, a 5.1 point (26%) higher probability of UOLF and 11 weeks (28%) more unemployment (see columns 1, 3 and 5). Across the three outcomes, adjusting for educational attainment reduced the distress coefficient by 20% without altering significance levels (columns 2, 4 and 6), indicating that the mental health employment penalty was only partly explained by different levels of education.

Table S6.2. Regressions examining the association between mental health in 2000 and three labor market outcomes over 2000-11 (i) probability of unemployment (ii) probability of unemployment + being out of the labor force (UOLF) (iii) total number of weeks unemployed.

Outcome	Unemployed <sup>a</sup>	Unemployed <sup>a</sup>	UOLF <sup>a</sup>	UOLF <sup>a</sup>	Weeks U <sup>b</sup>	Weeks U <sup>b</sup>
Observations	3,099,028	3,091,841	4,002,558	3,992,488	7,125	7,108
N	7,104	7,087	7,125	7,108	7,125	7,108
Column	1	2	3	4	5	6
High Distress <sup>c</sup>	0.027*** (0.004)	0.022*** (0.004)	0.051*** (0.008)	0.040*** (0.008)	11.074*** (1.719)	9.100*** (1.690)
Intelligence <sup>d</sup>	-0.030*** (0.002)	-0.017*** (0.002)	-0.047*** (0.003)	-0.026*** (0.004)	-11.118*** (0.695)	-7.050*** (0.745)
Phys. Health <sup>e</sup>	0.012*** (0.004)	0.009** (0.004)	0.024*** (0.009)	0.017** (0.009)	4.965*** (1.855)	3.999** (1.819)
Female	-0.013*** (0.003)	-0.004 (0.003)	0.025*** (0.006)	0.037*** (0.005)	-5.915*** (1.162)	-3.406*** (1.152)
Education <sup>f</sup>	N	Y	N	Y	N	Y

Included in analyses but not shown are: race, socioeconomic status, age (all columns) and year of observation (columns 1-4). <sup>a</sup> Probit marginal effects coefficients, clustered by individual. <sup>b</sup> OLS coefficients. <sup>c</sup> High Distress was classified as scoring +1 SD or above on the Mental Health Inventory. Low Distress is the base category. <sup>d</sup> Intelligence is standardized. <sup>e</sup> Physical health problems were defined as having any one of ten chronic conditions in 1997, including diabetes, cancer and asthma. <sup>f</sup> Educational attainment was coded as 0 = No Degree, 1 = GED, 2 = High School, 3 = Junior / Associate College, 4 = Graduate Degree. Standard errors in parentheses. \*\*\*p<0.01, \*\*p<0.05, \*p<0.1

Table S6.3 describes the results of our regressions restricted to the sample of 2,986 siblings with complete data on all covariates. Comparing columns 1, 3 and 5 in Tables S6.3 and S6.4 shows that the coefficients are similar in the main sample and sibling sample before adjusting for sibling differences. After adjusting for sibling differences (columns 2, 4 and 6 in Table S6.4), high distress in 2000 was associated with a 2.5 percentage point (33%) higher probability of unemployment over 2000-11, a 2.9 point (17%) higher probability of UOLF and 11 weeks (28%) more unemployment. On average across the two unemployment outcomes (columns 1-2, 5-6), adjusting for sibling differences decreased the distress coefficient by 9%, suggesting that high distress carries a substantial unemployment penalty above and beyond the contributing effects of background family characteristics. For the UOLF outcomes (columns 3-4), adjusting for sibling differences reduced the distress coefficient by 48%. Given that the results in columns 1-2 establish that sibling differences do not substantially diminish the distress coefficient for predicting unemployment, this suggests that the effect of family background is operating more strongly on the OLF portion of the UOLF group, which is three times larger than the unemployed portion. We thus observe an interesting discrepancy: unobserved family characteristics are quite important in determining selection out of the labor force through the pathway of high distress, but the same mechanism does not appear to operate as strongly for selection into unemployment.



Table S6.3. Regressions restricted to the sibling sample examining the association between mental health in 2000 and three labor market outcomes over 2000-11 (i) probability of unemployment (ii) probability of unemployment + being out of the labor force (UOLF) (iii) total number of weeks unemployed.

Outcome	Unemployed <sup>a</sup>	Unemployed <sup>a</sup>	UOLF <sup>a</sup>	UOLF <sup>a</sup>	Weeks U <sup>b</sup>	Weeks U <sup>b</sup>
Observations	1,287,643	1,246,301	1,684,984	1,682,904	2,986	2,986
N	2,974	2,876	2,986	2,980	2,986	2,986
Column	1	2	3	4	5	6
High Distress <sup>c</sup>	0.030*** (0.006)	0.025*** (0.006)	0.056*** (0.013)	0.029*** (0.011)	11.785*** (2.675)	11.218*** (3.356)
Intelligence <sup>d</sup>	-0.030*** (0.003)	-0.022*** (0.004)	-0.047*** (0.005)	-0.027*** (0.006)	-10.298*** (1.151)	-7.594*** (1.885)
Phys. Health <sup>e</sup>	0.016** (0.007)	0.002 (0.007)	0.016 (0.014)	-0.025* (0.013)	6.888** (3.054)	4.578 (3.927)
Female	-0.015*** (0.004)	-0.016*** (0.004)	0.023*** (0.009)	0.026*** (0.008)	-6.680*** (1.828)	-8.569*** (2.283)
Sibling FE <sup>f</sup>	N	Y	N	Y	N	Y
No. of families	1,387	1,338	1,387	1,384	1,387	1,387

Included in analyses but not shown are: race, socioeconomic status, age (all columns) and year of observation (columns 1-4). <sup>a</sup> Probit marginal effects coefficients, clustered by individual. <sup>b</sup> OLS coefficients. <sup>c</sup> High Distress was classified as scoring +1 SD or above on the Mental Health Inventory. Low Distress is the base category. <sup>d</sup> Intelligence is standardized. <sup>e</sup> Physical health problems were defined as having any one of ten chronic conditions in 1997, including diabetes, cancer and asthma. <sup>f</sup> Sibling fixed effects models include a set of family-specific dummy variables. Standard errors in parentheses. \*\*\*p<0.01, \*\*p<0.05, \*p<0.1

Table S6.4 shows the difference-in-difference results. Because the least educated cohort members experienced the sharpest decrease in employment rate after 2008, and because this group was also the most highly distressed, we included controls in columns 2 and 4 for educational attainment and an interaction term of educational attainment and recession. Comparing the results with and without the education controls will show to what extent the post-2008 decrease in employment rate for those with high distress was driven by the least educated exiting employment.

Comparing 2006-08 to 2009-11, the average predicted probability of unemployment for the group with low distress (high distress) rose from 6.4 per cent to 10.2 per cent (8.4 per cent to 13.6 per cent). Contrasting these periods, the difference in average unemployment level between these groups therefore increased by 1.5 pct points (from a 1.9 point gap to a 3.5 point gap;  $b = 0.015$ ,  $SE = 0.008$ ,  $p = 0.07$ ). This difference decreased to 1 pct point ( $b = 0.010$ ,  $SE = 0.008$ ,  $p = 0.20$ ) when controlling for education. Over the same periods, the average predicted probability of UOLF for the group with low distress (high distress) rose from 21.7 per cent to 24.8 per cent (26.0 per cent to 31.5 per cent). The difference in average UOLF rate between these groups therefore increased by 2.5 pct points (from a 4.2 point gap to a 6.7 point gap;  $b = 0.025$ ,  $SE = 0.011$ ,  $p = 0.02$ ), reducing to 1.6 points when controlling for education ( $b = 0.016$ ,  $SE = 0.010$ ,  $p = 0.13$ ). These results show that the highly distressed were more likely to exit employment after 2009 and the effect was largely driven by the least educated.

Table S6.4. Difference-in-difference estimates describing the probability of unemployment and UOLF in 2006-08 (pre-recession) and 2009-11 (post-recession) by levels of distress as measured in 2000.

Outcome	Unemployed <sup>a</sup>	Unemployed <sup>a</sup>	UOLF <sup>a</sup>	UOLF <sup>a</sup>
Observations	1,594,137	1,590,411	1,916,186	1,911,118
N	6,606	6,590	6,717	6,700
<i>Pre-recession</i>				
<i>(2006-08)</i>				
Low Distress	0.064 (0.002)	0.065 (0.002)	0.217 (0.004)	0.218 (0.004)
High Distress	0.084 (0.005)	0.079 (0.005)	0.260 (0.010)	0.250 (0.010)
Pre-recession difference	0.019*** (0.005)	0.015*** (0.005)	0.042*** (0.011)	0.031*** (0.010)
<i>Post-recession</i>				
<i>(2009-11)</i>				
Low Distress	0.102 (0.003)	0.103 (0.003)	0.248 (0.004)	0.250 (0.004)
High Distress	0.136 (0.008)	0.128 (0.007)	0.315 (0.012)	0.297 (0.011)
Post-recession difference	0.034*** (0.008)	0.025*** (0.008)	0.067*** (0.013)	0.047*** (0.012)
<i>DiD<sup>b</sup></i>				
Post-recession - pre- recession difference	0.015* (0.008)	0.010 (0.008)	0.025** (0.011)	0.016 (0.010)
Education <sup>c</sup>	N	Y	N	Y

Included in analyses but not shown are: gender, intelligence, physical health, race,

socioeconomic status and age. <sup>a</sup> Predicted probabilities calculated after a Probit regression,

clustered by individual. <sup>b</sup> The difference-in-difference coefficients and standard errors were calculated using the 'lincm' command in Stata. <sup>c</sup> The education controls are educational attainment and an educational attainment\*recession interaction variable. Robust standard errors in parentheses. \*\*\*p<0.01, \*\* p<0.05, \* p<0.1

**Section 6.6. Supplemental regressions.**

Regressions stratified by gender (Table S6.5) show that the distress coefficients were significant for both men and women across the three outcomes. In percentage terms, high distress predicted greater relative penalties for men for unemployment (35% higher probability for men compared to 30% for women), UOLF (35% vs. 20%) and the total number of weeks of unemployment (33% more weeks for men vs. 22% for women). Given that the 702 cohort members with no educational qualifications had both the highest average unemployment rate (25% over 2000-11 compared to 5% for those with a university degree) and the highest rates of high distress (19% compared to 10% for those with a university degree), we conducted regressions stratified by educational attainment (Tables S6.6a, S6.6b, S6.6c) to examine whether this group was disproportionately driving our main results. This revealed that distress was an important predictor of unemployment and UOLF for groups other than the least educated.

Table S6.5. Regressions stratified by gender examining the association between mental health in 2000 and three labor market outcomes over 2000-11 (i) probability of unemployment (ii) probability of unemployment + being out of the labor force (UOLF) (iii) total number of weeks unemployed.

Outcome	Unemployed <sup>a</sup>	Unemployed <sup>a</sup>	UOLF <sup>a</sup>	UOLF <sup>a</sup>	Weeks U <sup>b</sup>	Weeks U <sup>b</sup>
Observations	1,584,529	1,514,499	2,002,632	1,999,926	3,641	3,484
N	3,631	3,473	3,641	3,484	3,641	3,484
Gender	M	F	M	F	M	F
High Distress <sup>c</sup>	0.032*** (0.007)	0.024*** (0.005)	0.068*** (0.013)	0.041*** (0.011)	12.770*** (3.449)	10.099*** (2.322)
Intelligence <sup>d</sup>	-0.027*** (0.003)	-0.033*** (0.003)	-0.029*** (0.005)	-0.065*** (0.005)	-10.787*** (1.013)	-11.405*** (0.989)
Phys. Health <sup>e</sup>	0.011* (0.006)	0.014** (0.006)	0.014 (0.012)	0.036*** (0.014)	5.178* (2.874)	4.755* (2.820)

Included in analyses but not shown are: race, mother's education, age (all columns) and year of observation (columns 1-4).

<sup>a</sup> Probit marginal effects coefficients, clustered by individual. <sup>b</sup> OLS coefficients. <sup>c</sup> High Distress was classified as scoring +1 SD or above on the Mental Health Inventory. Low Distress is the base category. <sup>d</sup> Intelligence is standardized. <sup>e</sup> Physical health problems were defined as having any one of ten chronic conditions in 1997, including diabetes, cancer and asthma. Standard errors in parentheses. \*\*\*p<0.01, \*\*p<0.05, \*p<0.1

Table S6.6a. Regressions stratified by educational attainment examining the association between having mental health in 2000 and probability of unemployment over 2000-11.

Outcome	Unemployed <sup>a</sup>	Unemployed <sup>a</sup>	Unemployed <sup>a</sup>	Unemployed <sup>a</sup>	Unemployed <sup>a</sup>
Observations	239,392	342,668	1,405,680	238,359	865,742
N	692	835	3,213	499	1,848
Education	None	GED	High School	Junior College	Graduate
High Distress <sup>b</sup>	0.041** (0.019)	0.019 (0.015)	0.025*** (0.005)	0.003 (0.012)	0.015*** (0.005)
Intelligence <sup>c</sup>	-0.037*** (0.012)	-0.015* (0.008)	-0.018*** (0.003)	-0.020*** (0.006)	-0.009*** (0.002)
Phys. Health <sup>d</sup>	-0.018 (0.021)	0.033* (0.017)	0.007 (0.007)	0.021 (0.016)	0.008* (0.005)
Female	0.015 (0.015)	-0.008 (0.012)	-0.005 (0.004)	0.004 (0.009)	-0.007** (0.003)

Included in analyses but not shown are: race, mother's education, age and year of observation.

<sup>a</sup> Probit marginal effects coefficients, clustered by individual. <sup>b</sup> High Distress was classified as scoring +1 SD or above on the Mental Health Inventory. Low Distress is the base category.

<sup>c</sup> Intelligence is standardized. <sup>d</sup> Physical health problems were defined as having any one of ten chronic conditions in 1997, including diabetes, cancer and asthma. Standard errors in parentheses. \*\*\*p<0.01, \*\*p<0.05, \*p<0.1

Table S6.6b. Regressions stratified by educational attainment examining the association between having mental health in 2000 and probability of unemployment + being out of the labor force (UOLF) over 2000-11.

Outcome	UOLF <sup>a</sup>	UOLF <sup>a</sup>	UOLF <sup>a</sup>	UOLF <sup>a</sup>	UOLF <sup>a</sup>
Observations	378,412	481,239	1,763,303	285,057	1,084,477
N	702	836	3,222	499	1,849
Education	None	GED	High School	Junior College	Graduate
High Distress <sup>b</sup>	0.072*** (0.027)	0.023 (0.023)	0.046*** (0.012)	0.013 (0.028)	0.023 (0.014)
Intelligence <sup>c</sup>	-0.049** (0.019)	-0.016 (0.013)	-0.032*** (0.005)	-0.028** (0.012)	-0.013** (0.006)
Phys. Health <sup>d</sup>	0.013 (0.031)	0.029 (0.025)	0.020 (0.013)	0.030 (0.030)	0.007 (0.013)
Female	0.121*** (0.021)	0.061*** (0.018)	0.059*** (0.008)	0.032* (0.019)	-0.033*** (0.009)

Included in analyses but not shown are: race, mother's education, age and year of observation.

<sup>a</sup> Probit marginal effects coefficients, clustered by individual. <sup>b</sup> High Distress was classified as scoring +1 SD or above on the Mental Health Inventory. Low Distress is the base category.

<sup>c</sup> Intelligence is standardized. <sup>d</sup> Physical health problems were defined as having any one of ten chronic conditions in 1997, including diabetes, cancer and asthma. Standard errors in parentheses. \*\*\*p<0.01, \*\*p<0.05, \*p<0.1



Table S6.6c. Regressions stratified by educational attainment examining the association between having mental health in 2000 and total number of weeks unemployed over 2000-11.

Outcome	Weeks U <sup>a</sup>	Weeks U <sup>a</sup>	Weeks U <sup>a</sup>	Weeks U <sup>a</sup>	Weeks U <sup>a</sup>
Observations	702	836	3,222	499	1,849
N	702	836	3,222	499	1,849
Education	None	GED	High School	Junior College	Graduate
High Distress <sup>b</sup>	10.109 (6.440)	6.445 (5.829)	10.837*** (2.511)	0.106 (5.755)	7.688*** (2.324)
Intelligence <sup>c</sup>	-12.627*** (3.982)	-6.688** (3.173)	-7.195*** (1.072)	-9.134*** (2.552)	-4.165*** (0.920)
Phys. Health <sup>d</sup>	-4.502 (7.725)	15.879** (6.817)	2.114 (2.666)	9.168 (6.523)	4.059* (2.240)
Female	-6.394 (5.105)	-6.827 (4.620)	-3.391** (1.678)	2.480 (3.909)	-1.886 (1.390)

Included in analyses but not shown are: race, mother's education, age.

<sup>a</sup> Probit marginal effects coefficients, clustered by individual. <sup>b</sup> High Distress was classified as scoring +1 SD or above on the Mental Health Inventory. Low Distress is the base category. <sup>c</sup> Intelligence is standardized. <sup>d</sup> Physical health problems were defined as having any one of ten chronic conditions in 1997, including diabetes, cancer and asthma. Standard errors in parentheses. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$

## CHAPTER 7

### Discussion

The opening chapter of this thesis reviewed the literature on the childhood cognitive and noncognitive skills which predict future labour market success. Chapters 3-6 added empirical evidence to this literature by demonstrating robust associations between self-control, conscientiousness, mental health, and the hitherto relatively neglected outcome of unemployment. This concluding chapter summarizes these findings, relates them to existing literature, highlights strengths and limitations, discusses policy implications, and provides recommendations for future research.

#### *7.1 Summary*

The four empirical papers in this thesis identified childhood/adolescent self-control (chapter 3), conscientiousness (4) and mental health (5-6) as important predictors of future unemployment. In chapter 3 I used the British Cohort Study and National Child Development Study to examine how self-control, measured using teacher-ratings between the ages of 7 and 11, predicted differences in unemployment from ages 16 to 50. In chapter 4 I used the British Cohort Study to examine how self-reported adolescent Big Five personality predicted unemployment from age 16 to 38. In chapter 5 I used the National Child Development Study and Longitudinal Study of Young People in England to examine the association between teacher-rated and self-rated mental health between the ages of 7 and 14 predicted youth unemployment from ages 16 to 23. Lastly, in chapter 6 I used the National Longitudinal Study of Youth 1997 to examine how self-rated mental health in late adolescence predicted unemployment up to the age of 30.

Each chapter provided a unique contribution. Chapters 3 and 4 are the first studies to link pre-labour market measures of self-control and conscientiousness with unemployment, chapter 5 is the first to examine how childhood psychological distress prospectively predicts unemployment over the life-course, and chapter 6 is the first to estimate this relationship while comparing the outcomes of siblings. Chapters 3, 5 and 6 are also the first papers to examine how individual psychological characteristics interact with recessions to produce differential unemployment outcomes. Chapter 3 found that children with poor self-control (-1SD) were disproportionately (70%) more likely to become unemployed after the 1980 UK recession than children with good self-control (+1SD), and chapters 5 and 6 found that children and adolescents with high psychological distress were disproportionately (55% across the two chapters) more likely than those with low distress to become unemployed after the 1980 UK recession and 2007 US recession respectively. These latter findings have particular contemporary relevance given the large rise in global unemployment rates in the years following the 2007 recession.

As well as meeting conventional definitions of statistical significance (a p-value of 0.05 or lower), the predictive power of greater self-control, conscientiousness and distress was striking. A useful comparison is intelligence, traditionally considered the strongest predictor of labor market outcomes (Roberts, Kuncel, Shiner, Caspi, & Goldberg, 2007). In chapter 3, a 1 SD increase in childhood self-control predicted fewer total months of unemployment with a magnitude similar to a 1.1 SD increase in intelligence across both studies. In chapter 4, a 1 SD increase in adolescent conscientiousness or intelligence predicted a similar increase in the probability of unemployment. In chapter 5, a measure of intelligence was available only in the National Child Development Study. In that study, children with high psychological distress were much more likely than those with low distress to experience more total months of youth unemployment, with an effect size similar to a 2.4

SD decrease in intelligence. Lastly, in chapter 6 adolescents with high distress were much more likely than those with low distress to experience more total weeks of unemployment with an effect size similar to a similar to a 1 SD decrease in intelligence.

Chapters 3 and 4 add to the growing body of evidence showing that higher levels of self-control and conscientiousness in childhood or adolescence predict better socioeconomic outcomes (Moffitt et al., 2011; Slutske et al., 2012). Chapters 5 and 6 add to the literature showing that poor mental health in early life is a robust predictor of worse employment outcomes throughout adulthood (Goodman et al., 2011, Smith & Smith, 2010, Delaney & Smith, 2012). The finding that those with poor mental health were disproportionately more likely to become unemployed in two different periods of recession suggests that the rise in the reported frequency of mental health disorders among the unemployed in Europe after the Great Recession (Evans-Lacko et al., 2013) may be partly due to a priori distressed individuals having been more likely to become unemployed, rather than unemployment worsening the mental health of a priori healthy individuals. More broadly, chapters 3 to 6 add to the literature (reviewed in chapter 1) showing the importance of early noncognitive skills for later socioeconomic outcomes.

## *7.2 Strengths and Limitations*

This thesis has several notable strengths. Firstly, it used four large, nationally-representative longitudinal cohort studies with a cumulative sample size of 47,328 individuals across the four empirical papers (the British Cohort Study in chapters 3 and 4, the National Child Development Study in chapters 3 and 5, the Longitudinal Study of Young People in

England in chapter 5, and the National Longitudinal Study of Youth 1997 in chapter 6)<sup>11</sup>. This large pool of observations allowed for a high degree of statistical certainty in the analyses (i.e. small standard errors), and the relatively representative nature of the samples allows the findings to be more generalizable than small or convenience samples. Additionally, all the cohort studies had comprehensive information on the participants' background characteristics, so the analyses could reduce potential confounding issues by controlling for important established determinants of future labor market performance (e.g. intelligence, social class) which were likely to correlate with the main independent variable; chapter 6 also included family fixed-effects in a more stringent attempt to rule out unobserved background factors. The cohort data also contained extremely rich employment history data, which allowed for a detailed examination of unemployment trends over the life-course (e.g. see Figures 3.3, 4.1, and 6.2). These strengths contrast with many existing papers which have been limited by the absence of important control variables or by limited coverage of the participants' unemployment history. For example, on the topic of Big Five personality and unemployment examined in chapter 4, Viinikainen and Kokko (2012) rely on a small sample (N = 151) from one area of central Finland, Uysal and Pohlmeier (2012) do not control for intelligence or social class, and Fletcher (2013b) relies on a single snapshot measure of unemployment at age 30. In contrast, the study in chapter 4 uses a large sample (N = 4,206) drawn from across all regions of the UK, controls for intelligence and social class, and uses 16 years of month-by-month employment history data to build a comprehensive picture of the cohort members' unemployment trajectories. This example is also representative of the strengths of chapters 3, 5 and 6 with respect to many studies in prior literature.

---

<sup>11</sup> Some cohort members are counted more than once because some data-sets are used more than once across multiple chapters: the National Child Development Study in chapters 3 and 5, and the British Cohort Study in chapters 3 and 4.

The second main strength of this thesis is that the main independent variables in chapters 3 to 6 were all measured before the respondent had substantial (if any) experience in the labour market. This clarifies the direction of influence as running from the psychological variable to the labour market outcome rather than the other way around (e.g. this is not a case of work experience making a person more conscientious or a spell of unemployment worsening their mental health). This is a concern given that unemployment can change personality (Boyce, Wood, Daly, & Sedikides, 2015). While some studies using personality measures elicited after labor market entry have attempted to overcome this issue by using tests of reverse causality, these tests are often incomplete. For example, Viinikainen and Kokko (2012) compare personality measures elicited at age 33 and 50 with unemployment over the same time period, and conclude that the effect of unemployment on personality is modest. They do however acknowledge that they are unable to test for whether unemployment may have changed personality by age 33. The use of pre-labor market measures obviates the need for such tests.

The third main strength is the use of an interdisciplinary approach which drew on rich psychology literatures concerning individual psychological differences in self-control, mental health, and personality as operationalized by the Big Five, and the economics literature on how noncognitive skills relate to individual economic success to motivate examination of the psychological predictors of unemployment. This approach helped identify gaps in the literature. For example, as noted previously, the studies in chapters 5 and 6 are the first to use early-life measures of psychological distress to prospectively predict future unemployment in large, representative samples, despite the enormous existing literature examining the relationship between these two variables, such as the 324 studies examined in Paul and Moser (2009). Similarly, many studies in psychology examining personality and employment have tended to focus on outcomes such as occupational attainment (e.g. Roberts et al., 2007),

which is quite different from unemployment, whereas many economists have not traditionally focused on using psychological measures to explain economic behaviours (as suggested by Layard's (2013) recent call for labor economists to embrace the "new frontier" of mental health as an important determinant of employment).

The two main limitations of this thesis are bound up with its strengths in that they represent the downside of cohort data. Firstly, the extent to which these results can be causally interpreted is limited by the fact that the cohort data are observational. The data are not, for example, drawn from randomized controlled trials which assign comparable groups of people to treatment and control groups. The lack of randomization means that unobserved confounding variables may be the true explanation of the main finding. Supplemental analyses in chapters 3 and 5 attempt to address this issue by controlling for an extensive set of background characteristics (e.g. childhood physical health, demographic variables, information on difficulties in the childhood home) which might influence the relationship between the psychological characteristics and later unemployment. After controlling for these additional background circumstances there continued to be a statistically significant relationship between the main psychological variable and unemployment in almost all cases, although the magnitude of the relationship was typically diminished. These additional analyses do not prove that the relationships are causal, but they do suggest that they are robust. Similarly, chapter 6 used sibling comparisons to implicitly control for a vast set of unobserved characteristics (e.g. shared genetic endowments, exposure to common parenting regimes and schools). In that chapter the results were very similar in the full sample and sibling-only sample, suggesting that unobserved family-specific characteristics did not confound the relationship between distress and unemployment.

The second main limitation is measurement error in the main independent variables. In chapter 3 for example, I used teacher-rated self-control measures which were collected up

to 50 years ago. However, it is possible to address this issue to some extent. In chapter 3, two methods were used to validate the self-control measures, which were elicited in 1965, 1969 and 1980: (i) examining the convergent and discriminant validity of the self-control scales against other variables present in the data, which found that the older self-control measures had high positive correlations with alternative measures of self-control present in the data and low to moderate negative correlations with dissimilar concepts such as neuroticism and introversion and (ii) conducting an online validation study with 100 parents of children aged 5-12, which found that the correlation between the older measures and modern self-control scales was relatively high (above  $r = 0.7$ ). Measurement error may also arise from the use of relatively brief scales, such as the 3-item measures used to construct the personality variables in chapter 4. In order to address this issue, the scores on the 3-item measures were compared against scores on a longer, contemporary personality scale in an online sample of 389 adults. The four personality traits used in chapter 4 all correlated highly with their counterparts in the modern scale ( $r = .78$  on average).

Ultimately this issue of measurement error is almost unavoidable when using historical data. It is rare to have both decades of individual-level employment data and a measure of a psychological construct elicited in the person's childhood which conforms to the best practises of contemporary research. Even a study deployed today containing state-of-the-art measures will likely come to seem anachronistic or otherwise deficient to future researchers. Additionally, while some of the scales in the cohort data no doubt contain some degree of measurement error, the validation tests in chapters 3 and 4 suggest that they are accurate enough to be useful. Future studies would ideally address this issue by combining multiple measures of the same construct, such as behavioural tasks, self-report questionnaire scores, individual tests and observer-ratings, as has been done in Duckworth and Seligman (2005) and Moffit et al. (2011). Meeting this standard should become easier in the future as



major data-sets begin to include multiple measures of the same construct, such as the Millennium Cohort Study (a cohort of 19,000 UK children born in 2000) which includes teacher-, parent- and carer-rated measures of the Strengths and Difficulties Questionnaire (a tool for identifying behavioural and emotional problems) for the study participants.

### *7.3 Policy Implications*

This thesis has identified self-control, conscientiousness and mental health, all psychological characteristics measureable from an early age using relatively simple psychometric scales, as important predictors of future unemployment. With the above strengths and limitations in mind, how can these findings inform policy makers who wish to reduce population unemployment levels? I suggest that these results might inform two broad categories of intervention; short-run remedial programs targeted at those who are already unemployed or at risk of unemployment, and long-run preventative programs designed to improve the stock of skills of young people before they even enter the labour market. Since these interventions focus on the individual, they do not address macroeconomic tools such as market reforms, monetary policy or government stimulus spending which may be effective at addressing structural causes of unemployment.

In the short-term, the findings in this thesis may affect the design of unemployment interventions. Many governments provide active labor market programs (ALMPs) in order to encourage unemployed individuals back into employment. However, the evidence on the efficacy of ALMPs suggests that they are not a panacea. A recent meta-analysis of 207 studies from 47 countries by Card, Kluve, and Weber (2015) examined the efficacy of four types of ALMPs; those delivered in classrooms or on-the-job, assistance with the job search process, sanctioning people for failing to search for a job, and the provision of subsidies to employers in exchange for hiring job-seekers. The authors found that these programs had

relatively modest effects on the probability of the participants entering employment. While they did test for sources of heterogeneity, finding that ALMPs were on average more effective for women and the long-term unemployed, they did not examine whether individual psychological differences explained differences in unemployed individuals' propensity to re-enter employment. A meta-analysis of job search behaviours by Kanfer, Wanberg, and Kantrowitz (2001) did examine such heterogeneity, and found that higher conscientiousness and self-esteem (a component of mental health) predicted greater job search intensity which in turn predicted faster re-entry into employment. This seems plausible given that people with low levels of conscientious tend to be less goal-oriented, persistent and organized, all desirable qualities in the job search process. Similarly, people who are depressed and anxious may be more pessimistic about their futures and consequently be less motivated to search intensively.

An example of how an ALMP could explicitly take mental health into account is described in Caplan, Vinokur, Price, and Van Ryn (1989). They examined a program targeted at 928 unemployed individuals in Michigan in 1986 which had the explicit goal of preventing poor mental health and loss of motivation to seek reemployment. Participants who were randomly assigned to the treatment condition participated in 24 hours of training seminars over two weeks. These seminars taught practical job search skills such identifying job-relevant skills, using social networks to obtain leads, and preparing a resume. The psychological component of the seminars promoted psychological inoculation against setbacks and positive social reinforcement by emphasizing the importance of persistence in the face of adversity, teaching problem-appraisal skills which required participants to identify ways in which their job search efforts might be unsuccessful (i.e. anticipating the importance of impression management during job interviews), and having participants share their successes and setbacks with each other to provide mutual peer support. Four months after the

program ended, the participants who attended the seminars were 11 percentage points more likely to be in employment compared to control group participants who had only received a booklet providing job search tips. Among those who remained unemployed after four months, the treated participants also had higher self-efficacy and job search motivation scores than the control. The results of this program suggest that, in addition to improving skills, job search programs should aim to maintain and promote good mental health and motivation in order to improve employment outcomes. This conclusion is supported by a recent meta-analysis of 47 experimental and quasi-experimental job search interventions, which found that job search interventions were most effective at promoting employment when programs not only taught job search skills, but also provided improved the participants' motivation by encouraging greater self-efficacy, proactivity, goal-setting, self-presentation and by emphasizing the importance of enlisting social support (Liu, Huang, & Wang, 2014).

This connection between good mental health and better job search success may also have implications for the use of sanctioning as a tool in job assistance programs. In the UK, the Department of Work and Pensions (DWP) website states that *"It's your responsibility to do all you can to find work. In return, you'll get your benefit payment and our support. Most people do everything they can. If you don't, your benefit payment could be stopped (sanctioned) or your claim could be ended"* (Department of Work & Pensions, 2016). Tying financial support to the condition that the unemployed actively look for a job is standard practise in many countries; what is however of potential concern is whether improperly applied sanctions could adversely affect unemployed individuals with poor mental health, possibly to the point where it may be counter-productive to the goal of helping them find employment (as well as raising ethical questions about the appropriateness of punishing people suffering from serious health issues). Webster (2014) raises this concern in a report examining the recent rise in the use of sanctions against unemployed people in the UK, citing

the results of a poll of 1,500 people who had used mental health services in the previous two years: of this group 13% reported having considered or attempted suicide partly due to the fear of losing, or the loss of, welfare benefits. One recent report by a body of the UK Parliament (Work and Pensions Select Committee, 2015) concludes that change is required, recommending that the Department of Work & Pensions, “*drawing on specialist advice from health experts, [should] develop guidance on vulnerability which is specifically intended to assist JCP [Jobcentre Plus] staff in identifying vulnerable JSA [Jobseeker’s Allowance] claimants, including those with mental health problems*”. As well as efforts to maintain good psychological health among the newly unemployed (such as those documented in the previous paragraph), ALMPs should therefore consider including evaluative procedures which identify claimants with existing mental health issues in order to provide them with more tailored support.

ALMPs might also be made more successful by more effectively encouraging conscientious behaviour. Cagliesi and Hawkes’s (2015) on-the-ground study of a UK Jobcentre found that the program’s services often tended towards sanctioning clients for failing to complete job search behaviours in the recent past, rather than encouraging job search behaviours in the near future (e.g. by providing assistance with resume development and application preparation). The authors suggest that the Jobcentre environment could be modified to encourage job-seekers towards more conscientiousness behaviours by encouraging them to think in terms of life goals, and then emphasizing how acquiring a job could act as a step towards that goal. The Behavioural Insights Team (2015) has conducted experiments along these lines. One set of trials across multiple job centres (N = 110,833) increased the amount of people exiting unemployment benefits by 2 percentage points by encouraging job-seekers to focus on making specific commitments to future job search activities and by linking these to their daily routines.

Another short-run policy implication of the findings in this thesis, distinct from the design of job search interventions, concerns the perception and treatment of mental health issues. Mental illness incurs substantial economic costs. A recent estimate of the global cost of mental health conditions in 2010 by The World Economic Forum set the figure at \$2.5 trillion, two-thirds of which came from indirect costs such as lower productivity and foregone income (Bloom et al., 2011). The relationship between mental health and unemployment is particularly well-established: Paul and Moser's (2009) meta-analysis of 324 studies found that, on average, 34% of the unemployed had psychological problems compared to 16% of employed individuals. Despite these enormous economic costs, Layard (2013) notes that many people with mental illnesses do not receive treatment. Layard attributes this to perceptions of stigma and embarrassment around mental health issues, a relative lack of treatment facilities, and a lack of awareness of existing treatment options. Normalizing the perception of mental health issues, so that receiving treatment for depression or anxiety attracts no more stigma than receiving care for a broken leg or heart disease, may be an effective way to reduce unemployment and boost economic productivity more generally. One positive sign of a move towards greater recognition of mental health in the United Kingdom is the passage of the Health and Social Care Act in 2012, which requires the UK National Health Service to deliver 'parity of esteem' between physical and mental health.

In the long-run, policymakers may wish to implement policies which take a preventative approach towards preventing unemployment, and indeed towards improving socioeconomic outcomes more generally, by improving the human capital of future workers. The idea has been called "predistribution, not redistribution" by the economist James Heckman, meaning governments should invest in disadvantaged individuals early in life to improve their lifelong skill development, rather than supplementing their income later in life by redistributing the income of higher earners. It is motivated by the literature, discussed in

chapter 1, documenting the predictive power of early life cognitive and noncognitive skills for future economic success, and the efficacy of some early-life interventions for improving these skills in a lasting way: exhaustive documentation of such programs is provided in recent reports by the World Bank (Guerra, Modecki, & Cunningham, 2014), the United Nations (Young, 2014) the OECD (Kautz, Heckman, Diris, ter Weel, & Borghans, 2014), and Elango, Heckman, Garcia, and Hojman (2015). Although the standard framework for many of these programs is a government-led effort delivered through the school system, this is not the only approach available. A recent Brookings report (Whitehurst, 2015) proposes instead offering families direct financial subsidies, paired with targeted support for children with special needs and greater availability of child care workers, as a way of indirectly improving children's skill development by equipping their parents with greater resources. Another model is suggested by the "Moving to Opportunity" program, which improved the long-run earnings and university attendance rates of children from families randomly allocated vouchers to move from high-poverty areas to lower-poverty neighbourhoods (Chetty, Hendren, & Katz, 2016). In this experiment the gains from moving decreased the older the child was at the time of the move (e.g. it was better to move at age 7 than age 9, and better still to move at age 5), providing support for the contention of the Heckman and Cunha lifecourse model (2007) that early intervention is essential in order to see compounding benefits over time.

The findings of this thesis suggest that interventions designed to encourage self-control, conscientiousness and good mental health among young people may be effective at promoting long-run economic success. Specific examples of programs promoting these behaviours already exist. Regarding self-control, a meta-analysis of 4,693 children under the age of 10 participating in 34 predominantly US based randomized controlled trials found that children assigned to programs teaching self-control skills later had better self-control scores

in childhood and adolescence and had fewer behavioural problems (Piquero, Jennings, & Farrington, 2010). Regarding mental health, one recent study provides an overview of 46 different meta-analyses, 8 of which concerned programs designed to prevent depression or anxiety among participants ranging in age from 1 to 21 years (Sandler et al., 2014). Those 8 meta-analyses had a total sample size of over 60,000 drawn from 287 different studies, the majority of which used RCT designs. The intervention types included cognitive behavioural therapy, exercise programs, educational programs and mindfulness interventions. All 8 meta-analyses found positive effects of the interventions on post-intervention depression or anxiety scores. On average the effect sizes were small but significant and sustained over time, and were larger for programs targeted at at-risk rather than universal populations. While these studies provide valuable evidence on the malleability of these psychological characteristics, their main limitation in the context of this thesis and the broader literature discussed in chapter 1 is that they did not go on to examine whether treated individuals also had better long-run labor market outcomes.

#### *7.4 Future Research*

There is considerable scope for future research to expand on this thesis. An obvious first step would be to test whether these findings replicate when using better measures of mental health, or self-control, or Big Five personality, in order to reduce measurement error and produce more accurate estimates. This could be done by combining multiple scores of the psychological construct (e.g. evaluating self-control using observer-ratings, self-ratings, individual tests, and behavioural tasks) or in the case of mental health in particular, by conducting clinical assessments. The latter would be particularly useful as it would allow researchers to decompose the effects of different mental health conditions (e.g. schizophrenia, depression, drug addiction) on future outcomes. A second way to expand on this thesis would

be to retest its findings in different countries, given that this thesis drew only on data from the United Kingdom and the United States.

More broadly, and as noted in chapter 1, more work is needed in this literature to identify the noncognitive skills which causally determine later socioeconomic success, rather than merely predict it. There are two main methodologies currently used in this literature for demonstrating causality. The first is randomized controlled trials or natural experiments. Randomizing participants into a treatment group designed to improve noncognitive skills such as self-control, conscientiousness or mental health, and comparing their long-run outcomes with a comparable control group can demonstrate evidence of a causal relationship, contingent on the study having low levels of attrition and avoiding other potential issues of selection bias. Historical examples in the context of childhood noncognitive skill development are the Perry Preschool Program and the Abecedarian Project; more recent ones are the Moving to Opportunity experiment and the Head Start program. Natural experiments take advantage of the fortuitous sorting of otherwise similar groups of people into something resembling control and treatment groups; one example is a study which found that the children from American Indian families who began receiving income supplements went on to experience a major decrease in the number of psychiatric disorders compared to similar children who were not receiving such supplements (Costello, Compton, Keeler, & Angold, 2003). The second main tool for isolating causality is the use of sibling or twin comparisons, which implicitly control for a vast set of unobserved characteristics. Moffitt et al. (2011) examined self-control differences in 5-year old twins and found at age 12 the twin with better self-control was less likely to be a smoker, perform poorly in school or engage in antisocial behaviour. Fletcher (2013b) used sibling comparisons to estimate the effect of personality on employment and earnings at a single point in time when the study participants were aged 28-32. Lundborg, Nilsson, and Rooth's (2014) analysis of over 275,000 male Swedish siblings



found that 1 standard deviation increases in cognitive and noncognitive skills in late adolescence predicted respective increases of 11% and 7.7% in future earnings. Maczulskij and Viinikainen (2015) are the first to employ a twin study design to examine the effects of personality on labor market performance in a large sample; they find that “achievement” (a subfacet of conscientiousness), measured in the participants’ early twenties, predicts higher lifetime earnings in a sample of monozygotic Finnish twins. Several recent studies have also employed sibling and twin studies to examine how mental health predicts future outcomes such as educational attainment and employment, although not all of these studies used mental health measures measured early in life (Currie et al., 2010; Smith & Smith, 2010; Fletcher, 2013a; Fletcher, 2013b; Lundborg et al., 2014).

Ultimately, studies using causal designs are still relatively rare in this literature. An increase in their number, and an increased use of good outcome measures of earnings and employment, would allow much richer cost-benefit evaluations of intervention programs and provide greater perspective on their long-term value. Chetty et al.’s (2016) examination of the Moving to Opportunity experiment, which linked detailed background characteristics of 13,000 individuals with their federal income tax data, is an exemplar of this approach. An important barrier to addressing this concern is the fact that only around 13 countries (UK, USA, Ireland, Canada, France, Germany, Belgium, Netherlands, Switzerland, New Zealand, Australia, Brazil, Colombia, South Africa) currently run large, longitudinal studies of their populations. Not all of these data-sets are publicly available, nor are all of them nationally-representative, nor do many of these countries have the administrative infrastructure in place to link the information from these datasets to the individual-level tax and employment records typically contained in government archives. There is also an “endogeneity of data”<sup>12</sup>

---

<sup>12</sup> This useful term should properly be attributed to my supervisor Professor Liam Delaney, who really should write a paper on the issue.

issue: because only the wealthiest, most advanced countries tend to fund and maintain these sort of complex longitudinal studies, researchers can mostly only study the populations from some of the world's wealthiest countries, which are not obviously representative of the labor markets of most of the rest of the world.

Future research should also seek to improve our understanding the mechanisms operating between scores on a childhood psychological construct and later economic outcomes. For example, the studies in this thesis did not determine to what extent lower levels of self-control predict unemployment because they causally worsen educational attainment, impair the job search process, diminish the cohort members' social network, or any number of other possible pathways which may in turn affect the probability of unemployment. Mediation analysis in chapter 4 found that different levels of academic motivation and educational attainment explained some of the link between conscientiousness and unemployment, but could not account for over 90% of this association; similar analysis in chapter 6 found that different levels of educational attainment explained only 20% of the association between mental health and unemployment. Explaining more of these associations would provide a richer framework for understanding the relationship between noncognitive skills and later socioeconomic success.

A final broad recommendation for future research, noted in chapter 1, is the need to specify guidelines for early-life skill development programs and to provide intervention templates which incorporate the best available evidence. There is an enormous level of interest in such programs from academics and major policy-making bodies, but this has yet to translate to an availability of "off-the-shelf" programs which policy-makers can reliably implement in different environments and with different populations. Until such templates are developed, this body of research is unlikely to translate into effective policies. Whether such

interventions should be delivered in schools, or directly targeted at families, also requires greater discussion.

## References

- A05 NSA: Employment, unemployment and economic inactivity by age group (not seasonally adjusted). Retrieved July 20, 2016 from <http://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/datasets/employmentunemploymentandeconomicinactivitybyagegroupnotseasonallyadjusteda05nsa>
- Aiken, L. S., & West, S. G. (1991). *Multiple regression: Testing and interpreting interactions*. Newbury Park, CA: Sage.
- Alan, S., & Ertac, S. (2014). Good things come to those who (are taught how to) wait: Results from a randomized educational intervention on time preference. *SSRN Electronic Journal*. doi:10.2139/ssrn.2566405
- Almlund, M., Duckworth, A., Heckman, J. & Kautz, T. (2011). *Personality psychology and economics* (NBER Working Paper 16822). Cambridge, MA: National Bureau of Economic Research. doi:10.3386/w16822
- Arulampalam, W. (2001). Is unemployment really scarring? Effects of unemployment experiences on wages, *The Economic Journal*, *111*, 585-606. doi:10.1111/1468-0297.00664
- Ayers, J., Althouse, B., Allem, J-P, & Childers, M. (2012). Novel surveillance of psychological distress during the great recession. *Journal of Affective Disorders*, *142*, 323-330. doi:10.1016/j.jad.2012.05.005
- Bakker, A., Demerouti, E., & ten Brummelhuis, L. (2012). Work engagement, performance, and active learning: The role of conscientiousness. *Journal of Vocational Behaviour*, *80*, 555-564. doi:10.1016/j.jvb.2011.08.008
- Banks, M. (1983). Validation of the General Health Questionnaire in a young community

sample. *Psychological Medicine*, 13, 349-353. doi:10.1017/s0033291700050972

Barkley, R. (1997). *ADHD and the nature of self-control*. New York: Guilford Press.

Barrick, M., & Mount, M. (1991). The Big Five personality dimensions and job performance: A meta-analysis. *Personnel Psychology*, 44, 1-26. doi:10.1111/j.1744-6570.1991.tb00688.x.

Barrick, M., Mount, M., & Judge, T. (2001). Personality and Performance at the Beginning of the New Millennium: What Do We Know and Where Do We Go Next?. *International Journal of Selection and Assessment*, 9, 9-30. doi:10.1111/1468-2389.00160

Baumeister, R., Vohs, K., & Tice, D. (2007). The strength model of self-control. *Current Directions in Psychological Science*, 16, 351-355. doi:10.1111/j.1467-8721.2007.00534.x

The Behavioural Insights Team (2015). The Behavioural Insights Team Update report 2013-2015. Retrieved September 23, 2015, from [http://www.behaviouralinsights.co.uk/wp-content/uploads/2015/07/BIT\\_Update-Report-Final-2013-2015.pdf](http://www.behaviouralinsights.co.uk/wp-content/uploads/2015/07/BIT_Update-Report-Final-2013-2015.pdf)

Berndt, E., Koran, L., Finkelstein, S., Gelenberg, A., Kornstein, S., Miller, I...Keller, M. (2000). Lost human capital from early-onset chronic depression. *American Journal of Psychiatry*, 157, 940-947. doi:10.1176/appi.ajp.157.6.940

Berry, C., Ones, D., & Sackett, P. (2007). Interpersonal deviance, organizational deviance, and their common correlates: A review and meta-analysis. *Journal of Applied Psychology*, 92, 410-424. <http://dx.doi.org/10.1037/0021-9010.92.2.410>

Berwick, D., Murphy, J., Goldman, P., Ware, J., Barsky, A., & Weinstein, M. (1991). Performance of a five-item mental health screening test. *Medical Care*, 29, 169-176. doi:10.1097/00005650-199102000-00008

Bloom, D.E., Cafiero, E.T., Jané-Llopis, E., Abrahams-Gessel, S., Bloom, L.R., Fathima, S. ... Weinstein, C. (2011). *The global economic burden of noncommunicable diseases*. Geneva: World Economic Forum.

Borghans, L., Duckworth, A., Heckman, J., & ter Weel, B. (2008). The economics and psychology of personality traits. *Journal of Human Resources*, *43*, 972-1059.

doi:10.1353/jhr.2008.0017

Borghans, L., Golsteyn, B., Heckman, J., & Humphries, J. (2011). Identification problems in personality psychology. *Personality and Individual Differences*, *51*, 315-320.

doi:10.1016/j.paid.2011.03.029

Bound, J., & Solon, G. (1999). Double trouble: on the value of twins-based estimation of the return to schooling. *Economics of Education Review*, *18*, 169-182. doi:10.1016/s0272-7757(98)00048-x

Boyce, C., & Wood, A. (2011). Personality and the marginal utility of income: Personality interacts with increases in household income to determine life satisfaction. *Journal of Economic Behavior & Organization*, *78*, 183-191. doi:10.1016/j.jebo.2011.01.004

Boyce, C., Wood, A., & Brown, G. (2010). The dark side of conscientiousness: Conscientious people experience greater drops in life satisfaction following unemployment. *Journal of Research in Personality*, *44*, 535-539.

doi:10.1016/j.jrp.2010.05.001

Boyce, C., Wood, A., Daly, M., & Sedikides, C. (2015). Personality change following unemployment. *Journal of Applied Psychology*, *100*, 991-1101. doi:10.1037/a0038647

Butterworth, P., Leach, L., Pirkis, J., & Kelaher, M. (2011). Poor mental health influences risk and duration of unemployment: a prospective study. *Social Psychiatry and Psychiatric*

*Epidemiology*, 47, 1013-1021. doi:10.1007/s00127-011-0409-1

Callard, F. (2012). *Mental illness, discrimination, and the law*. Chichester, West Sussex, UK: Wiley-Blackwell.

Campbell, F., Ramey, C., Pungello, E., Sparling, J., & Miller-Johnson, S. (2002). Early childhood education: Young adult outcomes from the Abecedarian Project. *Applied Developmental Science*, 6, 42-57. doi:10.1207/s1532480xads0601\_05

Caplan, R., Vinokur, A., Price, R., & Van Ryn, M. (1989). Job seeking, reemployment, and mental health: A randomized field experiment in coping with job loss. *Journal of Applied Psychology*, 74, 759-769. doi:10.1037//0021-9010.74.5.759

Card, D. (1999). In O. Ashenfelter, & D. Card (Eds.), *The causal effect of education on earnings*. *Handbook of labor economics*, Vol. 3A, Amsterdam: Elsevier

Card, D., Kluve, J., & Weber, A. (2015). *What works? A meta-analysis of recent active labor market program evaluations* (NBER Working Paper 21431). Cambridge, MA: National Bureau of Economic Research. doi:10.3386/w21431

Carroll, J. (1993). *Human cognitive abilities*. Cambridge: Cambridge University Press.

CASEL. (2015). *SEL Defined*. Retrieved May 7, 2015, from <http://www.casel.org/social-and-emotional-learning/>

Cagliesi, G. & Hawkes, D. (2015). Behavioural Insights on Youth Employment Services: Evidence from the UK. Retrieved September 23, 2015, from <https://www.whatdotheyknow.com/request/248233/response/619634/attach/4/Behavioural%20Insights%20on%20Youth%20Employment%20Services%20DoQSS.PPTX.pptx>

- Casey, B., Somerville, L., Gotlib, I., Ayduk, O., Franklin, N., & Askren, M. et al. (2011). Behavioral and neural correlates of delay of gratification 40 years later. *Proceedings Of The National Academy Of Sciences*, *108*, 14998-15003. doi:10.1073/pnas.1108561108
- Caspi A., Wright B., Moffitt T.E., Silva P. (1998). Early failure in the labor market: Childhood and adolescent predictors of unemployment in the transition to adulthood. *American Sociology Review*, *63*, 424–451. doi:10.2307/2657557
- Chang, S-S., Stuckler, D., Yip, P., & Gunnell, D. (2013). Impact of 2008 global economic crisis on suicide: time trend study in 54 countries *BMJ*, *347*. doi:10.1136/bmj.f5239
- Chatterji, P., Alegría, M., Lu, M., & Takeuchi, D. (2007). Psychiatric disorders and labor market outcomes: evidence from the National Latino and Asian American Study. *Health Econ.*, *16*, 1069-1090. doi:10.1002/hec.1210
- Chatterji, P., Alegria, M., & Takeuchi, D. (2011). Psychiatric disorders and labor market outcomes: Evidence from the National Comorbidity Survey-Replication. *Journal of Health Economics*, *30*, 858-868. doi:10.1016/j.jhealeco.2011.06.006
- Chazan, M. (1968). Inconsequential behaviour in school children. *British Journal of Educational Psychology*, *38*, 5-7. doi:10.1111/j.2044-8279.1968.tb01973.x
- Cheng, H., & Furnham, A. (2012). Childhood cognitive ability, education, and personality traits predict attainment in adult occupational prestige over 17 years. *Journal of Vocational Behavior*, *81*, 218-226. doi:10.1016/j.jvb.2012.07.005
- Chetty, R., Hendren, N., & Katz, L. (2016). The effects of exposure to better neighborhoods on children: New evidence from the Moving to Opportunity project. *American Economic Review*, *106*. doi:10.1257/aer.20150572



- Chiaburu, D.S., Oh, I., Berry, C.M., Li, N., & Gardner R.G. (2011). The five-factor model of personality traits and organizational citizenship behaviors: A meta-analysis. *Journal of Applied Psychology*, 96, 1140–1166. doi:10.1037/a0024004
- Colquitt, J., LePine, J., & Noe, R. (2000). Toward an integrative theory of training motivation: A meta-analytic path analysis of 20 years of research. *Journal of Applied Psychology*, 85, 678-707. doi:10.1037//0021-9010.85.5.678
- Clark, A., Georgellis, Y., Sanfey, P. 2001. Scarring: The psychological impact of past unemployment. *Economica*. 68(270), 221-241. doi:10.1111/1468-0335.00243
- Conners, C. (1969). A teacher rating scale for use in drug studies with children. *American Journal of Psychiatry*, 126, 884–888. doi:10.1176/ajp.126.6.884
- Cooper, B. (2011). Economic recession and mental health: An overview. *Neuropsychiatry*, 25, 113-117.
- Cornaglia, F., Crivellaro, E., & McNally, S. (2015). Mental health and education decisions. *Labour Economics*, 33, 1-12. doi:10.1016/j.labeco.2015.01.005
- Costa, P. T., & McCrae, R. R. (1985). *The NEO personality inventory manual*. Odessa, FL; Psychological Assessment Resources.
- Costello, J., Compton, S., Keeler, G., & Angold, A. (2003). Relationships between poverty and psychopathology: A natural experiment. *JAMA*, 290, 2023-2029. doi:10.1001/jama.290.15.2023.
- Cunha, F., & Heckman, J. (2007). The technology of skill formation. *American Economic Review*, 97, 31-47. doi:10.1257/aer.97.2.31
- Cunha, F., Heckman, J., & Schennach, S. (2010). Estimating the technology of cognitive and noncognitive skill formation. *Econometrica*. 78(3), 883-931. doi:10.3982/ecta6551

- Currie, J., & Stabile, M. (2009). Mental health in childhood and human capital. *An Economic Perspective on the Problems of Disadvantaged Youth*, Jonathan Gruber (ed.) (Chicago: University of Chicago Press for NBER).
- Currie, J., Stabile, M., Manivong, P., & Roos, L. (2010). Child health and young adult outcomes. *Journal of Human Resources*, *45*, 517-548. doi:10.1353/jhr.2010.0013
- Currie, J., & Widom, C. (2010). Long-term consequences of child abuse and neglect on adult economic well-being. *Child Maltreatment*, *15*, 111-120. doi:10.1177/1077559509355316
- Daly, M. (2011). Intelligence differences may explain the link between childhood psychological problems and adult socioeconomic status. *Proceedings of the National Academy of Sciences*, *108*, 251. doi:10.1073/pnas.1106552108
- Daly, M., & Delaney, L. (2013). The scarring effect of unemployment throughout adulthood on psychological distress at age 50: Estimates controlling for early adulthood distress and childhood psychological factors. *Social Science & Medicine*, *80*, 19-23. doi:10.1016/j.socscimed.2012.12.008
- Daly, M., Delaney, L., Egan, M., & Baumeister, R. (2015). Childhood self-control and unemployment throughout the life span: Evidence from two British cohort studies. *Psychological Science*, *26*, 709-723. doi:10.1177/0956797615569001
- Daly, M., Egan, M., & O'Reilly, F. (2015). Childhood general cognitive ability predicts leadership role occupancy across life: Evidence from 17,000 cohort study participants. *The Leadership Quarterly*, *26*, 323-341. doi:10.1016/j.leaqua.2015.03.006
- de Feyter, T., Caers, R., Vigna, C., & Berings, D. (2012). Unraveling the impact of the Big Five personality traits on academic performance: The moderating and mediating effects of self-efficacy and academic motivation. *Learning and Individual Differences*, *22*, 439-448. doi:10.1016/j.lindif.2012.03.013

de Ridder, D., Lensvelt-Mulders, G., Finkenauer, C., Stok, F. & Baumeister, R. (2012).

Taking stock of self-control: a meta-analysis of how trait self-control relates to a wide range of behaviors. *Personality and Social Psychology Review*, *16*, 76–99.

doi:10.1177/1088868311418749

Deary, I., Taylor, M., Hart, C., Wilson, V., Smith, G., Blane, D., & Starr, J. (2005).

Intergenerational social mobility and mid-life status attainment: Influences of childhood intelligence, childhood social factors, and education. *Intelligence*, *33*, 455-472.

doi:10.1016/j.intell.2005.06.003

Deary, I., Strand, S., Smith, P., & Fernandes, C. (2007). Intelligence and educational achievement. *Intelligence*, *35*, 13-21. doi:10.1016/j.intell.2006.02.001

Deary, I., Pattie, A., & Starr, J. (2013). The stability of intelligence from age 11 to age 90 years: The Lothian Birth Cohort of 1921. *Psychological Science*, *24*, 2361-2368.

doi:10.1177/0956797613486487

Delaney, L., & Smith, J. (2012). Childhood health: Trends and consequences over the life course. *The Future of Children*, *22*, 43-63. doi:10.1353/foc.2012.0003

Diamond, A. & Lee, K. (2011). Interventions shown to aid executive function development in children 4 to 12 years old. *Science*, *333*, 959–964. doi:10.1126/science.1204529

Diamond, A. (2012). Activities and programs that improve children's executive functions.

*Current Directions in Psychological Science*, *21*, 335–341. doi:10.1177/0963721412453722

Diamond, A. (2013). Executive functions. *Annual Review of Psychology*, *64*, 135–168.

doi:10.1146/annurev-psych-113011-143750

- Diestel, S. & Schmidt, K. H. (2012). Lagged mediator effects of self-control demands on psychological strain and absenteeism. *Journal of Occupational and Organizational Psychology*, 85, 556-578. doi: 10.1111/j.2044-8325.2012.02058.x
- Digdon, N., & Howell A. (2008). College students who have an eveningness preference report lower self-control and greater procrastination. *Chronobiology International*, 25, 1029–1046. doi: 10.1080/07420520802553671
- Duckworth, A. & Seligman, M. E. P. (2005). Self-discipline outdoes IQ predicting academic performance in adolescents. *Psychological Science*, 16, 939–944. doi: 10.1111/j.1467-9280.2005.01641.x
- Duckworth, A. L. & Seligman, M. E. P. (2006). Self-discipline gives girls the edge: Gender differences in self-discipline, grades, and achievement test scores. *Journal of Educational Psychology*, 98, 198–208. doi: 10.1037/0022-0663.98.1.198
- Duckworth, A., Quinn, P., Lynam, D., Loeber, R., & Stouthamer-Loeber, M. (2011). Role of test motivation in intelligence testing. *Proceedings of the National Academy of Sciences*, 108(19), 7716-7720. doi:10.1073/pnas.1018601108
- Duckworth, A. L., Tsukayama, E., & Kirby, T. (2013). Is it really self-control? Examining the predictive power of the delay of gratification test. *Personality and Social Psychology Bulletin*, 39, 843–855. doi:10.1177/0146167213482589
- Duncan, G., & Magnuson, K. (2013). Investing in preschool programs. *Journal of Economic Perspectives*, 27, 109-132. doi:10.1257/jep.27.2.109
- Durlak, J., Weissberg, R., Dymnicki, A., Taylor, R., & Schellinger, K. (2011). The impact of enhancing students' social and emotional learning: A meta-analysis of school-based universal interventions. *Child Development*, 82, 405-432. doi:10.1111/j.1467-8624.2010.01564.x

Department for Work & Pensions (2016). *Jobseeker's Allowance sanctions: how to keep your benefit payment*. Retrieved August, 23, 2016, from

<https://www.gov.uk/government/publications/jobseekers-allowance-sanctions-leaflet/jobseekers-allowance-sanctions-how-to-keep-your-benefit-payment>

Eccles, J., & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual Review of Psychology*, *53*, 109-132. doi:10.1146/annurev.psych.53.100901.135153

Egan, M., Daly, M., & Delaney, L. (2015). Childhood psychological distress and youth unemployment: Evidence from two British cohort studies. *Social Science & Medicine*, *124*, 11-17. doi:10.1016/j.socscimed.2014.11.023

Egan, M., Daly, M., & Delaney, L. (2016). Adolescent psychological distress, unemployment, and the Great Recession: Evidence from the National Longitudinal Study of Youth 1997. *Social Science & Medicine*, *156*, 98-105. doi:10.1016/j.socscimed.2016.03.013

Eisenberg, N., Duckworth, A., Spinrad, T. & Valiente, C. (2014). Conscientiousness: Origins in childhood? *Developmental Psychology*, *50*, 1331–1349. doi: 10.1037/a0030977

Elango, S., Heckman, J., Garcia, J., & Hojman, A. (2015). *Early childhood education* (NBER Working Paper 21766). Cambridge, MA: National Bureau of Economic Research. doi:10.3386/w21766

Elliott, C., Murray, D. & Pearson, L. (1978). *British ability scales*. Windsor: National Foundation for Educational Research.

Ent, M. R., Baumeister, R. F., & Tice, D. (2015). Trait self-control and the avoidance of temptation. *Personality and Individual Differences*, *74*, 12–15. doi:10.1016/j.paid.2014.09.031

Ettner, S., Frank, R., & Kessler, R. (1997). The impact of psychiatric disorders on labor market outcomes. *ILR Review*, *51*, 64-81. doi:10.1177/001979399705100105

Evans-Lacko, S., Knapp, M., McCrone, P., Thornicroft, G., & Mojtabai, R. (2013). The mental health consequences of the recession: Economic hardship and employment of people with mental health problems in 27 European countries. *Plos ONE*, *8*, e69792.

doi:10.1371/journal.pone.0069792

Fergusson, D., Boden, J., & Horwood, L. (2007). Recurrence of major depression in adolescence and early adulthood, and later mental health, educational and economic outcomes. *The British Journal of Psychiatry*, *191*, 335-342. doi:10.1192/bjp.bp.107.036079

Findley, M., & Cooper, H. (1983). Locus of control and academic achievement: A literature review. *Journal of Personality and Social Psychology*, *44*, 419-427. doi:10.1037/0022-3514.44.2.419

Fletcher, J. (2008). Adolescent depression: diagnosis, treatment, and educational attainment. *Health Economics*, *17*, 1215-1235. doi:10.1002/hec.1319

Fletcher, J. (2010). Adolescent depression and educational attainment: Evidence from sibling fixed effects. *Health Economics*, *19*, 855-871. doi:10.1002/hec.1526

Fletcher, J. (2013a). Adolescent depression and adult labor market outcomes. *Southern Economic Journal*, *80*, 26-49. doi:10.4284/0038-4038-2011.193

Fletcher, J. (2013b). The effects of personality traits on adult labor market outcomes: Evidence from siblings. *Journal of Economic Behavior & Organization*, *89*, 122-135.

doi:10.1016/j.jebo.2013.02.004

French, D., & Tait, R. (2004). Measurement invariance in the General Health Questionnaire-

12 in young Australian adolescents. *European Child & Adolescent Psychiatry*, *13*, 1-7.

doi:10.1007/s00787-004-0345-7

Gale, C., Hatch, S., Batty, G., & Deary, I. (2009). Intelligence in childhood and risk of psychological distress in adulthood: The 1958 National Child Development Survey and the 1970 British Cohort Study. *Intelligence*, *37*, 592-599. doi:10.1016/j.intell.2008.09.002

Goldberg, L. (1992). The development of markers for the Big-Five factor structure.

*Psychological Assessment* *4*, 26-42. doi:10.1037/1040-3590.4.1.26

Goldberg, D., & Williams, P. (1988). A user's guide to the General Health Questionnaire (1st ed.). NFER-NELSON.

Golsteyn, B., Grönqvist, H., & Lindahl, L. (2014). Adolescent time preferences predict lifetime outcomes. *Economic Journal*, *124*, 739-761. doi:10.1111/eoj.12095

Goodman, R. (1997). The Strengths and Difficulties Questionnaire: A research note. *Journal of child psychology and psychiatry*, *38*, 581-586. doi:10.1111/j.1469-7610.1997.tb01545.x

Goodman, A., Joshi, H., Nasim, B., & Tyler, C. (2015). Social and emotional skills in childhood and their long-term effects on adult life. London: Institute of Education.

Goodman, A., Joyce, R., & Smith, J. (2011). The long shadow cast by childhood physical and mental problems on adult life. *Proceedings of the National Academy of Sciences*, *108*, 6032-6037. doi:10.1073/pnas.1016970108

Goodman, S., Rouse, M., Connell, A., Broth, M., Hall, C., & Heyward, D. (2011). Maternal depression and child psychopathology: A meta-analytic review. *Clinical Child and Family Psychology Review*, *14*, 1-27. doi:10.1007/s10567-010-0080-1

Gottfredson, L. (1997). Mainstream science on intelligence: An editorial with 52 signatories, history, and bibliography. *Intelligence*, 24, 13-23. doi:10.1016/s0160-2896(97)90011-8

Gottfried, A. E. (1990). Academic intrinsic motivation in young elementary school children. *Journal of Educational Psychology*, 82, 525–538. doi:10.1037/00220663.82.3.525

Gregg, P., & Tominey, E. (2005). The wage scar from male youth unemployment. *Labour Economics*, 12, 487-509. doi:10.1016/j.labeco.2005.05.004

Guerra, N., Modecki, K., Cunningham, W. (2014). Developing social-emotional skills for the labor market: The PRACTICE model. *Policy Research Working Paper 7123*. Washington, DC: World Bank.

Gutman, L. M., & Schoon, I. (2013). The impact of non-cognitive skills on outcomes for young people: Literature review. London: Institute of Education.

Hagger, M. S., Wood, C., Stiff, C., & Chatzisarantis, N. L. D. (2010). Ego depletion and the strength model of self-control: A meta-analysis. *Psychological Bulletin*, 136, 495–525. doi:10.1037/a0019486

Hawkes, D., & Plewis, I. (2006). Modelling non-response in the national child development study. *Journal of Royal Statistical Society: Series A*, 169, 479–491. doi:10.1111/j.1467-985x.2006.00401.x

Heckman, J. (2006). Skill formation and the economics of investing in disadvantaged children. *Science*, 312, 1900-1902. doi:10.1126/science.1128898

Heckman, J. (2008). Schools, skills and synapses. *Economic Inquiry*, 46, 289-324. doi:10.1111/j.1465-7295.2008.00163.x



Heckman, J., & Rubinstein, Y. (2001). The importance of noncognitive skills: Lessons from the GED testing program. *American Economic Review*, *91*, 145-149.

doi:10.1257/aer.91.2.145

Heckman, J., Moon, S., Pinto, R., Savelyev, P., & Yavitz, A. (2010). Analyzing social experiments as implemented: A reexamination of the evidence from the HighScope Perry Preschool Program. *Quantitative Economics*, *1*, 1-46. doi:10.3982/qe8

Heckman, J., Pinto, R., & Savelyev, P. (2013). Understanding the mechanisms through which an influential early childhood program boosted adult outcomes. *American Economic Review*, *103*, 2052-2086. doi:10.1257/aer.103.6.2052

Heckman, J., Stixrud, J., & Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics*, *24*, 411-482. doi:10.1086/504455

Heckman, J., & Kautz, T. (2013). *Fostering and measuring skills: Interventions that improve character and cognition* (NBER Working Paper 19656). Cambridge, MA: National Bureau of Economic Research doi:10.3386/w19656

Henkel, D. (2011). Unemployment and substance use: a review of the literature (1990–2010). *Current Drug Abuse Reviews*, *4*, 4-27. doi:10.2174/1874473711104010004

Henrich, J., Heine, S., & Norenzayan, A. (2010). The weirdest people in the world?. *Behavioral and Brain Sciences*, *33*, 61-83. doi:10.1017/s0140525x0999152x

Hofmann, W., Schmeichel, B. & Baddeley, A. (2012). Executive functions and self-regulation. *Trends in Cognitive Sciences*, *16*, 4-27. doi: 10.1016/j.tics.2012.01.006

Hofmann, W., Vohs, K. D., & Baumeister, R. F. (2012). What people desire, feel conflicted about, and try to resist in everyday life. *Psychological Science, 23*, 582–588.

doi:10.1177/0956797612437426

Hogan, R., Chamorro-Premuzic, T., & Kaiser, R. (2013). Employability and career success: Bridging the gap between theory and reality. *Industrial and Organizational Psychology, 6*, 3-16. doi:10.1111/iops.12001

Jenkins, J. (2010). The labor market in the 1980s, 1990s and 2008/09 recessions. *Economic & Labour Market Review, 4*, 29-36. doi:10.1057/elmr.2010.110

Judge, T., Bono, J., Ilies, R., & Gerhardt, M. (2002). Personality and leadership: A qualitative and quantitative review. *Journal of Applied Psychology, 87*, 765-780. doi:10.1037//0021-9010.87.4.765

Judge, T., Heller, D., & Mount, M. (2002). Five-factor model of personality and job satisfaction: A meta-analysis. *Journal of Applied Psychology, 87*, 530-541.

doi:10.1037//0021-9010.87.3.530

Judge, T., Higgins, C., Thoresen, C., & Barrick, M. (1999). The big five personality traits, general mental ability, and career success across the life span. *Personnel Psychology, 52*, 621-652. doi:10.1111/j.1744-6570.1999.tb00174.x

Judge, T., & Ilies, R. (2002). Relationship of personality to performance motivation: A meta-analytic review. *Journal of Applied Psychology, 87*, 797-807. doi:10.1037//0021-9010.87.4.797

Judge, T., Rodell, J., Klinger, R., Simon, L., & Crawford, E. (2013). Hierarchical representations of the five-factor model of personality in predicting job performance:

- Integrating three organizing frameworks with two theoretical perspectives. *Journal of Applied Psychology*, 98, 875-925. doi:10.1037/a0033901
- Kanfer, R., Wanberg, C., & Kantrowitz, T. (2001). Job search and employment: A personality-motivational analysis and meta-analytic review. *Journal of Applied Psychology*, 86, 837-855. doi:10.1037/0021-9010.86.5.837
- Kaur, S., Kremer, M. & Mullainthan, S. (2010). Self-control and the development of work arrangements. *American Economic Review Papers and Proceedings*, 100, 624-628. doi:10.1257/aer.100.2.624
- Kautz, T., Heckman, J., Diris, R., ter Weel, B., & Borghans, L. (2014). Fostering and measuring skills: Improving cognitive and non-cognitive skills to promote lifetime success. *OECD Education Working Papers*. doi: 10.1787/19939019
- Kawakami, N., Abdulghani, E., Alonso, J., Bromet, E., Bruffaerts, R., & Caldas-de-Almeida, J. et al. (2012). Early-life mental disorders and adult household income in the world mental health surveys. *Biological Psychiatry*, 72, 228-237. doi:10.1016/j.biopsych.2012.03.009
- Kelly, M., Dunstan, F., Lloyd, K., & Fone, D. (2008). Evaluating cutpoints for the MHI-5 and MCS using the GHQ-12: A comparison of five different methods. *BMC Psychiatry*, 8, 10. doi:10.1186/1471-244x-8-10
- Knudsen, E., Heckman, J., Cameron, J., & Shonkoff, J. (2006). Economic, neurobiological, and behavioral perspectives on building America's future workforce. *Proceedings of the National Academy of Sciences*, 103, 10155-10162. doi:10.1073/pnas.0600888103
- Kohler, U., Bernt Karlson, K., & Holm, A. (2011). Comparing coefficients of nested nonlinear probability models. *Stata Journal*, 11, 420-438.

Kokko, K., Bergman, L.R., & Pulkkinen, L. (2003). Child personality characteristics and selection into long-term unemployment in Finnish and Swedish longitudinal samples.

*International Journal of Behavioral Development, 27*, 134-144.

doi:10.1080/01650250244000137

Komaraju, M., Karau, S., & Schmeck, R. (2009). Role of the big five personality traits in predicting college students' academic motivation and achievement. *Learning and Individual Differences, 19*, 47–52. doi:10.1016/j.lindif.2008.07.001

*Individual Differences, 19*, 47–52. doi:10.1016/j.lindif.2008.07.001

Krueger, A. B., & Mueller, A.I. (2012). Time use, emotional well-being, and unemployment: Evidence from longitudinal data, *American Economic Review, 102*, 594–599.

doi:10.1257/aer.102.3.594

Kubzansky, L. D., Martin, L. T., & Buka, S. L. (2009). Early manifestations of personality and adult health: A life course perspective. *Health Psychology, 28*, 364–372.

doi:10.1037/a0014428

Kuhn, P., & Weinberger, C. (2005). Leadership skills and wages. *Journal of Labor Economics, 23*, 395-436. doi:10.1086/430282

Lagerveld, S., Bültmann, U., Franche, R., van Dijk, F., Vlasveld, M., van der Feltz-Cornelis, C... & Nieuwenhuijsen, K. (2010). Factors associated with work participation and work functioning in depressed workers: A systematic review. *Journal of Occupational Rehabilitation, 20*, 275-292. doi:10.1007/s10926-009-9224-x

Layard, R. (2013). Mental health: The new frontier for labour economics. *IZA Journal of Labor Policy, 2*, 1-16. doi: 10.1186/2193-9004-2-2

Lenton, P. (2014). *Personality characteristics, educational attainment and wages: An economic analysis using the British Cohort Study* (Sheffield Economic Research Paper

Series 2014011). Retrieved October 10, 2014, from

[http://www.sheffield.ac.uk/polopoly\\_fs/1.397279!/file/serps\\_2014011.pdf](http://www.sheffield.ac.uk/polopoly_fs/1.397279!/file/serps_2014011.pdf)

Lerner, D., & Henke, R. (2008). What does research tell us about depression, job performance, and work productivity?. *Journal of Occupational and Environmental Medicine*, 50, 401-410. doi:10.1097/jom.0b013e31816bae50

Lindqvist, E., & Vestman, R. (2011). The labor market returns to cognitive and noncognitive ability: Evidence from the Swedish enlistment. *American Economic Journal: Applied Economics*, 3, 101-128. doi:10.1257/app.3.1.101

Liu, S., Huang, J., & Wang, M. (2014). Effectiveness of job search interventions: A meta-analytic review. *Psychological Bulletin*, 140, 1009-41. doi: 10.1037/a0035923

Liu, Y., Croft, J., Chapman, D., Perry, G., Greenlund, K., Zhao, G. & Edwards, V. (2013). Relationship between adverse childhood experiences and unemployment among adults from five U.S. states. *Social Psychiatry and Psychiatric Epidemiology*, 48, 357–369. doi:10.1007/s00127-012-0554-1

Long, J.S., & Freese, J. (2014). *Regression Models for Categorical Dependent Variables in Stata*. 3rd ed. College Station, TX: Stata Press.

Lundborg, P., Nilsson, A., & Rooth, D. (2014). Adolescent health and adult labor market outcomes. *Journal of Health Economics*, 37, 25-40. doi:10.1016/j.jhealeco.2014.05.003

Maczulskij, T., & Viinikainen, J. (2015). Personality characteristics and long-term labor market outcomes: Evidence from twins. *Working papers 299*.

Makowska, Z., Merecz, D., Moscicka, A., & Kolasa, W. (2002). The validity of general health questionnaires, GHQ-12 and GHQ-28, in mental health studies of working people. *International Journal of Occupational Medicine and Environmental Health*, *15*, 353-362.

MacKinnon, D., Lockwood, C., Hoffman, J., West, S., & Sheets, V. (2002). A comparison of methods to test mediation and other intervening variable effects. *Psychological Methods*, *7*, 83-104. doi:10.1037/1082-989x.7.1.83

McKee-Ryan, F., Song, Z., Wanberg, C., & Kinicki, A. (2005). Psychological and physical well-being during unemployment: A meta-analytic study. *Journal of Applied Psychology*, *90*, 53-76. doi:10.1037/0021-9010.90.1.53

Milner, A., Page, A., & LaMontagne, A. (2013). Long-Term Unemployment and Suicide: A Systematic Review and Meta-Analysis. *Plos ONE*, *8*(1), e51333. doi:10.1371/journal.pone.0051333

Moffitt, T., Arseneault, L., Belsky, D., Dickson, N., Hancox, R., & Harrington, H. et al. (2011). A gradient of childhood self-control predicts health, wealth, and public safety. *Proceedings of the National Academy of Sciences of the United States of America*, *108*, 2693-2698. doi:10.1073/pnas.1010076108

Mossakowski, K. (2008). Is the duration of poverty and unemployment a risk factor for heavy drinking?. *Social Science & Medicine*, *67*, 947-955. doi:10.1016/j.socscimed.2008.05.019

Moutafi, J., Furnham, A., & Tsaousis, I. (2006). Is the relationship between intelligence and trait Neuroticism mediated by test anxiety?. *Personality and Individual Differences*, *40*, 587-597. doi:10.1016/j.paid.2005.08.004

Muck, P., Hell, B., & Gosling, S. (2007). Construct validation of a short five-factor model instrument. *European Journal of Psychological Assessment, 23*, 166-175. doi:10.1027/1015-5759.23.3.166

Multon, K., Brown, S., & Lent, R. (1991). Relation of self-efficacy beliefs to academic outcomes: A meta-analytic investigation. *Journal of Counseling Psychology, 38*, 30-38. doi:10.1037/0022-0167.38.1.30

National Institute of Mental Health (2015), *NIMH Statistics*, Retrieved 29 May 2015, from <http://www.nimh.nih.gov/health/statistics/index.shtml>

National Longitudinal Surveys (2015). *NLS Investigator*. Retrieved 3 June 2015, from <https://www.nlsinfo.org/investigator/>

NBER (2010), *Announcement by the Business Cycle Dating Committee*, Retrieved 5 June 2015, from <http://www.nber.org/cycles/sept2010.html>

Nores, M., & Barnett, W. (2010). Benefits of early childhood interventions across the world: (Under) Investing in the very young. *Economics of Education Review, 29*, 271-282. doi:10.1016/j.econedurev.2009.09.001

O'Connor, T., Rutter, M., Beckett, C., Keaveney, L., & Kreppner, J. (2000). The effects of global severe privation on cognitive competence: Extension and longitudinal follow-up. *Child Development, 71*, 376-390. doi:10.1111/1467-8624.00151

OECD (2014). *Education at a Glance 2014: OECD Indicators*. OECD Publishing, Paris. doi:10.1787/eag-2014-en

Ones, D. S., Dilchert, S., Viswesvaran, C., & Judge, T. A. (2007). In support of personality assessment in organizational settings. *Personnel Psychology*, *60*, 995–1027.

doi:10.1111/j.1744-6570.2007.00099.x

Ons.gov.uk. (2015). *Data Explorer (Beta)*. Retrieved 20 September 2015, from

<http://web.ons.gov.uk/ons/data/dataset-finder>

Ostroff, J., Woolverton, K., Berry, C., & Lesko, L. (1996). Use of the Mental Health Inventory with adolescents: A secondary analysis of the Rand Health Insurance Study. *Psychological Assessment*, *8*, 105-107. doi:10.1037/1040-3590.8.1.105

Paul, K., & Moser, K. (2009). Unemployment impairs mental health: Meta-analyses. *Journal of Vocational Behavior*, *74*, 264-282. doi:10.1016/j.jvb.2009.01.001

Peeters, M., van Tuijji, H., Rutte, C., Reymen, I. (2006). Personality and team performance: A meta-analysis. *European Journal of Personality*, *20*, 377-396. doi:10.1002/per.588

Pigeon, D. A. (1964). Tests used in the 1954 and 1957 surveys. In J. W. B. Douglas (Ed.), *The home and the school: A study of ability and attainment in the primary school* (appendix 1). London: Macgibbon & Kee.

Piquero, A. R., Jennings, W. G., & Farrington, D. P. (2010). Self-control interventions for children under age 10 for improving self-control and delinquency and problem behaviors. *Campbell Systematic Reviews*, *2*. doi: 10.4073/csr.2010.2.

Poropat, A. (2009). A meta-analysis of the five-factor model of personality and academic performance. *Psychological Bulletin*, *135*, 322-338. doi:10.1037/a0014996

Posner, M., Rothbart, M., & Tang, Y. (2013). Developing self-regulation in early childhood. *Trends in Neuroscience and Education*, *2*, 107-110. doi:10.1016/j.tine.2013.09.001



Rammstedt, B., & John, O. (2007). Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German. *Journal of Research in Personality, 41*, 203-212. doi:10.1016/j.jrp.2006.02.001

Ritchie, S., & Bates, T. (2013). Enduring links from childhood mathematics and reading achievement to adult socioeconomic status. *Psychological Science, 24*, 1301-1308. doi:10.1177/0956797612466268

Roberts, B., Chernyshenko, O., Stark, S., & Goldberg, L. (2005). The structure of conscientiousness: An empirical investigation based on seven major personality questionnaires. *Personnel Psychology, 58*, 103-139. doi:10.1111/j.1744-6570.2005.00301.x

Roberts, B., Kuncel, N., Shiner, R., Caspi, A., & Goldberg, L. (2007). The power of personality: The comparative validity of personality traits, socioeconomic status, and cognitive ability for predicting important life outcomes. *Perspectives on Psychological Science, 2*, 313-345. doi:10.1111/j.1745-6916.2007.00047.x

Roberts, B., Lejuez, C., Krueger, R., Richards, J., & Hill, P. (2014). What is conscientiousness and how can it be assessed? *Developmental Psychology, 50*, 1315-1330. doi:10.1037/a0031109

Roelfs, D., Shor, E., Davidson, K., & Schwartz, J. (2011). Losing life and livelihood: A systematic review and meta-analysis of unemployment and all-cause mortality. *Social Science & Medicine, 72*, 840-854. doi:10.1016/j.socscimed.2011.01.005

Rothbart, M., Ellis, L., Rueda, M., & Posner, M. (2003). Developing mechanisms of temperamental effortful control. *Journal of Personality, 71*, 1113-1145. doi:10.1111/1467-6494.7106009

Rubin, D. (1987). *Multiple imputation for nonresponse in surveys*. New York: Wiley.

Rumpf, H., Meyer, C., Hapke, U., & John, U. (2001). Screening for mental health: validity of the MHI-5 using DSM-IV Axis I psychiatric disorders as gold standard. *Psychiatry Research*, *105*, 243-253. doi:10.1016/s0165-1781(01)00329-8

Rüsch, N., Angermeyer, M., & Corrigan, P. (2005). Mental illness stigma: Concepts, consequences, and initiatives to reduce stigma. *European Psychiatry*, *20*, 529-539. doi:10.1016/j.eurpsy.2005.04.004

Rutter, M. (1967). A children's behaviour questionnaire for completion by teachers: preliminary findings. *Journal of Child Psychology and Psychiatry*, *8*, 1-11. doi:10.1111/j.1469-7610.1967.tb02175.x

Rutter, M., Tizard, J., & Whitmore, K. (1970). *Education, health and behaviour*. Harlow: Longman.

Sandler, I., Wolchik, S., Cruden, G., Mahrer, N., Ahn, S., Brincks, A., & Brown, C. (2014). Overview of Meta-Analyses of the Prevention of Mental Health, Substance Use, and Conduct Problems. *Annual Review Of Clinical Psychology*, *10*, 243-273. doi:10.1146/annurev-clinpsy-050212-185524

Scheid, T. (1999). Employment of individuals with mental disabilities: business response to the ADA's challenge. *Behavioral Sciences & The Law*, *17*, 73-91. doi:10.1002/(sici)1099-0798(199901/03)17:1<73::aid-bsl326>3.3.co;2-v

Schmidt, K. H., Hupke, M., & Diestel, S. (2012) Does dispositional capacity for self-control attenuate the relation between self-control demands at work and indicators of job strain? *Work & Stress*, *26*, 21-38. doi:10.1080/02678373.2012.660367

Schoon, I. (2008). A transgenerational model of status attainment: The potential mediating role of school motivation and education. *National Institute Economic Review*, *205*, 72-82.

doi:10.1177/0027950108096590

Shoda, Y., Mischel, W., & Peake, P. (1990). Predicting adolescent cognitive and self-regulatory competencies from preschool delay of gratification: Identifying diagnostic conditions. *Developmental Psychology*, *26*, 978-986. doi:10.1037//0012-1649.26.6.978

Slutske, W. S., Moffitt, T., Poulton, R., & Caspi, A. (2012). Undercontrolled temperament at age 3 predicts disordered gambling at age 32: a longitudinal study of a complete birth cohort. *Psychological Science*, *23*, 510–516. doi:10.1177/0956797611429708

Smith, J., & Smith, G. (2010). Long-term economic costs of psychological problems during childhood. *Social Science & Medicine*, *71*, 110-115. doi:10.1016/j.socscimed.2010.02.046

Specht, J., Egloff, B., & Schmukle, S. (2011). Stability and change of personality across the life course: The impact of age and major life events on mean-level and rank-order stability of the big five. *Journal of Personality and Social Psychology*, *101*, 862-882.

doi:10.1037/a0024950

Stata Corp, *Stata Multiple-Imputation Reference Manual: Release 13* (College Station, TX: StataCorp LP, 2013).

Steel, P. (2007). The nature of procrastination: A meta-analytic and theoretical review of quintessential self-regulatory failure. *Psychological Bulletin*, *133*, 65-94. doi:10.1037/0033-2909.133.1.65

Störmer, S., & Fahr, R. (2013). Individual determinants of work attendance: evidence on the role of personality. *Applied Economics*, *45*, 2863-2875. doi:10.1080/00036846.2012.684789

- Stott, D. H. (1969). *The social-adjustment of children: Manual to the Bristol social-adjustment guides*. London: University of London Press.
- Strenze, T. (2007). Intelligence and socioeconomic success: A meta-analytic review of longitudinal research. *Intelligence*, 35, 401-426. doi:10.1016/j.intell.2006.09.004
- Stuart, H. (2006). Mental illness and employment discrimination. *Current Opinion in Psychiatry*, 19, 522-526. doi:10.1097/01.yco.0000238482.27270.5d
- Sturman, M. (1999). Multiple approaches to analyzing count data in studies of individual differences: The propensity for type I errors, illustrated with the case of absenteeism prediction. *Educational and Psychological Measurement*, 59, 414–430. doi:10.1177/00131649921969956
- Suhrcke, M., & Stuckler, D. (2012). Will the recession be bad for our health? It depends. *Social Science & Medicine*, 74, 647-653. doi:10.1016/j.socscimed.2011.12.011
- Tangney, J., Baumeister, R. and Boone, A. (2004). High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. *Journal of Personality*, 72, 271–324. doi:10.1111/j.0022-3506.2004.00263.x
- Taylor, G., Jungert, T., Mageau, G., Schattke, K., Dedic, H., Rosenfield, S., & Koestner, R. (2014). A self-determination theory approach to predicting school achievement over time: the unique role of intrinsic motivation. *Contemporary Educational Psychology*, 39, 342-358. doi:10.1016/j.cedpsych.2014.08.002
- Terman, L. M. (Ed.) (1925). *Genetic studies of genius, vol I: Mental and physical traits of a thousand gifted children*. Stanford University Press.
- Terman, L. M. (Ed.) (1959). *Genetic studies of genius, vol V: The gifted group at mid-life, thirty-five years' follow-up of the superior child*. Stanford University Press.

- Tsukayama, E., Duckworth, A. L., & Kim, B. E. (2013). Domain-specific impulsivity in school-age children. *Developmental Science, 16*, 879–893. doi:10.1111/desc.12067
- UK Data Service (2015). *UK Data Service*. Retrieved 3 June 2015, from <http://ukdataservice.ac.uk/>
- Uysal, S., & Pohlmeier, W. (2011). Unemployment duration and personality. *Journal of Economic Psychology, 32*, 980-992. doi:10.1016/j.joep.2011.03.008
- Viinikainen, J., & Kokko, K. (2012). Personality traits and unemployment: Evidence from longitudinal data. *Journal of Economic Psychology, 33*, 1204-1222. doi:10.1016/j.joep.2012.09.001
- Vinokur, A., Schul, Y., Vuori, J., & Price, R. (2000). Two years after a job loss: Long-term impact of the JOBS program on reemployment and mental health. *Journal of Occupational Health Psychology, 5*, 32-47. doi:10.1037/1076-8998.5.1.32
- Wanberg, C. (2012). The individual experience of unemployment. *Annual Review of Psychology, 63*, 369-396. doi:10.1146/annurev-psych-120710-100500
- White, I., Royston, P., & Wood, A. (2010). Multiple imputation using chained equations: Issues and guidance for practice. *Statistics in Medicine, 30*, 377-399. doi:10.1002/sim.4067
- Whitehurst, G. (2016). Family support or school readiness? Contrasting models of public spending on children's early care and learning. *Brookings Evidence Speaks Reports, 1*. Retrieved 10 August 2016, from <https://www.brookings.edu/research/family-support-or-school-readiness-contrasting-models-of-public-spending-on-childrens-early-care-and-learning/>

Webster, D. (2016). *Briefing: The DWP's JSA/ESA sanctions statistics release*. Retrieved 23 August 2016, from <http://www.cpag.org.uk/sites/default/files/uploads/16-05%20Sanctions%20Stats%20Briefing%20-%20D%20Webster%2031%20May%202016.docx>

Work and Pensions Select Committee (2015). *Work and Pensions - Fifth report: Benefit sanctions policy beyond the Oakley Review. HC 814*. Retrieved 23 August 2016, from <http://www.publications.parliament.uk/pa/cm201415/cmselect/cmworpen/814/81402.htm>

Young, M. (2014). *Addressing and Mitigating Vulnerability across the Life Cycle: The Case for Investing in Early Childhood. UNDP Occasional Paper*.

Yusoff, M., Rahim, A., & Yaacob, M. (2010). Prevalence and sources of stress among Universiti Sains Malaysia medical students. *Malaysian Journal of Medical Sciences, 17*, 30-37.

Zeidner, M., & Matthews, G. (2000). Intelligence and personality. In R. Sternberg (Ed.), *Handbook of Intelligence*, 581–610. New York, NY, USA: Cambridge University Press.

Zentner, M. & Bates, J. (2008). Child temperament: An integrative review of concepts, research programs, and measures. *European Journal of Developmental Science, 2*, 7–37. doi: 10.3233/DEV-2008-21203