Essays on Well-being and Mental Health: Determinants and Consequences

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Abstract

This thesis presents three empirical studies, each providing insights into topics relating to subjective well-being and mental health, namely bullying, antisocial behaviour, and natural disasters.

The first study uses data from the UK to explore how being bullied at age 11 affects subjective well-being as an adult. A range of methods are used including random effects ordered probit models, Hausman tests, and Heckman models. The results suggest that childhood bullying victimisation is associated with lower adult subjective well-being. The findings indicate that preventing children from being bullied in schools may increase their subjective well-being as adults.

The second study uses UK data to investigate how the mental health of adolescents affects their participation in antisocial behaviour. The analysis uses random effects probit, multivariate probit, and conditional logit models. The findings suggest that externalising problems (mental health problems directed at others) are positively associated with participation in fighting, vandalism, shoplifting, and truancy; and internalising problems (mental health problems directed at the individual) positively predict fighting behaviour. Hence, the results suggest that the mental health problems of adolescents may adversely affect their behaviour.

The final study explores the effects of three natural disasters (the 2004 Indian Ocean tsunami, Hurricane Katrina in 2005, and the 2010 Haiti earthquake) on subjective well-being in the US. Using a difference-in-difference approach, the results suggest that Hurricane Katrina reduced the subjective well-being of Americans who lived in the states that were directly affected by the disaster. It is also found that the Indian Ocean tsunami and the Haiti earthquake increased the subjective well-being of Americans who lived closest to the disaster areas. It is argued that following the extensive media coverage of these disasters, Americans may have compared themselves favourably to the disaster victims, thus their subjective well-being increased because they were grateful to be unaffected.

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The empirical analysis in Chapter 3 is based on data from Understanding Society, waves 1-6. Understanding Society is an initiative funded by the Economic and Social Research Council and various Government Departments, with scientific leadership by the Institute for Social and Economic Research, University of Essex, and survey delivery by NatCen Social Research and Kantar Public. The research data are distributed by the UK Data Service.

The empirical analysis in Chapter 4 makes use of data from the US Behavioural Risk Factor Surveillance System collected by the Centre for Disease Control and Prevention. The Behavioural Risk Factor Surveillance System is sponsored by the National Centre for Chronic Disease Prevention and Health Promotion; and federal agencies, such as the Health Resources and Services Administration, Administration on Aging, Department of Veterans Affairs, and Substance Abuse and Mental Health Services Administration.

Abbreviations

2SRI - Two stage residual inclusion
ADHD - Attention deficit hyperactivity disorder
ASB - Antisocial behaviour
BHPS - British Household Panel Survey
BRFSS - Behavioural Risk Factor Surveillance System
BSAG - Bristol Social Adjustment Guide
CES-D - Centre for Epidemiologic Studies Depression scale
EP - Externalising problems
fMRI - Functional Magnetic Resonance Imaging
GCSE - General Certificate of Secondary Education
GDP - Gross domestic product
GHQ - General Health Questionnaire
GHQ(36) - 36 point General Health Questionnaire
IP - Internalising problems
IV - Instrumental variable
NCDS - National Child Development Study
OLS - Ordinary least squares
ONS - Office for National Statistics
SD - Standard deviation
SDQ - Strengths and Difficulties Questionnaire
SF-12 - Short Form 12 Health Survey
SF-12-MCS - Short Form 12 Mental Health Component Summary
SF-12-PCS - Short Form 12 Physical Health Component Summary
SWB - Subjective well-being
UK - United Kingdom
US - United States

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Chapter 1: Introduction

1.1 Motivation and Aims

"*The ultimate purpose of economics, of course, is to understand and promote the enhancement of well-being*".

"*The only orthodox object of the institution of government is to secure the greatest degree of happiness possible to the general mass of those associated under it*".[1]

As suggested by Ben Bernanke and Thomas Jefferson, increasing subjective well-being (SWB) may be viewed as the ultimate maximand of government policy. As well as the philosophical case for the importance of SWB, there are many important reasons why economists are increasingly interested in analysing SWB.[2] Firstly, macroeconomic policymakers typically face trade-offs such as that between inflation and unemployment. Using SWB data from European countries, Di Tella et al. (2001) present evidence to suggest that a 1% point increase in the unemployment rate requires a 1.7% point reduction in the inflation rate to compensate in terms of SWB. This finding is in stark contrast to the "misery index" of Arthur Okun which simply sums the rates of unemployment and inflation and thus implicitly assumes that they have an equal effect on SWB, see Tien and Lovell (2000). Thus, the analysis of SWB data can help inform the policies of governments and central banks who must trade off important macroeconomic objectives.

Secondly, SWB data can be used as a useful approximation of individual utility and can therefore allow economists to test important assumptions of economic theory. For example, classical economics assumes that unemployment is voluntary; unemployed people choose to remain unemployed because the benefits of working are outweighed by the costs, see Minford (1983). In contrast, Keynesian economics assumes that unemployment is involuntary; the unemployed are out of work because they cannot find a job, see Yellen (1984). Research using SWB data can shed light on this important controversy and suggests that unemployment has a large adverse effect on SWB, (see Clark and Oswald, 1994; Kassenboehmer and Haisken-DeNew, 2009). As a result, research exploring the effects of unemployment on SWB supports the case that unemployment is predominantly involuntary, rather than voluntary.

[1] The former quote is of Ben Bernanke, former Chairman of the US Federal Reserve, speaking in 2012 at the 32nd General Conference of the International Association for Research in Income and Wealth. The latter quote is from Thomas Jefferson, former US president, writing in 1812, see the National Archives (2017).

[2] Frey and Stutzer (2002) present a comprehensive account of the importance of SWB research to economists.

Thirdly, analysis of SWB data can help us to shed light on important empirical puzzles, which contradict with economic theory. One important example of such a puzzle is the famous Easterlin (1974) paradox, which states that despite rapid increases in per-capita income between 1946 and 1970 in the United States (US), average SWB remained constant. However, at a given point in time, income is positively associated with SWB within societies.

Easterlin (1974) presented two explanations for this paradox: relative income and adaptation. The relative income hypothesis states that SWB is positively affected by the income of the individual, but is adversely affected by the incomes of others, such as that of a reference group, see Card et al. (2012). SWB data can be utilised to shed light on the relative income hypothesis. For example, using data from the US, Luttmer (2005) suggests that SWB may be adversely related to the incomes of those living in close proximity. In comparison to the relative income hypothesis, the adaptation hypothesis states that individuals may compare their current income to their past income and may thus adapt to increases in income. For example, using data from Germany, Di Tella et al. (2010) find substantial adaptation to income.

Fourthly, as an alternative to existing approaches such as willingness to pay methods, SWB data may be used to value public and non-market goods. For example, Levinson (2012) and Van Praag and Baarsma (2005) use SWB data to value the effects of air quality and airport noise, respectively.

Due to the widespread availability of SWB data in social surveys it is often used as a proxy for individual utility, (see, Di Tella et al., 2002, for example). Arguably, SWB data has a number of advantages when viewed as a measure of utility. Firstly, in contrast to revealed preference methods, SWB measures do not suffer from issues relating to projection bias, where individuals systematically mispredict the consequences of their actions for their own utility[3], (see, for example Benjamin et al., 2012; Loewenstein et al., 2003).

Secondly, previous research indicates that SWB ratings are positively associated with smiling and brain activity, (see, for example, Fernández-Dols et al., 1995; Sandvik et al., 1993; Shizgal, 1999). Thirdly, reports of SWB predict individual behaviours such as suicide and job quits, (see Clark et al., 1998; Koivumaa-Honkanen et al., 1995). Arguably, if choices and facial expressions are related to utility then SWB data may offer a useful proxy for utility.

It is also important to acknowledge the disadvantages of SWB data as a proxy for utility. Firstly, SWB reports are malleable and are thus sensitive to contextual factors such as the day of the week, mode of interview, and question ordering. For instance,

[3] For instance, people who shop when they are hungry are more likely to over-shop (buy foods that were not on their shopping list), (see Gilbert et al., 1998; Nisbett and Kanouse, 1968). People who are hungry project their current preferences for food (at the time of shopping) onto their future preferences for food (at the time of eating), see Loewenstein et al. (2003).

using UK data, Taylor (2006) suggest that people interviewed on a Friday report higher job satisfaction and lower mental distress than people interviewed from Tuesday to Thursday. In addition, Dolan and Kavetsos (2016) use UK data to suggest that people report lower SWB in face to face interviews, relative to telephone interviews. Strack et al. (1988) indicate that the relationship between the frequency that they go on a date and their SWB is affected by the ordering of the two survey questions[4].

A second limitation of SWB data as a proxy for individual utility is that people may not make decisions solely to maximise their own SWB. For example, Benjamin et al. (2012) utilise hypothetical choice experiments to investigate how people's predicted SWB rankings affect their (hypothetical) choices between two alternatives[5]. Their findings indicate that in 80% of cases, survey respondents chose the hypothetical alternative that they thought would maximise their SWB. In addition to the important role of predicted SWB in explaining hypothetical choices, their findings indicate that hypothetical choices are also explained by sense of purpose, control over life, family happiness, and social status. Consequently, the findings of Benjamin et al. (2012) support the case that individuals do not only seek to maximise SWB, but rather that SWB is an important component of utility[6]. Thus, SWB data arguably provides a useful proxy for individual utility despite the limitations described above.

On top of the increasing interest of economists in research using SWB data, governments around the world are considering the potential role of measures of SWB in government policy.[7] For example, speaking at the Google Zeitgeist conference in 2006, David Cameron, the former leader of the Conservative party said:

"*It's time we admitted that there's more to life than money, and it's time we focused not just on GDP [gross domestic product], but on GWB - general well-being... Improving our society's sense of well-being is, I believe, the central political challenge of our times.*"

Within 6 months of election as Prime Minister in 2010, David Cameron commissioned the Office for National Statistics to begin collecting national statistics relating to SWB, as well as traditional measures of material well-being such as gross domestic product

[4] When individuals reported their SWB prior to reporting their dating frequency, dating frequency had no statistically significant effect on SWB. In contrast, when the question ordering was reversed, dating frequency and SWB were positively correlated.

[5] For instance, survey respondents ranked their SWB between a job that allowed more sleep but a lower income, versus a job with a higher income and less sleep. Individuals provided their predicted SWB ranking between the two alternatives for the following measures of SWB; life satisfaction, happiness with life as a whole, and felt happiness. The authors explore how the respondent's predicted SWB rankings affect their choices between the hypothetical alternatives.

[6] For a comprehensive discussion of SWB as a measure of utility, see Clark et al. (2008).

[7] Bache and Reardon (2016) provide a detailed account of the rise of well-being in government policy.

(GDP).[8] There has been increasing interest in SWB in France too. For example, recommendation 10 of the Stiglitz et al. (2009) report on the Measurement of Economic Performance and Social Progress commissioned by former French President Nicolas Sarkozy states:

"*Measures of both objective and subjective well-being provide key information about people's quality of life. Statistical offices should incorporate questions to capture people's life evaluations, hedonic experiences and priorities in their own survey*". (p. 16).

Research using SWB data is important for policymakers who care about SWB for a number of reasons. Firstly, SWB research can inform policymakers about the determinants of SWB and the relative size of their effects on SWB. Knowledge of the relative magnitudes of the determinants of SWB is essential for policymakers to intervene, where appropriate, using the most cost-effective approach. Secondly, SWB research is essential to inform policymakers as to what stage in the life course to intervene, see Layard et al. (2014).

This thesis presents three empirical studies in the areas of SWB and mental health and each study aims to contribute to the existing literature in the following ways[9]. The first empirical chapter uses cohort data from the United Kingdom (UK) to investigate whether being bullied as a child affects SWB as an adult.[10] It is important to explore the effects of being bullied as a child on adult SWB for several reasons. Firstly, Understanding Society data from 2013 suggests that approximately 19% of a UK sample of 4,427 adolescents aged between 11-15 report to have been bullied by other children, see Understanding Society (2013). The high incidence of being bullied amongst children makes it important to understand the effects of being bullied, including the long-term effects on adult SWB.

Secondly, research exploring the long-term effects of childhood for SWB in adulthood is important because it can inform policymakers about when to intervene to promote SWB over the life course. For instance, if being bullied as a child has a negative effect on adult SWB then policymakers may wish to intervene to prevent bullying in schools. Whereas, if being bullied as an adult negatively affects adult SWB then policymakers

[8] The Office for National Statistics collects statistics relating to each of the 3 components of SWB: affective, eudemonic, and evaluative. Affective well-being relates to momentary mood, eudemonic well-being relates to feelings of purpose, and evaluative well-being relates to an individual's assessment of their life overall (or a specific domain, such as their job), see Dolan and Metcalfe (2012). The 4 measures of SWB collected by the Office for National Statistics are: "overall, how satisfied are you with your life nowadays?", "overall, to what extent do you feel the things you do in your life are worthwhile?", "overall, how happy did you feel yesterday?", and "overall, how anxious did you feel yesterday?". For further information about the SWB measures collected by the Office for National Statistics, see Office for National Statistics (2016c).

[9] Section 1.2 summarises the measures of SWB and mental health used in this thesis and discusses their relation to utility.

[10] Henceforth, we utilise the terms being bullied and bullying victimisation interchangeably.

may wish to intervene in the workplace by promoting good worker behaviour and human resources practices, for example.

The second empirical chapter makes use of panel data from the UK to explore how the mental health of adolescents affects their antisocial behaviour (ASB)[11]. It is important to understand the effects of the mental health of adolescents on their participation in ASB for several reasons. Becker (1968) argued that people engage in crime if their perceived expected utility from participating in crime outweighs their perceived expected utility from legal activities.[12] Marco et al. (2009) suggest that externalising mental health problems such as ADHD are characterised by reduced self-control and lower discount rates. For this reason, adolescents who have greater symptoms of ADHD may more heavily discount the future repercussions of their behaviour, thus increasing their participation in ASB, see Fletcher and Wolfe (2009). Moreover, people who have internalising problems such as anxiety are more likely to view the future as uncertain, (see Macleod, 1999; Liao and Wei, 2011). As a result, Anderson et al. (2015) argue that individuals who have anxiety may have a lower assessment of their life expectancy and may be more likely to discount the future consequence of their actions. Consequently, individuals who have internalising problems may be more likely to engage in ASB. Hence, it is important to explore the effects of the mental health of adolescents on whether they commit ASB to shed light on these implications of Becker's theory.

The final empirical study uses cross-sectional data to explore the effects of three large-scale, unanticipated natural disasters on SWB in the US. The natural disasters under consideration are the Indian Ocean tsunami in 2004, Hurricane Katrina in 2005, and the 2010 Haiti earthquake. To explore the effects of natural disasters on SWB in the country of the disaster we investigate how Hurricane Katrina affected SWB in the US. We also explore the effects of the 2004 Indian Ocean tsunami and the 2010 Haiti earthquake, which occurred thousands of miles away from the US. Hence, we are able to compare the effects of natural disasters on SWB in the country of the disaster with the effects on the SWB of people who do not live in the country that was affected by the disaster.

Research exploring the effects of natural disasters on SWB in the area that was affected by the disaster is important for informing government responses to natural disasters. If natural disasters adversely affect the SWB of those individuals who live in

[11] Chapter 3 also explores how the mental health of parents, as measured by the General Health Questionnaire, affects the ASB of adolescents. For brevity, we discuss the findings in Chapter 3.

[12] Crime is defined as "an action or omission which constitutes an offence and is punishable by law", see Hawker et al. (2012) (p. 164). In contrast, The Police Reform and Social Responsibility Act (2011), Chapter 13 defines ASB as "behaviour by a person which causes or is likely to cause harassment, alarm or distress." (p. 63). However, the distinction between crime and ASB is unclear because the term ASB may encompass a number of minor crimes, such as vandalism, see Harradine et al. (2004). Due to the fuzzy distinction between crime and ASB, we make use of the term ASB to refer to both ASB and minor crime committed by adolescents.

the disaster area then policymakers may wish to intervene in the immediate aftermath to support those individuals who were adversely affected. For example, mental health service providers may offer counselling to individuals who are suffering distress due to the disaster.

It is particularly interesting to explore the effects of natural disasters on the SWB of individuals who live far from the disaster area to explore the interdependence of utility functions. Economics assumes that utility depends primarily upon the utility of the individual, and secondly upon the utility of the members of their family, see Becker (1981). Further, economics generally assumes that utility is independent of that of strangers[13]. Natural disasters, such as the Indian Ocean tsunami and the Haiti earthquake were vast, unanticipated, negative shocks to millions of people living thousands of miles from the US.[14] Consequently, exploring the effects of the Indian Ocean tsunami and the Haiti earthquake on SWB in the US allows us to explore how utility is affected by that of strangers.

The three empirical chapters presented within this thesis each explore important topics relating to SWB and mental health. There are several key links between the empirical chapters of this thesis. Firstly, each of the chapters explores "negative" areas relating to SWB and mental health. Secondly, the first empirical chapter investigates how "negative" events in childhood affect SWB as an adult, or, how adult SWB is affected by "*what others do to you*" during your childhood. In comparison, the second empirical chapter investigates the effects of mental health on the ASB of adolescents, i.e. how mental health affects "*what you do to others*".

Thirdly, the first and the final empirical chapters explore how "negative" events affect SWB. The first empirical chapter investigates the consequences of "negative" events in childhood for adult SWB. In contrast with the first empirical chapter, the final empirical chapter explores how the wider context of world events affects SWB. In other words, how "*what happens to others*" affects your own SWB. Finally, it is important to acknowledge that each of the chapters of this thesis make use of non-experimental methods and therefore the findings should be viewed as associative or predictive in nature, rather than causal.

[13] One exception relates to the charitable giving literature, which is discussed in Chapter 4.

[14] Athukorala and Resosudarmo (2005) estimate that the Indian Ocean tsunami killed approximately 216,683 people and displaced a further 1.99 million people. Peek and Erikson (2008) suggest that Hurricane Katrina killed approximately 1,800 people and displaced a further 1.5 million. Data from the United Nations General Assembly (2011) estimates that the Haiti earthquake killed approximately 222,570 people and displaced approximately 2.3 million people.

1.2 Structure and Content of the Thesis

The three empirical studies of this thesis are presented in Chapters 2 to 4. All of the studies utilise individual level data and micro-econometric methods to explore distinct, yet related, hypotheses relating to the determinants and consequences of well-being and mental health. Thus, each of the studies constitutes an independent empirical investigation. This thesis makes use of a number of different measures of SWB and mental health, depending upon the research question investigated and the availability of data. Chapter 2 makes use of two measures of SWB: life satisfaction and the Rutter Malaise Inventory. Life satisfaction is a global retrospective judgement of one's life and is thus typically considered to be a measure of evaluative/ cognitive well-being, (see Dolan and Metcalfe, 2012). Life satisfaction is likely to most closely reflect "remembered utility" because it requires people to recall their lives so far and to provide a judgement, (see Kahneman and Krueger, 2006). Remembered utility relates to people's recollections of experiences after they have taken place, in contrast to experienced utility which relates to people's feelings about experiences in real-time, (see Kahneman et al., 1997)[15]. The Rutter Malaise Inventory, a measure of affective well-being, is an index that is composed of 9 items (see Section 2.3.2) that measure the respondent's symptoms of psychological distress or depression, see Rutter et al. (1970). Arguably, the Rutter Malaise Inventory is closest to a measure of remembered utility because it relates to how the individual feels in general, rather than at the time of completing the survey.

The measure of the mental health problems of adolescents that is used in Chapter 3 is the Strength's and Difficulties Questionnaire (SDQ), a popular screening instrument for children's mental health problems. The SDQ is made up of four 5-item subscales: emotional problems, peer relationship problems, conduct problems, and hyperactivity/ inattention problems[16]. The emotional problems subscale is arguably the subscale that most closely relates to the utility of the child[17]. In common with the Rutter Malaise Inventory, the emotional problems subscale relates to how the adolescent feels in general and may thus be argued to be a proxy for their remembered, rather than their experienced, utility. Chapter 3 utilises the General Health Questionnaire (GHQ) as a measure of the SWB of parents. The GHQ is a screening instrument that was initially developed to diagnose psychiatric disorders

[15] It is important to note that life satisfaction has been shown to be affected in part by the current mood of the respondent. Schwarz (1987) investigated the effect of current mood on life satisfaction using a laboratory experiment. Prior to the respondents completing the questionnaire, the author asked them to photocopy a sheet of paper. For a randomly chosen half of the sample, a dime was placed on the photocopier. Reported life satisfaction was substantially higher for survey respondents who found the dime, thus suggesting the importance of momentary mood in affecting life satisfaction.

[16] The former two subscales relate to internalising mental health problems (mental health problems directed at the individual) and the latter two subscales relate to externalising mental health problems (mental health problems directed at others). The statements of the SDQ are presented in Table 3.4.

[17] The statements of the emotional problems subscale relate to worries, fears, unhappiness, nervousness, and headaches.

such as depression, see Goldberg and Williams (1988). The GHQ is arguably a measure of remembered utility because it reflects people's emotions "recently", rather than at the time of the interview.

Chapter 4 utilises one measure of SWB, which relates to the number of days of poor self-reported mental health (stress, depression, and problems with emotions) in the past 30 days. Arguably, the number of days of poor self-reported mental health may most closely reflect an individual's remembered utility, because the individual is required to recall their feelings over the past month[18].

Chapter 5 provides the overall conclusions of the thesis. A summary of the content and findings of Chapters 2 to 4 is outlined below.

1.2.1 Overview of Chapter 2

This chapter explores how "*what others do to you*" affects SWB as an adult. The empirical analysis of Chapter 2 utilises cohort data drawn from the UK National Child Development Study (NCDS) to explore the effect of bullying victimisation at age 11 on adult SWB. The dependent variables are life satisfaction and the Rutter Malaise Inventory (a measure of psychological distress or depression), see Rutter et al. (1970)[19].

Due to the ordered nature of the SWB variables, the empirical analysis of Chapter 2 uses two alternative approaches: random effects ordered probit models and random effects models that treat SWB as continuous. We account for several methodological issues that may arise when investigating the effect of being bullied at age 11 on adult SWB: reverse causality, omitted variable bias, and sample selection bias. Reverse causality may occur if individuals who are unhappy are more likely to be bullied as children. The measure of bullying is reported when the child is aged 11, in advance of the reporting of the SWB variables. For this reason, by construction, the effects of bullying victimisation cannot suffer from reverse causality.

Secondly, omitted variable bias may occur if unobserved childhood characteristics affect the probability that an individual is bullied and affect their SWB as an adult. To help reduce the likelihood of omitted variable bias, we control for the child's mental health problems at age 7 and their birth-weight to account for pre-existing differences between children who are bullied and those children who are not bullied. As well as conditioning upon these important childhood variables, following Mundlak (1978), we

[18] Note that all of the measures of SWB and mental health utilised in this thesis relate to remembered utility, rather than experienced utility. This likely reflects a dearth of measures of experienced well-being in large scale social surveys. One exception relates to the "Mappiness" data source, which allows respondents to record how happy, relaxed, and awake they feel at that particular moment, who they are with, and what they are doing. Bryson and MacKerron (2017) use the "Mappiness" data source to suggest that people are less happy when at work than when taking part in all 38 other activities (except for being sick in bed).

[19] Hereafter, we refer to the Rutter malaise index as total malaise.

include the within-person averages of the time-varying adult control variables. Mundlak averages are included to account for fixed unobserved heterogeneity, which may affect both adult SWB and the likelihood of being bullied. In addition, we make use of two stage residual inclusion (2SRI) models and Hausman tests to test for endogeneity, see Terza et al. (2008).

Thirdly, sample selection bias may occur if individuals who suffered the greatest psychological harm from being bullied have the greatest likelihood of being absent from the estimation samples. Sample selection bias may therefore bias the effects of bullying victimisation on SWB as an adult towards zero, leading to an underestimation of the psychological harm resulting from being bullied. We correct for sample selection bias using linear Heckman models.

The empirical findings of Chapter 2 suggest that bullying victimisation at age 11 has an adverse effect on life satisfaction and total malaise in adulthood. The estimated effect of being bullied on life satisfaction is large in magnitude: approximately 30% of the estimated effect of unemployment. In addition, individuals who were bullied have approximately 0.18 points lower total malaise, roughly 12% of a standard deviation lower SWB. To test the robustness of our results we correct for sample selection bias using linear Heckman selection models, though doing so leads to little substantive change in the findings. Additionally, Hausman tests provide no evidence to suggest that the estimates are affected by omitted variable bias, supporting the case that they are due to the effect of being bullied. Hence, the empirical findings of Chapter 2 suggest that government policies to prevent bullying in childhood may increase SWB in adulthood.

1.2.2 Overview of Chapter 3

Chapter 3 focuses on how mental health affects "*what you do to others*". Using UK longitudinal data from Understanding Society, we explore the effects of the mental health problems of adolescents on their participation in ASB. The core analysis makes use of binary dependent variables indicating whether the adolescent engages in fighting, vandalism, shoplifting, and truancy. We measure the mental health of adolescents using the Strengths and Difficulties Questionnaire (SDQ), a broad measure of children's mental health problems, see Goodman (1997). Additionally, we explore the relative effects of internalising and externalising mental health problems on ASB. Finally, as an extension, we investigate the effects of the mental health of adolescents on their participation in harmful substance use and prosocial behaviour.[20]

We implement three methodological approaches to explore the effects of the mental health of adolescents on their participation in ASB: random effects probit models, multivariate probit models, and conditional logit models. Initially, we investigate the

[20] The measures of harmful substance use are drinking alcohol, smoking cigarettes, and taking drugs; and the measures of prosocial behaviour are volunteering, and helping with housework.

effects of the mental health of adolescents on their ASB using random effects probit models. However, the decisions to participate in the four ASBs are likely to be related via unobserved characteristics that jointly affect participation in each of the ASBs. Consequently, we extend the existing literature by making use of multivariate probit models to increase the efficiency of our estimates. In addition, the estimated effects of mental health on ASB may suffer from omitted variable bias if unobserved variables (such as family socioeconomic status) affect both mental health and whether adolescents participate in ASB. As a result, we explore the robustness of the findings by using conditional logit models to account for unobserved variables (such as family socioeconomic status) that affect both the mental health of adolescents and their ASB.

The findings suggest that poorer overall mental health of adolescents is positively associated with the probability of participating in fighting, vandalism, shoplifting, and truancy. In addition, the results from the random effects probit, multivariate probit, and conditional logit models suggest that the propensity of adolescents to externalise is positively associated with the probability that they engage in ASB. In contrast, the results from the random effects probit and multivariate probit models suggest that the propensity to internalise is positively associated with fighting behaviour, but has no statistically significant effect on vandalism, shoplifting, and truancy. The results from conditional logit models show no statistically significant effect of internalising problems on participation in fighting, vandalism, shoplifting, and truancy.

Bergman and Andershed (2009) show that adolescents who commit ASB have a greater likelihood of engaging in crime as adults. For this reason, mental health interventions to reduce the externalising problems of adolescents may help to reduce future crime. For example, Gevensleben et al. (2009) show that neurofeedback helps to relieve symptoms of externalising problems in 8-12 year olds.[21] Also, the findings indicate that externalising problems of adolescents are positively (negatively) associated with the probability of participating in harmful substance use (volunteering) in the next wave. Consequently, the results suggest that externalising mental health problems of adolescents may have detrimental effects on their behaviour, by increasing engagement in "negative" behaviours, and reducing engagement in "good" behaviours.

1.2.3 Overview of Chapter 4

Chapter 4 analyses the effects of "*what happens to others*" on SWB. The empirical analysis explores the effects of three natural disasters on the SWB of Americans and investigates how their effects varied by proximity to the areas that were directly affected. The natural disasters are the 2004 Indian Ocean tsunami, Hurricane Katrina in 2005, and the 2010 Haiti earthquake. We investigate the effects of the natural disasters using data from the Behavioural Risk Factor Surveillance System (BRFSS). The

[21] Neurofeedback is a mental health treatment that aims to improve control over brain activity patterns.

dependent variable is the number of days of poor self-reported mental health in the past 30 days.

To investigate the effects of the natural disasters on SWB in the US we make use of a difference-in-difference approach. We account for the large proportion of individuals who report 0 days of poor mental health using a zero inflated negative binomial model. In addition, we extend Zahran et al. (2011) by utilising placebo tests to test for common trends prior to each of the natural disasters.

Chapter 4 presents two important findings. Firstly, in common with the previous literature, the first finding suggests that Hurricane Katrina adversely affected the SWB of Americans living in the states that were affected by the disaster. This finding illustrates the importance of government intervention in the immediate aftermath of natural disasters to help alleviate the adverse effects of the disasters on the SWB of people living in the affected areas. For instance, suitable mental health counselling could be provided to people who are suffering distress and unhappiness in the aftermath of natural disasters.

The second finding suggests that the Indian Ocean tsunami and the Haiti earthquake increased the SWB of Americans living in the states closest to the areas that were directly affected. We argue that this paradoxical finding may be due to the interdependence of utility. In the immediate aftermath of the disasters, Americans may have viewed the widespread media coverage of the disasters and thought about the shocking implications of the disasters for the disaster victims. For this reason, Americans living closest to the areas that were directly affected may have favourably compared themselves to the victims of the disasters, thus leading to increases in their SWB. The positive SWB effect may reflect gratitude for not having been affected directly.

The empirical findings of Chapter 4 cast doubt upon the independence of the utility functions of strangers, an assumption generally made in economics. Brown et al. (2015) show that the relative income effect is highly sensitive to whether the reference group is defined as "*people like you*" or "*people near you*". As a result, Chapter 4 also explores whether the effects of the Indian Ocean tsunami and the Haiti earthquake were more pronounced for individuals of the same ethnicity as the disaster victims. The empirical results do not suggest that this was the case. Thus, the results support the case that proximity to the affected area, rather than sharing similar characteristics to the disaster victims, may determine the effects of natural disasters on the SWB of individuals who live outside of the disaster area. In other words, the findings suggest that following natural disasters in other countries you are more likely to compare yourself to "*people near you*" rather than "*people like you*".

Chapter 2: Adult Subjective Well-being and Childhood Bullying Victimisation

2.1 Introduction

In this chapter, we investigate the effects of bullying victimisation in childhood on subjective well-being (SWB) as an adult using cohort data from the UK. We therefore explore how "*what others do to you*" as a child affects SWB as an adult.

2.1.1 Motivation

It is important to investigate how being bullied as a child affects SWB as an adult for several reasons. Firstly, as previously discussed in Section 1.1, over the past few decades a large, interdisciplinary literature has developed which studies SWB. Predominantly, this literature has investigated how SWB is affected by adult outcomes such as unemployment and marital status, (see, for example Clark and Oswald, 1994; Stutzer and Frey, 2006).[22] Additionally, the research in this field has investigated how SWB affects other outcomes such as future income, risk-avoiding behaviour, and longevity, (see De Neve and Oswald, 2012; Goudie et al. 2014; Danner et al., 2001). However, there remains relatively little literature exploring the effects of childhood on SWB as an adult. Bullying victimisation is a relatively common experience and it is therefore important to explore the effects of being bullied as a child on adult SWB to contribute to the literature exploring the long-term effects of childhood for SWB as an adult.

Secondly, as outlined in Chapter 1, increasing the SWB of the population is becoming an increasing focus of public policy, (see Stiglitz et al., 2009; Cameron, 2006). For this reason, it is important to understand the factors that influence SWB and the relative magnitudes of their effects. This will help shape government policies to improve the SWB of citizens in the most cost-effective way.

Thirdly, this avenue of research matters because it can help to inform policymakers regarding when policy intervention should take place in order to promote SWB throughout the life course. For example, in the event that childhood bullying victimisation adversely affects adult SWB then policymakers may wish to intervene to prevent bullying in schools. Similarly, if being bullied as an adult reduces SWB then policymakers may wish to target the bullying of adults, by promoting good worker behaviour and human resources practices, for example.

[22] For an overview of the literature exploring the effects of adult outcomes on SWB, (see Dolan et al., 2008; Stutzer and Frey, 2010).

Fourthly, understanding the role of childhood in influencing adult SWB is of increasing importance following increases in life expectancy. OECD (2011) data shows that between 1983 and 2008, the life expectancy of OECD countries rose by an average of 6 years. Greater longevity means that people have longer to benefit from, or suffer the consequences of, the effects of their childhood for their SWB as adults.[23] For this reason, a utilitarian perspective suggests that higher life expectancy strengthens the case for understanding the long-term effects of childhood for SWB as an adult.

Fifthly, a large interdisciplinary literature has explored the effects of childhood on a wide range of adult outcomes. For example, Fronstin et al. (2001) investigate how parental divorce affects adult labour market outcomes such as employment status and income. This literature is relevant because it shows that childhood can have important long-term consequences for outcomes in later life. For this reason, to promote SWB over the life course it is essential for policymakers to understand how childhood affects adult SWB, as well as understanding the role of adult outcomes.

Finally, bullying is a common feature of childhood in countries worldwide. For example, Understanding Society data from 2013 suggests that approximately 19% of a sample of 4,427 children aged 11-15 from the UK report to have been bullied by other children, see Understanding Society (2013). Furthermore, in 2010 across 29 high-income countries, the average proportion of children aged 11-15 who report to have been bullied by other children was approximately 28%, see Adamson (2013). Bullying is also prevalent amongst children who live in low and middle-income countries. For instance, Fleming and Jacobsen (2010) use a sample of 91,398 children aged 13 to 15 who were interviewed from 2003 to 2006. The authors suggest that approximately 34% of children from 19 low and middle-income countries report to have been bullied by other children. The prevalence of bullying across the world therefore makes it important to understand both the short-term and the long-term consequences of bullying victimisation, including the effect of being bullied on adult SWB.

2.1.2 Summary of the Findings

We investigate the effect of being bullied at age 11 on two proxies for adult SWB: life satisfaction and total malaise. The results suggest that bullying victimisation has a large, adverse effect on both measures of SWB. The magnitudes of the estimated effects of being bullied on life satisfaction are approximately 30% of the magnitude of the estimated effect of unemployment on life satisfaction. The existing literature has established that unemployment has a large, adverse effect on life satisfaction, see Kassenboehmer and Haisken-DeNew (2009), for example. In addition to the sizeable adverse effect on life satisfaction, bullying victimisation at age 11 is associated with an

[23] It is important to note that the influence of being bullied on SWB may not be constant, hedonic adaptation may occur. There is some evidence that hedonic adaptation occurs following many life events. For example, Oswald and Powdthavee (2008) find substantial adaptation to disability.

8% of a standard deviation reduction in total malaise (lower SWB). The estimated effects of bullying victimisation on SWB are robust to controlling for a rich set of variables: birth-weight, mental health at age 7, and a wide range of adult characteristics. In a similar fashion, Hausman tests indicate no evidence of endogeneity. Finally, adjusting for non-response using linear Heckman sample selection models leads to little change in the findings, supporting the case that being bullied reduces SWB as an adult.

This chapter proceeds as follows. Section 2.2 reviews the literature from economics and psychology that explores the determinants of whether children are bullied. Also, Section 2.2 discusses the evidence from psychiatry exploring the effects of bullying victimisation on the mental health of children. Thirdly, we analyse the existing literatures from economics, psychiatry, and public health exploring the effects of childhood on adult SWB. Finally, Section 2.2 reviews the literature from economics and psychology exploring the effects of bullying victimisation on educational attainment and adult labour market outcomes. Section 2.3 discusses the data, the samples, the dependent variables, the measures of bullying victimisation, and the summary statistics. Section 2.4 outlines the methods, empirical specifications, and the steps taken to address the issues of endogeneity and non-response. As well as interpreting the main results, Section 2.5 investigates whether the effect of bullying victimisation on SWB is dependent upon the frequency that an individual is bullied. Sections 2.6 and 2.7 discuss the findings from robustness checks for endogeneity and non-response, respectively. Section 2.8 concludes.

2.2 Literature Review

2.2.1 The Determinants of Whether a Child is Bullied: Evidence from Economics and Psychology

There are relatively few studies of the determinants of whether a child is bullied. An exception from economics is Brown and Taylor (2008) who use a subsample of 8,477 individuals from the National Child Development Study (NCDS) to explore the determinants of being bullied. Their measure of bullying victimisation was recorded when the child was age 11 and denotes whether the individual was reported by their mother to have been never bullied, sometimes bullied, or frequently bullied. Using an ordered probit model, they find that the probability of bullying victimisation at age 11 is positively associated with being male, being unattractive, having greater mental health problems, and being easily upset by new environments. Children who were bullied at age 7 were more likely to be bullied at age 11 thus indicating the persistence of bullying between these ages. The authors do not find any statistically significant effects of any school or family characteristics on the likelihood of being bullied at either age 7 or age 11.

One area that Brown and Taylor (2008) do not explore concerns the role of personality. In contrast, in the psychology literature, Tani et al. (2003) investigate the relationship between being bullied and the "big five" personality characteristics. To explore this issue, they use a sample of 232 schoolchildren who were aged 8 to 10 drawn from two primary schools in Central Italy. The big five personality characteristics, as identified by Costa and McCrae (1992) are: extraversion, agreeableness, openness, neuroticism, and conscientiousness. Using multivariate analysis of variance techniques, Tani et al. (2003) find that children who are bullied tend to have low conscientiousness, high emotional instability and a high degree of neuroticism. However, these characteristics were observed at the time of being bullied, rather than prior to being bullied. For this reason, it may be argued that these characteristics may be a consequence of, instead of the cause of, bullying victimisation.

2.2.2 The Effects of Being Bullied on Child Mental Health: Evidence from Psychiatry

Arseneault et al. (2008) investigate the effects of being bullied on internalising problems. The authors use the Environmental Risk Longitudinal Twin Study dataset, containing 1,116 pairs of identical twins born in England and Wales from 1994 to 1995. Their mothers reported whether the twins were bullied when the twins were aged 10. Internalising problems were measured by summing the Internalising Problems Scales from the Achenbach (1991a) "Child Behaviour Checklist" and the Achenbach (1991b) "Teacher's Report Form". The "Child Behaviour Checklist" and "Teacher's Report Form" are answered by the child's mother and teacher, respectively. The Internalising Problems Scales are the sum of the responses to statements such as "cries a lot" and "worries". These statements are used to assess the child's symptoms of depression, anxiety, and social withdrawal.

Conditioning upon their pre-existing internalising problems at age 7, Arseneault et al. (2008) find that twins who had been bullied between ages 7 and 9 had more internalising problems at the age of 10 relative to twins who were not bullied. The authors use a fixed effects model to estimate the effect of being bullied on internalising problems. This approach uses variation in the experiences of being bullied within pairs of twins. Hence, Arseneault et al. (2008) demonstrate one mechanism via which childhood bullying victimisation may affect SWB, namely, by increasing the number of internalising problems of an individual.

In a similar vein, Kaltiala-Heino et al. (2000) use Finnish data on 26,430 adolescents aged 14 to 16 from the School Health Promotion Study to explore the effects of being bullied on mental health problems. The authors use a self-reported bullying variable concerning the individual's experience of being bullied during the past school term. Using logit models, they show that anxiety and psychosomatic symptoms were more common amongst children who were bullied than children who were not. However, note that this may be due to unobserved factors that affect both a child's likelihood of being bullied and their likelihood of having anxious and psychosomatic symptoms.

2.2.3 The Effects of Childhood on Adult Subjective Well-being: Evidence from Economics, Psychiatry, and Public Health

There is relatively little evidence exploring how childhood affects SWB as an adult. One exception from economics is Frijters et al. (2014) who use the NCDS to investigate how childhood characteristics predict adult life satisfaction. The authors find that having a lower birth-weight, more mental health problems (at ages 7, 11 and 16) and certain personality traits at age 16 (such as being timid) predict substantially lower adult life satisfaction. They estimate that between 30-45% of the variation in adult life satisfaction is fixed whilst the remaining 55-70% is transitory. In other words, 30-45% of the variation in adult life satisfaction is due to factors that do not vary in adulthood, whilst the remaining 55-70% can be attributed to characteristics that vary in adulthood. Thus, factors that are fixed as an adult play an important role in determining adult life satisfaction. In addition, the authors find that lower adult life satisfaction is predicted by lower teacher-assessed cognitive ability at age 7 and poorer mental health at ages 7 and 11.

Frijters et al. (2014) use the Bristol Social Adjustment Guide (BSAG) as a measure of the mental health problems of a child.[24] They deploy a sequential modelling approach to build up a set of explanatory variables, beginning by only using information available at birth. Frijters et al. (2014) then sequentially include variables observed when the individual was aged 7, 11 and 16, including measures of social class, health, and both cognitive and non-cognitive skills. For example, Frijters et al. (2014) control for mental health problems at ages 7 and 11. The authors argue that the inclusion of repeated measures of the same variables may increase the rate of false positives (i.e. of falsely rejecting the null hypothesis). To address this problem, Frijters et al. (2014) use P-values of 0.005, lower than the conventional P-values that are used for samples of this size. This approach to addressing the multiple comparisons problem was first proposed by Benjamini and Hochberg (1995). Note that the use of lower P-values reduces the probability that they find their explanatory variables to be statistically significant. Finally, note that the authors do not attempt to isolate the causal effect of childhood characteristics on adult life satisfaction; the model simply allows a predictive or associative interpretation.

[24] The BSAG is described in detail in Section 2.4.

A further contribution from the economics literature is Layard et al. (2014) who estimate a life course model of SWB using data from the 1970 British Cohort Study. The life course model of Layard et al. (2014) explores how both outcomes as a child and outcomes as an adult affect life satisfaction at age 34. Their model investigates how children's emotional health (i.e. internalising problems), conduct (i.e. externalising problems), intellectual performance, and family background predict their life satisfaction at age 34.[25] They measure the internalising problems and externalising problems of the child using the Rutter Behaviour Scale, which was reported by the mother. The findings of Layard et al. (2014) suggest that the best childhood predictor of life satisfaction at age 34 is the internalising problems of the child, followed by the externalising problems of the child. Their findings also indicate that the least powerful childhood predictor of life satisfaction at age 34 was the intellectual performance of the child. Hence, the results of Layard et al. (2014) reinforce the case that the mental health of children affects their SWB as an adult.

One particular paper of interest from the psychiatry literature is Takizawa et al. (2014). Using a sample of 7,771 observations drawn from the UK NCDS, the authors investigate the long-term effects of being bullied on a wide range of measures of well-being at ages 23, 33, 42, 46 and 50. The analyses of Takizawa et al. (2014) were performed using ordered logit and linear regression models. Their findings indicate that being bullied in childhood is associated with lower life satisfaction, poorer social relationships, greater depression, a lower likelihood of living with a spouse or partner, greater anxiety, greater economic hardship, and being more likely to have suicidal thoughts.

In their analysis, Takizawa et al. (2014) control for the child’s intelligence quotient, the father’s occupation, the child’s experience of being in care, the degree of parental involvement, and a range of (retrospectively reported) childhood adversities. These adversities are poverty, poor parental mental health, parental drug and alcohol problems, family conflict, and physical and sexual abuse. However, they do not control for adult characteristics (such as income) that have previously been shown to affect SWB, see Powdthavee (2010), for example. Omitting income may bias the estimates of the effect of bullying victimisation on life satisfaction.[26]

[25] Layard et al. (2014) measure the intellectual development, internalising problems, and externalising problems of the child at ages 5, 10, and 16. The measures of family background are the father's labour force status (averaged across ages 0, 5, and 10), father's socioeconomic group (aged 10), family income (aged 10), number of siblings (aged 10), mother's mental health (average of when the child was aged 5 and 10) and whether their parents were separated (age 10). For variables measured at multiple points in childhood they create composite variables. The coefficients of the composite variables are the sum of the separate coefficients of the variables measured at each point in time, multiplied by the standard deviation of the composite variables.

[26] This issue is explored in more detail in Sections 2.3 and 2.4.

Takizawa et al. (2014) propose several explanations for how being bullied as a child may reduce adult SWB. Firstly, childhood bullying victimisation may have an immediate and permanent effect on mental health outcomes and may thus reduce adult SWB. Secondly, bullying victimisation may lead to other forms of abuse in the future, which may reduce adult SWB directly. This explanation originates from the work of Finkelhor et al. (2007), who find that adolescents who reported to have been bullied also had an increased probability of reporting to have been victims of domestic abuse and child maltreatment. Finkelhor et al. (2007) use a nationally representative sample of 2,030 American children aged 2-17. Thus, individuals who were bullied at age 11 may report lower SWB because they experience other forms of victimisation at the time, or later in life.

Thirdly, Takizawa et al. (2014) offer a biological explanation for their findings. They suggest that reduced adult SWB may be due to blunted cortisol response amongst those who were bullied. Cortisol is a hormone secreted as a response to stress, see Van Eck et al. (1996). This mechanism is based on the findings of Ouellet-Morin et al. (2013), which suggest that twins who were bullied had lower cortisol secretion at age 10, relative to their twin who was not bullied. Ouellet-Morin et al. (2013) use a subsample of 28 pairs of twins from the Environmental Risk Longitudinal Twin Study of identical twins from England and Wales who were born between 1994 and 1995. However, note that Ouellet-Mori et al. (2013) do not offer evidence of a permanent effect of bullying victimisation on cortisol response.

The analysis of this chapter extends the work of Takizawa et al. (2014) in several ways. Firstly, unlike Takizawa et al. (2014), we test for endogeneity using Hausman tests. Secondly, we adjust for non-response using Heckman sample selection models. Thirdly, we explore the effects of childhood bullying victimisation on two measures of SWB, whereas they only consider the effects of being bullied on life satisfaction.

In the public health literature, Oshio et al. (2012) investigate the effects of being bullied on two measures of SWB, namely, self-reported happiness and subjective health. They use of a subsample of 3,292 individuals aged 25-50 drawn from the Japanese Study of Stratification, Health, Income and Neighbourhood dataset.

For their analysis, Oshio et al. (2012) utilise three-step hierarchical probit regressions. In the first step, the authors use a probit model to estimate the effect of being bullied on SWB, conditioning upon measures of adult social support and socioeconomic status. For the second step, they calculate the proportion of the effect of being bullied on adult SWB that is due to the indirect effect of bullying victimisation on social support and socioeconomic status. This is called mediation analysis, for details, see Baron and Kenny (1986). In the final step, the authors use interaction terms to investigate whether the effect of being bullied on SWB as an adult is dependent on an individual's social support and socioeconomic status. Oshio et al. (2012) use three measures of social support: emotional support (offers of concern), instrumental support (material assistance), and negative support (excessive demands and criticism).

In the first step, Oshio et al. (2012) find a negative correlation between bullying victimisation and self-reported happiness. Using mediation analysis, the authors find that approximately 39% of the effect of bullying victimisation on self-reported happiness results from the effect of being bullied on adult social support and socioeconomic status. In the third step, Oshio et al. (2012) find no evidence that having a high socioeconomic status or extensive social support as an adult ameliorates the effects of being bullied on adult SWB. However, their results may suffer from reverse causality because of the use of retrospectively reported accounts of childhood bullying victimisation. If less satisfied adults are more likely to remember being bullied, the estimated effect of being bullied on adult SWB may be biased, see Hardt et al. (2006).

In the economics literature, Powdthavee (2012) uses data from the British Household Panel Survey (BHPS) to investigate whether the reduction in SWB from being unemployed is dependent upon their fear of bullying as a child. Their analysis is carried out using self-reported fear of bullying data from the BHPS youth questionnaire. The BHPS youth questionnaire interviews 11-15 year olds and then collects data on their SWB when they complete the adult questionnaire from age 16 onwards. The fear of bullying variable is derived from the question "How much do you worry about being bullied at school?": "not at all", "a little", and "a lot".

The author’s findings indicate that when adults who reported "a lot" of worry about being bullied as children became unemployed they suffered a reduction in life satisfaction that was approximately 4 times as large as the reduction experienced by adults who had reported little fear of bullying. Additionally, individuals who experienced fear of bullying as a child showed no signs of hedonic adaptation to being unemployed. In other words, their second year of unemployment was as miserable as their first year. In comparison, for individuals who experienced no fear of bullying during childhood there was strong evidence of adaptation to unemployment.

However, Powdthavee (2012) utilises the BHPS, which contains no data on the child’s actual experience of bullying victimisation. Instead, Powdthavee uses the child’s reports of whether they experienced lots of fear of bullying. This measure has several drawbacks. Firstly, the fear of bullying that a child reports may be affected by their personality characteristics, such as their timidity, which may affect their loss of SWB from unemployment. For this reason, their measure of fear of bullying may not reflect the child’s actual experience of being bullied.

Secondly, even if the "fear of bullying" variable does reflect the child’s actual experience of bullying victimisation, these results do not demonstrate causality. Arguably, factors such as personality traits may determine both whether an individual is bullied and the loss of SWB they experience when they become unemployed.

Powdthavee (2012) tests this using interaction terms between being unemployed and the big five personality types: extraversion, agreeableness, openness, neuroticism, and conscientiousness. However, this has little effect on his findings: individuals who experienced lots of fear of bullying still suffer greater psychological harm from being unemployed.

Making use of child self-esteem as a dependent variable, Powdthavee (2012) estimates a fixed effects model to test whether fear of bullying reduces self-esteem, finding an adverse effect of fear of bullying. However, the author is selective in his application of the Rosenberg self-esteem scale. Powdthavee measures self-esteem using an index, formed by summing the responses to six statements. Five of the statements: "I feel I have a number of good qualities", "I certainly feel useless at times", "I am inclined to feel I am a failure", "I don't have much to be proud of", and "I am as able as most people" are statements from the original 10-item Rosenberg (1979) self-esteem scale. The final statement, which is not from the Rosenberg self-esteem scale, is "I am a likeable person". However, the statement "at times I feel I am no good at all" is not used in the self-esteem index of Powdthavee (2012).[27] This statement is part of the Rosenberg (1979) self-esteem scale and is asked in all waves of the BHPS youth questionnaire, for further details, see the Institute for Social and Economic Research (2002). Arguably, the exclusion of this statement from the self-esteem index may change the effect of fear of bullying on self-esteem.

Powdthavee (2012) finds a large, negative effect of fear of bullying on self-esteem; to compensate a child's self-esteem for experiencing lots of fear of bullying requires an increase in the number of close friends the child has from 0 to 16. However, the effect of fear of bullying on self-esteem may suffer from reverse causality. For example, an exogenous reduction in self-esteem may cause some children to report more fear of bullying than others. Nevertheless, despite these limitations, the analysis of Powdthavee (2012) casts light on a possible mechanism via which bullying may affect SWB as an adult: via the indirect effect of bullying on self-esteem.

2.2.4 The Effects of Being Bullied on Educational Attainment and Adult Labour Market Outcomes: Evidence from Economics and Psychology

A small economics literature investigates the effect of being bullied as a child on educational attainment and adult labour market outcomes. This literature provides further evidence to suggest that childhood bullying victimisation has negative long-term consequences. Using data from the NCDS dataset and ordinary least squares (OLS), Brown and Taylor (2008) investigate the effect of being bullied on adult earnings, finding a direct, negative effect. Using a probit model, the authors find that individuals who were bullied have a lower probability of having a degree at age 23.

[27] The remaining four questions from the Rosenberg self-esteem scale are not asked in the BHPS youth questionnaire.

Hence, their analysis indicates both a direct and indirect effect of being bullied as a child on labour market earnings as an adult.

Also, in the economics literature, Eriksen et al. (2014) investigate the effects of being bullied on educational attainment using survey and register-based data for Danish children born from 1990 to 1992. Using the proportion of children in a child's class who are from troubled homes as an instrumental variable (IV), the authors find detrimental effects of being bullied on educational attainment at ages 15-16. What is more, they find evidence of a "dose-response" relationship between the severity that an individual is bullied and their educational attainment. In other words, individuals who were bullied more severely suffer a greater loss of human capital relative to those individuals who were bullied less severely. Their findings accord with the findings of Brown and Taylor (2008) and support the view that bullying victimisation may adversely affect human capital accumulation.

In a similar vein, in the psychology literature, Varhama and Bjorkqvist (2005) find a positive association between long-term unemployment and whether an individual was bullied during childhood. They use a sample of 68 adults from Finland who were taking part in a training programme for the long-term unemployed. 29% of the individuals in long-term unemployment reported to have been bullied on a weekly basis during childhood, relative to just 8% of adults in the general population.

However, this study has several limitations. Firstly, it uses retrospective reports of bullying victimisation, which may lead to reverse causality. Indeed, studies such as Clark and Oswald (1994) find that unemployment reduces SWB. Moreover, Bower (1981) provides experimental evidence to suggest that randomly selected individuals who were induced to feel sad were more likely to recall unpleasant memories from childhood relative to individuals who were induced to feel happy. As a result, it may be argued that the unhappiness associated with being unemployed may make unemployed individuals more likely to remember being bullied as children.

Secondly, they do not use a formal modelling strategy; they simply use F-tests to test whether the proportion of individuals in long-term unemployment who were bullied differs from the proportion that were bullied in the general population. Thirdly, the authors use a very small sample of just 68 individuals.

The existing literature surrounding the implications of bullying victimisation as a child arguably has two main problems. Firstly, a large proportion of the literature uses retrospective reports of childhood bullying and thus the results may suffer from reverse causality. Secondly, it may be argued that the literature pays too little attention to unobserved heterogeneity between children who are bullied and children who are not bullied. The steps taken to address these methodological issues are discussed in detail in Section 2.4.

2.3 Data

This chapter analyses data from the NCDS, a British cohort study.[28] The NCDS target sample contains all children born in England, Scotland, and Wales between 3rd and 9th March 1958. At wave 0 (birth), wave 1 (age 7), wave 2 (age 11) and wave 3 (age 16), the cohort member's mother, doctor, and teacher were interviewed. Following this, the cohort members were interviewed at wave 4 (age 23), wave 5 (age 33), wave 6 (age 42), wave 7 (age 46), and wave 8 (age 50). For more information on the NCDS, see the Centre for Longitudinal Studies (2013).

2.3.1 The Estimation Samples

Four estimation samples are used to investigate the effects of bullying victimisation on life satisfaction and total malaise, and a final sample is used to explore the issue of non-response. The size of each of the estimation samples is determined by the availability of the measures of life satisfaction and total malaise in the NCDS.

Firstly, Sample 1 (life satisfaction balanced panel) contains 2,774 individuals and 11,096 person-year observations: each individual is observed at ages 33, 42, 46, and 50. Secondly, in Sample 2, the life satisfaction unbalanced panel, there are 6,322 individuals and 19,200 person-year observations. Each individual in the life satisfaction unbalanced panel is observed at least once at ages 33, 42, 46 and 50, and approximately 3 times, on average.

Thirdly, Sample 3 (total malaise balanced panel) is made up of 3,254 individuals and 9,762 person-year observations: each individual is observed at ages 33, 42, and 50. Fourthly, in Sample 4 (total malaise unbalanced panel) contains 6,333 individuals and 14,907 person-year observations: each individual in this sample is observed one or more times at ages 33, 42 and 50. On average, individuals who are in the total malaise unbalanced panel are observed 2.4 times.

An individual's experience of bullying victimisation may affect their likelihood of being absent from the estimation samples. We investigate the issue of non-response using Sample 5; which contains every individual whose mother reported his or her child to be never, sometimes, or frequently bullied at age 11. Table 2.1 presents a summary of each of the estimation samples and the issue of non-response is discussed in detail in Section 2.4.3.

[28] To the author's knowledge, the NCDS is the only large UK longitudinal dataset suitable for this analysis though two alternative datasets are the British Cohort Study and the Avon Longitudinal Study of Parents and Children. The age 10 interview of the British Cohort Study asks "Do other children often break friends or fall out with you?" and "Do you think that other children often say nasty things about you?". However, these questions do not explicitly ask about bullying. Additionally, the Avon Longitudinal Study of Parents and Children is unsuitable because it is unrepresentative of the UK population, and the cohort members are currently only 25 years of age.

2.3.2 The Dependent Variables

To assess the robustness of the findings, this chapter analyses the effects of being bullied on two outcome measures: life satisfaction and total malaise. This is in contrast to Frijters et al. (2014) who only model the associations between childhood characteristics and adult life satisfaction, and to Takizawa et al. (2014) who only consider life satisfaction in their study of bullying victimisation.

Life satisfaction is generally considered a good measure of cognitive or evaluative well-being, though it does not measure affective well-being. Evaluative well-being measures are a subjective assessment by the individual of their satisfaction with life overall (e.g. life satisfaction) or their satisfaction within a specific domain (such as job satisfaction). For a detailed discussion of measures of evaluative well-being, see Dolan and Metcalfe (2012). In contrast to evaluative well-being, affective well-being is a measure of mood commonly used in the psychology literature, see Watson et al. (1988).

For an example of the use of life satisfaction as a measure of SWB, see Powdthavee (2009). For the life satisfaction measure in the NCDS, the respondents are asked "on a scale from 0 to 10, where ‘0’ means that you are completely dissatisfied and ‘10’ means that you are completely satisfied, what number corresponds with how satisfied or dissatisfied you are with the way life has turned out so far?". This question is asked at ages 33, 42, 46 and 50. Approximately 80% of adults report a life satisfaction score of 7 to 10 as illustrated by Figure 2.1.

The second dependent variable used in the analysis is total malaise, an index composed of 9 items from the 24-item Rutter Malaise Inventory, see Rutter et al. (1970). The malaise index is a measure of psychological distress or affective well-being. Specifically, the malaise index is formed by summing the answers to the following statements: whether the cohort member "feels tired most of the time", "often feels miserable and depressed", "often gets worried about things", "often gets into a violent rage", "is often suddenly scared for no good reason", "is easily upset or irritated", "is constantly keyed up and jittery", "every little thing gets on their nerves", and "if their heart often races like mad". The respondents answer yes or no in response to each of these questions. The malaise index is reversed so that 9 (answering no to all questions) denotes the lowest distress (highest SWB), and 0 (answering yes to all questions) indicates the highest distress (lowest SWB). We reversed the total malaise index to aid the comparison of the effects of being bullied across the two measures of SWB used in this analysis.

Figure 2.1 shows that approximately 70% of observations report a total malaise score that ranges from 7 to 9. The malaise index is recorded at ages 33, 42, and 50, but is not recorded at age 46. Rutter et al. (1970) state that the Rutter Malaise Inventory "differentiates moderately well between individuals with and without psychiatric disorder". (p.160). For a detailed discussion of the use of the Rutter Malaise Inventory in population samples such as the NCDS, see Rodgers et al. (1999). For a recent analysis of the Rutter Malaise Inventory as an indicator of SWB, see Dolan and Lordan (2013).

2.3.3 The Key Explanatory Variables

The main explanatory variable of interest is the mother's response (reported when the individual is aged 7 and 11) to the question "Is the child bullied by other children?". To gauge the frequency that the child was bullied, the mother answers with "never", "sometimes", or "frequently".

Table 2.2 presents summary statistics for the original responses to the bullying question at ages 7 and 11 and the responses for the 4 estimation samples. At ages 7 and 11, the majority of individuals were reported to have never been bullied.[29] In addition, it is evident that bullying victimisation is more prevalent at age 7 relative to age 11 in the NCDS. It is possible that this may reflect the greater susceptibility of younger children to report to have been bullied to their mother, in line with the findings of Oliver and Candappa (2003). Oliver and Candappa (2003) analyse a sample of 779 year 8 pupils (ages 12-13) and 174 year 5 pupils (ages 9-10) from 12 primary schools across the UK. Their findings indicate that the 9-10 year old pupils were more likely to state that they would report to have been bullied to their parents, relative to the 12-13 year old pupils.

It is evident that a smaller proportion of individuals were frequently bullied at age 11 in the balanced panels, relative to in the unbalanced panels. Also, in each of the estimation samples, a smaller proportion of individuals were bullied frequently at age 11, relative to the proportion of respondents to the age 11 interview. It is therefore evident that individuals who were bullied frequently have higher rates of non-response, relative to individuals who were never bullied. This may signal endogenous non-response, an issue discussed in further detail in Section 2.4.3.

There are several criticisms of the measure of bullying used in this chapter. Firstly, Takizawa et al. (2014) argue that this question is vague because it does not require the mother to consider a specific time period or definition of bullying. As a result, this may lead mothers with certain characteristics to be more likely to report that their child was bullied, regardless of whether the child was actually bullied. For example, neurotic mothers may be more likely to report that their child is bullied by other children and may be more likely to have neurotic children. If this is the case, the effects of bullying victimisation on SWB may be biased because adults who were reported to have been bullied as children may report lower SWB because they are neurotic, rather than

[29] In the age 7 (11) responses, 1.53% (2.32%) of mothers indicated that they did not know whether their child had been bullied by other children. These responses were coded as missing and omitted from the sample.

because they were bullied. However, the prevalence of bullying suggested by this variable in the NCDS dataset is similar to more recent estimates obtained by asking children directly about their experiences of bullying victimisation. For example, approximately 19% of a sample of 4,427 11-15 year olds from the UK reported to have been bullied or picked on by other children, a slightly smaller proportion than that of the NCDS. For further details, see Understanding Society (2013).

Secondly, arguably the reliability of the bullying measures is dependent on the quality of communication between the mother and their child. If communication between the mother and child is poor, this may reduce the reliability of the results. However, recent evidence presented by Oliver and Candappa (2003) suggests that 78% of year 5 pupils said it would be "very easy" or "quite easy" to talk to their parents about their experiences of being bullied. On this basis, it may be argued that this measure of bullying is likely to be a relatively accurate reflection of whether the individual was bullied as a child.

2.3.4 Bullying and Subjective Well-being: Summary Statistics

Table 2.3 contains summary statistics showing the association between being bullied at age 11 and the two measures of SWB, namely life satisfaction and total malaise. These summary statistics are presented for Sample 1 (the life satisfaction balanced panel), Sample 2 (the life satisfaction unbalanced panel), Sample 3 (the total malaise balanced panel), and Sample 4 (the total malaise unbalanced panel). Note that the total malaise index is reversed and therefore higher scores represent higher, rather than lower, SWB.

In Sample 1, individuals who were frequently bullied have an average life satisfaction score of 6.97, 0.59 points lower than individuals who were never bullied. This difference is approximately one third of the standard deviation of the life satisfaction variable. Also, note that life satisfaction is inversely associated with the frequency of bullying victimisation. On average, adults who were frequently bullied report lower life satisfaction (6.97 points) relative to adults who were sometimes bullied (7.36 points). In a consistent fashion with the findings for Sample 1, there is also an inverse association between the frequency of bullying victimisation and life satisfaction in Sample 2. Thus, in both the balanced and unbalanced panels, the frequency of bullying victimisation at age 11 is negatively correlated with adult life satisfaction. The differences in life satisfaction between each of the three groups are statistically significant at the 5% significance level.

In Sample 3, individuals who were frequently bullied at age 11 have an average total malaise score of 7.24, 0.48 points lower than individuals who were never bullied. Also, individuals who were sometimes bullied have an average malaise score of 7.52. The findings relating to the Sample 4 indicate an inverse association between the frequency that an individual was bullied and their total malaise. The differences in the mean malaise scores are all statistically significant at the 5% significance level.

The summary statistics contained in Table 2.3 indicate a negative correlation between the frequency that an individual was bullied at age 11 and both indicators of SWB. Additionally, note that SWB is typically higher in the balanced, relative to the unbalanced, panels. Moreover, note that the difference in SWB between the balanced and unbalanced panels is larger for individuals who were frequently bullied at age 11. A plausible explanation for this is endogenous non-response; the individuals who suffered the greatest reduction in well-being from being bullied may be the most likely to drop out of the survey.

2.4 Methodology

2.4.1 Empirical Specifications and Estimation Methods

Equation (2.1) is a fixed effects estimator, accounting for time invariant unobserved heterogeneity as follows:

$$SWB_{it} = \beta_0 + \beta_1 Bull_{i11} + \boldsymbol{\beta X}_{it}^{a} + a_i + \varepsilon_{it} \qquad (2.1)$$

SWB_{it} denotes individual i's SWB at age t, as measured by either the measure of life satisfaction or total malaise. $Bull_{i11}$ is a binary variable taking the value 1 if individual i was sometimes or frequently bullied at age 11, and 0 if they were never bullied.[30] $\boldsymbol{X}_{it}^{a}$ indicates a vector of the adult characteristics of individual i. a_i denotes an individual fixed effect: the characteristics of the individual that have a constant effect on their SWB at ages 33, 42, 46 and 50. ε_{it} represents a time and individual specific error term and β_0 denotes a constant.

The SWB variables, which were recorded from age 33 onwards, are predated by the measurement of the bullying variable (recorded at age 11). As a result, if a fixed effect estimator is used, the effects of being bullied at age 11 on SWB is absorbed into a_i. For this reason, the fixed effects estimator cannot be used to estimate the effect of bullying victimisation as a child on adult SWB. A random effects estimator is used instead, as shown by equation (2.2):

$$SWB_{it} = \beta_0 + \beta_1 Bull_{i11} + \boldsymbol{\beta X}_{it}^{a} + u_i + \varepsilon_{it} \qquad (2.2)$$

u_i indicates a randomly generated, time invariant individual effect. Unlike a_i, which may be correlated with the explanatory variables, u_i is assumed to be randomly distributed across individuals, and hence uncorrelated with the explanatory variables.

[30] For robustness, the results have also been replicated using binary variables denoting whether the individual was sometimes bullied or frequently bullied at age 11. These results are summarised in Section 2.5.3.

In the context of the effects of being bullied at age 11 on adult SWB, the random effects estimator assumes that the stable unobserved individual characteristics that affect SWB are uncorrelated with whether an individual was bullied at age 11. However, as previously discussed, the mother's report of whether the child was bullied is not exogenous: a child's characteristics may affect their likelihood of bullying victimisation. If these characteristics also affect SWB, then equation (2.2) is likely to suffer from omitted variable bias. To reduce this bias, Mundlak averages are included in the following analysis, see Mundlak (1978). Mundlak averages account for fixed individual heterogeneity that may affect both SWB and the likelihood of being bullied. The inclusion of the Mundlak averages is an alternative to using a fixed effect estimator.

Due to the nature of the dependent variable, the results from random effects ordered probit models are presented. Random effects ordered probit estimators have been used to model SWB and self-reported health data in the existing literature, (see, for example Winkelmann, 2005; Contoyannis et al., 2004). The measures of life satisfaction and total malaise are ordinal and take integer values. An individual reporting a score of 7 is assumed to have a higher level of well-being than if the same individual reports a score of 6, as argued by Ferrer-i-Carbonell and Frijters (2004). However, SWB is not measured on a cardinal scale: the difference between a score of 7 and a score of 8 may not be the same as the difference between a score of 5 and a score of 6[31]. The random effects ordered probit model applies equation (2.2) to an ordered probit specification. Due to the ordered, rather than cardinal nature of the SWB variable, a latent variable approach is used. The latent variable, SWB_{it}^{*}, is shown by equation (2.3):

$$SWB_{it}^{*} = \beta_0 + \beta_1 Bull_{i11} + \boldsymbol{\beta X}_{it}^{a} + u_i + \varepsilon_{it} \qquad (2.3)$$

Assume that the measure of SWB has J potential responses. The probability of each single response to the SWB question (denoted j) being reported by individual i is thus determined by the value of the latent SWB variable, SWB_{it}^{*}, relative to the values of the thresholds (μ_j). This is demonstrated by equation (2.4):

$$SWB_{it} = j \text{ if } \mu_{j-1} < SWB_{it}^{*} \leq \mu_j \; \forall_j = 0 \dots J \; \forall_j \text{denotes for all } j \qquad (2.4)$$

Hence, an individual's reported SWB score equals j if $SWB_{it,}^{*}$ the latent variable, lies between the threshold values of μ_{j-1} and μ_j. Therefore, assuming that the error terms (ε_{it}) follow a cumulative normal distribution, the probability that at time t, individual i reports a SWB score of j is given by equation (2.5):

[31] In contrast to measures of SWB, height is measured on a cardinal scale because the difference between a height of 150 cm and 160 cm equals the difference between heights of 160 cm and 170 cm.

$$P_{it} = P(SWB_{it} = j) = \phi\left(\mu_j - \beta_0 - \beta_1 Bull_{i11} - \boldsymbol{\beta}\boldsymbol{X}_{it}^a - u_i\right) \qquad (2.5)$$
$$-\phi\left(\mu_{j-1} - \beta_0 - \beta_1 Bull_{i11} - \boldsymbol{\beta}\boldsymbol{X}_{it}^a - u_i\right)$$

Where ϕ denotes the cumulative normal distribution. Initially, the analysis makes use of a random effects ordered probit model to estimate the effect of bullying victimisation as a child on adult SWB. Following this, for robustness, the models are re-estimated using a random effects model, which assumes that the measures of SWB are continuous. In this chapter, two specifications are estimated to cast light on the effects of being bullied as a child on adult SWB; the first is outlined by equation (2.6):

$$SWB_{it} = \beta_0 + \beta_1 Bull_{i11} + \boldsymbol{\beta}\boldsymbol{X}_{it}^a + \boldsymbol{\alpha}\mathbf{X}_{\mathrm{it}}^{\mathrm{p}} + \boldsymbol{\lambda}\overline{\boldsymbol{X}}_{\boldsymbol{it}}^a + u_i + \varepsilon_{it} \qquad (2.6)$$

$\boldsymbol{X}_{it}^a$ indicates a vector of individual i's time-varying adult characteristics at age t: household income, marital status, labour force status, disability status, and homeownership status[32]. The existing literature suggests that these characteristics affect SWB. Powdthavee (2010) finds that income has a positive effect on happiness. Thus, the log of monthly household income is included as a control variable. Stutzer and Frey (2006) find that married individuals report to be happier than unmarried individuals. For this reason, binary variables indicating whether the individual is married or cohabiting; and separated, divorced, or widowed, are included in the analysis. Single individuals form the base category. Unemployment is found by Clark and Oswald (1994) to reduce SWB. Therefore, binary variables indicating that the individual is unemployed or out of the labour force are included as conditioning variables. Employees form the base category. Also, Hu (2013) finds that homeowners tend to report higher SWB. Consequently, binary variables indicating whether the individual owns their home outright, owns their home with a mortgage, or rents privately are included as control variables. Individuals who live in "other" housing or social housing form the base category.

$\mathbf{X}_{\mathrm{it}}^{\mathrm{p}}$ denotes a vector of time invariant (permanent) and rarely changing adult characteristics: gender, ethnicity, and highest educational attainment[33]. For instance, Stevenson and Wolfers (2009) find that males report higher SWB than females and therefore a binary variable taking the value 1 if the individual is male, and 0 if female is included in the analysis. Oreopoulos (2007) finds that high school dropouts report lower SWB, relative to individuals who did not drop out of high school. As a result, binary variables indicating that the individual's highest educational attainment is a degree, A-levels, or O-levels are included in analysis. Individuals without qualifications form the base category. Oswald and Powdthavee (2008) find that individuals who have

[32] The proportion of individuals in the estimation samples for which these variables vary from age 33 to age 50 is as follows: household income (100%), marital status (23%), disability status (19%), homeownership status (45%), and labour force status (28%).
[33] The individual's highest educational attainment does not vary between age 33 and 50 for approximately 90% of the individuals in the estimation samples.

health problems which limit their daily activities report lower SWB. Unfortunately, the NCDS contains no variables detailing how an individual's health affects their ability to carry out day to day activities. Thus, as an alternative, a binary variable is included which is equal to 1 if the individual is registered disabled, and 0 if the individual is not registered disabled.

Stevenson and Wolfers (2012) find that Blacks report lower SWB than Whites. For this reason, binary variables indicating whether the individual is African, Asian or another ethnicity are used as conditioning variables. Whites form the base category. Table 2.4 contains full definitions of the variables used in this chapter and Table 2.5 presents summary statistics.

$\overline{\boldsymbol{X}}_i$ denotes a vector of Mundlak averages. The Mundlak averages are the "within-person" averages of the time-varying adult control variables. These variables are disability status, the log of monthly household income, marital status, homeownership status, disability status, and employment status. The second specification is shown by equation (2.7):

$$SWB_{it} = \beta_0 + \beta_1 Bull_{i11} + \boldsymbol{\beta X}_{it}^{a} + \boldsymbol{\alpha}\mathbf{X}_{\mathrm{it}}^{\mathrm{p}} + \boldsymbol{\lambda}\overline{\boldsymbol{X}}_{\boldsymbol{it}}^{a} + \boldsymbol{\gamma X}_{i}^{c} + u_i + \varepsilon_{it} \quad (2.7)$$

$\boldsymbol{X}_i^c$ indicates a vector of childhood characteristics: these are the individual's BSAG score (see below) at age 7 and their birth-weight. The BSAG and birth-weight variables are included to account for pre-existing differences between children who are and are not bullied. Black et al. (2007) suggest that birth-weight predicts a range of adult socioeconomic outcomes, such as educational attainment and earnings. In addition, Frijters et al. (2014) find that higher birth-weight predicts higher reported adult life satisfaction.

Frijters et al. (2014) suggest that poorer mental health as a child predicts lower adult life satisfaction. As a result, we condition upon the individual's mental health as a child, as measured by the BSAG at age 7.[34] We control for the BSAG at age 7, rather than at age 11, because bullying victimisation at age 11 cannot affect mental health problems at age 7. The BSAG questionnaire contains 11 phrases that describe a child's mental health problems and their teacher is asked to underline the phrases which best characterise the child.[35] The scores for each of these 11 "syndromes" are summed to give a total "syndrome" score, a measure of the number of mental health problems

[34] For further information on the BSAG, see Stott (1987). For other uses of the BSAG, (see Delaney and Doyle, 2012; Goodman and Sianesi, 2005; and McAllister et al., 2012).

[35] Each "syndrome score" measures the extent to which the child has a specific problem or "syndrome". Clark et al. (2007) argue that 6 of the "syndrome" scores measure externalising problems and 4 measure internalising problems. "Hostility towards children", "hostility towards adults", "inconsequential behaviour", "restlessness", "anxiety for acceptance by children" and "anxiety for acceptance by adults" are measures of the propensity to externalise. Whereas, the measures of the propensity to internalise are "depression", "withdrawal", "unforthcomingness", and the "writing off of adults and adult standards". The final "syndrome" score is "miscellaneous symptoms" which is a measure of neither internalising nor externalising problems.

associated with the child. The index is normalised so that the highest observed total "syndrome" score is equal to 1 and the lowest observed score equals 0, an approach used by Frijters et al. (2014). A value of 1 (0) denotes the individual with the most (fewest) mental health problems.

By construction, the estimate of β_1 in equation (2.7) cannot be characterised by reverse causality because the bullying variable clearly predates the SWB variables. However, equation (2.7) may still suffer from omitted variable bias. The results will suffer from omitted variable bias if the error terms of the SWB models, conditioning on a rich set of controls as well as their adult averages, still contain unobservables that affect the likelihood of being bullied at age 11.

2.4.2 Two Stage Residual Inclusion

As previously discussed, it is possible that bullying victimisation is endogenous. In other words, children who are bullied at age 11 may have unobserved characteristics that cause them to be bullied as well as reducing their adult SWB. If this is the case, this is likely to lead equation (2.7) to overestimate the psychological harm due to being bullied.

In order to account for endogeneity, we make use of 2SRI models, which are an extension of the commonly used 2SLS methodology to a non-linear framework, see Terza et al. (2008). 2SLS models are composed of two stages. In the first stage, the endogenous variable is regressed against a vector of control variables and an instrumental variable (IV). In the second stage, the predicted (fitted) values of the endogenous variable are regressed against the outcome variable and a vector of control variables[36]. However, Terza et al. (2008) demonstrate that 2SLS is inconsistent when applied to a non-linear framework and thus we utilise 2SRI models as an alternative to 2SLS. For a detailed discussion of 2SRI models, see Terza et al. (2008).

The first stage of 2SRI, as shown by equation (2.8), is identical to the first stage of the conventional 2SLS model. However, in this case, due to the dichotomous nature of the bullying variable, the first stage equation is estimated using a probit model. The estimated residuals from the first stage are then calculated by subtracting the predicted probability that the individual was bullied from the binary variable denoting whether or not the individual was bullied. In the second stage of 2SRI, the outcome variable is regressed against a vector of explanatory variables, the endogenous variable (the measure of bullying), and the estimated residuals from the first stage (bullying) equation. The 2SRI and 2SLS estimators are identical, except that in the

[36] The IV must meet the following conditions, see Wooldridge (2002). Firstly, the IV must affect the endogenous variable (e.g. bullying victimisation), after conditioning upon the explanatory variables. Secondly, the IV must have no effect on the dependent variable (e.g. SWB), other than via its indirect effect on the endogenous variable (e.g. bullying victimisation).

second stage of 2SRI the predicted (fitted) values from the first stage are not included as control variables.

The second stage of 2SRI, as shown by equation (2.9), is estimated using a non-linear estimator, in this case a random effects ordered probit model. The second stage of 2SRI is equivalent to the Hausman (1978) test for endogeneity. The Hausman test investigates whether unobserved characteristics that affect the likelihood an individual is bullied (i.e. r_i) are correlated with the unobserved characteristics that affect SWB. If τ in equation (2.9) is found to be statistically insignificant, the Hausman test indicates no evidence that endogeneity is an issue. The first and second stages of 2SRI are shown by equations (2.8) and (2.9), respectively.

$$Bull_{i11} = \boldsymbol{\rho X_i^b} + \theta Z_i + r_i \tag{2.8}$$

$$SWB_{it} = \beta_0 + \beta_1 Bull_{i11} + \boldsymbol{\beta X_{it}^a} + \boldsymbol{\alpha}\mathbf{X}_{\mathrm{it}}^{\mathrm{p}} + \boldsymbol{\lambda \overline{X}_{it}^a} + \boldsymbol{\gamma X_i^c} + \tau r_i + \varepsilon_{it} \tag{2.9}$$

$Bull_{i11}$ is a binary variable assuming the value 1 if the individual was bullied at age 11, and 0 otherwise. $\boldsymbol{X_i^b}$ denotes a vector of observable childhood characteristics that are known to determine the likelihood that children are bullied.[37] r_i denotes the estimated residuals from the "bullying equation": an estimate of the unobserved characteristics that affect an individual's likelihood of being bullied at age 11. The estimated residuals are calculated by subtracting the predicted probability that an individual is bullied from the binary variable denoting whether or not the individual was bullied. $\boldsymbol{\overline{X}_i}$ indicates a vector of Mundlak averages and $\boldsymbol{X_i^c}$ denotes a vector of childhood characteristics. Z_i is an IV and θ is the estimated effect of the IV on the likelihood an individual is bullied at age 11. ε_{it} denotes the SWB equation residuals, an estimate of the effect of unobserved characteristics on individual i's adult SWB at age t.

The IV must meet two conditions. Firstly, the IV must be uncorrelated with ε_{it}, in equation (2.9). In other words, the IV must be uncorrelated with adult life satisfaction after conditioning on the childhood characteristics, the adult characteristics, and the Mundlak averages. Secondly, after accounting for these childhood characteristics, the IV must be correlated with a child's experience of being bullied in equation (2.8), i.e. $\theta \neq 0$.

To instrument the bullying variable, a suitable IV may be a temporary physical characteristic that increases an individual's susceptibility to being bullied. If this characteristic ceases before the individual is age 33, it may have no direct effect on adult SWB, thus meeting the first condition. For example, if a child had eczema, wore

[37] In this case, the BSAG score and birth-weight are used in equation (2.9). Unlike in most IV estimation, it is not appropriate to use all the control variables from the second stage equation in the first stage because the adult characteristics are pre-dated by the child's experience of being bullied. The characteristics that Brown and Taylor (2008) found to determine an individual's likelihood of being bullied at age 11 are also included: whether the individual is male, was reported to be bullied at age 7, was upset by new environments at age 7. Being unattractive at age 7 is excluded because it reduces the available sample size by 3,200 observations.

glasses or a hearing aid, had abnormal skin, a twitch, a squirm, or a squint, it may fulfil the first condition if the individual did not have these characteristics as an adult. However, there are relatively few individuals reporting these problems in the NCDS dataset and therefore they are not suitable IVs.

Height growth between ages 7 and 11 is used as an IV in this chapter: two adults of equal height may have experienced growth spurts at different ages. The adult who had the late growth spurt may have been small relative to their peers at age 11, increasing their likelihood of being bullied. However, Steckel (1995) finds material deprivation to be correlated with slower growth spurts. If this is the case, height growth may be a poor IV because children from poorer backgrounds may become less satisfied adults, regardless of their experience of bullying victimisation. The analysis of Section 2.6 tests the validity of height growth between ages 7 and 11 as an IV.

2.4.3 Non-Response

This section discusses the approaches used to investigate the effects of non-response of individuals from the age 11 survey to the estimation samples. The four estimation samples are Sample 1 (the life satisfaction balanced panel), Sample 2 (the life satisfaction unbalanced panel), Sample 3 (the total malaise balanced panel), and Sample 4 (the total malaise unbalanced panel).

Hawkes and Plewis (2006) argue that non-response from a longitudinal dataset can take a number of forms: unit non-response, wave non-response, item non-response, and attrition. Firstly, unit non-response occurs when a cohort member is absent from a study from the outset. Secondly, wave non-response relates to the temporary loss of a cohort member from a study. Thirdly, item non-response occurs if an individual does not respond to a specific question. Finally, attrition in a longitudinal dataset is the permanent loss of cohort members from the target sample, as argued by Hawkes and Plewis (2006).

When the individuals were aged 11, the mothers of 13,430 individuals reported that their child was never, sometimes, or frequently bullied. However, Samples 1, 2, 3, and 4 have sample sizes of 2,774, 6,322, 3,254 and 6,333 individuals, respectively. Thus, there is a substantial reduction in the sample size from the age 11 questionnaires to the estimation samples. The large reduction in sample size from the age 11 measure of bullying to the estimation samples may result from attrition, wave non-response, or item non-response (for example, if an individual does not report their life satisfaction in a given wave)[38].

[38] Note that the substantial reduction in sample size from the age 11 bullying variable to the estimation samples cannot result from unit non-response because unit non-response relates to the absence of a cohort member from the outset of a study.

In addition, as previously discussed in Section 2.3.3, in all four estimation samples, a smaller proportion of individuals were reported to be frequently bullied, compared to that in the sample of age 11 respondents. Arguably, individuals who were harmed most by being bullied may have the greatest likelihood of being absent from the estimation samples. If this is the case, the estimated effects of bullying victimisation on SWB may be biased towards zero, leading to an underestimation of the psychological harm that results from being bullied. The estimates would therefore suffer from sample selection bias, see Heckman (1979).

This chapter uses two approaches to investigate the effects of the loss of sample size from age 11 to the estimation samples. Approach 1 uses cross-sectional probit models to investigate whether an individual's experience of being bullied at age 11 affects their likelihood of being absent from Sample 1 and Sample 3. Approach 2 makes use of panel probit analysis to investigate whether bullying victimisation at age 11 affects the likelihood of absence from Sample 2 and Sample 4.

To investigate the effect of non-response in Sample 1 and Sample 3, approach 1 uses the original sample of all individuals reported by their mother to be never, sometimes, or frequently bullied; a sample of 13,430 individuals. Approach 1 is an adaptation of model (1) of Hawkes and Plewis (2006) although approach 1 utilises cross-sectional, rather than panel, data. Approach 1, represented by equation (2.10), utilises a cross-sectional sample because an individual's absence from the balanced panels is time invariant.

$$\begin{aligned}\mathrm{Pr}(\mathrm{Abssample1_i} = 1) = \mathrm{F}(&\varphi_1\mathrm{Freq_{i11}} + \varphi_2\mathrm{Some_{i11}} + \varphi_3\mathrm{Male_i}\\ &+\varphi_4\mathrm{Reading_{i16}} + \varphi_5\mathrm{ReadingMiss_{i16}} + \mathrm{p_i})\end{aligned} \tag{2.10}$$

Where $Pr(Abssample1_i = 1)$ denotes the probability of individual i being absent from Sample 1 (the life satisfaction balanced panel). $Abssample1$ is a binary variable taking the value 1 if individual i is absent from Sample 1, and 0 if present. Equivalently, $Abssample1_i = 1$ can be replaced with the binary variable ($Abssample3$) to denote individual i's absence from Sample 3 (the total malaise balanced panel). $Freq_{i11}$ and $Some_{i11}$ are binary variables denoting that individual i was bullied *frequently* or *sometimes* at age 11, respectively. Individuals who were never bullied at age 11 form the base category. $Male_i$ is a binary variable that assumes the value 1 if individual i is male, and 0 if female. Hawkes and Plewis (2007) find that non-response at age 42 is predicted by an individual's reading ability at age 16. Thus, $\mathrm{Reading_{i16}}$ denotes the reading comprehension score of individual i at age 16. Due to a large number of missing values on this variable, $\mathrm{Reading_{i16}}$ is set equal to 0 if the individual's age 16 reading comprehension score is missing[39]. In addition, $\mathrm{ReadingMiss_{i16}}$ is a binary

[39] The measure of age 16 reading ability is missing for approximately 35% of individuals in the life satisfaction balanced panel (Sample 1).

indicator that equals 1 if the individual's age 16 reading score is missing, and 0 if their reading score is not missing. p_i indicates the error term of the latent variable equation.

The parameters φ_1 (φ_2) denote the estimated effect of being bullied frequently (sometimes) on an individual's likelihood of being absent from estimation sample, relative to individuals who were never bullied. If φ_1 (φ_2) is positive, this suggests that individuals who were frequently (sometimes) bullied at age 11 are more likely to be absent from Sample 1 and Sample 3, relative to individuals who were never bullied. If this is the case, the estimated effects presented in this chapter may be underestimated due to sample selection bias.

Approach 2 uses probit regression models to test whether the probability of being absent from Sample 2 and Sample 4 is determined by bullying victimisation at age 11, and hence whether non-response is likely to bias the unbalanced panel estimates of the effect of being bullied on SWB. In common with approach 1, approach 2 utilises a sample of all the individuals who were reported by their mother at the age of 11 to be never, sometimes or frequently bullied: a sample of 13,430 individuals. Life satisfaction (total malaise) is recorded 4 (3) times in the NCDS dataset and therefore a sample of 53,720 observations are used to explore the issue of non-response in Sample 2 (Sample 4). Approach 2 is shown by equation (2.11), a probit model:

$$\begin{aligned}\mathrm{Pr}(\mathrm{Abssample2_{it}} = 1) = \mathrm{F}(&\vartheta_1\mathrm{Freq_{i11}} + \vartheta_2\mathrm{Some_{i11}} + \vartheta_3\mathrm{Male_i} \\ &+\vartheta_4\mathrm{Reading_{i16}} + \vartheta_5\mathrm{ReadingMiss_{i16}} + \mathrm{o_{it}})\end{aligned} \tag{2.11}$$

$Pr(Abssample2_{it} = 1)$ denotes the probability that individual i is absent from Sample 2 (the life satisfaction unbalanced panel) at age t. $Abssample2_{it}$ is a binary variable that equals 1 if individual i was absent from Sample 2 (the life satisfaction unbalanced panel) at age t, and equals 0 if present. Equivalently, $Abssample2_{it}$ can be replaced with a binary variable ($Abssample4_{it}$) denoting that individual i was absent from Sample 4 (the total malaise unbalanced panel) at age t. o_{it} denotes the error term of the latent variable equation.

Equation (2.11) is used to ascertain whether an individual's likelihood of absence from Sample 2 and Sample 4 is affected by their experience of being bullied at age 11. The parameter ϑ_1 (ϑ_2) denotes the estimated effect of being bullied frequently (sometimes) at age 11 on an individual's likelihood of being absent from Sample 2 and Sample 4 at age t, relative to individuals who were never bullied. If ϑ_1 (ϑ_2) is positive, this provides evidence that individuals who were frequently (sometimes) bullied at age 11 have a greater likelihood of being absent from the unbalanced panels, relative to individuals who were never bullied. If this is the case, the unbalanced panel estimates of the effect of being bullied on SWB may be affected by sample selection bias.

Equations (2.10) and (2.11) are used to investigate whether individuals who were bullied at age 11 have a greater likelihood of being absent from the estimation samples. If this is the case, the estimated effects of being bullied on adult SWB may be affected by sample selection bias. For this reason, to adjust for sample selection bias, linear Heckman sample selection models are used.

To estimate a Heckman model, an instrument is required which must satisfy two conditions. Firstly, the instrument must affect the likelihood of being present in the estimation samples. Secondly, conditioning on the explanatory variables, the instrument must not affect SWB, see Wooldridge (2002). Using the NCDS, Hawkes and Plewis (2006) find that the probability of non-response at age 42 is higher for individuals who did not respond to the NCDS questionnaire at age 33. As discussed in Section 2.3.2, the SWB of respondents of the NCDS is first reported at age 33. Thus, a binary variable denoting whether the individual did not respond to the NCDS questionnaire at age 23 is used as an instrument. To satisfy the conditions stated above, non-response at age 23 must be correlated with the likelihood of being present in the estimation samples but must not affect SWB. The first and second stage of the Heckman selection model specification are presented by equations (2.12) and (2.13), respectively.

$$\mathrm{Sample_{it}} = \alpha_1\mathrm{Bull_{i11}} + \alpha_2\mathrm{Male_i} + \alpha_3\mathrm{Reading_{i16}} + \alpha_4\mathrm{ReadingMiss_{i16}} + \alpha_5\mathrm{Noresp_{i23}} + \mathrm{o_{it}} \qquad (2.12)$$

Where $\mathrm{Sample_{it}}$ is a binary variable that equals 1 if individual i is present in the estimation sample (Sample 1, 2, 3 or 4) at wave t, and 0 if the individual is not present in the estimation sample at wave t. $\mathrm{Bull_{i11}}$ is a binary variable that equals 1 if individual i was bullied at age 11, and 0 otherwise. $\mathrm{Male_i}$ is a binary variable that equals 1 if the individual is male, and 0 if the individual is female. $\mathrm{Reading_{i16}}$ denotes the reading comprehension score of individual i at age 16. Due to a large number of missing values on this variable, $\mathrm{Reading_{i16}}$ is set equal to 0 if the individual's age 16 reading comprehension score is missing[40]. In addition, $\mathrm{ReadingMiss_{i16}}$ is a binary indicator that equals 1 if the individual's age 16 reading score is missing, and 0 if their reading score is not missing. Finally, $\mathrm{Noresp_{i23}}$ is a binary variable that equals 1 if individual i did not respond to the NCDS questionnaire at age 23, and 0 otherwise.

After estimating equation (2.12), the first stage of the Heckman selection model, the inverse mills ratio is constructed using the estimation results. The inverse mills ratio is the ratio of the standard normal density and the cumulative distribution function, see Wooldridge (2008).

$$SWB_{it} = \beta_0 + \beta_1 Bull_{i11} + \boldsymbol{\beta X}_{it}^{a} + \boldsymbol{\alpha}\mathbf{X}_{\mathrm{it}}^{\mathrm{p}} + \boldsymbol{\lambda}\overline{\boldsymbol{X}}_{\boldsymbol{it}}^{a} + \boldsymbol{\gamma X}_{i}^{c} + \sigma\lambda + \varepsilon_{it} \qquad (2.13)$$

[40] The measure of age 16 reading ability is missing for approximately 35% of individuals in the life satisfaction balanced panel (Sample 1).

Where λ denotes the inverse mills ratio, which is calculated from equation (2.12)[41]. If σ does not equal zero, this provides evidence of non-response bias.

[41] All remaining control variables are identical to those presented in equation (2.7).

There are a number of alternative approaches to exploring the issue of non-response bias. One alternative approach is to make use of variable addition tests, an approach proposed by Nijman and Verbeek (1992). Variable addition tests involve including information relating to an individual's response to the survey into the estimation equations. For example, variable addition tests can be performed by estimating equation (2.7) using an unbalanced panel and including control variables indicating the number of number waves for which the individual is in the sample. The logic underpinning this test is that if non-response is random, an individual's history of responding to the survey should be uncorrelated with the dependent variable (SWB), conditional upon the explanatory variables, see Jones et al. (2006). In contrast, if non-response is non-random then the number of waves for which an individual is in the sample is likely to be correlated with the dependent variable (SWB).

A second approach to investigating the issue of attrition bias is to compare the unbalanced panel (individuals who are observed in the sample in at least one wave) estimates with the balanced panel (individuals who are observed in the sample for all waves). If non-response bias is present then the balanced and unbalanced panel estimates are likely to differ because non-response bias may affect the balanced and unbalanced panel estimates in a different fashion, see Jones et al. (2006).

2.5 Results

2.5.1 Random Effects Ordered Probit Model

Table 2.6(a) presents the coefficients from estimating equations (2.6) and (2.7) using a random effects ordered probit model. Life satisfaction is the dependent variable. Columns (1) and (3) illustrate the results from estimating equation (2.6) using Sample 1 (the life satisfaction balanced panel) and Sample 2 (the life satisfaction unbalanced panel), respectively. Columns (2) and (4) show the findings from estimating equation (2.7) using Sample 1 and Sample 2, respectively.

All four specifications demonstrate negative, statistically significant effects of bullying victimisation at age 11 on adult life satisfaction. The estimates using Sample 1 and Sample 2 are of a similar magnitude, supporting the robustness of the findings. The coefficient of the measure of bullying victimisation at age 11 is approximately 30% of the magnitude of the unemployment coefficient. Unemployment is a heavily researched determinant of individual life satisfaction, see Kassenboehmer and Haisken-DeNew (2009), for example. Additionally, the magnitude of the effects of being bullied at age 11 on life satisfaction is approximately a quarter of the absolute magnitude of the effect of being married or cohabiting (relative to being single). After conditioning on the childhood characteristics, the coefficient of the bullying variable diminishes in magnitude; this is the case for both Sample 1 and Sample 2.

For comparison, Table 2.6(b) replicates the analysis of Table 2.6(a) but excludes the Mundlak averages. After removing the Mundlak averages, the coefficient of the measure of bullying victimisation becomes approximately 20% larger. This suggests that unobserved characteristics that positively affect life satisfaction are negatively associated with the probability of being bullied at age 11.

There are two explanations for this change. Firstly, cohort members with certain early childhood characteristics may be more likely to be bullied at age 11 because of these characteristics. These characteristics may also affect the Mundlak averages. Secondly, bullying victimisation at age 11 may affect the Mundlak averages. Whatever the explanation, the large reduction in the effect of bullying victimisation when accounting for the Mundlak averages is of note, indicating the importance of conditioning upon the individual effects.

Previous literature indicates that children who are bullied have lower educational attainment, lower income, and are more likely to be unemployed as adults, (see, for example, Eriksen et al., 2014; Brown and Taylor, 2008; Varhama and Bjorkqvist, 2005) . Thus, one pathway via which bullying victimisation in childhood may affect SWB as an adult may be via the indirect effect of being bullied on these outcomes. To explore this possibility, Table 2.6(c) presents simplified specifications excluding the household income, labour force status, homeownership status, and highest educational attainment variables. The findings indicate that the effect of being bullied at age 11 on life satisfaction is robust to the exclusion of these control variables. What is more, note that the coefficients become larger in magnitude relative to the estimates presented in Table 2.6(b). This supports the notion that one mechanism via which being bullied at age 11 may affect life satisfaction as an adult is via the indirect effect on adult labour market outcomes.

Table 2.7(a) is presented in an identical fashion to Table 2.6(a) though the dependent variable is total malaise, rather than life satisfaction. Note that the total malaise index is reversed and hence higher scores represent higher, rather than lower, SWB. Columns (1) to (2) and (3) to (4) illustrate the findings for Sample 3 (the total malaise balanced panel) and Sample 4 (the total malaise unbalanced panel), respectively. In common with the life satisfaction results, in each of the four specifications the measure of whether the child was bullied at age 11 has a negative coefficient. In addition, note that if birth-weight and mental health problems are included as control variables, the coefficient of the bullying variable reduces in magnitude.

Table 2.7(a) contains some findings that do not accord with the existing literature. For example, there is no statistically significant effect of unemployment on total malaise. This is surprising; a substantial literature has demonstrated the detrimental effect of unemployment on SWB, see Clark and Oswald (1994). The table also suggests that individuals who are not in the labour force report lower total malaise (lower SWB) relative to employed individuals. This effect is statistically significant at the 1% level.

One explanation for this somewhat surprising result is that there is not a clear distinction between being unemployed and being out of the labour force, as argued by Blackaby et al. (2007) and Brown et al. (2010). However, this result is inconsistent with the findings for life satisfaction that demonstrate a detrimental effect of unemployment, and a smaller, negative effect of being out of the labour force.

A second explanation for this difference is a selection effect: individuals in the life satisfaction samples may have a different experience of unemployment, relative to individuals in the total malaise samples. To investigate this explanation, the regressions presented in Tables 2.6(a) and 2.7(a) were re-estimated using a common estimation sample.[42] However, this re-estimation leads to little substantive change in the coefficients of the labour force status variables in the models utilising total malaise and life satisfaction as dependent variables. This indicates that the difference in the effects of labour market status on life satisfaction and total malaise is due to the different measures of SWB, rather than a selection effect, thus highlighting the importance of exploring a range of measures of SWB.

Table 2.7(b) shows the equivalent results to Table 2.7(a), without including the Mundlak averages. Relative to Table 2.7(a), the sizes of the coefficients of the measure of whether an individual was bullied at age 11 on total malaise are approximately 20% larger. In summary, the findings presented in this section indicate an adverse effect of bullying victimisation at age 11 on both measures of SWB.[43]

As previously argued, childhood bullying may affect SWB via its indirect effect on adult labour market outcomes. To explore this, we re-estimate the models presented in Tables 2.7(b) after excluding the household income, labour force status, homeownership status, and highest educational attainment variables. The findings, presented in Table 2.7(c), indicate that the effect of bullying victimisation remains statistically significant and negative after removing these. In addition, relative to the estimates presented in Table 2.7(b), the magnitude of the coefficients of the bullying variable is larger. This indicates that childhood bullying victimisation may affect total malaise via its indirect effect on these adult labour market outcomes.

2.5.2 Random Effects Results (Continuous Dependent Variable)

To explore the robustness of the previous results, Table 2.10 illustrates the results from estimating equations (2.6) and (2.7) using a random effects estimator that treats

[42] The results are available upon request.

[43] For robustness, this analysis has been replicated using a binary variable indicating whether the individual was bullied at age 7. The findings indicate that being bullied at age 7 is inversely associated with both measures of SWB. Predominantly, the estimates are statistically significant at the 5% significance level and are consistently statistically significant at the 10% level. However, the coefficients are smaller in magnitude, ranging from 30% to 70% of the magnitude of the coefficients relating to the effects of being bullied at age 11. These results are summarised in Tables 2.8 and 2.9.

the life satisfaction measure as if it were continuous. Table 2.10 is presented in an identical manner to Table 2.6(a).

Column (1) indicates that holding the adult characteristics and Mundlak averages constant, individuals who were bullied at age 11 report 0.161 points lower life satisfaction, relative to individuals who were never bullied. This effect is approximately 40% of the magnitude of the estimated effect of being unemployed on life satisfaction, or approximately 30% of the (absolute) magnitude of the effect of being married or cohabiting. Stutzer and Frey (2006) find that happier single individuals are more likely to marry in the future. If this selection effect is present in the NCDS data, the estimated effect of being married/ cohabiting on life satisfaction may be overestimated. Thus, arguably the findings presented in Table 2.10 may underestimate the true ratio of the effect of bullying on life satisfaction to the effect of marriage.

Column (2) includes the childhood characteristics as control variables, reducing the magnitude of the estimated effect of being bullied by approximately a tenth, to -0.147. This indicates that birth-weight and mental health problems at age 7 are confounding variables. The use of Sample 2 increases the magnitude of the estimated effects of being bullied by approximately 10%. This may be because the more severely an individual was bullied at age 11, the greater their likelihood of absence from Sample 1.

Another notable feature of Table 2.10 is how the effect of the type of housing tenure varies from Sample 1 to Sample 2. In Sample 1, the estimated effects of being a private renter (relative to living in "social or other housing") are statistically insignificant. In contrast, in Sample 2, the estimated effects are negative and statistically significant at the 5% level. In Sample 1 and Sample 2 there are 948 and 1,989 renters, respectively. Thus, the differences in the estimated effects of renting on life satisfaction may be due to differences in the number of renters between the samples.

A similar pattern exists for the "owns home outright" variable. The analysis using Sample 1 demonstrates no significant effect of outright homeownership on life satisfaction, relative to living in "social/ other housing". However, the findings for Sample 2 demonstrate negative effects of outright homeownership on life satisfaction; these effects are significant at the 5% level. The results using Sample 1 also demonstrate small, negative effects of being male, relative to female, on life satisfaction. These effects are significant at the 10% level. In Sample 2, these coefficients are larger in magnitude and statistically significant at the 1% level. This may be because the least happy males are more likely to drop out of Sample 2.

Making use of Sample 1, the estimated effect of mental health problems (measured using the BSAG) at age 7 on life satisfaction is negative and statistically significant at the 5% level. This indicates that individuals with more mental health problems at age 7 report lower life satisfaction as adults. Thus, a one standard deviation increase in age 7 mental health problems reduces life satisfaction by approximately 0.05 points, a small effect. These results contrast with the findings using Sample 2, which show no statistically significant effect of mental health problems at age 7 on adult life satisfaction. A possible explanation for the inconsistent effect is that in Sample 2, mental health problems may be positively correlated with other characteristics that increase life satisfaction, such as low expectations.

Table 2.11 replicates the analysis of Table 2.10 using total malaise as the dependent variable. Columns (1) and (3) present the results from estimating equation (2.6) using Sample 3 (the total malaise balanced panel) and Sample 4 (the total malaise unbalanced panel), respectively. Columns (2) and (4) reveal the findings from estimating equation (2.7) using Sample 3 and Sample 4, respectively. Note that higher total malaise scores indicate higher SWB. In common with the life satisfaction results presented in Table 2.10, each specification is characterised by large, negative effects of being bullied at age 11 on SWB, as measured by total malaise. In all specifications, the estimated effects of being bullied are statistically significant at the 1% level.

The findings given in column (1) indicate that, conditioning on the adult characteristics and Mundlak averages, individuals who were bullied at age 11 have 0.193 points lower total malaise, relative to individuals who were never bullied. Column (2) includes birth-weight and mental health problems as control variables, reducing the magnitude of the estimated effect of being bullied by approximately 7%. Also, note that for both outcome measures, the estimated effects of bullying victimisation on SWB are larger for the unbalanced panel, relative to the balanced panel, which may be due to non-response.

However, note that Table 2.11 presents some results that do not accord with the existing literature. For example, there is no statistically significant effect of marriage or cohabiting on total malaise, which may be due to adaptation to marriage, as found by Lucas and Clark (2006). The estimated effects of being registered disabled on total malaise are positive and statistically significant at the 1% significance level. Oswald and Powdthavee (2008) suggest that having health problems which limit an individual's daily activities has a negative effect on mental distress and life satisfaction. One explanation for the difference between our results and theirs is that people who are registered as disabled may not be more likely to have health problems that limit their daily activities, relative to people who are not registered as disabled.[44]

Similarly, the estimated effects of monthly household income on total malaise are found to be negative, contrary to the conclusions of the existing SWB literature, see Frijters et al. (2004). This may be due to collinearity between monthly household income, highest educational attainment, and the homeownership status variables. However, re-estimation of the results without controlling for homeownership status leads to little change in the estimated effects of monthly household income on total malaise.

2.5.3 Bullying Frequency and Subjective Well-being

Arguably, SWB may be affected by the frequency that an individual was bullied. Thus, the analysis presented in this chapter was replicated using binary variables that denote whether an individual was sometimes bullied or frequently bullied at age 11.[45] The results from this analysis demonstrate that the effect of bullying victimisation on SWB is dependent on the frequency of the bullying. Compared to individuals who were never bullied, individuals who were frequently bullied (sometimes bullied) report approximately 0.37 (0.12) points lower life satisfaction. Hence, the effect of being bullied frequently is approximately 3 times the magnitude of the effect of being bullied sometimes. However, there is a smaller differential effect for total malaise. Individuals who were frequently bullied (sometimes bullied) at age 11 report 0.3 (0.18) points lower total malaise scores, relative to individuals who were never bullied. Note that the total malaise index is reversed and therefore higher scores represent higher SWB.

[44] As previously discussed in Section 2.4.1, the NCDS does not contain any information detailing how an individual's health affects their ability to carry out day to day activities.
[45] The results are available upon request.

To summarise, the findings presented so far suggest that individuals who were bullied at age 11 report lower SWB as adults, as measured by either life satisfaction or total malaise. Moreover, the estimated effects of bullying victimisation at age 11 are large, relative to the estimated effects of other widely researched determinants of SWB, such as unemployment. Also, note that the estimated effects of bullying victimisation on SWB are larger for the unbalanced than the balanced panels.

2.6 Robustness Check 1: Two Stage Residual Inclusion

The findings presented in Section 2.5 may be affected by omitted variable bias if an unobserved childhood characteristic affects both the likelihood that an individual is bullied and their SWB as an adult. 2SRI models are used to test for omitted variable bias, see Terza et al. (2008).

The coefficients and average marginal effects from estimating equation (2.8) using a probit model (the first stage of 2SRI) are shown in Table 2.12. Average marginal effects are the effect of discrete or partial changes in the independent variable, averaged over all of the observations, see Bartus (2005). The dependent variable is a binary variable equalling 1 if the individual was bullied at age 11, and 0 otherwise. Columns (1) and (3) display the coefficients using Sample 1 (the life satisfaction balanced panel) and Sample 3 (the total malaise balanced panel), respectively. Columns (2) and (4) display the average marginal effects for Sample 1 and Sample 3, respectively. For both samples, the estimated effects of birth-weight on the likelihood of being bullied at age 11 are statistically significant and negative; individuals with a lower birth-weight have a greater likelihood of being bullied.

These results also suggest that having mental health problems at age 7, being bullied at age 7, and being male are all positively associated with the likelihood of being bullied at age 11. In contrast, being upset by new environments is inversely associated with the probability of being bullied at age 11, though this effect is not statistically significant. The estimated effects of a child's growth in height between ages 7 and 11 on the likelihood of being bullied at age 11 is not found to be statistically significant, indicating that it is a poor IV. In Sample 1, at the mean values of the covariates, individuals who were not bullied at age 7 have a 15.3% probability of being bullied at age 11, 22.8% points lower than individuals who were bullied at age 7. In addition, in Sample 3, at the mean values of the covariates, individuals who were not bullied at age 7 have a 15.6% probability of being bullied at age 11, 22% points lower than individuals who were bullied at age 7. These results indicate the persistence of bullying victimisation between ages 7 and 11.

Table 2.13 presents the second stage results; obtained by estimating equation (2.9) using a random effects ordered probit model. Columns (1) and (2) present the findings for when life satisfaction and total malaise are the dependent variables, respectively. Columns (1) and (2) use Sample 1 and Sample 3, respectively. The total malaise index is reversed and hence higher scores represent higher SWB. The sign and statistical insignificance (at the 5% significance level) of the bullying equation residuals suggest no evidence of endogeneity[46]. In other words, the results show no evidence that unobserved factors that affect an individual's likelihood of being bullied affect their SWB, conditioning on the control variables. However, in column (1), the estimated effect of the bullying equation residuals on adult life satisfaction is positive and statistically significant (albeit at the 10%, but not the 5%, significance level). This indicates weak evidence that unobserved factors that increase the likelihood that an individual is bullied at age 11 are positively correlated with adult life satisfaction. It also suggests that any endogeneity present may act in the opposite direction to that previously hypothesised. After the inclusion of the bullying residuals, the coefficient of the bullying victimisation variable becomes larger in magnitude, relative to the models found in column (2) of Tables 2.6(a) and 2.7(a).

2.7 Robustness Check 2: Non-Response

As outlined previously, there is a substantial reduction in the available sample size from the childhood samples to the adult estimation samples. If an individual's probability of non-response is associated with their experience of bullying victimisation, the estimated effects of being bullied on SWB may be biased. Arguably, individuals who suffered the greatest psychological harm from being bullied may be the most likely to be absent from the estimation samples, leading to an underestimation of the effects of bullying victimisation. Also, note that the balanced panel estimates of the effects of being bullied on SWB are smaller in absolute size than the unbalanced panel estimates, suggesting that non-response may affect the results.

Table 2.14 presents the average marginal effects from cross-sectional probit estimation of equation (2.10). In columns (1) and (2), the dependent variable equals 1 if the individual is absent from Sample 1 (the life satisfaction balanced panel) and Sample 3 (the total malaise balanced panel), respectively. Individuals who were present in the samples form the base category.

Column (1) demonstrates that relative to individuals who were never bullied at age 11, individuals who were frequently bullied are 3.88% points more likely to be absent from Sample 1 (the life satisfaction balanced panel), on average. The estimated effect is statistically significant at the 1% level and indicates that being absent from Sample 1 is more common for individuals who were frequently bullied. Column (1) demonstrates that individuals who were sometimes bullied at age 11 do not have a higher rate of absence from Sample 1, relative to individuals who were never bullied.

Column (2) indicates no statistically significant effect of being bullied frequently or sometimes on the likelihood of being absent from Sample 3, relative to those

[46] These are the residuals from equation (2.8).

individuals who were never bullied. In accordance with the findings of Hawkes and Plewis (2006), the probability of being absent from both samples is higher for males and individuals who had a lower reading ability at age 16. Additionally, the probability of being absent from Samples 1 and 3 is inversely associated with having a missing reading score at the age of 16.

Table 2.14 illustrates that being frequently bullied at age 11 is positively associated with the likelihood of being absent from the life satisfaction balanced panel, but does not affect the likelihood of absence from the total malaise balanced panel. Hence, these results suggest that the (balanced panel) estimates of the effects of being bullied may underestimate the effect of bullying victimisation on life satisfaction.

Table 2.15 reveals the average marginal effects from probit estimation of equation (2.11). In column (1), the dependent variable equals 1 if the individual is absent from Sample 2 (the life satisfaction unbalanced panel) at ages 33, 42, 46 or 50, and 0 if the individual is present. In column (2), the dependent variable is a binary variable which assumes the value 1 if individual i is absent from Sample 4 (the total malaise unbalanced panel) at ages 33, 42, or 50, and equals 0 if present.

Columns (1) and (2) show no statistically significant effect of being frequently or sometimes bullied at age 11 on the likelihood of being absent from Samples 2 and 4. In common with the findings relating to the balanced panels, columns (1) and (2) indicate that males and individuals who had a lower reading ability at age 16 have an increased probability of being absent from Samples 2 and 4. Individuals for which the measure of age 16 reading ability is missing have a higher likelihood of absence from Samples 2 and 4, relative to individuals for which the measure is non-missing.

Given that the choice of instruments is generally an area of debate, the central results of this chapter are not corrected for sample selection bias. However, Tables 2.14 and 2.15 reveal that individuals who were bullied frequently at age 11 have an increased likelihood of being absent from the life satisfaction balanced panel, but does not affect the likelihood of absence from Samples 2, 3, and 4. If individuals who were frequently bullied suffered the most psychological harm, the balanced panel estimates of the effect of being bullied on life satisfaction may be biased towards zero, underestimating the psychological harm that results from bullying victimisation. To test for sample selection bias, linear Heckman selection models are used.

Heckman (1979) selection models have two stages: the first stage uses a dependent variable that equals 1 if the individual is present in the estimation sample for the second stage, and 0 otherwise. The dependent variable is regressed against binary variables denoting that the individual is male, their reading score at age 16, a binary variable indicating that their reading score was missing at age 16, whether they were bullied at age 11, and a binary indicator denoting that they did not respond to the NCDS questionnaire at age 23. This latter variable is an instrument that must affect the likelihood of being present in the estimation samples for the second stage, but must not affect SWB. Note that further controls are not included because their inclusion substantially reduces the available sample size. In the second stage, SWB is regressed against an individual's adult characteristics, Mundlak averages, childhood characteristics, and the inverse mills ratio from the first stage. The inverse mills ratio is the ratio of the standard normal density and the cumulative distribution function, see Wooldridge (2008). The inverse mills ratio is used to test whether the estimated effects of being bullied on SWB are affected by sample selection bias.

The estimation results from the Heckman selection model using life satisfaction as the dependent variable are shown in Table 2.16. Columns (1) and (3) reveal the coefficients from the first stage equation. In column (1), the dependent variable equals 1 if the individual is observed in Sample 1 (the life satisfaction balanced panel), and 0 otherwise. The dependent variable in column (3) equals 1 if the individual is present in Sample 2 (the life satisfaction unbalanced panel), and 0 otherwise. Columns (2) and (4) indicate the key coefficients from the second stage equation using Sample 1 and Sample 2, respectively. The dependent variable is life satisfaction. The results provided in columns (1) and (3) show that non-response at age 23 is negatively associated with an individual's probability of being present in Samples 1 and 2. The inverse mills ratio in column (2) is negative but statistically insignificant, suggesting that sample selection bias is unlikely to be an issue in Sample 1. However, in column (4), the inverse mills ratio is negative and statistically significant; indicating that the estimates of the effect of being bullied at age 11 on life satisfaction may be downwardly biased.

One explanation for this is that non-response at age 23 may affect life satisfaction, causing it to be a poor instrument. To test this hypothesis, life satisfaction is regressed against the full set of conditioning variables and a binary variable indicating that the individual did not respond to the NCDS questionnaire at age 23. These results indicate that non-response at age 23 is inversely associated with life satisfaction in Sample 2 but has no statistically effect on life satisfaction in Sample 1.[47] As a result, it cannot be argued that the significance of the inverse mills ratio may be because non-response at age 23 is a poor instrument. In addition, relative to the results presented in column (4) of Table 2.10 (which do not correct for sample selection bias), there is a mere 2% reduction in the magnitude of the estimated effect of being bullied on life satisfaction. It is therefore evident that adjusting for sample selection bias leads to little substantive change in the estimated effect of being bullied on life satisfaction.

Table 2.17 is identical to Table 2.16, though the measure of SWB is total malaise rather than life satisfaction. The total malaise index is reversed and hence higher scores indicate higher SWB. Columns (1) and (3) indicate that individuals who did not respond to the NCDS questionnaire at age 23 are less likely to be present in Sample 3 and

[47] The results are available upon request.

Sample 4, respectively.[48] Additionally, the statistical insignificance of the inverse mills ratio in columns (1) and (3) supports the case that sample selection bias is not an issue in Sample 3 and Sample 4, respectively. Thus, the findings from linear Heckman models indicate the robustness of the results to adjusting for sample selection bias.

2.8 Conclusion

Using the NCDS, this chapter investigated the effect of childhood bullying victimisation on SWB as an adult. The empirical analysis suggested that being bullied has a large, negative effect on SWB as an adult. This effect cannot be due to reverse causality because the measures of childhood bullying clearly predate the SWB variables. Moreover, the estimated effect is robust to controlling for birth-weight, mental health problems at age 7, contemporaneous adult characteristics, and average adult characteristics. In addition, the effect is robust to the use of 2 measures of SWB: life satisfaction and total malaise. The magnitude of the estimated effect of being bullied on life satisfaction is large, approximately 30% of the magnitude of the effect of unemployment on life satisfaction. A similar effect is found for total malaise, a psychological distress index. Individuals who were bullied at age 11 have approximately 10% of a standard deviation lower SWB for this measure. Hence, the analysis presented in this chapter strengthens the case for policy interventions to prevent bullying. These are discussed in more detail below.

However, it is important to acknowledge that this study has some shortcomings. Firstly, arguably, the estimated effects may suffer from omitted variable bias. The findings may be due to an unobserved characteristic that affects both an individual's likelihood of being bullied and their life satisfaction. However, to bias the estimates, this omitted variable should have no additional effect after conditioning on the Mundlak averages and the rich set of control variables. Also, Hausman tests show no evidence to suggest that the findings are affected by omitted variable bias. On top of that, the use of a Heckman sample selection model leads to little change in the estimated effects of bullying victimisation on SWB. Moreover, this effect exists for 2 measures of SWB: total malaise and life satisfaction. These measures gauge different aspects of well-being: life satisfaction is a measure of evaluative well-being, whilst total malaise is a measure of affective well-being.

Secondly, present-day bullying is arguably different to bullying which occurred during the 1960s and thus these results may not be relevant today. For example, during the 1960s cyber-bullying did not exist. However, arguably cyber-bullying may have a more harmful effect on SWB as an adult if it leads to greater bullying. Unfortunately, we will have to wait several decades to investigate the long-term effect of cyber-bullying on

[48] After conditioning on an individual's adult characteristics, Mundlak averages and childhood characteristics, there is no statistically significant effect of non-response at age 23 on total malaise. This suggests that non-response at age 23 is a valid instrument.

SWB during mid-life. A greater availability of detailed, individual level bullying data in longitudinal datasets is essential for research in this area.

Thirdly, it may be contested that these results are not generalisable to the present-day due to changes in attitudes towards bullying in schools. During the 1960s, there was arguably less awareness of bullying and fewer measures in place to prevent bullying. Nevertheless, the findings of this chapter strengthen the case for an increased awareness of bullying in schools.

Finally, the estimated effects of being bullied at age 11 on SWB may be due to adult, rather than childhood, bullying. Bullying may be persistent during the life course: children who are bullied may also be bullied as adults. For example, being bullied as a child may lead to bullying victimisation in the workplace, which may directly reduce adult well-being. If this is the case, it may be important to strengthen workplace harassment policies to prevent bullying in the workforce. Unfortunately, it is not possible to investigate the effect of workplace bullying on SWB using the NCDS dataset because it does not contain any workplace bullying data. However, future research could explore the effects of workplace bullying on SWB using matched employee-workplace level datasets such as the Workplace Employee Relations Survey.

On the other hand, this chapter has several strengths. Firstly, unlike a large proportion of the existing literature surrounding the consequences of bullying victimisation, we do not rely on retrospective reports of being bullied. Hence, by construction, the estimated effects cannot suffer from reverse causality. Secondly, whilst the possibility remains that the estimates may be affected by omitted variable bias, tests for endogeneity indicate no evidence to support this claim.

Thirdly, unlike Takizawa et al. (2014), we show that the effect of being bullied on adult SWB exists after controlling for the marital status, employment status, and income. Fourthly, in comparison to Takizawa et al. (2014), we adjust for sample selection using Heckman selection models though doing so has little substantive effect on the findings.

Finally, whilst the mechanisms through which being bullied may affect adult SWB are little understood, the findings demonstrate that parental reports of a child's experience of bullying victimisation may be used by policymakers as a "red flag". In other words, being bullied as a child may be used by policymakers as a predictor of low SWB as an adult.

The analysis indicated a large, adverse effect of being bullied at age 11 on 2 measures of SWB: life satisfaction and total malaise. Hence, our results support the notion that "*what others do to you*" as a child may have long-term effects on SWB as an adult. As a result, interventions to prevent bullying from taking place in schools may improve the SWB of a relatively large proportion of the adult population.

For instance, Ttofi and Farrington (2009) conduct a meta-analysis of the effective elements of 59 school-based anti-bullying interventions. Their findings suggest that the most effective components of school based anti-bullying programmes are improved supervision in school playgrounds[49], more severe punishment for bullies, and better classroom management techniques to improve the detection of bullying. Consequently, the analysis of this chapter supports the case that anti-bullying interventions that include these components may help increase SWB as an adult. What is more, preventing bullying may improve well-being indirectly, via the effects on educational attainment and income.

The mechanisms via which adult SWB may be affected by childhood bullying are little understood, future research is needed to address this. To investigate the importance of the institutional context in which bullying occurs, future research could investigate the effect of bullying victimisation on adult SWB using longitudinal data from countries other than the UK, including low and middle-income countries. Additionally, future research could investigate the effect of bullying victimisation on other measures that are related to well-being, such as hypertension, which is not available in the NCDS.

[49] Lunch and break times are common times for children to be bullied at school, see Ttofi and Farrington (2009).

2.9 A2 Appendix 1: Figures and Tables

Figure 2.1: The Distribution of Life Satisfaction and Total Malaise by Estimation Sample

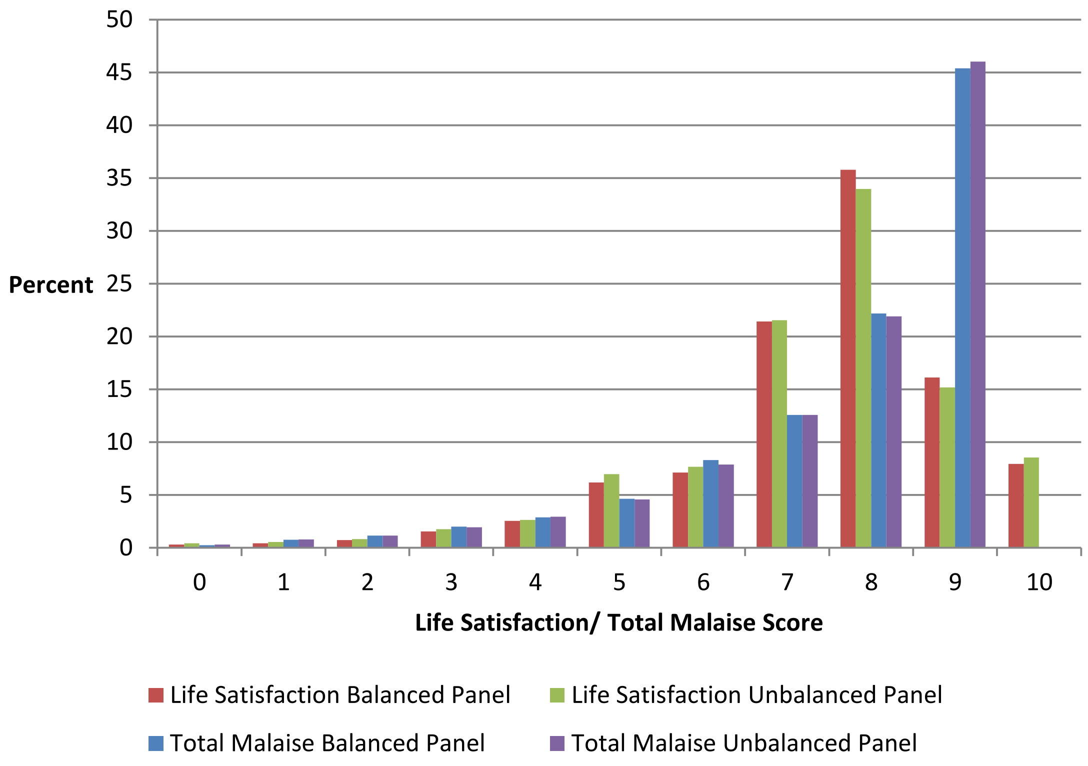


Table 2.1: Summary of the Estimation Samples

Sample No.	Type of Sample	Observations	Individuals	Ages
1	Life Satisfaction Balanced Panel	11,096	2,774	33,42, 46, & 50
2	Life Satisfaction Unbalanced Panel	19,200	6,322	33,42, 46, & 50
3	Total Malaise Balanced Panel	9,762	3,254	33,42, & 50
4	Total Malaise Unbalanced Panel	14,907	6,333	33,42, & 50
5	Age 11 Respondents	13,787	13,787	11

Table 2.2: Bullying Prevalence at Age 11 by Estimation Sample and for the Original Survey Respondents

	Age 7 Response	Age 11 Response (Sample 5)	Life Satisfaction Balanced (Sample 1)	Life Satisfaction Unbalanced (Sample 2)	Total Malaise Balanced (Sample 3)	Total Malaise Unbalanced (Sample 4)
Never	64.06	73.20	76.50	75.13	76.06	75.07
Sometimes	29.09	20.54	20.66	21.07	20.56	21.16
Frequently	5.31	3.94	2.85	3.80	3.38	3.77
Do not know	1.53	2.32	-	-	-	-
Individuals	14,604	13,787	2,774	6,322	3,254	6,333
Observations	14,604	13,787	11,096	19,200	9,762	14,907

Note: Columns 3-7 relate to bullying at age 11 and rows 2 to 5 denote percent. N indicates the number of individuals.

Table 2.3: Age 11 Bullying and Average Adult Life Satisfaction and Total Malaise by Estimation Sample

	Average Life satisfaction		Average Total Malaise	
Age 11 Bullying Experience	Balanced (Sample 1)	Unbalanced (Sample 2)	Balanced (Sample 3)	Unbalanced (Sample 4)
Never	7.56	7.46	7.72	7.74
Sometimes	7.36	7.21	7.52	7.51
Frequently	6.97	6.80	7.24	7.02
Observations	11,096	19,200	9,762	14,907
Number of Individuals	2,774	6,322	3,254	6,333

Note: Life satisfaction assumes integer values between 0 and 10. Total malaise assumes integer values between 0 and 9. The total malaise index is reversed and hence higher scores represent higher, rather than lower, SWB.

Table 2.4: Variable Definitions for Variables Included in the Main Analysis

Variable	**Definition**
Adult Variables	
Life satisfaction	Life satisfaction is self-reported. The respondents were given a scale from 0 to 10 and were then told, "0 means that you are completely dissatisfied and 10 means that you are completely satisfied. Please ring one number to show just how dissatisfied or satisfied you are about the way your life has turned out so far".
Total Malaise	Total malaise is an index produced by summing the answers to the following statements. Whether the cohort member "feels tired most of the time", "often feels miserable and depressed", "often gets worried about things", "often gets into a violent rage", "often suddenly scared for no good reason", "is easily upset or irritated", "is constantly keyed up and jittery", "every little thing gets on their nerves" and "heart often races like mad". The cohort member answers the questions yes or no. This index is formed so that 9 (answering no to every question) denotes the lowest distress (highest SWB) and 0 (answering yes to every question) indicates the highest distress (lowest SWB).
Male	Binary variable takes the value 1 if the individual is male, and 0 if female.
Household Income	Log of the individual's real monthly household income, measured in £.
Highest Educational Attainment	
Highest: Degree	Binary variable takes the value 1 if the individual’s highest educational attainment is a university degree.
Highest: A-Level	Binary variable takes the value 1 if the individual's highest educational attainment is A-Level.
Highest: O-Level	Binary variable takes the value 1 if the individual's highest educational attainment is O-Level.
No Qualifications	Base category indicates that the individual has no qualifications.
Homeownership Status	
Private Renter	Binary variable takes the value 1 if the individual is a private renter.
Owns: Mortgage	Binary variable takes the value 1 if the individual owns their home with a mortgage.
Owns: Outright	Binary variable takes the value 1 if the individual owns their home outright.
Other/ Social Housing	Base category denotes that the individual lives in "other" housing or social housing.
Marital Status	
Married or Cohabiting	Binary variable takes the value 1 if the individual is married or cohabiting.
Separated, Div, or Wid	Binary variable takes the value 1 if the individual is separated, divorced, or widowed.
Single	Base category indicates that the individual is single.
Labour Force Status	
Unemployed	Binary variable takes the value 1 if the individual is unemployed.
Not in Labour Force	Binary variable takes the value 1 if the individual is not in the labour force.
Employed	Base category indicates that the individual is employed.
Registered Disability	Binary variable takes the value 1 if the individual is registered disabled and 0 if the individual is not registered disabled.
Ethnicity	
African	Binary variable takes the value 1 if the individual is African.
Asian	Binary variable takes the value 1 if the individual is Asian.
Other Ethnicity	Binary variable takes the value 1 if the individual is of another ethnicity.
White	Base category denotes that the individual is White.

Note: Table continues on the next page.

Table 2.4 (continued): Variable Definitions for Variables Included in the Main Analysis

Variable	Definition
Child Variables	
Bullied at Age 11	Takes the value 1 if the mother reported when the child was age 11 that the child was bullied "sometimes" or "frequently" by other children, and 0 if the child was "never" bullied by other children.
Bullied at Age 7	As above for age 7.
Birth-weight	Individual's birth-weight measured in KG.
Age 7 BSAG	Bristol Social Adjustment Guide measured when the individual was age 7. These questions are combined to give scores for particular "syndromes" which are "unforthcomingness", "withdrawal", "depression", "anxiety", "hostility towards adults", "writing off adults and adult standards", "anxiety for acceptance by children", "hostility towards children", "restlessness", "inconsequential behaviour", "miscellaneous symptoms" and "miscellaneous nervous symptoms". This combined score is termed the total syndrome score. The index is normalised so that the highest observed value of the index in the age 7 NCDS sample is 1 and the lowest observed value is equal to 0. 1 (0) indicates the individual with the most (fewest) mental health problems.

Table 2.5: Summary Statistics by Estimation Sample: Variables Included In The Main Analysis

	Life satisfaction Balanced (1)				**Life satisfaction Unbalanced (2)**				**Total Malaise Balanced (3)**				**Total Malaise Unbalanced (4)**			
Continuous Variables	*Mean*	*S.D*	*Min*	*Max*	*Mean*	*S.D*	*Min*	*Max*	*Mean*	*S.D*	*Min*	*Max*	*Mean*	*S.D*	*Min*	*Max*
Life satisfaction	7.50	1.65	0	10	7.43	1.74	0	10								
Total Malaise									7.67	1.76	0	9	7.68	1.77	0	9
Ln(Household Income)	5.98	0.94	0.11	10.46	5.87	1.00	0.07	11.47	5.80	0.92	0.11	11.22	5.69	1.00	0.08	11.47
Birth-weight	3.34	0.51	1.02	5.73	3.34	0.52	1.02	5.78	3.34	0.51	1.02	5.73	3.34	0.52	1.02	5.78
Age 7 BSAG	0.11	0.12	0.00	0.75	0.12	0.13	0.00	0.87	0.11	0.12	0.00	0.87	0.12	0.13	0.00	0.98
Binary Variables	*Percent (%)*				*Percent (%)*				*Percent (%)*				*Percent (%)*			
Male	44.63				49.75				44.62				49.52			
Highest: Degree	16.09				15.08				15.21				14.31			
Highest: A-Level	31.29				29.47				30.31				29.40			
Highest: O-Level	39.28				38.77				37.95				36.75			
No qualifications	13.34				16.68				16.53				19.54			
Private Renter	8.54				10.36				9.09				10.20			
Owns Home: Mortgage	75.52				74.92				74.38				72.36			
Owns Home: Outright	11.83				11.83				10.93				9.77			
Other Housing Status	4.11				2.89				5.60				7.67			
Married or Cohabiting	85.81				82.98				85.90				83.88			
Separated, Div, or Wid	9.22				9.83				8.99				8.98			
Single	4.97				7.19				5.11				7.14			
Unemployed	1.55				2.03				1.77				2.35			
Not in Labour Force	11.10				12.47				12.63				13.46			
Employed	87.35				85.50				85.60				84.19			
Registered Disabled	5.97				6.55				7.33				7.76			
African	0.32				0.31				0.31				0.32			
Asian	0.22				0.22				0.22				0.22			
Other Ethnicity	0.11				0.11				0.06				0.10			
White	99.35				99.36				99.41				99.36			
Observations	11,096				19,200				9,762				14,907			
Number of Individuals	2,774				6,322				3,254				6,333			

Table 2.6(a): Random Effects Ordered Probit Model Coefficients: The Effects of Being Bullied at Age 11 on Life Satisfaction

	(1)	(2)	(3)	(4)
Dependent Variable	Life Satisfaction			
	Life Satisfaction Balanced (Sample 1)	Life Satisfaction Balanced (Sample 1)	Life Satisfaction Unbalanced (Sample 2)	Life Satisfaction Unbalanced (Sample 2)
Bullied at Age 11	-0.1196***	-0.1083**	-0.1227***	-0.1185***
	(0.0462)	(0.0463)	(0.0323)	(0.0324)
Male	-0.1215***	-0.1200***	-0.1496***	-0.1591***
	(0.0421)	(0.0430)	(0.0295)	(0.0301)
Ln(Household Income)	0.0405***	0.0408***	0.0351***	0.0351***
	(0.0142)	(0.0142)	(0.0108)	(0.0108)
Highest: Degree	0.0034	-0.0141	-0.0226	-0.0287
	(0.0630)	(0.0634)	(0.0451)	(0.0456)
Highest: A-Levels	-0.1200**	-0.1337**	-0.0958**	-0.1010***
	(0.0548)	(0.0550)	(0.0384)	(0.0388)
Highest: O-Levels	0.0130	0.0049	-0.0028	-0.0048
	(0.0459)	(0.0460)	(0.0325)	(0.0327)
Private Renter	-0.0078	-0.0068	-0.0575	-0.0577
	(0.0688)	(0.0688)	(0.0483)	(0.0483)
Owns Home: Mortgage	0.0715	0.0723	0.0087	0.0088
	(0.0668)	(0.0668)	(0.0481)	(0.0481)
Owns Home: Outright	-0.0487	-0.0474	-0.0873	-0.0869
	(0.0765)	(0.0765)	(0.0566)	(0.0566)
Married or Cohabiting	0.4163***	0.4163***	0.4161***	0.4158***
	(0.0959)	(0.0959)	(0.0714)	(0.0714)
Separated, Div, or Wid	-0.2677**	-0.2673**	-0.1611**	-0.1613**
	(0.1075)	(0.1075)	(0.0803)	(0.0803)
Unemployed	-0.3354***	-0.3356***	-0.3352***	-0.3353***
	(0.0994)	(0.0994)	(0.0722)	(0.0722)
Not in Labour Force	-0.0819*	-0.0822*	-0.0590	-0.0592
	(0.0470)	(0.0470)	(0.0365)	(0.0365)
Registered Disabled	0.0253	0.0252	0.0123	0.0122
	(0.0527)	(0.0527)	(0.0410)	(0.0410)
African	-0.5728*	-0.5460	-0.2933	-0.2840
	(0.3410)	(0.3406)	(0.2461)	(0.2460)
Asian	-0.3699	-0.3845	-0.3070	-0.2880
	(0.4172)	(0.4168)	(0.2892)	(0.2893)
Other Ethnicity	0.1634	0.1529	0.1612	0.1734
	(0.5941)	(0.5933)	(0.3979)	(0.3977)
Birth-weight		0.0618		0.0712***
		(0.0388)		(0.0270)
Age 7 BSAG		-0.3391**		-0.0162
		(0.1663)		(0.1136)
Observations	11,096	11,096	19,200	19,200
Number of Individuals	2,774	2,774	6,322	6,322
Mundlak Averages	Yes	Yes	Yes	Yes

Standard errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Note: Life satisfaction is measured at ages 33, 42, 46, and 50. BSAG = Bristol Social Adjustment Guide, which is a measure of child mental health (see Table 2.4).

Table 2.6(b): Random Effects Ordered Probit Model Coefficients: The Effects of Being Bullied at Age 11 on Life Satisfaction: Findings Excluding Mundlak Averages

	(1)	(2)	(3)	(4)
Dependent Variable	Life Satisfaction			
	Life Satisfaction Balanced (Sample 1)	Life Satisfaction Balanced (Sample 1)	Life Satisfaction Unbalanced (Sample 2)	Life Satisfaction Unbalanced (Sample 2)
Bullied at Age 11	-0.1453***	-0.1286***	-0.1500***	-0.1408***
	(0.0468)	(0.0469)	(0.0325)	(0.0327)
Observations	11,096	11,096	19,200	19,200
Number of Individuals	2,774	2,774	6,322	6,322
Mundlak Averages	No	No	No	No
Childhood Characteristics	No	Yes	No	Yes

Standard errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Note: Life satisfaction is measured at ages 33, 42, 46, and 50. The remaining explanatory variables are identical to those presented in Table 2.6(a).

Table 2.6(c): Random Effects Ordered Probit Model Coefficients: The Effects of Being Bullied at Age 11 on Life Satisfaction: Simplified Specifications

	(1)	(2)
Dependent Variable	Life Satisfaction	
	Life Satisfaction Balanced (Sample 1)	Life Satisfaction Unbalanced (Sample 2)
Bullied at Age 11	-0.1384***	-0.1611***
	(0.0476)	(0.0331)
Birth-weight	0.0824**	0.0864***
	(0.0399)	(0.0276)
BSAG at Age 7	-0.6306***	-0.3340***
	(0.1677)	(0.1127)
Male	-0.0636	-0.1237***
	(0.0414)	(0.0289)
Married or Cohabit	0.6835***	0.6829***
	(0.0706)	(0.0450)
Sep, Div, Wid	-0.1624**	-0.0813
	(0.0817)	(0.0539)
Registered Disabled	-0.0632	-0.1288***
	(0.0489)	(0.0365)
African	-0.5353	-0.2632
	(0.3505)	(0.2518)
Asian	-0.4591	-0.3510
	(0.4286)	(0.2960)
Other Race	0.0679	0.1641
	(0.6087)	(0.4067)
Observations	11096	19200
Number of Individuals	2774	6322
Mundlak Averages	No	No
Childhood Characteristics	Yes	Yes

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01
Note: Life satisfaction is measured at ages 33, 42, 46, and 50. Highest educational attainment, labour force status, homeownership status, and household income are excluded as control variables.

Table 2.7(a): Random Effects Ordered Probit Model Coefficients: The Effects of Being Bullied at Age 11 on Total Malaise

	(1)	(2)	(3)	(4)
Dependent Variable	Total Malaise			
	Total Malaise Balanced (Sample 3)	Total Malaise Balanced (Sample 3)	Total Malaise Unbalanced (Sample 4)	Total Malaise Unbalanced (Sample 4)
Bullied at Age 11	-0.1954***	-0.1844***	-0.2046***	-0.1915***
	(0.0516)	(0.0518)	(0.0393)	(0.0394)
Male	0.5478***	0.5679***	0.5245***	0.5502***
	(0.0477)	(0.0488)	(0.0365)	(0.0372)
Ln(Household Income)	-0.1038***	-0.1029***	-0.0920***	-0.0909***
	(0.0182)	(0.0182)	(0.0151)	(0.0151)
Highest: Degree	0.1227*	0.0974	0.1406**	0.1048*
	(0.0710)	(0.0716)	(0.0561)	(0.0567)
Highest: A-Level	0.1149*	0.0941	0.1876***	0.1579***
	(0.0609)	(0.0613)	(0.0469)	(0.0474)
Highest: O-Level	0.0735	0.0610	0.1131***	0.0944**
	(0.0513)	(0.0514)	(0.0404)	(0.0406)
Private renter	-0.3291***	-0.3283***	-0.3630***	-0.3623***
	(0.0702)	(0.0702)	(0.0556)	(0.0556)
Owns Home: Mortgage	-0.1162	-0.1164	-0.1711***	-0.1718***
	(0.0723)	(0.0723)	(0.0584)	(0.0584)
Owns Home: Outright	-0.2519***	-0.2511***	-0.3221***	-0.3213***
	(0.0845)	(0.0845)	(0.0699)	(0.0699)
Married or Cohabiting	-0.1536	-0.1551	-0.1548*	-0.1567*
	(0.1071)	(0.1071)	(0.0886)	(0.0886)
Separated, Div, or Wid	-0.4310***	-0.4315***	-0.4376***	-0.4387***
	(0.1205)	(0.1205)	(0.1000)	(0.1000)
Unemployed	0.0210	0.0233	-0.0068	-0.0054
	(0.1122)	(0.1122)	(0.0901)	(0.0901)
Not in Labour Force	-0.2492***	-0.2493***	-0.2249***	-0.2250***
	(0.0501)	(0.0501)	(0.0425)	(0.0425)
Registered Disabled	0.2033***	0.2028***	0.1979***	0.1974***
	(0.0570)	(0.0570)	(0.0482)	(0.0482)
African	-0.2259	-0.2015	0.0949	0.1116
	(0.3889)	(0.3889)	(0.2998)	(0.2996)
Asian	-0.6978	-0.7379	-0.6085*	-0.6592*
	(0.4610)	(0.4608)	(0.3430)	(0.3429)
Other Ethnicity	-0.1728	-0.2063	-0.3773	-0.3681
	(0.8691)	(0.8685)	(0.4871)	(0.4870)
Birth-weight		-0.0063		-0.0181
		(0.0435)		(0.0329)
Age 7 BSAG		-0.5244***		-0.6020***
		(0.1821)		(0.1372)
Observations	9,762	9,762	14,907	14,907
Number of Individuals	3,254	3,254	6,333	6,333
Mundlak Averages	Yes	Yes	Yes	Yes

Standard errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Note: Total malaise is measured at ages 33, 42, and 50. The total malaise index is reversed and hence higher scores represent higher, rather than lower, SWB. BSAG = Bristol Social Adjustment Guide, which is a measure of child mental health (see Table 2.4).

Table 2.7(b): Random Effects Ordered Probit Model Coefficients: The Effects of Being Bullied at Age 11 on Total Malaise: Findings Excluding Mundlak Averages

	(1)	(2)	(3)	(4)
Dependent Variable	Total Malaise			
	Total Malaise Balanced (Sample 3)	Total Malaise Balanced (Sample 3)	Total Malaise Unbalanced (Sample 4)	Total Malaise Unbalanced (Sample 4)
Bullied at Age 11	-0.2353***	-0.2165***	-0.2455***	-0.2235***
	(0.0521)	(0.0524)	(0.0397)	(0.0398)
Observations	9,762	9,762	14,907	14,907
Number of Individuals	3,254	3,254	6,333	6,333
Mundlak Averages	No	No	No	No
Childhood Characteristics	No	Yes	No	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Total malaise is measured at ages 33, 42, and 50. The total malaise index is reversed and hence higher scores represent higher, rather than lower, SWB. The remaining explanatory variables are identical to those presented in Table 2.7(a).

Table 2.7(c): Random Effects Ordered Probit Model Coefficients: The Effects of Being Bullied at Age 11 on Total Malaise: Simplified Specifications

	(1)	(2)
	Total Malaise Balanced (Sample 3)	Total Malaise Unbalanced (Sample 4)
Bullied at Age 11	-0.2420***	-0.2606***
	(0.0530)	(0.0403)
Birth-weight	0.0255	0.0173
	(0.0446)	(0.0338)
BSAG at Age 7	-0.9715***	-1.1747***
	(0.1823)	(0.1364)
Male	0.6884***	0.6615***
	(0.0473)	(0.0361)
Married or Cohabit	-0.0122	0.0989*
	(0.0793)	(0.0555)
Sep, Div, Wid	-0.3664***	-0.3017***
	(0.0922)	(0.0674)
Registered Disabled	0.0680	-0.0579
	(0.0526)	(0.0427)
African	-0.1567	0.1589
	(0.3992)	(0.3081)
Asian	-0.7356	-0.6479*
	(0.4747)	(0.3530)
Other Race	-0.2874	-0.3221
	(0.8915)	(0.5006)
Observations	9762	14907
Number of Individuals	3254	6333
Mundlak Averages	No	No
Childhood Characteristics	Yes	Yes

Note: Total malaise is measured at ages 33, 42, and 50. The total malaise index is reversed and hence higher scores represent higher, rather than lower, SWB. Highest educational attainment, labour force status, homeownership status, and household income are excluded as control variables. Mundlak average excluded.

Table 2.8: Random Effects Ordered Probit Model Coefficients: The Effects of Being Bullied at Age 7 on Life Satisfaction

	(1)	(2)	(3)	(4)
Dependent Variable	Life Satisfaction			
	Life Satisfaction Balanced (Sample 1)	Life Satisfaction Balanced (Sample 1)	Life Satisfaction Unbalanced (Sample 2)	Life Satisfaction Unbalanced (Sample 2)
Bullied at Age 7	-0.1056***	-0.0986**	-0.0484*	-0.0454
	(0.0406)	(0.0406)	(0.0288)	(0.0288)
Male	-0.1288***	-0.1266***	-0.1574***	-0.1661***
	(0.0419)	(0.0428)	(0.0295)	(0.0301)
Ln(Household Income)	0.0406***	0.0409***	0.0350***	0.0351***
	(0.0142)	(0.0142)	(0.0108)	(0.0108)
Highest: Degree	0.0008	-0.0170	-0.0175	-0.0255
	(0.0630)	(0.0634)	(0.0451)	(0.0456)
Highest: A-Level	-0.1218**	-0.1358**	-0.0919**	-0.0986**
	(0.0548)	(0.0551)	(0.0384)	(0.0388)
Highest: O-Level	0.0106	0.0023	-0.0010	-0.0038
	(0.0459)	(0.0460)	(0.0325)	(0.0327)
Private renter	-0.0076	-0.0065	-0.0577	-0.0579
	(0.0688)	(0.0688)	(0.0484)	(0.0484)
Owns Home: Mortgage	0.0717	0.0725	0.0086	0.0087
	(0.0668)	(0.0668)	(0.0481)	(0.0481)
Owns Home: Outright	-0.0484	-0.0470	-0.0878	-0.0872
	(0.0765)	(0.0765)	(0.0566)	(0.0566)
Married or Cohabiting	0.4162***	0.4162***	0.4167***	0.4164***
	(0.0959)	(0.0960)	(0.0714)	(0.0714)
Separated, Div, or Wid	-0.2676**	-0.2673**	-0.1608**	-0.1609**
	(0.1075)	(0.1075)	(0.0803)	(0.0803)
Unemployed	-0.3353***	-0.3355***	-0.3356***	-0.3357***
	(0.0994)	(0.0994)	(0.0722)	(0.0722)
Not in Labour Force	-0.0819*	-0.0822*	-0.0593	-0.0595
	(0.0470)	(0.0470)	(0.0365)	(0.0365)
Registered Disabled	0.0253	0.0252	0.0123	0.0122
	(0.0527)	(0.0527)	(0.0410)	(0.0410)
African	-0.5486	-0.5233	-0.2993	-0.2888
	(0.3410)	(0.3406)	(0.2463)	(0.2462)
Asian	-0.3629	-0.3785	-0.3017	-0.2841
	(0.4172)	(0.4167)	(0.2895)	(0.2896)
Other Ethnicity	0.2259	0.2100	0.2028	0.2141
	(0.5941)	(0.5932)	(0.3982)	(0.3980)
Birth-weight		0.0638*		0.0741***
		(0.0388)		(0.0270)
Age 7 BSAG		-0.3454**		-0.0413
		(0.1661)		(0.1134)
Observations	11,096	11,096	19,200	19,200
Number of Individuals	2,774	2,774	6,322	6,322
Mundlak Averages	Yes	Yes	Yes	Yes

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01
Note: Life satisfaction is measured at ages 33, 42, 46, and 50. BSAG = Bristol Social Adjustment Guide, which is a measure of child mental health (see Table 2.4).

Table 2.9: Random Effects Ordered Probit Model Coefficients: The Effects of Being Bullied at Age 7 on Total Malaise

	(1)	(2)	(3)	(4)
Dependent Variable	Total Malaise			
	Total Malaise Balanced (Sample 3)	Total Malaise Balanced (Sample 3)	Total Malaise Unbalanced (Sample 4)	Total Malaise Unbalanced (Sample 4)
Bullied at Age 7	-0.1215***	-0.1136**	-0.1496***	-0.1423***
	(0.0458)	(0.0458)	(0.0351)	(0.0351)
Male	0.5340***	0.5548***	0.5143***	0.5416***
	(0.0475)	(0.0486)	(0.0364)	(0.0371)
Ln(Household Income)	-0.1039***	-0.1030***	-0.0922***	-0.0910***
	(0.0182)	(0.0182)	(0.0151)	(0.0151)
Highest: Degree	0.1251*	0.0982	0.1454***	0.1072*
	(0.0711)	(0.0716)	(0.0561)	(0.0567)
Highest: A-Level	0.1186*	0.0964	0.1920***	0.1604***
	(0.0610)	(0.0614)	(0.0469)	(0.0474)
Highest: O-Level	0.0730	0.0599	0.1153***	0.0955**
	(0.0513)	(0.0515)	(0.0404)	(0.0406)
Private renter	-0.3284***	-0.3276***	-0.3620***	-0.3614***
	(0.0702)	(0.0702)	(0.0556)	(0.0556)
Owns Home: Mortgage	-0.1167	-0.1168	-0.1704***	-0.1712***
	(0.0723)	(0.0723)	(0.0584)	(0.0584)
Owns Home: Outright	-0.2521***	-0.2512***	-0.3221***	-0.3212***
	(0.0845)	(0.0845)	(0.0699)	(0.0699)
Married or Cohabiting	-0.1543	-0.1559	-0.1558*	-0.1577*
	(0.1071)	(0.1071)	(0.0886)	(0.0886)
Separated, Div, or Wid	-0.4317***	-0.4322***	-0.4401***	-0.4411***
	(0.1205)	(0.1205)	(0.1000)	(0.1000)
Unemployed	0.0223	0.0246	-0.0088	-0.0072
	(0.1122)	(0.1122)	(0.0901)	(0.0901)
Not in Labour Force	-0.2493***	-0.2494***	-0.2260***	-0.2261***
	(0.0501)	(0.0501)	(0.0425)	(0.0425)
Registered Disabled	0.2030***	0.2025***	0.1972***	0.1967***
	(0.0570)	(0.0570)	(0.0482)	(0.0482)
African	-0.2180	-0.1919	0.0868	0.1055
	(0.3889)	(0.3889)	(0.2999)	(0.2997)
Asian	-0.6698	-0.7126	-0.5979*	-0.6505*
	(0.4616)	(0.4614)	(0.3430)	(0.3428)
Other Ethnicity	-0.0973	-0.1346	-0.2985	-0.2931
	(0.8702)	(0.8695)	(0.4874)	(0.4871)
Birth-weight		-0.0002		-0.0158
		(0.0435)		(0.0329)
Age 7 BSAG		-0.5472***		-0.6289***
		(0.1821)		(0.1370)
Observations	9,762	9,762	14,907	14,907
Number of Individuals	3,254	3,254	6,333	6,333
Mundlak Averages	Yes	Yes	Yes	Yes

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01
Note: Total malaise is measured at ages 33, 42, and 50. The total malaise index is reversed and hence higher scores represent higher, rather than lower, SWB. BSAG = Bristol Social Adjustment Guide, which is a measure of child mental health (see Table 2.4).

Table 2.10: Random Effects With a Continuous Dependent Variable Model Coefficients: The Effects of Being Bullied at Age 11 on Life Satisfaction

	(1)	(2)	(3)	(4)
Dependent Variable	Life Satisfaction			
	Life Satisfaction Balanced (Sample 1)	Life Satisfaction Balanced (Sample 1)	Life Satisfaction Unbalanced (Sample 2)	Life Satisfaction Unbalanced (Sample 2)
Bullied at Age 11	-0.1611***	-0.1467***	-0.1758***	-0.1680***
	(0.0514)	(0.0515)	(0.0389)	(0.0391)
Male	-0.0880*	-0.0841*	-0.1325***	-0.1392***
	(0.0468)	(0.0478)	(0.0356)	(0.0363)
Ln(Household Income)	0.0491***	0.0496***	0.0472***	0.0473***
	(0.0166)	(0.0166)	(0.0131)	(0.0131)
Highest: Degree	0.0542	0.0306	0.0526	0.0385
	(0.0714)	(0.0718)	(0.0546)	(0.0552)
Highest: A-Level	-0.0730	-0.0914	-0.0333	-0.0451
	(0.0620)	(0.0623)	(0.0465)	(0.0469)
Highest: O-Level	0.0510	0.0397	0.0477	0.0420
	(0.0526)	(0.0528)	(0.0395)	(0.0396)
Private renter	-0.0360	-0.0346	-0.1345**	-0.1345**
	(0.0814)	(0.0814)	(0.0595)	(0.0595)
Owns Home: Mortgage	0.1028	0.1039	-0.0124	-0.0120
	(0.0788)	(0.0788)	(0.0591)	(0.0591)
Owns Home: Outright	-0.0533	-0.0515	-0.1475**	-0.1463**
	(0.0900)	(0.0900)	(0.0693)	(0.0693)
Married or Cohabiting	0.4571***	0.4571***	0.5239***	0.5237***
	(0.1136)	(0.1136)	(0.0878)	(0.0878)
Separated, Div, or Wid	-0.4017***	-0.4011***	-0.2383**	-0.2382**
	(0.1273)	(0.1273)	(0.0988)	(0.0988)
Unemployed	-0.4040***	-0.4041***	-0.4226***	-0.4226***
	(0.1180)	(0.1180)	(0.0889)	(0.0889)
Not in Labour Force	-0.1451***	-0.1454***	-0.1128**	-0.1133**
	(0.0551)	(0.0551)	(0.0446)	(0.0446)
Registered Disabled	0.0060	0.0059	0.0059	0.0057
	(0.0620)	(0.0620)	(0.0503)	(0.0503)
African	-0.5946	-0.5599	-0.3472	-0.3326
	(0.3802)	(0.3798)	(0.2969)	(0.2967)
Asian	-0.4355	-0.4563	-0.2991	-0.2860
	(0.4656)	(0.4651)	(0.3498)	(0.3499)
Other Ethnicity	0.3071	0.2928	0.3320	0.3486
	(0.6595)	(0.6585)	(0.4800)	(0.4798)
Birth-weight		0.0716*		0.0835**
		(0.0432)		(0.0325)
Age 7 BSAG		-0.4546**		-0.1386
		(0.1851)		(0.1370)
Constant	5.1359***	5.2528***	5.7923***	5.5608***
	(0.3601)	(0.3337)	(0.1749)	(0.2053)
Observations	11,096	11,096	19,200	19,200
Number of Individuals	2,774	2,774	6,322	6,322
Mundlak Averages	Yes	Yes	Yes	Yes

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01
Note: Life satisfaction is measured at ages 33, 42, 46, and 50. BSAG = Bristol Social Adjustment Guide, which is a measure of child mental health (see Table 2.4).

Table 2.11: Random Effects With a Continuous Dependent Variable Model Coefficients: The Effects of Being Bullied at Age 11 on Total Malaise

	(1)	(2)	(3)	(4)
Dependent Variable	Total Malaise			
	Total Malaise Balanced (Sample 3)	Total Malaise Balanced (Sample 3)	Total Malaise Unbalanced (Sample 4)	Total Malaise Unbalanced (Sample 4)
Bullied at Age 11	-0.1928***	-0.1804***	-0.2156***	-0.2015***
	(0.0554)	(0.0557)	(0.0416)	(0.0417)
Male	0.4425***	0.4629***	0.4308***	0.4596***
	(0.0505)	(0.0516)	(0.0381)	(0.0388)
Ln(Household Income)	-0.0952***	-0.0943***	-0.0828***	-0.0817***
	(0.0192)	(0.0192)	(0.0157)	(0.0157)
Highest: Degree	0.0961	0.0678	0.1346**	0.0951
	(0.0757)	(0.0763)	(0.0589)	(0.0595)
Highest: A-Level	0.1215*	0.0984	0.1955***	0.1628***
	(0.0651)	(0.0656)	(0.0494)	(0.0500)
Highest: O-Level	0.0508	0.0369	0.1067**	0.0858**
	(0.0555)	(0.0557)	(0.0431)	(0.0433)
Private renter	-0.4399***	-0.4388***	-0.4730***	-0.4720***
	(0.0773)	(0.0773)	(0.0602)	(0.0602)
Owns Home: Mortgage	-0.1719**	-0.1715**	-0.2172***	-0.2169***
	(0.0780)	(0.0780)	(0.0619)	(0.0619)
Owns Home: Outright	-0.3429***	-0.3412***	-0.3983***	-0.3961***
	(0.0909)	(0.0909)	(0.0739)	(0.0739)
Married or Cohabiting	-0.1811	-0.1824	-0.1402	-0.1425
	(0.1152)	(0.1152)	(0.0931)	(0.0931)
Separated, Div, or Wid	-0.5478***	-0.5476***	-0.5109***	-0.5119***
	(0.1302)	(0.1302)	(0.1058)	(0.1058)
Unemployed	0.0053	0.0074	-0.0194	-0.0181
	(0.1217)	(0.1217)	(0.0956)	(0.0956)
Not in Labour Force	-0.3177***	-0.3177***	-0.2982***	-0.2982***
	(0.0554)	(0.0554)	(0.0464)	(0.0464)
Registered Disabled	0.2035***	0.2030***	0.2098***	0.2093***
	(0.0618)	(0.0618)	(0.0519)	(0.0519)
African	-0.1275	-0.1018	0.2297	0.2448
	(0.4234)	(0.4233)	(0.3162)	(0.3158)
Asian	-0.6989	-0.7414	-0.6219*	-0.6805*
	(0.5057)	(0.5056)	(0.3715)	(0.3713)
Other Ethnicity	0.1668	0.1319	-0.4180	-0.4136
	(0.9489)	(0.9484)	(0.5244)	(0.5237)
Birth-weight		-0.0018		-0.0230
		(0.0465)		(0.0348)
Age 7 BSAG		-0.5664***		-0.6733***
		(0.1957)		(0.1454)
Constant	6.3290***	6.1768***	6.7757***	7.0043***
	(0.3689)	(0.3365)	(0.1826)	(0.2162)
Observations	9,762	9,762	14,907	14,907
Number of Individuals	3,254	3,254	6,333	6,333
Mundlak Averages	Yes	Yes	Yes	Yes

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01
Note: Total malaise is measured at ages 33, 42, and 50. The total malaise index is reversed and hence higher scores represent higher, rather than lower, SWB. BSAG = Bristol Social Adjustment Guide, which is a measure of child mental health (see Table 2.4).

Table 2.12: Probit Model Coefficients and Average Marginal Effects: First Stage of 2SRI: The Determinants of Being Bullied at Age 11

	(1)	(2)	(3)	(4)
Dependent Variable	Bullied at Age 11			
	Life Satisfaction Balanced (Sample 1)	Life Satisfaction Balanced (Sample 1)	Total Malaise Balanced (Sample 3)	Total Malaise Balanced (Sample 3)
	Coefficients	Average Marginal Effects	Coefficients	Average Marginal Effects
Birth-weight	-0.1864***	-0.0530***	-0.2022***	-0.0580***
	(0.0562)	(0.0159)	(0.0513)	(0.0146)
BSAG at Age 7	0.8091***	0.2303***	0.8884***	0.2550***
	(0.2259)	(0.0639)	(0.2014)	(0.0573)
Growth in Height	0.7721	0.2197	0.6747	0.1937
	(0.6908)	(0.1965)	(0.6365)	(0.1826)
Upset	-0.0523	-0.0149	-0.0453	-0.0130
	(0.0465)	(0.0132)	(0.0432)	(0.0124)
Male	0.2338***	0.0665***	0.2149***	0.0617***
	(0.0591)	(0.0167)	(0.0544)	(0.0155)
Bullied at Age 7	0.7095***	0.2019***	0.7040***	0.2021***
	(0.0567)	(0.0149)	(0.0522)	(0.0138)
Constant	-0.5764**		-0.5149*	
	(0.2922)		(0.2688)	
Number of Individuals	2,774	2,774	3,254	3,254

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: Life satisfaction is measured at ages 33, 42, 46, and 50. Total malaise is measured at ages 33, 42, and 50. BSAG = Bristol Social Adjustment Guide, which is a measure of child mental health (see Table 2.4).

Table 2.13: Random Effects Ordered Probit Model Coefficients: Second Stage of 2SRI: The Effects of Being Bullied at Age 11 on Life Satisfaction and Total Malaise

	(1)	(2)
Dependent Variable	Life Satisfaction	Total Malaise
	Life Satisfaction Balanced (Sample 1)	Total Malaise Balanced (Sample 3)
Bullied at Age 11	-0.5211**	-0.4023*
	(0.2153)	(0.2394)
Male	-0.1024**	0.5620***
	(0.0458)	(0.0517)
Ln(Household Income)	0.0426***	-0.1107***
	(0.0146)	(0.0188)
Highest: Degree	-0.0545	0.0749
	(0.0655)	(0.0739)
Highest: A-Level	-0.1586***	0.0852
	(0.0571)	(0.0636)
Highest: O-Level	-0.0174	0.0524
	(0.0482)	(0.0538)
Private renter	0.0013	-0.3166***
	(0.0716)	(0.0730)
Owns Home: Mortgage	0.0618	-0.1345*
	(0.0694)	(0.0755)
Owns Home: Outright	-0.0638	-0.2720***
	(0.0794)	(0.0881)
Married or Cohabiting	0.4506***	-0.1788
	(0.0998)	(0.1105)
Separated, Div, or Wid	-0.2203**	-0.4695***
	(0.1115)	(0.1242)
Unemployed	-0.3270***	0.0193
	(0.1020)	(0.1151)
Not in Labour Force	-0.0985**	-0.2419***
	(0.0492)	(0.0523)
Registered Disabled	0.0344	0.1744***
	(0.0545)	(0.0591)
African	-0.5414	0.0149
	(0.3406)	(0.4118)
Asian	-0.3531	-0.6140
	(0.4569)	(0.5001)
Other Ethnicity	0.1716	-0.2081
	(0.5934)	(0.8671)
Birth-weight	0.0291	-0.0356
	(0.0414)	(0.0465)
Age 7 BSAG	-0.2975*	-0.3990**
	(0.1807)	(0.2004)
Bullying Equation Residuals	0.0881*	0.0482
	(0.0454)	(0.0505)
Observations	11,096	9,762
Number of Individuals	2,774	3,254
Mundlak Averages	Yes	Yes

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01
The total malaise index is reversed and hence higher scores represent higher SWB. BSAG = Bristol Social Adjustment Guide, which is a measure of child mental health (see Table 2.4).

Table 2.14: Probit Model Average Marginal Effects: Age 11 Bullying Frequency and Absence from the Life Satisfaction and Total Malaise Balanced Panels

	(1)	(2)
	Age 11 Respondents (Sample 5)	
Dependent Variable	Absent from Life Satisfaction Balanced	Absent from Total Malaise Balanced
Male	0.0547***	0.0638***
	(0.0069)	(0.0073)
Frequently Bullied at Age 11	0.0388**	0.0121
	(0.0193)	(0.0195)
Sometimes Bullied at Age 11	-0.0070	-0.0062
	(0.0086)	(0.0091)
Reading Score (Age 16)	-0.0075***	-0.0068***
	(0.0006)	(0.0006)
Missing Reading Score (Age 16)	-0.1273***	-0.1015***
	(0.0188)	(0.0195)
Observations	13430	13430

Note: Columns (1) and (2) make use of a sample of all responses to the bullying question at age 11.
Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 2.15: Probit Model Average Marginal Effects: Age 11 Bullying Frequency and Absence from the Life Satisfaction and Total Malaise Unbalanced Panels

	(1)	(2)
	Age 11 Respondents (Sample 5)	
Dependent Variable	Absent from Life Satisfaction Balanced	Absent from Total Malaise Balanced
Male	0.0453***	0.0495***
	(0.0041)	(0.0048)
Frequently Bullied at Age 11	0.0087	0.0021
	(0.0107)	(0.0124)
Sometimes Bullied at Age 11	-0.0082	-0.0109*
	(0.0051)	(0.0059)
Reading Score (Age 16)	-0.0075***	-0.0067***
	(0.0004)	(0.0004)
Missing Reading Score (Age 16)	-0.0895***	-0.0721***
	(0.0106)	(0.0123)
Observations	53720	40290
Number of Individuals		

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 2.16: Linear Two Stage Heckman Selection Model Coefficients: The Effects of Being Bullied at Age 11 on Life Satisfaction

	(1)	(2)	(3)	(4)
	Age 11 Respondents (Sample 5)	Life Satisfaction Balanced (Sample 1)	Age 11 Respondents (Sample 5)	Life Satisfaction Unbalanced (Sample 2)
Dependent Variable	Absent from Life Satisfaction Balanced Panel	Life Satisfaction	Absent from Life Satisfaction Unbalanced Panel	Life Satisfaction
	First Stage	Second Stage	First Stage	Second Stage
Non-response at Age 23	-0.5512***		-0.6676***	
	(0.0175)		(0.0150)	
Male	-0.1805***		-0.1013***	
	(0.0126)		(0.0114)	
Bullied at Age 11	0.0047	-0.1487***	0.0194	-0.1668***
	(0.0147)	(0.0354)	(0.0132)	(0.0280)
Reading Score (Age 16)	0.0254***		0.0180***	
	(0.0011)		(0.0010)	
Missing Reading Score (Age 16)	0.4830***		0.2664***	
	(0.0342)		(0.0294)	
Inverse Mills Ratio		-0.0643		-0.1202*
		(0.1019)		(0.0658)
Constant	-0.6171***	5.2244***	-0.1728***	5.6601***
	(0.0095)	(0.2809)	(0.0088)	(0.1709)
Observations	53,720	11,096	53,720	19,200
Number of Individuals	13,430	2,774	13,430	6,322
Childhood Characteristics	No	Yes	No	Yes
Mundlak Averages	No	Yes	No	Yes
Childhood Characteristics	No	Yes	No	Yes

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01
Note: Life satisfaction is measured at ages 33, 42, 46, and 50.

Table 2.17: Linear Two Stage Heckman Selection Model Coefficients: The Effects of Being Bullied at Age 11 on Total Malaise

	(1)	(2)	(3)	(4)
	Age 11 Respondents	Total Malaise Balanced	Age 11 Respondents	Total Malaise Unbalanced
Dependent Variable	Absent from Total Malaise Balanced Panel	Total Malaise	Absent from Total Malaise Unbalanced Panel	Total Malaise
	First Stage	Second Stage	First Stage	Second Stage
Non-response at Age 23	-0.5621***		-0.6527***	
	(0.0191)		(0.0170)	
Male	-0.1914***		-0.1109***	
	(0.0140)		(0.0130)	
Bullied at Age 11	0.0146	-0.1787***	0.0280*	-0.2013***
	(0.0163)	(0.0402)	(0.0152)	(0.0322)
Reading Score (Age 16)	0.0203***		0.0156***	
	(0.0012)		(0.0011)	
Missing Reading Score (Age 16)	0.3524***		0.2142***	
	(0.0372)		(0.0336)	
Inverse Mills Ratio		-0.0976		-0.1611**
		(0.1008)		(0.0785)
Constant	-0.4901***	6.3034***	-0.1387***	6.9277***
	(0.0106)	(0.3027)	(0.0101)	(0.1935)
Observations	40,290	9,762	40,290	14,907
Number of Individuals	13,430	3,254	13,430	6,333
Childhood Characteristics	No	Yes	No	Yes
Mundlak Averages	No	Yes	No	Yes
Childhood Characteristics	No	Yes	No	Yes

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01
Note: Total malaise is measured at ages 33, 42, and 50. The total malaise index is reversed and hence higher scores represent higher, rather than lower, SWB.

Chapter 3: Adolescent Antisocial Behaviour and Mental Health

3.1 Introduction

In this chapter we explore the effects of the mental health of adolescents on participation in antisocial behaviour (ASB); in other words how mental health affects "*what you do to others*". We investigate the relative effects of externalising problems (mental health problems directed at others) and internalising problems (mental health problems directed at the individual) on the ASB of adolescents. We also explore how the mental health of parents affects the ASB of adolescents.

3.1.1 Motivation

In his seminal theory on the economics of crime, Becker (1968) argued that the social costs of crime include the costs of policing, criminal justice, and the loss of earnings of victims. Recent estimates from England and Wales suggest that, in 2003 prices, the cost of crime committed in 2003/ 2004 against households amounted to approximately £36 billion, see Dubourg et al. (2005).[50] Of this total, they estimate that approximately 50% of the costs of crime were attributable to the direct costs including policing and criminal justice, and a further 50% was attributable to the intangible effects of crime on the physical and emotional health of victims.

Becker (1968) argued that people participate in crime if their perceived expected utility from engaging in crime is greater than their perceived expected utility from legal behaviour. As previously discussed in Chapter 1, the distinction between crime and ASB is fuzzy because the term ASB is frequently used to refer to minor crimes such as vandalism. Consequently, hereafter we use the term ASB to refer to both ASB and minor crime participated in by adolescents. Becker's theory supports a number of explanations for how the mental health of an individual may affect whether or not they engage in crime.

Firstly, people who have externalising problems such as attention deficit hyperactivity disorder (ADHD) typically have higher discount rates and may thus have inhibited self-control, (see Marco et al., 2009; American Psychiatric Association, 2013). For this reason, adolescents who have greater symptoms of externalising problems such as ADHD may be more likely to discount the future consequences of their actions, and may thus be more likely to participate in ASB, see Fletcher and Wolfe (2009).

[50] To our knowledge, Dubourg et al. (2005) present the most recent comprehensive estimates of the cost of crime in the UK. For a systematic review of the cost of crime in the UK, see Wickramasekera et al. (2015).

Secondly, Macleod (1999) and Liao and Wei (2011) suggest that internalising problems such as anxiety and depression are often characterised by viewing the future as uncertain. Therefore, individuals who have depression and anxiety may have a reduced assessment of their life expectancy. Accordingly, adolescents who have more symptoms of internalising problems may be more likely to overlook the future repercussions of their actions, thus increasing the likelihood that they participate in ASB, see Anderson et al. (2015).

However, the behaviour of adolescents may not be rational in the neo-classical sense and may thus be subject to systematic biases. For instance, adolescents may exhibit optimism bias which relates to the tendency to overestimate (underestimate) the likelihood of experiencing favourable (unfavourable) events, see Sharot (2011). For example, adult first time bungee jumpers believe that they are at a lower than average risk of injury than other jumpers, see Middleton et al. (1996). In addition, adolescent smokers were more likely than non-smokers to doubt that they would die from smoking if they smoked for 30-40 years, (see Arnett, 2000)[51]. Previous research indicates that the degree of optimism bias of an adolescent may be related to their mental health. For example, Strunk et al. (2006) indicates that internalising mental health problems such as depression are inversely associated with optimism bias[52]. Consequently, adolescents who have greater symptoms of depression may overestimate the risk that they will be caught participating in ASB. If this is the case, adolescents who have depression may be less likely to participate in ASB.

Hence, both Becker's theory of criminal behaviour and behavioural theories offer explanations for how the mental health of adolescents may affect their involvement in ASB. It is important to investigate the effects of the mental health of adolescents on whether or not they engage in ASB to investigate these theories.

Thirdly, there is a rapid expansion of mental health services underway in the UK. Data from the Independent Mental Health Taskforce (2016) suggests that in 2015/ 2016, approximately 17% of adults aged 16-75 in the UK suffered from depression or anxiety, of which, approximately 15% were in receipt of psychological therapy. Likewise, approximately 10% of children in the UK have a diagnosable mental health condition such as depression, anxiety, or ADHD, and again only 15% are in receipt of treatment, see Independent Mental Health Taskforce (2016). The Improving Access to Psychological Therapies programme aims to increase the rate of access to psychological therapies to 25% of adults with depression or anxiety by 2020/ 2021,

[51] Optimism bias has been demonstrated in a number of real world applications such underestimating the probability of being involved in a car accident, sports fans over-estimating the probability that the team they support will win, and graduates over-estimating their ability to repay their student debt, (see, for example, Deery, 1999; Love et al., 2015; Seaward and Kemp, 2000).

[52] Their findings indicate that people with minor depression do not typically exhibit optimism or pessimism bias. In contrast, people who have severe depression are typically characterised by pessimism bias. Pessimism bias is the tendency to underestimate (overestimate) the likelihood of favourable (unfavourable) events occurring.

thus expanding access to approximately 0.6 million more adults, see NHS England (2016).[53] In a similar fashion, the Children and Young People's Improving Access to Psychological Therapies programme aims to expand access to mental health treatments to 70,000 more children by 2020/ 2021, see Independent Mental Health Taskforce (2016).

Fourthly, O'Donnell et al. (2014) and Helliwell et al. (2015) argue that governments who wish to promote subjective well-being (SWB) should treat mental health problems on an equal footing to physical health problems. For this reason, it is important to explore the effects of the mental health of adolescents on their participation in ASB to cast light upon the wider ramifications of expanding access to treatments for mental health problems, and to portray the wider consequences of making SWB more centre-stage in policymaking. Fifthly, this field of research complements a growing literature showing how SWB affects other outcomes such as future income and risk-avoiding behaviour, (see De Neve and Oswald, 2012; Goudie et al., 2014).[54] Finally, adolescents who participate in ASB have an increased likelihood of committing crime as adults, see Farrington (1997) and Bergman and Andershed (2009), so these results can also inform longer term societal problems.

As well as exploring the effects of adolescent mental health on participation in ASB, we explore the effects of the mental health of parents on the ASB of adolescents. It is important to investigate this latter issue for several reasons. Firstly, in recent years, UK politicians have expressed an increased interest in families and how government policies can support them. One example of such a policy is the *"Troubled Families"* programme in England, which was launched in April 2012 by the Department for Communities and Local Government, see Day et al. (2016). The definition of a "*troubled family*" as outlined by the Department for Communities and Local Government (2012) are households who are involved in crime and ASB, have children who truant, claim out of work benefits, and incur high costs to the public purse[55]. In a speech in 2014 on the *"Troubled Families"* programme, the former Prime Minister, David Cameron, said:

[53] The Improving Access to Psychological Therapies programme was introduced in 2008 by the former Labour government to expand access to psychological therapies. For further information regarding the Improving Access to Psychological Therapies programme, see Layard and Clark (2015) and NHS England (2016).
[54] For an overview of the literature exploring the effects of SWB on other outcomes, see De Neve et al. (2013).
[55] The impact evaluation of the Troubled Families programme, published in 2016, indicated no consistent evidence that the programme had any statistically significant or consistent impact on a wide range of the key objectives of the programme such as employment, receipt of social welfare, truancy, and child welfare, see Day et al. (2016). However, despite the lack of evidence supporting the effectiveness of the programme in improving the outcomes of families, the Troubled Families programme was expanded in 2016 at an estimated total cost of £920m over the following five years, see Bate (2017).

"*What you [families] do is not just vital for the individuals and the families involved, it's vital for the whole country... Backing families in Britain also means supporting those families who are not coping at all*". (Cameron, 2014).

Arguably, a potential indicator of whether a family is "*coping*" is parental mental health. For that reason, it is important to explore the effects of the mental health of parents on the ASB of adolescents to investigate David Cameron's claim regarding the importance of families for society.

Secondly, a large literature in economics has explored how the characteristics of parents affect the characteristics of their children. For example, Chevalier et al. (2013) investigate how children's educational attainment is affected by their parent's income and educational attainment. In addition, Dohmen et al. (2011) investigate the effects of parental risk and trust attitudes on that of their children. Thus, it is important to investigate the effects of the mental health of parents on the ASB of adolescents to contribute to the existing literature exploring such intergenerational relationships.

3.1.2 Summary of the Findings

This chapter investigates how the mental health of adolescents affects their participation in four ASBs (fighting, vandalism, shoplifting, and truancy). The empirical analysis reveals that poorer overall mental health predicts a higher probability of participation in all four activities. In addition, the findings suggest that adolescent's internalising problems and externalising problems have different effects on their ASB.

For example, a one standard deviation increase in externalising problems is associated with an increase in the probability of engaging in fighting (vandalism) of 7.88% (4.98%) points, approximately 90% (160%) of the extent of the effect of being male. In a similar fashion, a one standard deviation increase in externalising problems predicts a 0.9% point increase in the probability of shoplifting, approximately 1.5 times the magnitude of the effect of being male. Likewise, a one standard deviation increase in externalising problems increases the probability of truancy by 3.03% points. In addition, a one standard deviation increase in the tendency to internalise is associated with an increase in the probability of fighting of 1.33% points. In contrast to the findings relating to externalising problems, the tendency to internalise has no statistically significant effect on participation in vandalism, shoplifting, or truancy.

We explore the robustness of our findings using multivariate probit and conditional logit models. The empirical results from multivariate probit models support the robustness of the effects of externalising problems on fighting, vandalism, shoplifting, and truancy. Moreover, the findings from conditional logit models suggest that greater externalising problems are positively associated with increases in the probability of fighting, vandalism, and truancy. Conditional logit models show no statistically significant effect of the propensity to internalise on fighting, vandalism, or truancy.

The core findings of this chapter suggest that mental health interventions to reduce the externalising problems of adolescents may reduce the prevalence of ASB. Farrington (1997) and Bergman and Andershed (2009) suggest that adolescents who engage in ASB have an increased likelihood of committing crime as adults. As a result, mental health interventions to reduce the propensity to externalise may indirectly reduce future crime, via their shorter-term effect on ASB. In comparison, our findings show no consistent effect of family income on ASB and therefore support the case that the mental health of adolescents has a greater effect on their ASB, relative to the effect of their socioeconomic background. This suggests that direct mental health interventions are needed rather than simply interventions to improve material well-being.

We also explore the effects of the mental health of parents on the ASB of adolescents. The evidence suggests that poorer maternal mental health is associated with an increased probability that adolescents participate in fighting, shoplifting, and truancy behaviours, but has no statistically significant effect on engagement in vandalism. In contrast to the findings relating to the effects of maternal mental health, there is no statistically significant effect of paternal mental health on subsequent fighting, shoplifting, and truancy behaviours.

As an extension, we investigate the effects of the mental health of adolescents on harmful substance use and prosocial behaviour. The empirical results suggest that the propensity to externalise is associated with a greater probability of harmful substance use in the next wave. Moreover, the findings suggest that externalising problems are inversely associated with the probability of volunteering, but have no statistically significant effect on whether adolescents help with housework. In contrast, internalising problems are inversely associated with the probability that the adolescent has ever drunk alcohol, but have no statistically significant effect on cigarette smoking or drug consumption. There is also no statistically significant effect of the tendency to internalise on whether adolescents volunteer or help with housework. The findings of this chapter therefore support the view that higher propensity to externalise may increase the prevalence of "negative" behaviours and reduce the prevalence of "good" behaviours.

This chapter proceeds as follows. Section 3.2 reviews the literature exploring the effects of externalising and internalising problems on antisocial and criminal behaviour. This literature is from the disciplines of economics, psychiatry, criminology, and psychology. Section 3.3 outlines the data, estimation samples, dependent variables, key explanatory variables, and discusses summary statistics showing the associations between mental health and ASB. Section 3.4 offers a justification for the use of random effects probit models, presents the empirical specifications, and details the robustness checks. Section 3.5 examines the core results and Sections 3.6 to 3.8 discusses the findings of the robustness checks. Section 3.9 concludes.

3.2 Literature Review

3.2.1 The Effects of Externalising Problems on Criminal and Antisocial Behaviour: Evidence from Economics, Psychiatry, and Criminology

The economics, psychiatry, and criminology literatures have explored the effects of externalising problems on antisocial and criminal behaviour. For example, in the economics literature, Fletcher and Wolfe (2009) investigate the effects of ADHD at ages 5 to 12 on criminal behaviour at ages 18-26 using a subsample of 12,046 adolescents drawn from the National Longitudinal Study of Youth dataset. They measure childhood ADHD retrospectively utilising 17 ratings of ADHD symptoms collected when the respondents were between the ages of 18 and 28.[56]

Fletcher and Wolfe (2009) estimate logit models controlling for neighbourhood and family fixed effects to explore the effect of childhood ADHD on the probability of stealing, drug dealing, burglary, robbery, arrest, conviction, and involvement in any crime. Their findings suggest that individuals who have ADHD in childhood have a greater probability of committing any crime, stealing, robbery, and being arrested at ages 18-26. In contrast, there is no statistically significant effect of childhood ADHD on the probability of burglary or the probability of being convicted of a crime.

However, their analysis arguably suffers from a number of shortcomings. Firstly, Fletcher and Wolfe (2009) utilise retrospective reports of ADHD symptoms, which may suffer from measurement error, thus leading to attenuation bias. Secondly, they explore the effects of ADHD on criminal behaviour using a series of single-equation models. However, the error terms of the models are likely related via unobserved characteristics affecting the decisions to commit each of the crimes. Hence, the efficiency of their estimates is likely to be reduced.

Thirdly, the authors do not account for other co-morbid mental health conditions such as depression, see Anderson (1987). Finally, they are selective of the measures of adult criminal behaviour that they make use of. For example, they do not investigate the effect of ADHD on the measures of violent criminal activity reported in the National Longitudinal Study of Youth.

An important contribution from the psychiatry literature is Murray et al. (2015), who explore the effects of hyperactivity and conduct problems at age 11 on criminal behaviour at age 18. The authors use data from the Brazilian Pelotas Birth Cohort Study (sample size = 3,618) and the Avon Longitudinal Study of Parents and Children (sample size = 4,103).

[56] The respondents, aged 18 to 28, were asked to recall whether they had 9 (8) symptoms of inattention (hyperactivity/ impulsivity) between the ages of 5 and 12.

They measure hyperactivity (conduct) problems using the hyperactivity/ inattention (conduct) problems subscales of the Strengths and Difficulties Questionnaire (SDQ). They measure nonviolent crime using a binary variable that equals 1 if in the past year the individual committed theft from shops, vehicles, or people; property damage; vehicle theft; drug dealing; burglary; handling stolen goods; or arson. Murray et al. (2015) measure violent crime using a binary variable that is equal to 1 if the individual engaged in robbery; assault; and carrying, or using, a weapon.

Making use of logit models, the authors find a positive association between hyperactivity at age 11 and participation in violent crime at age 18 for both males and females in Brazil. For the UK, their findings suggest that hyperactivity at age 11 has a statistically significant effect on whether males commit violent crime at age 18, but does not affect whether females commit violent crime at age 18. In addition, for both Brazil and Britain the authors offer no evidence to suggest that hyperactivity at age 11 increases the probability that an individual participates in nonviolent crime in both Brazil and the UK. In comparison, in Brazil and the UK, conduct problems at age 11 increase the probability that an individual engages in both violent and nonviolent crime.

Their analysis is arguably subject to a number of shortcomings. Firstly, the authors do not control for the adolescent's social characteristics such as whether they eat evening meals with their family; and whether they stay out late, without their parents knowing their whereabouts. Sen (2010) suggests that the frequency that adolescents eat evening meals with their family is inversely associated with their likelihood of participating in ASB. In a similar vein, Iacovou (2012) suggests that adolescents who stay out late without their parents knowing their whereabouts are at an increased risk of engaging in ASB. Secondly, in common with Fletcher and Wolfe (2009), they estimate a series of single-equation models, thus reducing the efficiency of their estimates.

In the criminology literature, Dalsgaard et al. (2013) investigate the effects of childhood ADHD on adult criminality in Denmark. The authors measure childhood ADHD using clinical diagnoses of 206 children aged 4-19 at the Risskov Psychiatric Hospital, Denmark, from 1969-1989. The authors match diagnoses of childhood ADHD to criminal convictions data from 2000 from the Danish National Crime Register. To form a control group, they utilise data on the criminal convictions of the general population, drawn from the Danish National Crime Register.

Dalsgaard et al. (2013) use Cox proportional hazards models to explore the effects of childhood ADHD on whether the individual receives a criminal record as an adult.[57] Dalsgaard et al. (2013) suggest that individuals who were diagnosed with ADHD as a

[57] Cox proportional hazard models are a class of survival model used to explore how a set of covariates affects the time until an event occurs (e.g. receiving a criminal record), see Greene (2011).

child were 5.6 times more likely to receive a criminal conviction as an adult relative to the general population.

However, their analysis is subject to a number of limitations. Firstly, Dalsgaard et al. (2013) utilise data on criminal convictions in adulthood rather than data relating to participation in criminal behaviour. Arguably, ADHD may affect the likelihood of an individual who has committed criminal behaviour being caught and convicted, rather than affecting the probability that they engage in criminal behaviour per se. If this is the case, their findings may not reflect the effects of ADHD on participation in criminal behaviour.

Secondly, previous research has indicated that the number of siblings is positively associated with the probability of ADHD diagnoses and adult criminality, (see Russell et al., 2015; Williams and Sickles, 2002). However, Dalsgaard et al. (2013) do not control for the number of siblings of an individual.

3.2.2 The Effects of Internalising Problems on Criminal and Antisocial Behaviour: Evidence from Economics, Psychology, and Criminology

The existing literature investigating the effects of internalising problems on antisocial and criminal behaviour is drawn from the disciplines of economics, psychology, and criminology. However, this literature yields inconsistent findings, which may result from differences in measures of ASB and internalising problems, methods, control variables, and datasets from different countries.

For example, in the economics literature, Anderson et al. (2015) investigate the effects of depression at ages 12-18 on future criminal behaviour at ages 25-32 using a subsample of 13,971 adolescents drawn from the US National Longitudinal Study of Youth dataset. The authors measure depression using the Centre for Epidemiologic Studies Depression (CES-D) scale, see Radloff (1977). To measure crime at ages 25-32 they utilise binary variables indicating participation in property, violent, drug dealing, or non-drug related crimes in the past year.[58]

Using sibling-fixed effects models and propensity score matching, Anderson et al. (2015) provide evidence to suggest that adolescents who have depression at ages 12-18 have an higher probability of committing property crime at ages 25-32, relative to adolescents who do not have depression. In comparison, the authors find no effect

[58] The measures of property crimes are, did you: "deliberately damage property that didn’t belong you?", "steal something worth less than $50?", "steal something worth more than $50?", and "go into a house or building to steal something?". The measures of violent crime are, did you: "use or threaten to use a weapon to get something from someone?", "hurt someone badly enough in a physical fight that he or she needed care from a doctor or nurse?", "pull a gun or knife on someone?", and "stab or shoot someone?". The measure of drug dealing is "how often did you sell marijuana or other drugs?". Finally, the non-drug related crime variable equals 1 if the adolescent committed property crime or violent crime, and 0 otherwise.

of depression on the likelihood of committing violent crime or drug dealing at ages 25-32.

However, Anderson et al. (2015) is subject to a number of limitations. Firstly, the authors utilise a series of single-equation models to investigate the effects of depression on criminal behaviour. For this reason, their estimates are likely to be inefficient. Secondly, they do not control for important social variables such as attitudes towards education, which previous research has indicated to be inversely associated with criminal behaviour, see Bernat et al. (2012).

An interesting contribution from the psychology literature is Beyers and Loeber (2003). The authors investigate the effects of depression on ASB using a subsample of 506 males aged 13-17 drawn from the Pittsburgh Youth Study, a longitudinal study of male delinquency in Pittsburgh, US. The authors measure depression using the 13-item Short Mood and Feelings Questionnaire, see Messer et al. (1995). To measure ASB they make us of the Self-Reported Delinquency Scale, a 25 point index of the total number of illegal acts committed by the adolescent (including vandalism and shoplifting). Their findings using Poisson regression techniques suggest that depression is associated with an increased likelihood of committing ASB.

However, the authors do not control for a number of important covariates such as family income and the frequency of eating evening meals as a family. It is important to account for family income because previous research has indicated that depression and ASB are more common amongst adolescents from low income backgrounds, (see Melchior et al., 2010; Piotrowska et al., 2015). What is more, adolescents who eat evening meals with their family are less likely to participate in ASB and have fewer symptoms of depression, (see Sen, 2010; Fulkerson et al., 2006). Consequently, the authors may overestimate the effects of depression on ASB.

In the criminology literature, Ritakallio et al. (2006) use a subsample of 3,679 adolescents aged 14-16 drawn from the Finnish School Health Promotion Study dataset. The authors investigate the effects of depression on property damage, shoplifting, and violent behaviour (fighting and "beating others up"). They measure depression using the 12-item Beck Depression Inventory, a self-reported measure of depression, see Beck and Beck (1972). The 12 items of the Beck Depression Inventory are scored from 0-3 according to the severity of the adolescent's symptoms, and hence give a minimum (maximum) score of 0 (36). The authors create a binary variable equal to 1 if the adolescent has moderate/ severe depression (a score of 8-36) and 0 if the adolescent does not have depression or has mild depression (a score of 0-7).

Their findings, using logit models, indicate that increased symptoms of depression are associated with committing a wider variety of offences amongst males and females. In addition, they suggest that depressed females have an increased likelihood of committing repeat offences of vandalism.

However, their analysis is subject to a number of drawbacks. For example, Ritakallio et al. (2006) do not control for any of the adolescent's demographic, family, or social characteristics which previous research indicates to affect both criminal behaviour and depression. See, for example, Ministry of Justice, 2015; Sariaslan et al., 2014; Piotrowska et al., 2015; Farrington, 1997; Animasahun, 2014; Farrington, 1993; Iacovou, 2012; Shang et al., 2010; Dunlop et al., 2003; Kantomaa et al., 2010. In common with Anderson et al. (2015), they utilise a series of single-equation models to explore the effects of depression on criminal behaviour, thus reducing the efficiency of their estimates.

In addition, in the psychology literature, Kofler et al. (2011) explore the effects of depression, an internalising mental health problem, on criminal behaviour in adolescence. The authors utilise a subsample of 3,604 adolescents drawn from the US National Survey of Adolescents. They measure depression using the 13-item National Survey of Adolescents depression index and they measure criminal behaviour using self-reported data indicating the number of illegal acts committed in the past year.[59]

Kofler et al. (2011) utilise latent growth modelling to investigate how depression at ages 12-17 affects the increase in the number of criminal acts committed in the next year (the change in the number of criminal acts committed by the adolescent from ages 12-17 to ages 13-18).[60] The authors suggest that symptoms of depression at ages 12-17 are positively associated with the increase in the number of criminal behaviours committed in the next year. To test for reverse causality, if criminal behaviour affects depression, they investigate the effects of criminal behaviour at ages 12-17 on the increase in an adolescent's symptoms of depression in the next year. Their findings suggest that criminal behaviour at ages 12-17 does not affect the increase in the number of depressive symptoms in the next year.

However, with the exception of the adolescent's age and gender, Kofler et al. (2011) do not account for any confounding variables such as the demographic, family, and social characteristics of the adolescent. As previously discussed, the existing literature suggests that it is important to control for these variables because they affect both depression and criminal behaviour.

To summarise, the existing literature exploring the effects of mental health on crime and ASB arguably suffers from several limitations. Firstly, it does not typically account for the family and social characteristics of adolescents such as their family income, the frequency of staying out late, and the frequency of eating evening meals with their family. For this reason, the estimates may suffer from omitted variable bias. Secondly, the existing literature typically uses single-equation models to explore the effects of

[59] The illegal acts are assault, drug dealing, burglary, car theft, robbery, attacking someone with a weapon, attacking someone with intent to seriously hurt or kill, being arrested, and being sent to jail.

[60] Latent growth modelling is a modelling approach used to split individuals into subgroups based on their rates of change in a given variable over time, see Andruff et al. (2009).

the mental health of adolescents on their participation in crime and ASB. As a result, it is likely that their estimates are not efficient because the correlation between the error terms of the equations are not accounted for, thus increasing the variance of the estimates, see (Maddala, 1986; Wooldridge, 2002). Section 3.4 outlines the steps taken to address these issues.

3.3 Data

This chapter analyses individual, household, and neighbourhood level data from waves 1 to 6 (2009 to 2015) of Understanding Society, see University of Essex (2017)[61]. Understanding Society is a nationally representative, longitudinal sample of approximately 40,000 households from across each of the 11 government office regions of the UK.

We utilise data on adolescents who completed the Understanding Society youth questionnaire, a self-reported survey of household members aged 10-15. The Understanding Society youth questionnaire is a short, paper based, self-completion questionnaire. At the age of 16, household members exit the youth sample and enter the adult survey.

We merge the data relating to adolescents with parent-level and household-level data from the adult and household questionnaires, respectively. We also match the Understanding Society household level data to police-reported crime data at the neighbourhood level using lower layer super output area codes obtained under the Understanding Society Special License agreement, see Understanding Society (2017). We provide additional detail regarding the neighbourhood level measures of crime in Section 3.4.1. For further information about Understanding Society, see Knies (2014).

3.3.1 The Dependent Variables

We explore the effect of adolescent’s mental health on whether they participate in three forms of behaviour: ASB (fighting, vandalism, shoplifting, and truancy); harmful substance use (drinking alcohol, smoking cigarettes, and taking drugs); and prosocial behaviour (volunteering and helping with housework). We discuss the measures of ASB, harmful substance use, and prosocial behaviour in detail below and outline the survey conditions where each of these behaviours are reported.

In order to reduce the adolescent's incentive to misreport their participation in ASB, immediately prior to the questions regarding the adolescent's participation in ASB the adolescent is reminded of the confidentiality of their responses[62]. The first measure of

[61] The individual interviews for each wave take place over a 2-year period and thus the periods of the waves overlap. Hence, the interviews for each wave of Understanding Society take place as follows: 1 (2009/2010), 2 (2010/ 2011), 3 (2011/ 2012), 4 (2012/ 2013), 5 (2013/ 2014), and 6 (2014/ 2015).
[62] The questionnaire states "Just to remind you, all your answers are confidential and will not be seen by anyone in your household", see Understanding Society (2014).

ASB is fighting. In waves 3 (2011/ 2012) and 5 (2013/ 2014) of Understanding Society, adolescents reported whether "in the past month, how often have you had a fight with someone that involved physical violence, such as hitting, punching, or kicking?". With the following options: "None", "Once", "2-5 times", "6-9 times", or "10 or more times". The second indicator of ASB is vandalism. In waves 3 and 5 of the Understanding Society youth questionnaire, adolescents reported whether "in the past year, have you deliberately broken or damaged property that didn't belong to you?". The categories are "never", "once or twice", "several times", or "often".

The third measure of ASB relates to participation in shoplifting. In waves 3 and 5 of Understanding Society, adolescents were asked "in the past year, have you taken something from a shop, supermarket or department store without paying?". The options are as follows: "never", "once or twice", "several times", or "often". The final indicator of ASB is an adolescent's involvement in truancy, reported in waves 1-6 (2009 to 2015) of Understanding Society. Adolescents report whether "in the last 12 months, have you ever played truant, that is missed school without permission, even if it was only for a half day or a single lesson?". We dichotomise the measures of ASB to equal 1 if the adolescent reported to have participated in the ASB, and 0 if they did not report to participate in the ASB.[63]

Sample 1 is used to explore how the adolescent's ASB is affected by their mental health, as well as that of their parents. Sample 1 is based on waves 3 and 5 of Understanding Society, and contains 3,249 person-year observations and 2,495 adolescents. On average, each adolescent is observed approximately 1.3 times in Sample 1. Table 3.1 shows the distributions of the indicators of ASB in Sample 1. Approximately 16% of the adolescents report to have been involved in fighting in the past month suggesting that this is the most prevalent ASB. Additionally, in the region of 8% (5%) of adolescents report to have vandalised (truanted) in the past year. The least prevalent ASB is shoplifting, which 2% of adolescents report to have participated in during the past year.

The first measure of harmful substance use is whether the adolescent has tried alcohol[64]. In waves 1 to 6 (2009 to 2015) of Understanding Society, adolescents were asked "have you ever had an alcoholic drink? That is a whole drink, not just a sip". We create a binary variable equal to 1 if they reported to have ever tried alcohol, and 0 otherwise. Our second measure of harmful substance use concerns whether they adolescent smokes cigarettes. In waves 1 to 6 (2009 to 2015) of Understanding Society,

[63] For robustness, we have also explored the effects of adolescent mental health on the frequency that an adolescent participates in fighting and vandalism using random effects ordered probit models. The results are available upon request. Unfortunately, random effects models exploring the effects of adolescent mental health on the frequency of participation in shoplifting do not converge which may be because of the relatively small number of adolescents who report to participate in shoplifting "several times" (0.22%) or "often" (0.03%) in the past year.

[64] Adolescents are also reminded that their answers are confidential prior to reporting whether they drink alcohol, smoke cigarettes, and take drugs.

adolescents were asked "do you ever smoke cigarettes at all?". We construct a binary variable that is equal to 1 if the adolescent smokes, and 0 otherwise.

The final measure of harmful substance use is drug consumption. In waves 2 (2010/ 2011), 4 (2012/ 2013), and 6 (2014/ 2015) of Understanding Society, adolescents reported whether they have ever tried "glue/ solvent sniffing", "cannabis (also known as marijuana, dope, hash, or skunk)", and "any other illegal drug (including ecstasy, cocaine, speed)". We utilise a binary variable equal to 1 if the adolescent reported to have tried 1 or more drugs, and 0 if they reported not to have tried any of the drugs.[65]

We explore the effects of adolescent's mental health on their harmful substance use using Sample 2, which contains data from waves 2, 4, and 6. Sample 2 contains 2,235 person-observations and 2,014 adolescents: each adolescent is observed approximately 1.1 times, on average.[66] Table 3.2 indicates the prevalence of alcohol consumption, cigarette smoking, and drug use in Sample 2. Note that approximately 33% of adolescents report to have tried an alcoholic drink, approximately 6 times the proportion who report to have tried drugs. Moreover, approximately 9% of adolescents report to have ever tried a cigarette.

We also explore the effects of the mental health of adolescents on two measures of participation in prosocial behaviour: volunteering and helping with housework. In waves 2 (2010/ 2011), 4 (2012/ 2013), and 6 (2014/ 2015) of Understanding Society, adolescents were asked "how often do you do voluntary or community work (including doing this as part of school)?".[67] The options are "most days", "at least once a week", "at least once a month", "several times a year", "once a year or less", or "never/ almost never". The measure of volunteering equals 1 if the adolescent volunteers "most days", "at least once a week", "at least once a month", "several times a year", or "once a year or less". The volunteering variable is equal to 0 if the adolescent volunteers "never/ almost never".

In a similar vein, in waves 2 (2010/ 2011), 4 (2012/ 2013), and 6 (2014/ 2015) of Understanding Society, adolescents report whether they help with housework: "how many hours do you spending doing or helping with housework in an average week, such as time spent tidying your bedroom, cooking, cleaning, or doing laundry?". The options are "Don't do any housework", "less than one hour", "1-3 hours", "4-6 hours", and "7 or more hours". We dichotomise the housework variable to equal 1 if the

[65] Note that 2.27%, 2.54%, and 0.53% of adolescents report to have ever sniffed glue, tried cannabis, or tried any other illegal drugs, respectively.

[66] We utilise Sample 2 to explore the effects of the mental health of adolescents on harmful substance use in the next wave. In contrast, Sample 1 is used to investigate the effects of the mental health of adolescents on their ASB in the same wave. As a result of the use of lagged measures of adolescent's mental health in the harmful substance use models, Sample 2 has fewer observations than Sample 1 despite drawing on data from a greater number of waves.

[67] Due to the inclusion of volunteering via school and community work, volunteering may not be a choice variable for some children in the standard sense.

adolescent helps with housework, and 0 if the adolescent does not help with housework.

Sample 3 utilises data from waves 2, 4 and 6 to investigate the effects of the mental health of adolescents on whether they participate in prosocial behaviour. Sample 3 contains 2,528 person-year observations and 2,267 adolescents. On average, each adolescent is observed approximately 1.2 times in Sample 3. The summary statistics illustrated in Table 3.3 indicate that approximately 57% (91%) of adolescents report to volunteer (help with housework).

3.3.2 Misreporting of Participation in Anti-Social Behaviour and Harmful Substance Use: The Survey Conditions

One concern relates to the possibility that the measures of participation in ASB/ harmful substances use may suffer from measurement error. For instance, adolescents may underreport or over-report their participation in ASB/ harmful substances use. Adolescents may under-report their participation in ASB/ harmful substances use due to the perceived social stigma, legal consequences, or the possibility of "getting in trouble" with their parents, (see Horm et al., 1996). Alternatively, adolescents may over-report their participation in ASB/ harmful substances use due to the perceived social pressure to "look cool", (see, for example, Carroll et al., 2017; Odgers et al., 1997). If the misreporting of ASB/ harmful substances use is associated with the mental health of the adolescent, then the effects of mental health on participation in ASB/ harmful substance use may be biased.

In the youth questionnaire, several steps are taken to increase the reliability of the data. Firstly, prior to completing the questionnaire, the child was informed that if they require help they should ask the interviewer and that their parents were not permitted to help them to complete the questionnaire[68]. Previous research indicates that adolescents are less likely to report sensitive information in the presence of their parents, see Horm et al. (1996). Secondly, the youth questionnaire is a paper based self-completion questionnaire. Typically, more impersonal, self-completion techniques have lower rates of the misreporting of sensitive information relative to telephone and face-to-face interviewing techniques, see Bowling (2005).

Thirdly, prior to completing the questionnaire, the child was informed that they should place the questionnaire in a sealed envelope and then hand it to the interviewer after completion. As a consequence, the child was informed prior to the interview that any sensitive information they revealed in the survey was confidential from both the interviewer and the other household members. Fourthly, as previously discussed, immediately prior to reporting their participation in ASB/ harmful substance use adolescents are reminded of the confidentiality of their responses, especially from

[68] Further information relating to how the youth questionnaire is conducted is presented in the United Kingdom Household Longitudinal Survey technical reports, see NatCen Social Research (2012).

other household members[69]. Arguably, reminding the adolescent of the confidentiality of their responses immediately prior to reporting their ASB/ harmful substance use may reduce the adolescent's incentive to misreport their participation in ASB. For the reasons outlined above, the design of the Understanding Society youth questionnaire promotes the reliability of their responses.

3.3.3 The Key Explanatory Variables

We measure the mental health of adolescents using the Strengths and Difficulties Questionnaire (SDQ) and the mental health of their parents using the General Health Questionnaire (GHQ).

In waves 1, 3, and 5 of the Understanding Society youth questionnaire, the mental health of adolescents is assessed using the SDQ. The SDQ is a popular screening instrument for the measurement of children's mental health problems, see Goodman (1997). The SDQ is composed of four 5-item subscales. The four subscales of the SDQ each measure distinct aspects of children's mental health problems: emotional, conduct, hyperactivity/ inattention, and peer relationship problems. In response to each of the 20 statements of the SDQ, the adolescent indicates whether the statement is not true (0), somewhat true (1), or certainly true (2). The 20 statements of the SDQ are summarised in Table 3.4. The SDQ total difficulties score is the sum of the four separate subscales of the SDQ and thus ranges from 0 (the fewest mental health problems) to 40 (the most mental health problems).

We also explore how the distinct aspects of the mental health of adolescents affect their behaviour. However, Goodman et al. (2010) suggest that the four separate subscales of the SDQ may not be able to differentiate sufficiently between the distinct aspects of mental health in low risk, population samples (such as Understanding Society). As a result, they recommend splitting the SDQ total difficulties score into the internalising problems and externalising problems, subscales.

The externalising problems subscale is the sum of the hyperactivity/ inattention subscale and the conduct problems subscale. On the other hand, the internalising problems subscale is the sum of the emotional problems and peer relationship problems subscales. Splitting the SDQ total difficulties score into the externalising and internalising subscales allows us to investigate how the distinct aspects of the mental health of adolescents affect their behaviour. The internalising and externalising problems subscales range from a minimum value of 0 to a maximum value of 20, where higher scores indicate poorer mental health.

For a recent analysis of the SDQ, see Clark et al. (2015) who investigate the effects of parental breakup on mental health using the Avon Longitudinal Study of Parents and

[69] For example, the wave 3 youth questionnaire states "Just to remind you, all your answers are confidential and will not be seen by anyone in your household", see Understanding Society (2014).

Children cohort study. For further information about the SDQ, see Youth In Mind (2012).

The distributions of the total difficulties, externalising problems, and internalising problems subscales are presented in Figures 3.1 to 3.3. Note that approximately 58% of adolescents have total difficulties scores ranging from 0 to 10. In addition, approximately 90% (95%) of adolescents have externalising (internalising) problems scores ranging from 0 to 10, thus suggesting a low prevalence of mental health problems.

We measure the mental health of parents using the General Health Questionnaire GHQ(36), a screening instrument initially developed to diagnose psychiatric disorders, see Goldberg and Williams (1988). A full list of the 12 questions that form the GHQ(36) is provided in Table 3.4. Each of the 12 questions that form the GHQ have four options: 0 (not at all), 1 (no more than usual), 2 (rather more than usual), and 3 (much more than usual). We create a "likert" measure of distress by summing the responses to these 12 questions. The "likert" measure ranges from 0 (all twelve responses indicating the best mental health) to 36 (all twelve responses indicating the poorest mental health). We make use of the GHQ(36) "likert" measure rather than the 12 point GHQ "caseness" measure because the 36 point "likert" measure has a more continuous distribution[70].

For other recent analyses of the GHQ(36), see Apouey and Clarke (2015) who investigate the effects of winning the lottery. The distribution of the GHQ(36) scores of parents is shown by Figures 3.4 to 3.5. On average, mothers report 0.31 points higher GHQ(36) (poorer mental health) scores relative to fathers, in common with the findings of Clark and Oswald (1994).

3.3.4 Adolescent Antisocial Behaviour and the Mental Health of Adolescents and Parents: Summary Statistics

The relationship between ASB and the mental health of adolescents for Sample 1 is summarised by the descriptive statistics revealed in Table 3.5. It is evident from Table 3.5 that adolescents who engage in each of the four ASBs have poorer overall mental health relative to adolescents who do not engage in ASB. For example, adolescents who did not fight in the past month have total difficulties score of 9.43, on average, 3.82 points lower than adolescents who were involved in fighting. Also, adolescents who vandalised in the past year have an average total difficulties score of 14.13, 4.43 points higher than adolescents who did not vandalise in the past year. The summary

[70] The "caseness" measure of GHQ is the number of times the individual reports "rather more than usual" and "much more than usual" and thus ranges from 0 (best mental health) to 12 (worst mental health). Approximately half of individuals have "caseness" scores of 0 and a further 12% have scores equal to 1.

statistics suggest that involvement in shoplifting and truancy in the past year are associated with poorer overall mental health.

As well as having poorer overall mental health, adolescents who commit each of the four ASBs have a higher propensity to externalise. For example, on average, adolescents who are involved in fighting (vandalising) have 2.86 (3.61) points higher externalising problems subscale scores relative to adolescents who do not fight (vandalise). In a similar fashion, adolescents who engage in ASB have an increased propensity to internalise. For instance, adolescents who shoplift (truant) have 1.12 (1.33) points higher internalising problems scores relative to adolescents who do not shoplift (truant). It is therefore evident that adolescents who engage in the four ASBs have poorer mental health relative to adolescents who do not.

Table 3.5 also illustrates the association between the ASB of adolescents and the mental health of their parents, as measured by the GHQ(36). The findings may suffer from reverse causality if badly behaved adolescents have an adverse effect on the mental health of parents.[71] Consequently, to help ease the risk of reverse causality, we measure parental mental health using the parent's GHQ(36) score in waves 1 or 2 of Understanding Society.[72] Note, for each of the four measures of ASB, the parents of adolescents who participate in ASB have poorer mental health. It is also evident that the mental health of mothers is more strongly associated with the ASB of adolescents than the mental health of fathers. The summary statistics presented in Table 3.5 suggest that poorer mental health of adolescents as well as their parents is associated with the participation of adolescents in ASB. Section 3.4 outlines the methodological approaches implemented to explore how the ASB of adolescents is affected by their mental health, and that of their parents.

3.4 Methodology

3.4.1 Empirical Specifications and Estimation Methods

In our primary analysis, we investigate the effects of adolescent's mental health on whether they fight, vandalise, truant, and shoplift. To do so, we utilise four separate binary dependent variables, which are equal to 1 if the adolescent participates in the respective ASB, and 0 otherwise. Hence, we outline the following baseline latent variable model:

[71] The core analysis of this chapter may also suffer from reverse causality if engaging in ASB has a detrimental effect on the mental health of adolescents. For robustness, we have further explored the effects of the mental health of adolescents on their ASB in the next wave. We discuss these results in greater detail in Section 3.8.

[72] We measure the mental health of parents using the first non-missing value of the GHQ(12) in either wave 1 or wave 2. For approximately 67% (33%) of the adolescents in Sample 1 we measure parental mental health in wave 1 (wave 2).

$$ASB^*_{ijt} = \boldsymbol{\alpha X_{ijt}} + \beta_1 SDQ_{ijt} + \varepsilon_{ijt} \quad (3.1)$$

where $ASB_{ijt} = 1$ if $ASB^*_{ijt} > 0$, and 0 otherwise

Where ASB^*_{ijt} denotes a latent ASB variable. $\boldsymbol{X_{ijt}}$ denotes a vector of explanatory variables for individual i in lower layer super output area j at time t. SDQ_{ijt} is the SDQ total difficulties score of individual i in lower layer super output area j and wave t. ε_{ijt}, the composite error term, is the sum of an unobserved, time invariant, individual specific error term (u_i) and a time varying error term (v_{ijt}). An individual is assumed to commit ASB ($ASB_{ijt} = 1$) if the latent ASB variable (ASB^*_{ijt}) is greater than 0, and 0 otherwise.

We estimate two empirical specifications to explore the effects of adolescent mental health on participation in ASB. The first specification, shown by equation (3.2), investigates the effects of adolescent's overall mental health on their ASB using a random effects probit model. We estimate equation (3.2) using Sample 1.

$$\begin{aligned} ASB_{ijt} &= \beta_0 + \beta_1 SDQ_{ijt} + \boldsymbol{\gamma X^d_{ijt}} + \boldsymbol{\tau X^f_{ijt}} \\ &+ \boldsymbol{\delta X^s_{ijt}} + \boldsymbol{\lambda Year_t} + \varphi LocalASB_{jt} + \boldsymbol{\xi_j} + u_i + v_{ijt} \end{aligned} \quad (3.2)$$

ASB_{ijt} is a binary dependent variable equal to 1 if individual i in lower layer super output area j at wave t participated in ASB, and 0 otherwise. We estimate equation (3.2) using four dependent variables (fighting, vandalism, shoplifting, and truancy), each a separate measure of ASB. SDQ_{ijt} denotes the SDQ total difficulties score of individual i in lower layer super output area j at wave t.

$\boldsymbol{X^d_{ijt}}$ indicates a vector of individual i's demographic characteristics at wave t such as their age, gender, and ethnicity. Hirschi and Gottfredson (1983) suggest that involvement in criminal behaviour increases during adolescence and peaks at age 20. Consequently, we control for the age of the adolescent, measured in years. Moreover, Moffitt et al. (2002) suggest that participation in ASB (stealing, cheating, fighting, and truanting) is higher amongst males relative to females. In a similar vein, Ministry of Justice (2015) data suggests that approximately 8% (4.5%) of adolescents convicted of an offence in 2013/ 2014 were Black (Asian). As a consequence, we include two binary variables denoting that the adolescent is Black and Asian, respectively. White adolescents form the base category.

In a similar fashion, $\boldsymbol{X^f_{ijt}}$ denotes a vector of the family characteristics of individual i in lower layer super output area j at wave t, specifically: quartile of real family income, the total number of children in the household, and the marital status of their parents. Sariaslan et al. (2014) use Swedish administrative data and find that childhood family income is inversely associated with the probability of having a conviction for violent crime or property crime by age 21. In a similar vein, Piotrowska et al. (2015) and Haggerty et al. (2013) present evidence to suggest that childhood family income is inversely associated with the probability of involvement in ASB, such as violence. Hence, the preceding analysis will control for three binary variables equal to 1 if an adolescent's total family income is in the 2^{nd}, 3^{rd}, or 4^{th} income quartile, and 0 otherwise. Adolescents whose parents are in the lowest income quartile form the base category. We measure total family income as the total monthly income of all adult family members, net of income tax and national insurance contributions.

The findings of Farrington (1997) indicate that adolescents who have more siblings are more likely to participate in both violent and nonviolent forms of ASB. For this reason, we control for the number of children in the household. In addition, Animasahun (2014) suggest that adolescents whose parents are divorced or separated have higher rates of ASB relative to adolescents whose parents are not divorced or separated. As a result, we include a binary variable equal to 1 if the individual's parents are separated or divorced, and 0 otherwise.

$\boldsymbol{X}_{ijt}^{s}$ denotes a vector of variables relating to the social characteristics of individual i in lower layer super output area j at time t. Specifically, the number of close friends; the frequency that the individual stays out past 9pm, without their parents knowing their whereabouts; the frequency that the adolescent eats evening meals with their family; and whether the individual reports that it is very important to perform well in their General Certificate of Secondary Education (GCSEs). Farrington (1993) suggests that adolescents who have few friends have an increased likelihood of participating in ASB. For this reason, we include two binary variables indicating whether the adolescent has 1 to 5, or 6 or more, close friends. Adolescents who have no close friends form the base category.

Iacovou (2012) indicate that there is a positive association between the frequency that an adolescent stays out past 9pm without their parents knowing their whereabouts and engagement in illegal activities (underage drinking, cigarette smoking, and cannabis use). Consequently, we include two binary variables indicating the frequency that the individual stayed out past 9pm in the past month without their parents knowing their whereabouts: once or twice, and 3 or more times. Adolescents who did not stay out past 9pm in the past month without their parents knowing their whereabouts form the base category. Sen (2010) suggests that adolescents who eat dinner with their family are less likely to engage in ASBs such as fighting, stealing, and vandalism. We thus include two binary variables indicating the frequency that the adolescent ate evening meals with their family in the past week: once or twice, or three or more times. Adolescents who did not eat evening meals with their family in the past week form the base category.

In a similar fashion, Bernat et al. (2012) suggest that attitudes towards education are negatively associated with the probability of participation in violence. As a result, we include a binary variable indicating that the adolescent reports that it is "very important" to do well in their General Certification of Secondary Education (GCSE) exams, and 0 otherwise.

$\boldsymbol{Year_t}$ is a vector of binary variables denoting the year of interview and u_i denotes a randomly generated, time invariant individual fixed effect. $LocalASB_{jt}$ indicates the total rate of crime and ASB per 1,000 residents in the local neighbourhood in year t.[73] For England and Wales, we measure crime and ASB at the lower layer super output area level. There are 32,844 (1,909) lower layer super output areas in England (Wales) and each lower layer super output area has a population of between 1,000 to 3,000 residents, and 400 to 1,200 households.[74] For Northern Ireland, we use the total rate of crime and ASB per 1,000 individuals in the Northern Ireland super output area. There are 890 Northern Ireland super output areas in Northern Ireland. Each Northern Ireland super output area has a population of between 1,000 to 3,000 individuals from 400 to 1,200 households.[75] We control for the rate of crime and ASB to account for social norms and opportunities to commit ASB at the local neighbourhood level.

ξ_j denotes a lower layer super output area fixed effect to control for the time invariant characteristics of the area in which the individual lives. u_i indicates a randomly generated, time invariant individual effect, and v_{ijt} denotes a time and individual specific error term. Table 3.4 presents full definitions of the variables used and Table 3.6 provides summary statistics for Sample 1.

The parameter estimate β_1 in equation (3.2) represents the effect of the overall mental health of adolescents (measured by the SDQ total difficulties scale) on ASB. As previously discussed in Section 3.3.2, the propensity to externalise and internalise may have different effects on the ASB of adolescents. To explore this issue, we split the SDQ total difficulties scale into the externalising and internalising problems subscales, as shown by equation (3.3) below:

$$ASB_{ijt} = \alpha_0 + \alpha_1 EP_{ijt} + \alpha_2 IP_{ijt} + \boldsymbol{\gamma X^d_{ijt}} + \boldsymbol{\tau X^f_{ijt}} + \boldsymbol{\delta X^s_{ijt}} + \boldsymbol{\lambda Year_t} + \varphi LocalASB_{jt} + \boldsymbol{\xi_j} + u_i + v_{ijt} \tag{3.3}$$

Where EP_{ijt} (IP_{ijt}) denotes the externalising (internalising) problems subscales of individual i in region j at time t. To contrast the effects of the propensity to externalise and internalise on ASB, we can compare the relative magnitudes of α_1 and α_2 in equation (3.3). As outlined in Section 3.1, we also investigate the effects of parental mental health on the ASB of adolescents using equation (A3.1) presented in Appendix 2.

[73] We sourced all crime data from UKCrimeStats (2016).

[74] For more information regarding local level geographies in England and Wales, see Office for National Statistics (2016b).

[75] Unfortunately, neighbourhood level crime data is not available for Scotland. As a consequence, we omit Scotland from the preceding analysis. For further information about local area geographies in Northern Ireland, see Northern Ireland Statistics and Research Agency (2016).

3.4.2 Robustness Check 1: Multivariate Probit Models

Note that the existing literature exploring the effects of mental health on ASB and crime typically estimates single-equation models, (see Fletcher and Wolfe, 2009; Murray et al., 2015). However, it is likely that the decisions to participate in fighting, vandalism, shoplifting, and truancy are related because they are affected by the unobserved characteristics of the adolescent (such as their attitudes towards risk). For this reason, we make use of a system of probit equations, where the error terms of each of the equations can be correlated. Thus, we outline a system of four latent ASB equations:[76]

$$ASB_i^{F*} = \boldsymbol{\beta X_i^F} + \varepsilon_i^F \tag{3.4a}$$

$$ASB_i^{V*} = \boldsymbol{\beta X_i^V} + \varepsilon_i^V \tag{3.4b}$$

$$ASB_i^{S*} = \boldsymbol{\beta X_i^S} + \varepsilon_i^S \tag{3.4c}$$

$$ASB_i^{T*} = \boldsymbol{\beta X_i^T} + \varepsilon_i^T \tag{3.4d}$$

Where F, V, S, T denote fighting, vandalism, shoplifting, and truancy, respectively. Also, ε_i^F, ε_i^V, ε_i^S, and ε_i^T denote the error terms of the respective equations. Following Cappellari and Jenkins (2003), we assume that the error terms of the 4 ASB models have a mean equal to 0 and variance-covariance matrix V, as illustrated below:

$$V = \begin{pmatrix} 1 & \rho_{FV} & \rho_{FS} & \rho_{FT} \\ \rho_{FV} & 1 & \rho_{SV} & \rho_{TV} \\ \rho_{FS} & \rho_{SV} & 1 & \rho_{TS} \\ \rho_{FT} & \rho_{TV} & \rho_{TS} & 1 \end{pmatrix} \tag{3.5}$$

Where, for example, ρ_{FV} denotes the correlation coefficient between ε_i^F and ε_i^V. For example, a value of $\rho_{FV} > 0$ implies that a common set of unobserved characteristics increase the probability that an adolescent participates in fighting and vandalism. In contrast, a value of $\rho_{FV} < 0$ implies that the unobserved characteristics that increase the probability that an individual participates in fighting have an inverse effect on the probability that they participate in vandalism. Finally, if $\rho_{FV} = 0$, the error terms of the fighting and vandalism equations are independent. If this is the case, the unobserved characteristics that affect fighting behaviour do not affect vandalising behaviour.

For other applications of the multivariate probit model, (see Brown, 2014; Reeve and Van Gool, 2013). The former explores the effects of neighbourhood ties on household financial behaviour, whereas, the latter investigates the effects of child abuse on adult mental health.

[76] We estimate the multivariate probit model by simulated maximum likelihood using the user-written mvprobit Stata command, see Cappellari and Jenkins (2003) for further details. The number of random draws is set equal to 500.

3.4.3 Robustness Check 2: Conditional Logit Models

The core analysis of this chapter explores the effects of the mental health of adolescents on their ASB using equations (3.2) and (3.3). However, the estimated effects of adolescent's mental health on their ASB may suffer from omitted variable bias if the error terms of the ASB models contain unobservables that also affect mental health. For example, unobserved family socioeconomic status and neighbourhood variables may affect both the mental health of adolescents and their ASB, thus leading to omitted variable bias. Consequently, to investigate the robustness of our initial findings, we control for family fixed effects using conditional logit models.[77]

Conditional logit models use within group variation in binary dependent variables, see Allison (2009). The conditional logit model shown by equation (3.6) utilises discordant reports of participation in ASB amongst adolescents who live in the same household. We present the case for households of 2 adolescents below:

$$ASB2_{ht} = \beta_1(\Delta SDQ_{ht}) + \boldsymbol{\gamma}(\Delta \boldsymbol{X^d_{ht}}) + \boldsymbol{\delta}(\Delta \boldsymbol{X^s_{ht}}) + \varepsilon_{ht} \qquad (3.6)$$

$ASB2_{ht}$ is a binary variable equal to 1 if adolescent 2 in household h at time t committed ASB, and 0 if adolescent 1 in household h committed ASB. Households where both adolescents report the same behaviour are omitted from the estimation samples because there is no within household variation in participation in ASB. We also omit households containing 1 adolescent from the analysis: approximately 53% of households.

We estimate equation (3.6) using three dependent variables, each a separate measure of ASB, namely, fighting, vandalism, and truancy.[78] For each of the three measures of ASB, we use a separate estimation sample. Firstly, for fighting behaviour, we estimate equation (3.6) using Sample 4(a), which contains 925 person-observations from 420 households. Sample 4(a) is composed of 343 households with 2 adolescents, 69 households with 3 adolescents, and 8 households with 4 adolescents.

Secondly, we estimate the effects of the mental health of adolescents on vandalising behaviour using Sample 4(b), containing 583 person-observations from 267 households. Sample 4(b) encompasses 225 households of 2 adolescents, 37 households of 3 adolescents, 3 households of 4 adolescents, and 2 households of 5 adolescents.

Finally, we explore the effects of the mental health of adolescents on participation in truancy using Sample 4(c). Sample 4(c) contains 339 person-observations from 155

[77] We estimate the conditional logit model via the clogit Stata command, see Long and Freese (2006) for further details.

[78] Unfortunately, conditional logit models exploring the effects of the mental health of adolescents on their participation in shoplifting suffer from problems of non-convergence that likely result from the small sample size. There are just 145 adolescents from 66 households where participation in shoplifting varies amongst adolescents within the same household.

households (131 households of 2 adolescents, 21 households of 3 adolescents, 1 household of 4 adolescents, and 2 households of 5 adolescents).[79]

ΔSDQ_{ht} denotes the difference in the SDQ total difficulties scores of adolescent 2 and adolescent 1 in household h ($\Delta SDQ_{ht} = SDQ_{2ht} - SDQ_{1ht}$). In addition, $\Delta\boldsymbol{X}_{\boldsymbol{ht}}^{\boldsymbol{d}}$ ($\Delta\boldsymbol{X}_{\boldsymbol{ht}}^{\boldsymbol{s}}$) indicates the difference in the demographic (social) characteristics between adolescent 2 and adolescent 1 in household h at time t. We control for the adolescent's demographic characteristics that vary within their household, such as age and gender. We also control for the adolescent's social characteristics such as the number of close friends; the frequency that they have stayed out past 9pm in the past week, without their parents knowing their whereabouts; and whether the individual reports that it is very important to perform well in their GCSEs. We omit all explanatory variables that do not vary within households such as ethnicity, family income, the total number of children, the lower layer super output area of residence, and the rate of crime and ASB in the local neighbourhood. ε_{ht} denotes an error term.

The parameter β_1 represents the effect of the overall mental health of adolescents on their ASB. However, as previously discussed, the tendency of adolescents to externalise and internalise may affect their ASB differently. As a result, we split the SDQ total difficulties scale into the externalising problems and internalising problems subscales, as shown by equation (3.7):

$$ASB2_{ht} = \alpha_1 \Delta EP_{ht} + \alpha_2 \Delta IP_{ht} + \boldsymbol{\gamma}(\Delta\boldsymbol{X}_{\boldsymbol{ht}}^{\boldsymbol{a}}) + \boldsymbol{\delta}(\Delta\boldsymbol{X}_{\boldsymbol{ht}}^{\boldsymbol{s}}) + \varepsilon_{ht} \tag{3.7}$$

ΔEP_{ht} (ΔIP_{ht}) indicates the difference in the externalising (internalising) problems subscales scores between adolescent 2 and adolescent 1 in household h at time t.

We estimate the conditional logit models specified in equations (3.6) and (3.7) to explore the effects of the mental health of adolescents on participation in fighting, vandalism, and truancy. The advantage of this approach is that it is possible to account for unobserved household level variables that affect both the ASB of adolescents and their mental health, such as socioeconomic status. Arguably, this approach may therefore reduce the likelihood of omitted variable bias.

As previously discussed, the conditional logit model utilises variation in participation in the ASB of adolescents from within the same household. As a consequence, single adolescent households and households where each of the adolescents report the same behaviour are excluded from the analysis. Thus, a disadvantage of this approach is that whilst it may allow for improved conditioning upon unobserved confounders (family fixed effects) it makes use of a substantially reduced sample size. Consequently, the findings may not generalise to the wider population of adolescents.

[79] Hence, there are 77, 42, and 24 households of 3 or more adolescents in Samples 4(a), 4(b), and 4(c), respectively. This estimation method can be extended to such households.

For other applications of the conditional logit estimator using variation in outcomes between siblings, see Oettinger (2008) and Black et al. (2007). The former explore the effects of sex education on teenage pregnancy, whereas, the latter investigate the effects of birth-weight on infant mortality.

3.5 Results

3.5.1 Adolescent Mental Health and Adolescent Antisocial Behaviour

To explore the effects of the overall mental health of adolescents on their ASB we estimate equation (3.2) using a random effects probit model. Likewise, we estimate equation (3.3) to explore how the tendencies to externalise and internalise affect the ASB of adolescents. To explore the effects of the mental health of adolescents on their ASB we utilise Sample 1.

Table 3.7(a) reveals the coefficients from random effects probit models exploring the effects of the mental health of adolescents on fighting and vandalism. Adolescents who have poorer overall mental health (i.e. higher SDQ total difficulties scores) have an increased likelihood of both participating in fighting and vandalism, as demonstrated by columns (1) and (3). The effects are statistically significant at the 1% level. Additionally, the evidence illustrated in columns (2) and (4) suggests that a greater tendency to externalise predicts increased participation in fighting and vandalism. In addition, a higher tendency to internalise is positively associated with fighting behaviour, but does not have a statistically significant effect on participation in vandalism.

The findings suggest that the number of children in the household are positively associated with fighting behaviour, but do not significantly affect vandalising behaviour. In contrast to the effects of the number of children in the household, the age of the adolescent is inversely associated with whether they report in fighting. This effect is statistically significant at the 1% significance level. In contrast to the findings of Heimer (1997), there is no statistically significant effect of family income on fighting and vandalism. One explanation for this finding is reporting bias. For instance, Piotrowska et al. (2015) suggest that the effect of socioeconomic status on the ASB of adolescents is larger when parents or teachers report the ASB, relative to measures reported by the adolescent.

In accordance with the existing literature, fighting and vandalism are more common amongst males relative to females, see Moffitt et al. (2002). Adolescents who frequently stay out late without their parents knowing their whereabouts have an increased probability of engaging in fighting and vandalism. In addition, Black adolescents have a greater probability of vandalising relative to Whites, but there is no statistically significant effect of ethnicity on fighting behaviour. In common with Bernat et al. (2012), the evidence suggests that attitudes towards education are inversely associated with the probability of participating in fighting and vandalism. Fighting and vandalism are not significantly affected by parental separation, the rate of crime and ASB in the local neighbourhood, or the frequency of eating evening meals as a family. The evidence suggests that adolescents who have more close friends are less likely to participate in fighting, but there is no statistically significant effect of the number of close friends on participation in vandalism.

To provide a quantitative interpretation of the findings, Table 3.7(b) reports the average marginal effects of the mental health of adolescents on ASB.[80] To offer some intuition as to the magnitudes of the effects of mental health on ASB, we also present the average marginal effects of being male. The existing literature suggests that males are more likely to engage in ASB, relative to females. For example, Moffitt et al. (2002) suggest that males have a higher probability of participating in ASB. What is more, in 2013/ 2014 approximately 105,000 males aged 10-17 were arrested by police, relative to just 20,000 females of the same ages, see Ministry of Justice (2015).

The marginal effects observed in columns (1) and (3) show the effects of adolescent's overall mental health on the probability that they engage in fighting and vandalism, respectively. The results suggest that, on average, a one standard deviation (5.41) increase in overall mental health problems is associated with a 7.62% (4.88%) point increase in the probability of fighting (vandalism). The effects of a one standard deviation increase in overall mental health problems on fighting (vandalism) are large, approximately 75% (110%) of the magnitude of the effect of being male.

Additionally, a one standard deviation (3.46) increase in the propensity to externalise predicts a 7.88% (4.98%) point increase in the probability participating in fighting (vandalism). The effects of externalising problems are large in magnitude: a one standard deviation increase in externalising problems on fighting (vandalism) is approximately 0.9 (1.6) times the size of the effect of being male. In contrast, the effect of a one standard deviation (3.10) increase in the tendency to internalise on fighting is smaller (approximately 15% of the magnitude of the effect of being male).

Arguably, the effects of internalising and externalising problems on ASB may vary depending on the gender of the adolescent. Consequently, we re-estimate equation (3.3) and include interaction terms between the internalising and externalising problems subscales and a binary variable indicating that the individual is male. The findings relating to the fighting and vandalising variables are presented in Table 3.7(c). Column (1) indicates that the interaction effect between the binary variable indicating that the adolescent is male and the externalising problems subscale is statistically insignificant. Hence, this finding suggests that the effects of externalising problems on fighting behaviour does not depend on the gender of the adolescent. In contrast, the interaction between the male binary variable and the internalising problems subscale

[80] Average marginal effects are the effect of a partial or discrete change in the independent variable, averaged across all of the observations, see Bartus (2005).

is negative, indicating that there may be a weaker relationship internalising problems and fighting behaviour for males relative to females. Note, however that the interaction term is statistically significant at the 10%, but not the 5%, significance level.

Table 3.8(a) reveals the coefficients from random effects probit models investigating the effects of the mental health of adolescents on participation in shoplifting and truancy. In common with our previous results, the evidence revealed in columns (1) and (3) suggests that poorer overall mental health is associated with an increased likelihood of participating in shoplifting and truancy. Additionally, the findings presented in columns (2) and (4) suggest that adolescents who have a greater tendency to externalise have a higher probability of participating in shoplifting and truancy. In accordance with the results relating to vandalism, there is no statistically significant effect of internalising problems on participation in shoplifting and truancy.

The evidence illustrated in Table 3.8(a) suggests that participation in shoplifting and truancy is positively associated with the age of adolescents; and the frequency that they stay out late, without their parents knowing their whereabouts. The results suggest that males have a greater probability of shoplifting, but there is no statistically significant effect of being male on truancy. Additionally, the findings suggest that the prevalence of shoplifting is not significantly affected by the ethnicity of the adolescent. In contrast, we find that Indians have a greater probability of participating in truancy, relative to Whites. In discordance with the findings of Defoe et al. (2013), the results suggest that participation in shoplifting is higher amongst adolescents whose family income is in the 2nd and 3rd quartiles of the income distribution, relative to the bottom quartile. However, we find no statistically significant effect of parental income on truancy behaviour.

Adolescents who ate evening meals with their family three or more times in the past week are less likely to truant relative to adolescents who never ate evening meals with their family. In contrast to the findings relating to truancy, there is no statistically significant effect of the frequency of eating evening meals on shoplifting behaviour. Lastly, we find no statistically significant effect of parental separation, the total number of children in the household, the number of close friends, and the rate of crime and ASB in the local neighbourhood on participation in shoplifting and truancy.

Table 3.8(b) presents the average marginal effects of the mental health of adolescents on shoplifting and truancy alongside the average marginal effects of being male. A one standard deviation (5.41) increase in overall mental health problems is associated with an increase in the probability of shoplifting of 0.6% points (approximately 90% of the magnitude of the effect of being male), as demonstrated by the findings shown in column (1). The results revealed in column (2) suggest that a one standard deviation (3.46) increase in the tendency to externalise is associated with an increase in the probability of shoplifting of 0.9% points (approximately 1.5 times the magnitude of the effect of being male).

Column (3) shows that a one standard deviation (5.41) increase in overall mental health problems predicts a 1.78% point increase in the probability of engaging in truancy. In contrast to the findings relating to the other measures of ASB, there is no statistically significant effect of being male on participation in truancy. On average, a one standard deviation (3.46) increase in the tendency to externalise is associated with an increase in the probability of truancy of 3.03% points, as indicated by column (4).

As previously argued, the effects of externalising and internalising problems of adolescents on their participation in ASB may vary depending upon the gender of the adolescent. To explore this possibility, we re-estimate equation (3.3) to include an interaction between the internalising and externalising problems subscales, and the binary variable indicating that the adolescent is male. Table 3.8(c) presents the coefficients from estimating these models using a random effects probit model. The dependent variables utilised in columns (1) and (2) are shoplifting and truancy, respectively. The findings illustrate that the interaction term between the binary variable indicating that the adolescent is male and the internalising and externalising subscales scores is statistically insignificant. Hence, the findings do not suggest that the effects of internalising and externalising problems on participation in shoplifting and truancy differ depending on the gender of the adolescent.

Arguably, some of the control variables including in the analysis presented in Tables 3.7(a) and 3.8(a) may be considered to be "bad controls". For instance, the mental health of an adolescent may affect their participation in ASB indirectly via the effect of adolescent mental health on the number of close friends, the frequency of staying out late, and educational aspirations. In other words, these control variables may be a consequence of adolescent mental health, rather than affecting mental health per se. To explore this possibility, the models estimated in Tables 3.7(a) and 3.8(a) were re-estimated excluding the number of close friends, the frequency of staying out late, and the educational aspirations as control variables. This does not affect the headline results.

The evidence presented in Tables 3.7(a) to 3.8(b) suggests that greater externalising problems of adolescents are positively associated with the probability that they participate in each of the ASBs[81]. In comparison, the findings suggest that the tendency to internalise is positively associated with the probability of engaging in fighting, but has no statistically significant effect on the likelihood of participating in vandalising, shoplifting, and truancy. Sections 3.6 to 3.7 further investigate the robustness of these findings using multivariate probit and conditional logit models.

[81] These results are available upon request.

3.5.2 Parental Mental Health and Adolescent Antisocial Behaviour

To explore the importance of families for society, we investigate how parental mental health affects the ASB of adolescents. It is also important to explore this issue to contribute to a large literature exploring how the characteristics of parents affect the characteristics of their children, (see Dohmen et al., 2011; Chevalier et al., 2013). To explore the effects of parental mental health on adolescent's ASB, we estimate the effects of the mother's and father's GHQ(36) score on the four measures of ASB using Sample 1. Badly behaved adolescents may have an adverse effect on the mental health of their parents thus leading to reverse causality. To mitigate this issue, we measure the mental health of parents in wave 1 or wave 2 of Understanding Society prior to the measurement of ASB.[82]

Table 3.9(a) presents the coefficients from estimating equation (A3.1), which is presented in Appendix 2. As demonstrated in panel (1), there is no statistically significant effect of paternal mental health on the participation of adolescents in the four ASBs.

However, the findings contained in panel (2) suggest that poorer maternal mental health is positively associated with fighting, shoplifting, and truancy behaviours. The effect of maternal mental health on truancy behaviour is statistically significant at the 10%, but not the 5%, level. There is no statistically significant effect of maternal mental health on vandalising behaviour. The marginal effects revealed in Table 3.9(b) suggest that a one standard deviation (5.21) increase in maternal mental health problems predicts a 1.46% point increase in the probability that adolescents participate in fighting. The effect of a one standard deviation increase in maternal mental health problems on fighting is approximately 20% of the size a one standard deviation increase in the overall mental health problems of the adolescent.

[82] We measure the mental health of parents using the first available measure of the GHQ(12) in wave 1 or wave 2 of Understanding Society. For approximately two thirds of adolescents we measure the mental health of parents in wave 1 and for a third of adolescents we measure the mental health of parents in wave 2. To explore the effects of parental mental health on adolescent's ASB we estimate equations (A3.1) outlined in Appendix 1.

One mechanism via which the mental health of mothers may affect the ASB of adolescents is via its indirect effect on the mental health of adolescents. To explore this possibility, the empirical specifications presented in Table 3.9(a) were re-estimated controlling for the contemporaneous mental health of the adolescent. In the models relating to fighting and truancy, after conditioning upon the mental health of the child, the coefficient of the maternal mental health variable shrinks in magnitude by approximately 50-60% and becomes statistically insignificant. In contrast, for the shoplifting variable, after controlling for the mental health of the adolescent, the coefficient of the maternal mental health variable becomes approximately 30% smaller but remains statistically significant at the 10%, but not the 5%, significance level[83]. In contrast, after controlling for the mental health of the adolescent, the effect of maternal mental health on vandalism increase in magnitude by approximately 300% and becomes statistically significant at the 5% level. This is a surprising finding for which there is no obvious explanation. Hence, these findings therefore support the case that one important pathway via which the mental health of mothers may affect the fighting, shoplifting, and truancy behaviours of adolescents is via the indirect effect of parental mental health on adolescent mental health.

The empirical results presented in Table 3.9(a) support the case that the mental health problems of mothers may have a larger effect on the ASB of adolescents, relative to the effects of the mental health problems of fathers. There are a number of explanations for this finding. Firstly, data from the UK Harmonised European Time Use Survey from 2015 suggests that, on average, fathers spend approximately 1.9 hours per week on childcare, 2.6 fewer hours per week than that spent by mothers, see Office for National Statistics (2016d). As a result, one explanation for the differences in the effects of the mental health of mothers and fathers on the ASB of adolescents is that mothers spend more time with their children, and therefore the mental health of mothers may have a greater effect on adolescent ASB than that of fathers.

Secondly, arguably, children may have a stronger bond with their mother than their father and hence the mental health of mothers may have a greater effect on the ASB of their child. For example, Lundberg et al. (1997) show that child benefits provided to the mother lead to a higher expenditure on the child than providing the income to the father, holding total family income constant. This finding supports the notion that mothers may have a stronger preference for the welfare of their children than fathers[84]. In addition, previous evidence indicates that young children typically turn to their mothers preferentially at times of feeling distressed, see Lamb (2010). One interpretation of these findings is that the mother-child bond may be stronger than the

[83] These results are available upon request.

[84] Additional evidence from evolutionary biology suggests that parental differences in altruism may result from differences in biology such as women possessing a larger gamete, internal fertilisation inside the mother, and lactation. For an interesting overview of how evolutionary biology may lead to differences in parental altruism written for an economist audience, see Alger and Cox (2013).

father-child bond and hence the mental health of mothers may have a more prominent effect on the ASB of adolescents than that of fathers.

3.6 Robustness Check 1: Multivariate Probit Models

To test the robustness of the findings revealed in Tables 3.7(a) to 3.8(b), we explore the effects of adolescent's mental health on their participation in ASB using multivariate probit models. Table 3.10 reveals selected coefficients from the multivariate probit models and the full estimation results are provided in Table A3.1 in Appendix 3. In common with our main findings shown in Tables 3.7(a) to 3.8(b) we utilise Sample 1. The evidence illustrated in column (1) of Table 3.10 suggests that poorer overall mental health of adolescents is positively associated with the probability that they participate in fighting, vandalism, shoplifting, and truancy.

The results contained in column (2) illustrate the relative effects of externalising problems and internalising problems on adolescent's participation in ASB. For each of the 4 indicators of ASB, the effect of externalising problems remains statistically significant at the 1% level. In addition, the effect of internalising problems on fighting behaviour remains statistically significant at the 10% level, in accordance with the estimates found in Table 3.7(a). In contrast to the findings presented in Table 3.8(a), the effect of internalising problems on truancy behaviour is borderline statistically significant (P-value = 0.053). In common with our previous findings, there is no statistically significant effect of the tendency to internalise on vandalising and shoplifting behaviours, as can be seen in column (2). Furthermore, note the standard errors in the joint modelling approach (presented in Table 3.10) are smaller relative to standard errors of the single-equation models. It is therefore evident that the joint modelling approach is more efficient.

For the measures of fighting, vandalism, and truancy, the coefficients of the mental health variables in the multivariate probit models are approximately 80% of the magnitude of the coefficients of the single-equation models (see Table 3.7(a) and 3.8(a)). In contrast, for the measure of shoplifting, the coefficients of the measures of mental health in the multivariate probit models are approximately 60% of the magnitude of those presented for the single-equation models. Shoplifting is the least prevalent ASB: approximately 2% of adolescents reported to participate in the past year (see Table 3.1). Consequently, the effects of adolescent mental health on participation in shoplifting may be more sensitive to the choice of model, relative to the more prevalent ASBs (fighting, vandalism, and truancy).

The rho parameter estimates at the bottom of Table 3.10 show the estimated correlations between the cross-equation error terms of the 4 ASB models (see Section 3.4.2 for further details). Note that each of the 6 rho parameters are positive and statistically significant, thus suggesting that the 4 ASB models are related via their error terms. The largest estimated correlation in the error terms is between the shoplifting and vandalism equations (0.47 and 0.41 in models (1) and (2), respectively). In contrast, the smallest correlation between the cross-equation error terms is between the shoplifting and fighting equations and is 0.24 and 0.18 in models (1) and (2), respectively. This suggests that unobserved characteristics that affect participation in shoplifting may have a larger effect on vandalism relative to their effect on fighting behaviour.

Also, the chi-squared test statistics for the likelihood ratio test of the multivariate probit model relative to the single-equation framework are greater than 110 for both models. As a consequence, we reject the null hypothesis of the independence of the error terms (i.e. $\rho_{FV} = \rho_{FS} = \rho_{FT} = \rho_{SV} = \rho_{TV} = \rho_{TS} = 0$) thus endorsing the joint modelling approach.

3.7 Robustness Check 2: Conditional Logit Models

The findings of Sections 3.5.1 and 3.6 support the case that adolescents who have a greater tendency to externalise are more likely to engage in ASB. As an additional robustness check, we estimate conditional logit models to explore the effects of the mental health of adolescents on their ASB using family fixed effects. The coefficients from the conditional logit models are shown in Table 3.11. We estimate the conditional logit models using Samples 4(a) to 4(c), for further details see Section 3.4.3.

The empirical analysis displayed in column (1) suggests that poorer overall mental health is positively associated with participation in fighting. This effect remains statistically significant at the 1% level. Additionally, the evidence revealed by column (2) suggests that greater externalising problems are positively associated with the probability of fighting. However, the coefficient of the internalising problems variable on fighting is statistically insignificant, but changes little in magnitude relative to the findings shown in Tables 3.7(a) and 3.10. This may be a result of the lower power of these smaller samples to detect an effect.

The evidence provided in column (3) suggests that poorer overall mental health of adolescents has a positive and statistically significant effect on the probability of participating in vandalism. The final column of Table 3.11 reveals that an increased tendency to externalise is associated with a higher probability of vandalism. This coefficient is statistically significant at the 1% level. In common with our previous findings, there is no statistically significant effect of the tendency to internalise on the probability that an adolescent participates in vandalism. The results also indicate that fighting is more common amongst males, younger adolescents, and adolescents who stay out late, and that males more commonly participate in vandalism.

In accordance with the previous results, the conditional logit estimates displayed in column (1) of Table 3.12 suggest that poorer overall mental health is associated with a greater probability of engaging in truancy. Additionally, the effect of externalising problems on truancy remains positive and statistically significant at the 1% level, but there is no statistically significant effect of internalising problems on truancy. Column (2) suggests that females are more likely to participate in truancy than males. In accordance with our previous findings, truancy is more common amongst older adolescents. Finally, adolescents who stayed out late three or more times in the past week have a greater probability of engaging in truancy, relative to adolescents who never stayed out late in the past week.

The conditional logit estimation results shown in Tables 3.11 to 3.12 suggest that the propensity of adolescents to externalise is positively associated with the probability of fighting, vandalism, and truancy, and hence support the robustness of our previous findings.

3.8 Extension 1: The Effects of Adolescent Mental Health on Harmful Substance Use and Prosocial Behaviour

The core results discussed in Sections 3.5 to 3.7 suggest that the tendency of adolescents to externalise is positively associated with the probability that they participate in the four ASBs. One plausible explanation for this finding is that externalising problems may adversely affect the behaviour of adolescents: increasing the prevalence of "negative" behaviours, and reducing the prevalence of "good" behaviours. As an extension, we investigate the effects of adolescent's mental health on two other types of behaviour: harmful substance use (drinking alcohol, smoking cigarettes, and taking drugs) and prosocial behaviour (volunteering and helping with housework). To explore the effects of the mental health of adolescents on harmful substance use we use Sample 2 to estimate equations (A3.2) to (A3.3) in Appendix 2.

Table 3.13 summarises the coefficients from random effects probit models exploring the effects of the mental health of adolescents on their alcohol consumption and cigarette smoking behaviours.[85] To reduce the risk of reverse causality, if alcohol consumption and cigarette smoking behaviour affect the mental health of adolescents, we measure the mental health of adolescents in the previous wave.[86] The analysis displayed in column (1) suggests that poorer overall mental health of adolescents in the previous wave is associated with an increased probability of having ever drunk an entire alcoholic drink. In addition, greater externalising problems in the previous wave are associated with an increased probability of having ever drunk alcohol, as indicated by the empirical analysis contained in column (2). In contrast to the effects of externalising problems, adolescents who have fewer internalising problems have an increased probability of having tried alcohol. Note that internalising problems and externalising problems have opposite effects on adolescent's alcohol consumption and are of a similar magnitude. We investigate the null hypothesis that these coefficients cancel each other out which gives a P-value of 0.12. Hence, we cannot reject the null hypothesis that the effects of externalising problems and internalising problems are equal and opposite in magnitude[87].

[85] Adolescent harmful substance use and prosocial behaviour is measured in waves 2, 4, and 6 of Understanding Society and mental health is measured in waves 1, 3, and 5. As previously discussed in Section 3.3, the periods of the waves of Understanding Society overlap and therefore a small proportion (approximately 3%) of adolescents in Samples 2 and 3 are interviewed twice within the same calendar year. Approximately 94% of adolescents in Samples 2 and 3 were interviewed in successive years and in the region of 3% of adolescents were interviewed two years apart.

[86] The effects of the mental health of adolescents on truancy and fighting are robust to measuring the mental health of adolescents in the wave prior to the measurement of truancy and fighting. The results are available upon request. However, the models exploring the effects of adolescent's mental health problems on vandalism and shoplifting behaviour in the next wave do not converge, which likely results from the reduced sample size (approximately 1,000 observations). We do not present these findings as the main results of this chapter because of the substantially reduced sample size associated with this approach.

[87] H0: α_1 = -α_2 (i.e. $\alpha_1+\alpha_2 = 0$) in equation A3.3 (see Appendix 2).

Columns (3) and (4) illustrate that poorer overall mental health of adolescents and a greater tendency to externalise are positively associated with the probability that an adolescent smokes in the next wave. In discordance with the results relating to the alcohol consumption, we find no statistically significant effect of the propensity to internalise on smoking behaviour.

The evidence revealed in Table 3.13 suggests that being older, having separated parents, being White, and having fewer children in the household are positively associated with having ever drunk alcohol. In comparison to the findings relating to alcohol consumption, there is no statistically significant effect of ethnicity on whether adolescents smoke. The results also suggest that adolescents whose family income is in the highest quartile of the income distribution have a greater probability of having drunk alcohol relative to those adolescents whose family income is in the bottom income quartile. In accordance with Iacovou (2012), adolescents who more frequently stay out late have a higher probability of smoking cigarettes and drinking alcohol. In addition, the rate of drug offences in the local neighbourhood is positively associated with the probability of smoking, but has no statistically significant effect on alcohol consumption. What is more, there is no statistically significant effect of attitudes towards education, or the frequency of eating evening meals as a family on whether adolescents drink alcohol and smoke cigarettes.

The coefficients from random effects probit models exploring the effects of the mental health of adolescents on their drug taking behaviour are shown in Table 3.14. Column (1) suggests that poorer overall mental health is positively associated with whether an adolescent reports in the next wave to have ever taken drugs. Also, in accordance with the findings relating to alcohol and cigarette consumption, the analysis suggests that greater externalising problems in the previous wave are associated with an increased likelihood of having ever taken drugs. In contrast, there is no statistically significant effect of the tendency to internalise on the drug use of adolescents.

The following variables do not have a statistically significant effect on drug taking behaviour: gender, ethnicity, family income, parental separation, the number of children in the household, the number of close friends, or the rate of drug offences in the local neighbourhood. Adolescent drug consumption is higher amongst adolescents who stay out late without their parents knowing their whereabouts but is lower amongst adolescents who reported to eat evening meals with their family 3 or more times in the past week.[88]

The coefficients of random effects probit models exploring the effects of the mental health of adolescents on whether they volunteer and help with housework are illustrated in Table 3.15. To investigate the effects of adolescent mental health on these measures of prosocial behaviour, we estimate equations A4 to A5 (presented in Appendix 2) with Sample 3. Volunteering and helping with housework may affect the mental health of adolescents thus leading to reverse causality. To help reduce the issue of reverse causality, we lag the measures of the mental health of adolescents.

The results found in column (1) suggest that poorer overall mental health of adolescents is inversely associated with whether they volunteer in the following wave. Column (2) suggests that the propensity of adolescents to externalise is negatively associated with whether they volunteer in the next wave. However, there is no statistically significant effect of the propensity to internalise on volunteering behaviour.

The findings revealed in column (3) suggest that poorer overall mental health of adolescents is inversely associated with the probability that they help with housework in the next wave. This finding is statistically significant at the 10%, but not the 5%, significance level. The analysis illustrated in column (4) shows no statistically significant effect of the tendency to externalise on whether adolescents help with housework in the following wave. The effect of internalising problems on participation in housework is negative, though this effect is statistically significant at the 10% level. Thus, the findings suggest that greater externalising mental health problems in the previous wave are associated with a reduced probability of volunteering, but have no statistically significant effect on whether adolescents help with housework. One explanation for this finding is that whether an adolescent helps with housework may be a decision of their parents, rather than the choice of the adolescent. Hence, an adolescent's externalising problems may have little effect on whether they help with housework.

Table 3.15 indicates that volunteering and helping with housework are less common amongst males than females. Volunteering is more prevalent amongst adolescents whose family income in the highest quartile of the income distribution, relative to adolescents whose family income is in the bottom quartile. Adolescents who stayed

[88] We have also explored the effects of the mental health of parents and adolescents on the cigarette smoking behaviour and alcohol consumption of parents. The findings suggest that the mental health of parents has no statistically significant effect on the probability that the parent drinks alcohol or smokes cigarettes in the next wave. The empirical results indicate that greater externalising problems of adolescents are positively associated with the probability that the parents smoke in the next wave, but do not affect the probability that parents drink alcohol in the next wave. However, there is no statistically significant effect of the internalising problems of adolescents on parental alcohol consumption and cigarette smoking behaviours. The results are available upon request.

out late once/ twice in the past month are also more likely to volunteer, relative to adolescents who did not stay out late in the past month. There is no statistically significant effect of ethnicity on the probability of volunteering, but Black adolescents are more likely to help with housework than Whites.

Adolescents who ate evening meals with their family 3 or more times in the past week have a greater likelihood of volunteering and helping with housework. However, there is no statistically significant effect of age, parental separation, the number of children in the household, the number of close friends, or an adolescent's attitude to education on their volunteering behaviour. The frequency of staying out late has no statistically significant effect on whether adolescents help with housework. In contrast, adolescents who ate evening meals as a family 3 or more times in the past week are more likely to help with housework, relative to adolescents who did not eat evening meals with their family.

The analysis of this section suggests that the propensity of adolescents to externalise is positively associated whether they participate in with harmful substance use, and inversely associated with whether they volunteer. Thus, the findings of this chapter support the notion that a greater tendency of adolescents to externalise may increase their participation in "negative" behaviours, whilst reducing their participation in "good" behaviours.

3.9 Conclusion

This chapter used data from Understanding Society to explore how the ASB of adolescents is affected by their mental health, as well as that of their parents. The effects of mental health on ASB are large in magnitude. For example, a one standard deviation increase in externalising problems is associated with an increase in the probability of fighting (vandalism) of approximately 90% (160%) of the magnitude of the effect of being male. In a similar fashion, the effect of a one standard deviation increase in the propensity to externalise on shoplifting is approximately 1.5 times the size of the effect of being male. Likewise, a one standard deviation increase in externalising problems predicts a 3.03% point increase in the probability of truancy, which is approximately 14% of a standard deviation.

The core findings suggest that a greater tendency to externalise is positively associated participation in ASB. As an extension, we investigated the effects of adolescent’s mental health on their harmful substance use (drinking alcohol, smoking cigarettes, and taking drugs) and prosocial behaviour (volunteering and helping with housework). The findings suggest that greater externalising problems of adolescents positively predict harmful substance use in the next wave. In addition, a greater propensity to externalise is associated with a reduced probability that adolescents volunteer in the following wave. However, there is no statistically significant effect of externalising problems on whether adolescents help with housework in the next wave. Hence, the results support the case that the tendency of adolescents to externalise may adversely affect their behaviour: increasing their participation in "negative" behaviours and reducing their participation in "good" behaviours.

It is important to acknowledge the shortcomings of this chapter. Firstly, the estimated effects of the externalising problems of adolescents on their ASB may suffer from omitted variable bias. Omitted variable bias may occur if, after conditioning on a rich set of demographic, family, social, and neighbourhood variables, unobserved variables affect externalising problems and ASB. On the other hand, our core results are robust to a variety of estimation techniques including random effects probit models, multivariate probit models, and accounting for family fixed effects using conditional logit models. However, the estimation results from conditional logit models may still suffer from omitted variable bias if unobserved variables affect both the difference in the propensities of siblings to externalise and also affect their ASB. In light of this, the findings of this chapter should arguably be viewed as correlations, rather than causal.

On the other hand, this chapter has a number of strengths. Firstly, the existing literature typically utilises single-equation models to explore the determinants of participation in crime and ASB. However, as previously argued, the decisions of adolescents to participate in each of the ASBs are likely to be related via the unobserved characteristics of the adolescent, such as their attitudes towards risk. Accordingly, we estimated a system of probit models to increase the efficiency of our estimates.

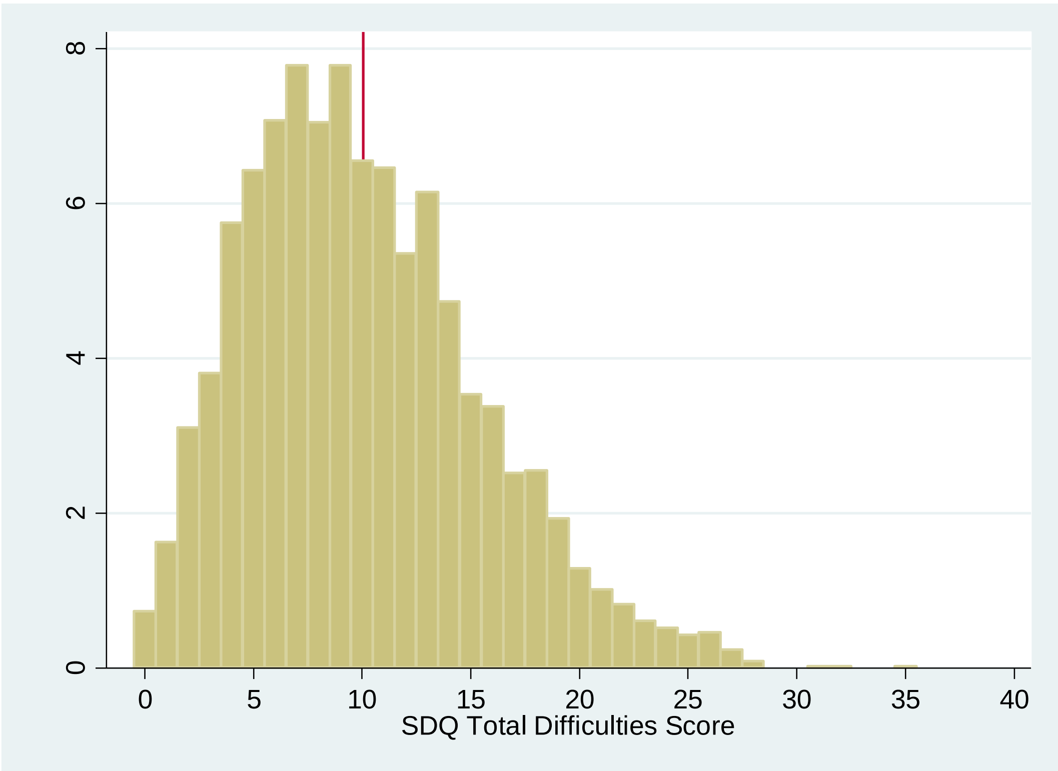
Secondly, in contrast to the existing literature, we account for important social characteristics of adolescents. For example, we control for the frequency that adolescents eat evening meals with their family; and stay out late, without their parents knowing their whereabouts. It is important to control for these social characteristics because they have been shown to affect both mental health and participation in ASB, (see Iacovou, 2012; Sen, 2010). Thirdly, in comparison to Murray et al. (2015) who only investigate the effects of externalising problems, we explored whether the tendencies to externalise and internalise affect participation in ASB differently.

The empirical findings have important implications for government policy. Previous research indicates that adolescents who commit ASB have an increased probability of committing crime in adulthood, see (Farrington, 1997; Bergman and Andershed, 2009). Our results suggest that a greater tendency of adolescents to externalise may increase the probability that they engage in ASB. In contrast, the findings did not indicate a consistent effect of family income on the ASB of adolescents. Thus, the analysis supports the case that interventions to improve material well-being are unlikely to be effective in reducing crime which results from children's ASB specifically, and direct interventions to improve mental health may be necessary. One example of such a mental health intervention is neurofeedback, a mental health treatment to increase self-control over brain activity patterns. Neurofeedback helps relieve symptoms of externalising problems in 8-12 year olds, see Gevensleben et al. (2009). In addition, our analysis suggests that government policies to expand access to mental health services for children (such as the Young Person's Improving Access to Psychological Therapies programme) may have positive effects on the behaviours of adolescents: increasing (reducing) the prevalence of "good" ("negative") behaviours

The findings support a growing literature demonstrating the economic and social costs of poor mental health such as reduced productivity, increased absenteeism, and increased physical healthcare costs, see Layard et al. (2012). We contribute to this literature by illustrating that poor mental health may also have an adverse effect on "*what you do to others*". Future research in this area should explore how the mental health of adolescents affects other measures of ASB such car theft and drug dealing. What is more, another interesting avenue for future research is to investigate how different types of ASB in adolescence relate to adult behaviour, using cohort datasets such as the Avon Longitudinal Study of Parents and Children.

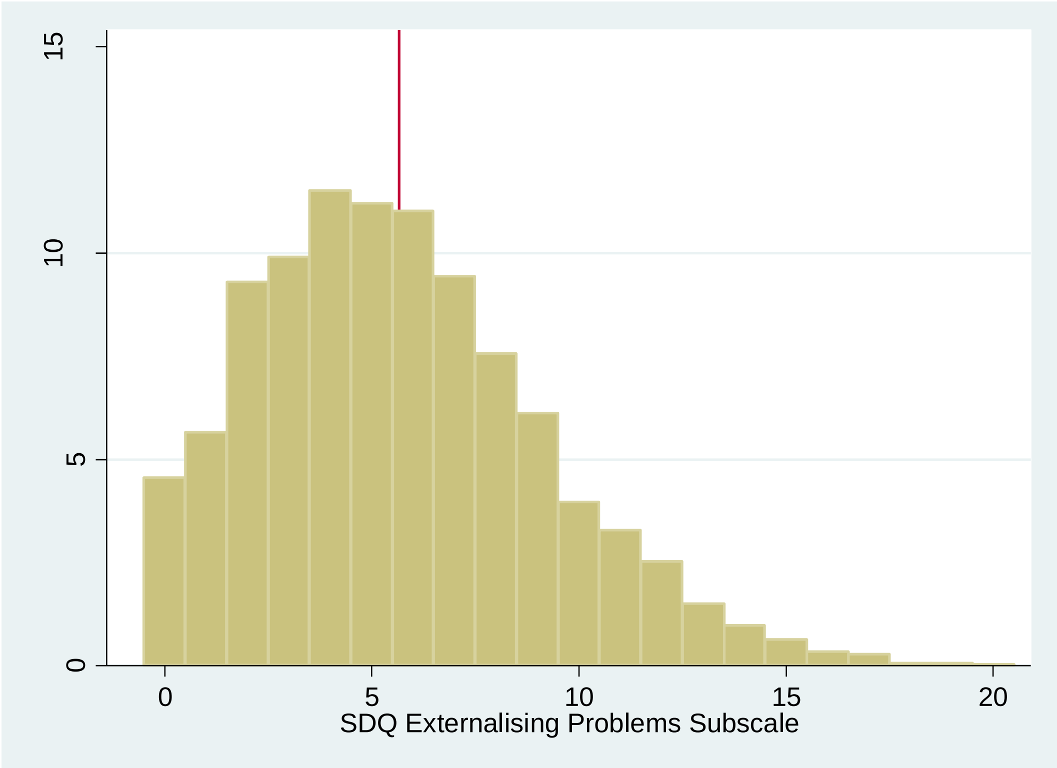
A3 Appendix 1: Figures and Tables

Figure 3.1: The Distribution of the Strengths and Difficulties Questionnaire Total Difficulties Score in Sample 1 (Waves 3 and 5)



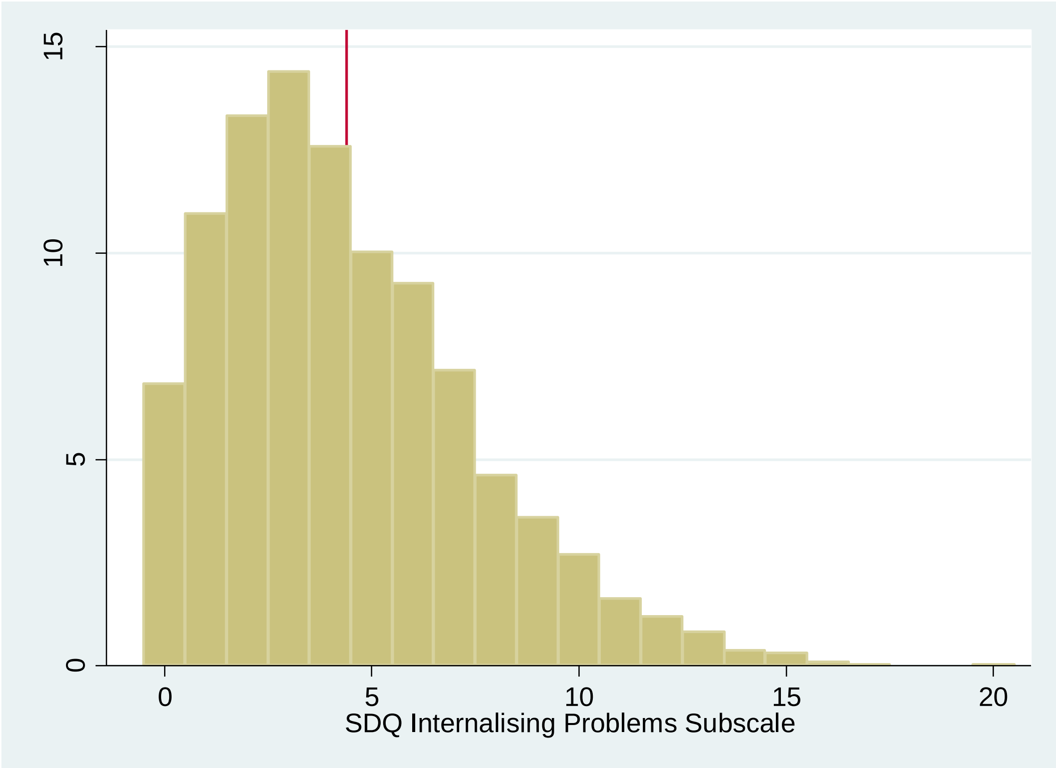
Note: The vertical red line indicates the mean (10.05). The standard deviation equals 5.42. The total difficulties score is the sum of the peer relationship problems, emotional symptoms, conduct problems, and hyperactivity problems, subscales.

Figure 3.2: The Distribution of the Strengths and Difficulties Questionnaire Externalising Problems Subscale in Sample 1 (Waves 3 and 5)



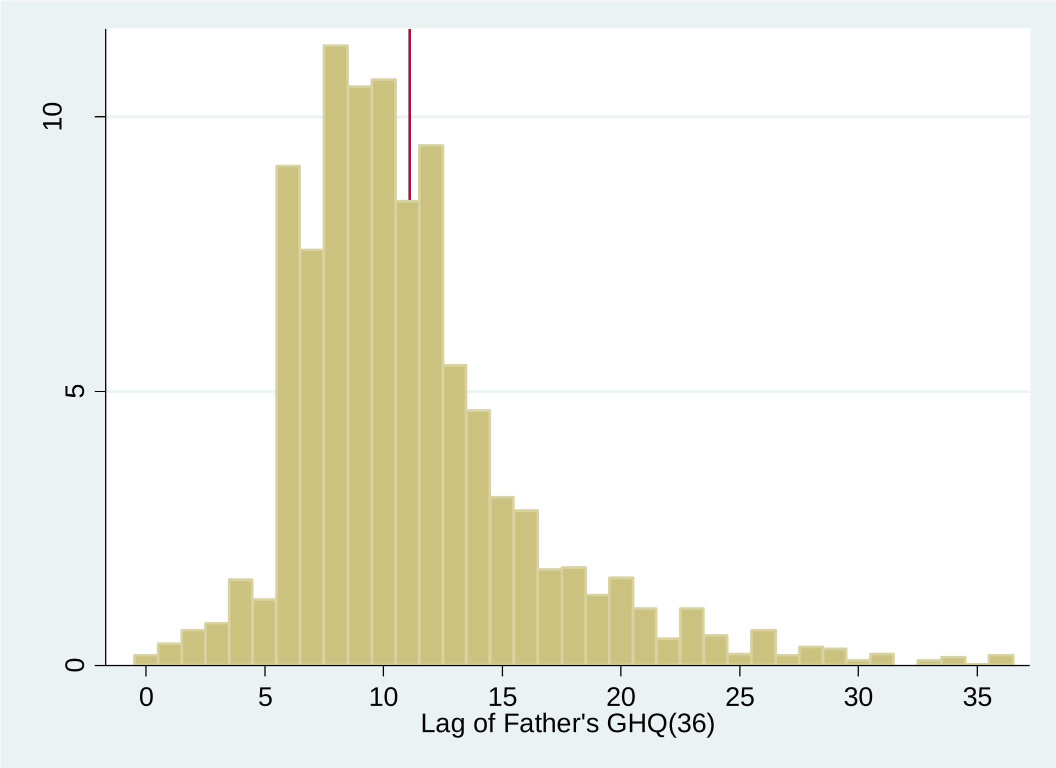
Note: The vertical red line indicates the mean (5.66). The standard deviation equals 3.47. The externalising problems subscale is the sum of the conduct problems and hyperactivity problems subscales.

Figure 3.3: The Distribution of the Strengths and Difficulties Questionnaire Internalising Problems Subscale in Sample 1 (Waves 3 and 5)



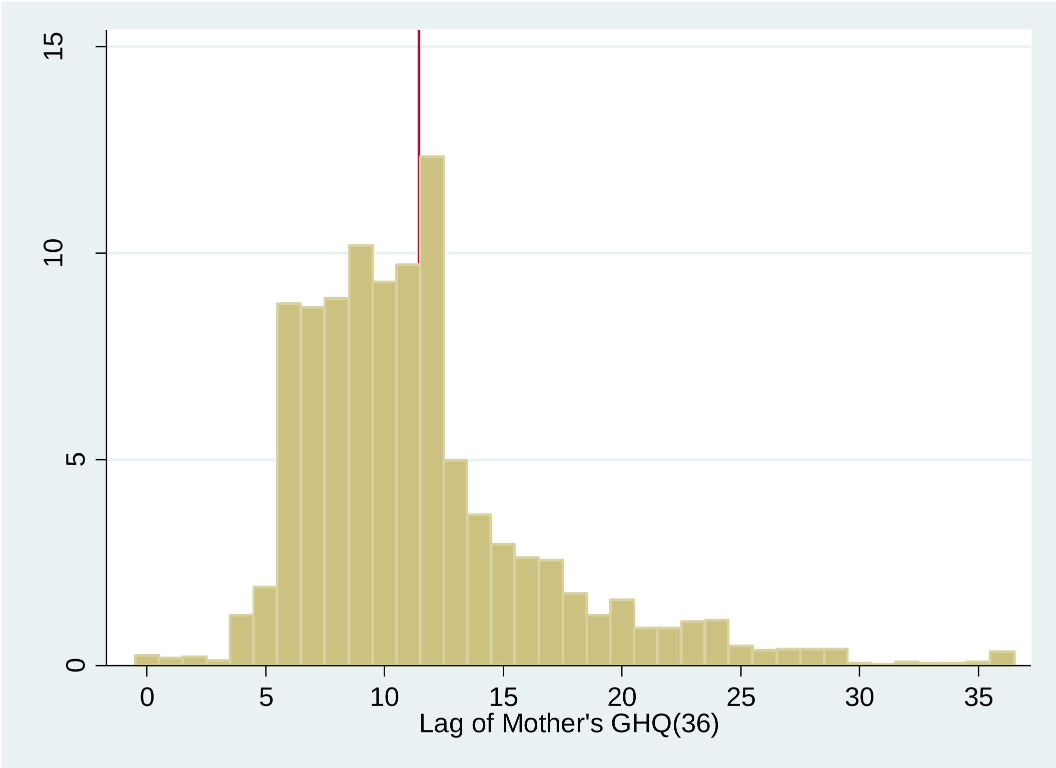
Note: The vertical red line indicates the mean (5.66). The standard deviation equals 3.10. The internalising problems subscale is the sum of the emotional symptoms and peer relationship problems subscales.

Figure 3.4: The Distribution of the 36 Point General Health Questionnaire Scores of Fathers in Sample 1 (Waves 3 and 5)



Note: The vertical red line indicates the mean (11.10). The standard deviation is equal to 5.06. The father's GHQ(36) is measured in waves 1 to 2 of Understanding Society (see Table 3.4).

Figure 3.5: The Distribution of the 12 Point General Health Questionnaire Scores of Mothers in Sample 1 (Waves 3 and 5)



Note: The vertical red line indicates the mean (11.44) and the standard deviation equals 5.21. The mother's GHQ(36) is measured in waves 1 to 2 of Understanding Society (see Table 3.4).

Table 3.1: Participation in Antisocial Behaviours (Fighting, Vandalising, Shoplifting, and Truanting): Sample 1 (Waves 3 and 5)

Behaviour	Frequency	Percent
Fighting		
Never Fights	2715	83.56
Fights	534	16.44
Vandalism		
Never Vandalised	2988	91.97
Vandalised	261	8.03
Shoplifting		
Never Shoplifted	3181	97.91
Shoplifted	68	2.09
Truancy		
Never Truanted	3088	95.04
Truanted	161	4.96
Observations	3249	

Table 3.2: Participation in Harmful Substance Use (Alcohol Consumption, Cigarette Smoking, and Drug Taking): Sample 2 (Waves 2, 4, and 6)

Behaviour	Frequency	Percent
Ever Drunk Alcohol		
Never Drunk	1489	66.62
Drunk Alcohol	746	33.38
Ever Smoke Cigarettes		
Never Smoke	2040	91.28
Smoke	195	8.72
Ever Taken Drugs		
Not Taken Drugs	2125	95.08
Taken Drugs	110	4.92
Observations	2235	

Table 3.3: Participation in Prosocial Behaviours (Volunteering and Helping With Housework): Sample 3 (Waves 2, 4, and 6)

Behaviour	Frequency	Percent
Volunteering		
Does not Volunteer	1085	42.92
Volunteers	1443	57.08
Helps with Housework		
Does not Help with Housework	220	8.70
Helps with Housework	2308	91.30
Observations	2528	

Table 3.4: Variable Definitions for Variables Included in the Main Analysis

Variable	**Definition**
Indicators of Antisocial Behaviour	
Fighting	Binary variable equals 1 if the adolescent reports to have been involved in a fight in the past month that involved physical violence, and 0 otherwise.
Vandalism	Binary variable equals 1 if the adolescent reports to have deliberately broken or damaged property that did not belong to them in the past year, and 0 otherwise.
Truancy	Binary variable equals 1 if the adolescent has played truant in the past year, and 0 otherwise.
Shoplifting	Binary variable equals 1 if in the past year the adolescent has taken something from a shop, supermarket, or department store without paying, and 0 otherwise.
Indicators of Harmful Substance Use	
Alcohol	Binary variable equals 1 if the adolescent has ever had a whole alcoholic drink, and 0 otherwise.
Smokes	Binary variable equals 1 if the adolescent ever smokes cigarettes, and 0 otherwise.
Drug Use	Binary variable equals 1 if the adolescent has ever tried 1 or more of the following drugs: glue, cannabis, or any other illegal drug, and 0 otherwise.
Indicators of Prosocial Behaviours	
Housework	Binary variable equals 1 if the adolescent helps with the housework in an average week, and 0 otherwise.
Volunteers	Binary variable equals 1 if the adolescent volunteers or does community work, and 0 otherwise.

Note: Table continues on the next page.

Table 3.4 (continued): Variable Definitions for Variables Included in the Main Analysis

Variable	Definition
Key Explanatory Variables	
SDQ Total Difficulties Score	Measure of the overall mental health of adolescents. The SDQ total difficulties score is the sum of the externalising problems and internalising problems subscales (outlined below). The SDQ total difficulties score ranges from 0 (the fewest mental health problems) to 40 (the most mental health problems).
Externalising Problems Subscale	Sum of the hyperactivity problems and conduct problems, subscales. The hyperactivity problems subscale is made up of the following statements: 1. "I am restless, I cannot stay still for long" 2. "I finish the work I'm doing" (reversed) 3. "I think before I do things" (reversed) 4. "I am constantly fidgeting or squirming" 5. "I am easily distracted, I find it difficult to concentrate". The conduct problems subscale is composed of the following statements: 1. "I am often accused of lying or cheating" 2. "I take things that are not mine from home, school or elsewhere" 3. "I fight a lot. I can make other people do what I want" 4. "I usually do as I am told" (reversed) 5. "I get very angry and often lose my temper". In response to each of the 20 statements the adolescent indicates whether the statement is not true (0), somewhat true (1), or certainly true (2). The "strengths" are reversed so that 2 = not true, 1 = somewhat true, and 0 = certainly true. The externalising problems subscale ranges from a minimum value of 0 to a maximum value of 20, where higher scores indicate greater externalising problems.
Internalising Problems Subscale	Sum of the emotional symptoms and peer relationship problems, subscales. The emotional symptoms subscale is made up of the following statements: 1. "I worry a lot" 2. "I have many fears. I am easily scared" 3. "I am often unhappy, down-hearted or tearful" 4. "I am nervous in new situations. I easily lose confidence" 5. "I get a lot of headaches, stomach-aches or sickness". The peer relationship problems subscale is composed of the following statements: 1. "Other people my age generally like me" (reversed) 2. "Other children or young people pick on me or bully me" 3. "I am usually on my own. I generally play alone or keep to myself" 4. "I get on better with adults than with people my own age" 5. "I have one good friend or more" (reversed) For each of the 20 statements the adolescent indicates whether the statement is not true (0), somewhat true (1), or certainly true (2). As indicated, the "strengths" are reversed so that 2 = not true, 1 = somewhat true, and 0 = certainly true. The internalising problems subscale ranges from a minimum value of 0 to a maximum value of 20, where higher scores indicate greater internalising problems.

Note: Table continues on the next page.

Table 3.4 (continued): Variable Definitions for Variables Included in the Main Analysis

Variable	Definition
Key Explanatory Variables	
GHQ(36) of the Father	The questions of the GHQ(36) are shown below. Have you recently: 1. "been able to concentrate" (reversed) 2. "lost much sleep over worry" 3. "felt that you were playing a useful part in things" (reversed) 4. "felt capable of making decisions" (reversed) 5. "felt constantly under strain" 6. "felt you could not overcome difficulties" 7. "been able to enjoy normal activities" (reversed) 8. "been able to face up to problems" (reversed) 9. "been feeling unhappy and depressed" 10. "been losing confidence" 11. "been thinking of yourself as worthless" 12. "been feeling reasonably happy" (reversed) Each have 4 options: 0 (not at all), 1 (no more than usual), 2 (rather more than usual), and 3 (much more than usual). We reverse statements 1, 3, 4, 7, 8, and 12. We sum the scores to create a likert measure of mental health where 0 (36) denotes the best (worst) mental health. We measure the GHQ(36) of the father using data from wave 1 or 2 of Understanding Society.
GHQ(36) of the Mother	As for the GHQ(36) of the Father (outlined above).
Adolescent Characteristics	
Male	Binary variable equals 1 if the adolescent is male, and 0 if female.
Age	The age of the adolescent measured in years.
Ethnicity	
Black	Binary variable equals 1 if the adolescent is Black or of mixed ethnicity.
Indian	Binary variable equals 1 if the adolescent is Indian, Pakistani, or Bangladeshi.
White	Whites form the base category.
Family Variables	
Household Income Quartile	Categorical variable denotes the real household income quartile. We measure total family income as the sum of the monthly incomes of all family members, net of income tax and national insurance contributions. Individuals whose household income is in the bottom quartile form the base category.
Parents Separated	Binary variable equals 1 if the parents of the adolescent are separated, and 0 otherwise.
Number of Kids	Variable denotes the number of children living in the household aged 15 or under.

Note: Table continues on the next page.

Table 3.4 (continued): Variable Definitions for Variables Included in the Analysis of Adolescent's Antisocial Behaviour, Harmful Substance Use, and Prosocial Behaviour

Variable	**Definition**
Social Characteristics	
Number of Close Friends	
1-5 Friends	Binary variable equals 1 if the adolescent has 1-5 close friends, and 0 otherwise.
6+ Friends	Binary variable equals 1 if the adolescent has 6 or more close friends, and 0 otherwise.
Zero friends	Individuals who have zero close friends form the base category.
Staying Out Late	Categorical variable denotes the frequency that the adolescent stayed out past 9pm in the past month without their parents knowing their whereabouts. The categories are once or twice, and 3 or more times. Individuals who did not stayed out past 9pm in the past month form the base category.
Importance of GCSEs	Binary variable equals 1 if the adolescent states that it is very important to do well in their GCSE exams, and otherwise.
Eating Evening Meals	Categorical variable indicates the frequency that the adolescent ate evening meals with their family in the past week. The categories are 1-2 times, and 3-7 times. Individuals who did not eat evening meals with their family in the past week form the base category.
Regional and Time Variables	
Year	Categorical variable indicates the year of interview. The categories are 2012, 2013, 2014, and 2015. Individuals who were interviewed in 2011 form the base category.
Crime and ASB Per 1,000	Variable denotes the annual rate of police-reported crime and ASB per 1,000 residents in the local neighbourhood. We measure crime and ASB at the lower layer super output area level for England and Wales; and at the Northern Ireland super output area level for Northern Ireland.
Drug Offences Per 1,000	Variable indicates the annual rate of police-reported drug offences per 1,000 residents in the local neighbourhood. For England and Wales (Northern Ireland) we measure drug offences at the lower layer super output area (Northern Ireland super output area) level.

Table 3.5: Adolescent Antisocial Behaviours (Fighting, Vandalism, Shoplifting, and Truancy) and the Mental Health of Adolescents and Parents: Sample 1 (Waves 3 and 5)

	Fighting				Vandalism				Shoplifting				Truancy					
	Never Fights		Fights		Never Vand.		Vand.		Never Shop.		Shop.		Never Tru.		Tru.		Total	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
SDQ: Total Difficulties	9.43	5.12	13.25	5.75	9.70	5.27	14.13	5.45	9.93	5.34	16.04	5.71	9.82	5.29	14.54	5.95	10.05	5.42
SDQ: Externalising Prob	5.19	3.23	8.05	3.66	5.37	3.31	8.98	3.55	5.56	3.39	10.56	3.58	5.50	3.38	8.88	3.50	5.66	3.47
SDQ: Internalising Prob	4.23	2.99	5.21	3.49	4.33	3.06	5.14	3.44	4.37	3.07	5.49	4.00	4.33	3.05	5.66	3.70	4.39	3.10
Lag of Father's GHQ(36)	11.06	5.04	11.35	5.16	11.09	5.06	11.27	5.12	11.1	5.08	11.29	4.49	11.09	5.06	11.47	5.17	11.1	5.06
Lag of Mother's GHQ(36)	11.33	5.12	12.01	5.6	11.45	5.2	11.33	5.36	11.4	5.18	13.47	6.06	11.39	5.14	12.46	6.32	11.44	5.21
Observations	2715		534		2988		261		3181		68		3088		161		3249	

Note: Vand., shop. and tru. denote vandalises, shoplifts, and truants, respectively. SD denotes the standard deviation. The GHQ(36) of parents is measured in waves 1 to 2 of Understanding Society (see Table 3.4).

Table 3.6: Summary Statistics Table For Key Explanatory Variables: Sample 1 (Waves 3 and 5)

Continuous Variables	**Mean**	**SD**	**Min**	**Max.**
SDQ: Total Difficulties	10.05	5.42	0	35
Externalising Problems	5.66	3.47	0	20
Internalising Problems	4.39	3.1	0	20
Lag of Father's GHQ(36)	11.10	5.06	0	36
Lag of Mother's GHQ(36)	11.44	5.21	0	36
Age	12.53	1.72	10	15
Number of Children	2.16	1.01	1	8
Binary Variables		*Percent (N)*		
Fought: Past Month		16 (534)		
Vandalised: Past Year		8 (261)		
Shoplifted: Past Year		2 (68)		
Truanted: Past Year		4 (161)		
Male		49 (1619)		
White		80 (2590)		
Black		9 (282)		
Indian		12 (377)		
1st Income Quartile		11 (373)		
2nd Income Quartile		24 (792)		
3rd Income Quartile		30 (996)		
4th Income Quartile		33 (1088)		
Parents Separated		4 (130)		
0 Friends		1 (40)		
1-5 Friends		52 (1718)		
6+ Friends		31 (1036)		
Never Out Past 9pm		88 (2889)		
Once/ Twice Out Past 9pm		7 (244)		
3+ Times Out Past 9pm		3 (116)		
GCSEs Very Important		81 (2632)		
Eats: 1/2		17 (573)		
Eats: 3+		77 (2505)		
Observations		3249		

Note: N indicates the number of observations.

Table 3.7(a): Random Effects Probit Model Coefficients: The Effects of Adolescent Mental Health on Fighting and Vandalism: Sample 1 (Waves 3 and 5)

Dependent Variable	(1) Fighting	(2) Fighting	(3) Vandalism	(4) Vandalism
SDQ: Total Difficulties	0.0874***		0.0880***	
	(0.0083)		(0.0110)	
Externalising Problems		0.1420***		0.1725***
		(0.0138)		(0.0205)
Internalising Problems		0.0221*		-0.0089
		(0.0123)		(0.0155)
Age	-0.1315***	-0.1264***	-0.0043	0.0004
	(0.0237)	(0.0233)	(0.0267)	(0.0272)
Male	0.6247***	0.5219***	0.5046***	0.3604***
	(0.0858)	(0.0817)	(0.1054)	(0.1027)
Black	0.0639	0.0721	0.3629**	0.4122**
	(0.1399)	(0.1384)	(0.1635)	(0.1681)
Indian	0.1644	0.1700	0.2308	0.2467*
	(0.1219)	(0.1209)	(0.1423)	(0.1477)
2nd Income Quartile	0.0025	-0.0016	0.1339	0.1533
	(0.1374)	(0.1347)	(0.1681)	(0.1740)
3rd Income Quartile	0.1546	0.1361	0.1944	0.1774
	(0.1311)	(0.1288)	(0.1649)	(0.1705)
4th Income Quartile	0.0651	0.0505	0.3154*	0.3024*
	(0.1324)	(0.1303)	(0.1655)	(0.1722)
Parents Separated	-0.0647	-0.1097	0.3641*	0.3495
	(0.2054)	(0.2033)	(0.2200)	(0.2246)
Number of Children	0.1471***	0.1414***	0.0432	0.0385
	(0.0388)	(0.0383)	(0.0426)	(0.0435)
1-5 Friends	-0.5543**	-0.6869**	-0.3826	-0.5684*
	(0.2663)	(0.2682)	(0.3294)	(0.3306)
6+ Friends	-0.5136*	-0.6979**	-0.2140	-0.4684
	(0.2696)	(0.2733)	(0.3303)	(0.3333)
Past 9pm: 1/2	0.2933**	0.2400*	0.4170***	0.3444**
	(0.1322)	(0.1295)	(0.1412)	(0.1423)
3+ Times Out Past 9pm	0.8451***	0.7564***	0.2697	0.1560
	(0.1771)	(0.1747)	(0.1969)	(0.1986)
GCSEs Very Important	-0.1601*	-0.1004	-0.3149***	-0.2286**
	(0.0904)	(0.0895)	(0.1037)	(0.1051)
Eats: 1/2	0.2429	0.3035*	0.0866	0.1794
	(0.1738)	(0.1698)	(0.2018)	(0.2113)
Eats: 3+	0.2200	0.2859*	-0.0154	0.0714
	(0.1605)	(0.1564)	(0.1864)	(0.1966)
Crime and ASB Per 1,000	0.0005	0.0004	0.0001	0.0001
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Observations	3249	3249	3249	3249
Number of Individuals	2,495	2,495	2,495	2,495

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: All models control for the year of interview and LSOA of residence.

Table 3.7(b): Random Effects Probit Model Average Marginal Effects: The Effects of Adolescent Mental Health on Fighting and Vandalism: Sample 1 (Waves 3 and 5)

Dependent Variable	(1) Fighting	(2) Fighting	(3) Vandalism	(4) Vandalism
Average Marginal Effects of Overall Mental Health Problems				
SDQ: Total Difficulties	0.0140***		0.0074***	
	(0.0012)		(0.0011)	
Implied Effects of a SD Increase in Overall Mental Health Problems				
Effect of SD Increase in TD	*7.62% pts.*		*4.88% pts.*	
Average Marginal Effects of Externalising Problems				
Externalising Problems		0.0229***		0.0143***
		(0.0019)		(0.0019)
Implied Effects of SD Increase in EP (% pts.)		*7.88%*		*4.98%*
Average Marginal Effects of Internalising Problems				
Internalising Problems		0.0036*		-0.0007
		(0.0020)		(0.0013)
Implied Effects of a SD Increase in IP (% pts.)		*0.95% pts.*		
Male (Average Marginal Effect)	0.0999***	0.0841***	0.0424***	0.0298***
	(0.0127)	(0.0125)	(0.0093)	(0.0086)
Observations	3249	3249	3249	3249
Number of Individuals	2,495	2,495	2,495	2,495

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Control variables as for Table 3.7(a). SD denotes the standard deviation and TD indicates the total difficulties score. EP and IP denote externalising problems and internalising problems, respectively. Standard deviation of total difficulties score = 5.41, standard deviation of externalising problems = 3.46, and standard deviation of internalising problems = 3.10. The implied effects of a one standard deviation increase in the mental health problems on the probability of participating in fighting and vandalism are presented in italics.

Table 3.7(c): Random Effects Probit Model Coefficients: The Effects of Adolescent Mental Health on Fighting and Vandalism: Interactions with Gender (Sample 1)

	(1) Fighting	(2) Vandalism
Male	0.5005***	0.1424
	(0.1755)	(0.2134)
Externalising Prob.	0.1194***	0.1531***
	(0.0193)	(0.0260)
Male x Externalising Prob.	0.0346	0.0317
	(0.0233)	(0.0279)
Internalising Prob.	0.0472**	-0.0058
	(0.0191)	(0.0225)
Male X Internalising Prob.	-0.0426*	-0.0031
	(0.0245)	(0.0300)
Observations	3249	3249
Number of Individuals	2,495	2,495

Standard errors in parentheses
All control variables as for Table 3.7(b).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.8(a): Random Effects Probit Model Coefficients: The Effects of Adolescent Mental Health on Shoplifting and Truancy: Sample 1 (Waves 3 and 5)

Dependent Variable	(1) Shoplifting	(2) Shoplifting	(3) Truancy	(4) Truancy
SDQ: Total Difficulties	0.1421***		0.0891***	
	(0.0328)		(0.0162)	
Externalising Problems		0.2421***		0.1352***
		(0.0503)		(0.0234)
Internalising Problems		0.0018		0.0297
		(0.0327)		(0.0190)
Age	0.1938***	0.1716***	0.1855***	0.1773***
	(0.0710)	(0.0642)	(0.0459)	(0.0440)
Male	0.8633***	0.5493**	0.1840	0.0877
	(0.3151)	(0.2561)	(0.1234)	(0.1188)
Black	0.3442	0.3458	-0.0517	-0.0266
	(0.3382)	(0.3147)	(0.2214)	(0.2153)
Indian	-0.4837	-0.4194	0.3865**	0.3716**
	(0.4512)	(0.4090)	(0.1928)	(0.1863)
2nd Income Quartile	0.8764**	0.7389**	0.1131	0.1012
	(0.3855)	(0.3610)	(0.2024)	(0.1953)
3rd Income Quartile	0.8039**	0.6937**	0.0631	0.0479
	(0.3688)	(0.3436)	(0.2003)	(0.1924)
4th Income Quartile	0.3410	0.2364	0.0236	0.0104
	(0.3607)	(0.3381)	(0.1998)	(0.1924)
Parents Separated	0.3585	0.3917	0.1692	0.1494
	(0.3485)	(0.3262)	(0.2417)	(0.2328)
Number of Children	0.0143	-0.0045	0.0596	0.0509
	(0.1102)	(0.1032)	(0.0606)	(0.0578)
1-5 Friends	-0.7988	-1.1502*	0.0436	-0.0767
	(0.6371)	(0.6284)	(0.4613)	(0.4479)
6+ Friends	-0.3262	-0.8156	0.0963	-0.0728
	(0.6151)	(0.6029)	(0.4663)	(0.4535)
Past 9pm: 1/2	0.7937***	0.6290**	0.4854***	0.4229**
	(0.2846)	(0.2496)	(0.1778)	(0.1730)
3+ Times Out Past 9pm	1.1380***	0.9702***	0.6105***	0.5294**
	(0.3803)	(0.3368)	(0.2225)	(0.2176)
GCSEs Very Important	0.1887	0.3347	-0.3060**	-0.2445*
	(0.2415)	(0.2256)	(0.1331)	(0.1294)
Eats: 1/2	-0.2455	-0.0358	-0.1818	-0.1218
	(0.3900)	(0.3809)	(0.2251)	(0.2173)
Eats: 3+	-0.1476	0.0301	-0.4340**	-0.3659*
	(0.3344)	(0.3311)	(0.2134)	(0.2055)
Crime and ASB Per 1,000	0.0002	0.0002	-0.0001	-0.0001
	(0.0007)	(0.0007)	(0.0005)	(0.0005)
Observations	3249	3249	3249	3249
Number of Individuals	2,495	2,495	2,495	2,495

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Control variables as for Table 3.7(a).

Table 3.8(b): Random Effects Probit Model Average Marginal Effects: The Effects of Adolescent Mental Health on Shoplifting and Truancy: Sample 1 (Waves 3 and 5)

Dependent Variable	(1) Shoplifting	(2) Shoplifting	(3) Truancy	(4) Truancy
Average Marginal Effects of Overall Mental Health Problems				
SDQ: Total Difficulties	0.0011**		0.0033***	
	(0.0005)		(0.0009)	
Implied Effects of a 1 standard deviation Increase in Overall Mental Health Problems				
Effect of SD Increase in TD (% pts.)	*0.60% pts.*		*1.78% pts.*	
Average Marginal Effects of Externalising Problems				
Externalising Problems		0.0026**		0.0056***
		(0.0010)		(0.0015)
Implied Effects of SD Increase in EP (% pts.)		*0.90% pts.*		*3.03% pts.*
Average Marginal Effects of Internalising Problems				
Internalising Problems		0.0000		0.0012
		(0.0004)		(0.0008)
Implied Effects of SD Increase in IP (% pts.)		*0.00% pts.*		*0.37% pts.*
Male (Average Marginal Effect)	0.0064**	0.0060**	0.0068	0.0036
	(0.0031)	(0.0029)	(0.0046)	(0.0049)
Observations	3249	3249	3249	3249
Number of Individuals	2,495	2,495	2,495	2,495

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: Control variables as for Table 3.7(a). SD denotes the standard deviation and TD indicate the total difficulties score. EP and IP denote externalising problems and internalising problems, respectively. Standard deviation of total difficulties score = 5.41, standard deviation of externalising problems = 3.46, and standard deviation of internalising problems = 3.10. The implied effects of a 1 standard deviation increase in the mental health problems on the probability of participating in shoplifting and truancy are presented in italics.

Table 3.8(c): Random Effects Probit Model Coefficients: The Effects of Adolescent Mental Health on Shoplifting and Truancy: Interactions with Gender(Sample 1)

	(1) Shoplifting	(2) Truancy
Male	1.0732	-0.0456
	(0.8120)	(0.2830)
Externalising Prob.	0.2842***	0.1412***
	(0.0853)	(0.0306)
Male x Externalising Prob.	-0.0604	-0.0080
	(0.0709)	(0.0314)
Internalising Prob.	-0.0032	0.0100
	(0.0435)	(0.0274)
Male x Internalising Prob.	0.0042	0.0368
	(0.0580)	(0.0368)
Observations	3249	3249
Number of Individuals	2,495	2,495

All control variables as for Table 3.8(c).
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9(a): Random Effects Probit Model Coefficients: The Effects of Parental Mental Health on Antisocial Behaviour: Sample 1 (Waves 3 and 5)

Dependent Variable	(1) Fighting	(2) Vandalism	(3) Shoplifting	(4) Truancy
Panel (1): The Effects of Father's Mental Health on ASB				
Lag of Father's GHQ(36)	0.0057	0.0023	0.0162	0.0055
	(0.0078)	(0.0083)	(0.0157)	(0.0103)
Panel (2): The Effects of Mother's Mental Health on ASB				
Lag of Mother's GHQ(36)	0.0179**	-0.0060	0.0423**	0.0168*
	(0.0074)	(0.0085)	(0.0184)	(0.0102)
Observations	3249	3249	3249	3249
Number of Individuals	2,495	2,495	2,495	2,495

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Control variables as for Table 3.7(a). We measure the GHQ(36) of the parents in wave 1 or wave 2 of Understanding Society, see Table 3.4.

Table 3.9(b): Random Effects Probit Model Average Marginal Effects: The Effects of Parental Mental Health on Antisocial Behaviour: Sample 1 (Waves 3 and 5)

Dependent Variable	(1) Fighting	(2) Vandalism	(3) Shoplifting	(4) Truancy
Panel (1): The Effects of Father's Mental Health				
Lag of Father's GHQ(36)	0.0009	0.0002	0.0001	0.0002
	(0.0012)	(0.0007)	(0.0001)	(0.0004)
Effect of SD Increase in GHQ(36) (% pts.)	*0.46% pts.*	*0.10% pts.*	*0.05% pts.*	*0.10% pts.*
Panel (2): The Effects of Mother's Mental Health				
Lag of Mother's GHQ(36)	0.0028**	-0.0005	0.0003	0.0006
	(0.0011)	(0.0007)	(0.0002)	(0.0004)
Effect of SD Increase in GHQ(36) (% pts.)	*1.46% pts.*	*-0.26% pts.*	*0.16% pts.*	*0.31% pts*
Observations	3249	3249	3249	3249
Number of Individuals	2,495	2,495	2,495	2,495

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Control variables as for Table 3.7(a). We measure the GHQ(36) of the parents in wave 1 or wave 2 of Understanding Society, see Table 3.4. SD denotes the standard deviation. Standard deviation of father's GHQ(36) =5.06. Standard deviation of mother's GHQ(36) = 5.21. The implied effects of a 1 standard deviation increase in the GHQ(36) scores of mothers and fathers are presented in italics.

Table 3.10: Multivariate Probit Model Coefficients: The Effects of Adolescent Mental Health on Antisocial Behaviour: Sample 1 (Waves 3 and 5)

	(1)	(2)
Dep. Var.: Fighting		
SDQ: Total Difficulties	0.0705***	
	(0.0055)	
Externalising Problems		0.1169***
		(0.0093)
Internalising Problems		0.0176*
		(0.0099)
Dep. Var.: Vandalising		
SDQ: Total Difficulties	0.0719***	
	(0.0061)	
Externalising Problems		0.1401***
		(0.0114)
Internalising Problems		-0.0058
		(0.0126)
Dep. Var.: Shoplifting		
SDQ: Total Difficulties	0.0840***	
	(0.0117)	
Externalising Problems		0.1613***
		(0.0206)
Internalising Problems		-0.0017
		(0.0206)
Dep. Var.: Truancy		
SDQ: Total Difficulties	0.0667***	
	(0.0075)	
Externalising Problems		0.1029***
		(0.0122)
Internalising Problems		0.0249*
		(0.0130)
Observations	3249	3249
Number of Individuals	2495	2495
Chi-Squared Statistic	147.46	112.29
Rho(Fighting-Vandalism)	0.3010***	0.2570***
	(0.0454)	(0.0469)
Rho(Shoplifting-Fighting)	0.2418***	0.1834***
	(0.0740)	(0.0782)
Rho(Truancy-Fighting)	0.2970***	0.2753***
	(0.0531)	(0.0538)
Rho(Shoplifting-Vandalism)	0.4702***	0.4130***
	(0.0699)	(0.0740)
Rho(Truancy-Vandalism)	0.3765***	0.3544***
	(0.0578)	(0.0589)
Rho(Truancy-Shoplifting)	0.3297***	0.3178***
	(0.0884)	(0.0913)

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: Random draws = 500. Chi-Squared Statistic denotes the chi-squared statistic for the likelihood ratio test of the correlation of the error terms. Control variables as for Table 3.7(a).

Table 3.11: Conditional Logit Model Coefficients (Family Fixed Effects): The Effects of Adolescent Mental Health on Fighting and Vandalism: Samples 4(a) to 4(b) (Waves 3 and 5)

	(1)	(2)	(3)	(4)
	4(a)	4(a)	4(b)	4(b)
Dependent Variable	Fighting	Fighting	Vandalism	Vandalism
SDQ: Total Difficulties	0.1042***		0.1314***	
	(0.0166)		(0.0215)	
Externalising Problems		0.1635***		0.2354***
		(0.0253)		(0.0347)
Internalising Problems		0.0217		0.0027
		(0.0299)		(0.0360)
Age	-0.2220***	-0.2163***	-0.0116	-0.0515
	(0.0427)	(0.0428)	(0.0548)	(0.0578)
Male	0.6124***	0.5026***	0.8705***	0.7903***
	(0.1633)	(0.1676)	(0.2133)	(0.2188)
1-5 Friends	-0.0029	-0.1582	-1.1426	-1.1803
	(0.5002)	(0.5149)	(0.7236)	(0.7799)
6+ Friends	-0.1864	-0.4082	-1.0909	-1.2286
	(0.5142)	(0.5316)	(0.7315)	(0.7877)
Once/ Twice Out Past 9pm	0.3257	0.3595	-0.1802	-0.2843
	(0.2689)	(0.2731)	(0.3177)	(0.3303)
3+ Times Out Past 9pm	1.2881***	1.2996***	0.4613	0.3508
	(0.3671)	(0.3748)	(0.4147)	(0.4376)
GCSEs Very Important	-0.0435	0.0257	-0.3726	-0.2857
	(0.1875)	(0.1918)	(0.2331)	(0.2424)
Observations	925	925	583	583
Number of Households	583	583	267	267

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.12: Conditional logit Model Coefficients (Family Fixed Effects): The Effects of Adolescent Mental Health on Truancy: Sample 4(c) (Waves 3 and 5)

Dependent Variable	(1) Truancy	(2) Truancy
SDQ: Total Difficulties	0.1033***	
	(0.0264)	
Externalising Problems		0.2571***
		(0.0527)
Internalising Problems		-0.0658
		(0.0497)
Age	0.3670***	0.3445***
	(0.0831)	(0.0870)
Male	-0.4287	-0.6370**
	(0.2906)	(0.3129)
1-5 Friends	1.5095	0.6860
	(1.1824)	(1.1947)
6+ Friends	1.7414	0.7634
	(1.1969)	(1.2130)
Once/ Twice Out Past 9pm	0.1825	0.1656
	(0.4324)	(0.4593)
3+ Times Out Past 9pm	1.5162**	1.4651**
	(0.6077)	(0.6286)
GCSEs Very Important	-0.2871	-0.1042
	(0.3489)	(0.3780)
Observations	339	339
Number of Households	155	155

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.13: Random Effects Probit Model Coefficients: The Effects of Adolescent Mental Health on Alcohol and Cigarette Consumption: Sample 2 (Waves 2, 4, and 6)

	(1)	(2)	(3)	(4)
Dependent Variable	Alcohol	Alcohol	Cigarette	Cigarette
Lag of Total Difficulties	0.0279***		0.0796***	
	(0.0095)		(0.0265)	
Lag of Externalising Problems		0.0933***		0.1442***
		(0.0184)		(0.0552)
Lag of Internalising Problems		-0.0636***		-0.0240
		(0.0186)		(0.0306)
Age	0.5635***	0.5752***	0.6321***	0.6208***
	(0.0732)	(0.0737)	(0.1909)	(0.2124)
Male	-0.0285	-0.1223	0.0431	-0.0677
	(0.0952)	(0.0996)	(0.1742)	(0.1825)
Black	-1.1144***	-1.1400***	-0.7088*	-0.7149
	(0.2237)	(0.2254)	(0.4304)	(0.4489)
Indian	-2.2713***	-2.3347***	-0.2071	-0.2392
	(0.3553)	(0.3659)	(0.2856)	(0.3006)
2nd Income Quartile	0.2907*	0.2519	0.2445	0.1763
	(0.1571)	(0.1587)	(0.2639)	(0.2601)
3rd Income Quartile	0.2954*	0.2598	-0.1690	-0.2148
	(0.1596)	(0.1618)	(0.2681)	(0.2798)
4th Income Quartile	0.4731***	0.4165**	-0.0891	-0.1813
	(0.1649)	(0.1651)	(0.2637)	(0.2722)
Parents Separated	0.4924***	0.5009***	0.3976	0.4271*
	(0.1453)	(0.1472)	(0.2432)	(0.2543)
Number of Children	-0.2127***	-0.2254***	0.0461	0.0475
	(0.0527)	(0.0535)	(0.0815)	(0.0825)
1-5 Friends	0.0981	-0.0203	-0.2293	-0.3202
	(0.3718)	(0.3929)	(0.6301)	(0.6756)
6+ Friends	0.0906	-0.0965	-0.2550	-0.4223
	(0.3686)	(0.3894)	(0.6380)	(0.6894)
Once/ Twice Out Past 9pm	0.7535***	0.6967***	1.5946***	1.5246***
	(0.1803)	(0.1765)	(0.4951)	(0.5520)
3+ Times Out Past 9pm	1.5298***	1.4604***	2.2246***	2.1369***
	(0.2623)	(0.2598)	(0.6544)	(0.7337)
GCSEs Very Important	-0.1294	-0.1004	-0.3368	-0.2995
	(0.1186)	(0.1207)	(0.2200)	(0.2239)
Eats: 1/2	0.0059	-0.0160	-0.2070	-0.2146
	(0.2085)	(0.2130)	(0.3394)	(0.3449)
Eats: 3+	-0.1586	-0.1422	-0.4527	-0.4475
	(0.1930)	(0.1970)	(0.3354)	(0.3448)
Drug Offences Per 1,000	0.0129	0.0122	0.0481**	0.0476**
	(0.0116)	(0.0119)	(0.0216)	(0.0235)
Observations	2235	2235	2235	2235
Number of Households	2,014	2,014	2,014	2,014

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: All models control for the year of interview and LSOA of residence.

Table 3.14: Random Effects Probit Model Coefficients: The Effects of Adolescent Mental Health on Drug Use: Sample 2 (Waves 2, 4, and 6)

Dependent Variable	(1) Drugs	(2) Drugs
Lag of Total Difficulties	0.0569***	
	(0.0150)	
Lag of Externalising Problems		0.1050***
		(0.0302)
Lag of Internalising Problems		0.0039
		(0.0247)
Age	0.2755***	0.2812***
	(0.0663)	(0.0733)
Male	0.0472	-0.0129
	(0.1355)	(0.1462)
Black	-0.2377	-0.2213
	(0.2490)	(0.2546)
Indian	0.1839	0.1611
	(0.2248)	(0.2412)
2nd Income Quartile	-0.0921	-0.1294
	(0.2159)	(0.2260)
3rd Income Quartile	-0.0433	-0.0600
	(0.2176)	(0.2284)
4th Income Quartile	0.2143	0.1675
	(0.2197)	(0.2239)
Parents Separated	-0.1783	-0.1856
	(0.1899)	(0.1968)
Number of Children	-0.0182	-0.0230
	(0.0664)	(0.0683)
1-5 Friends	-0.1418	-0.1661
	(0.4399)	(0.4637)
6+ Friends	-0.0647	-0.1164
	(0.4459)	(0.4693)
Once/ Twice Out Past 9pm	0.9154***	0.9107***
	(0.2168)	(0.2397)
3+ Times Out Past 9pm	1.4251***	1.4202***
	(0.2726)	(0.3079)
GCSEs Very Important	-0.3523**	-0.3281*
	(0.1664)	(0.1748)
Eats: 1/2	-0.1833	-0.1704
	(0.2420)	(0.2473)
Eats: 3+	-0.6391***	-0.6631***
	(0.2357)	(0.2509)
Drug Offences Per 1,000	0.0080	0.0081
	(0.0137)	(0.0140)
Observations	2235	2235
Number of Households	2,014	2,014

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: All models control for the year of interview and LSOA of residence.

Table 3.15: Random Effects Probit Model Coefficients: The Effects of Adolescent Mental Health on Prosocial Behaviour: Sample 3 (Waves 2, 4, and 6)

	(1)	(2)	(3)	(4)
Dependent Variable	Volunteering	Volunteering	Housework	Housework
Lag of Total Difficulties	-0.0128**		-0.0183*	
	(0.0057)		(0.0103)	
Lag of Externalising Problems		-0.0282***		-0.0040
		(0.0096)		(0.0162)
Lag of Internalising Problems		0.0036		-0.0312*
		(0.0104)		(0.0178)
Age	-0.0401*	-0.0388*	0.0682*	0.0706*
	(0.0225)	(0.0225)	(0.0406)	(0.0407)
Male	-0.2008***	-0.1828***	-0.5017***	-0.5217***
	(0.0631)	(0.0634)	(0.1305)	(0.1337)
Black	0.1603	0.1559	0.5686**	0.5839**
	(0.1120)	(0.1119)	(0.2556)	(0.2571)
Indian	-0.1351	-0.1357	-0.1650	-0.1506
	(0.1027)	(0.1023)	(0.1709)	(0.1704)
2nd Income Quartile	0.2260**	0.2294**	0.0658	0.0630
	(0.0954)	(0.0952)	(0.1607)	(0.1607)
3rd Income Quartile	0.0168	0.0192	0.1918	0.1854
	(0.0966)	(0.0963)	(0.1726)	(0.1731)
4th Income Quartile	0.2960***	0.3035***	0.3752**	0.3733**
	(0.0967)	(0.0966)	(0.1825)	(0.1830)
Parents Separated	-0.0805	-0.0793	0.2892*	0.2857*
	(0.0896)	(0.0892)	(0.1690)	(0.1693)
Number of Children	0.0123	0.0133	0.0854	0.0816
	(0.0301)	(0.0299)	(0.0558)	(0.0557)
1-5 Friends	0.2378	0.2606	0.0945	0.0782
	(0.2372)	(0.2374)	(0.3667)	(0.3692)
6+ Friends	0.3574	0.3922	0.0435	0.0257
	(0.2393)	(0.2398)	(0.3695)	(0.3719)
Once/ Twice Out Past 9pm	0.2366**	0.2547**	-0.1640	-0.1801
	(0.1073)	(0.1074)	(0.1785)	(0.1794)
3+ Times Out Past 9pm	-0.0733	-0.0482	-0.1263	-0.1565
	(0.1434)	(0.1441)	(0.2367)	(0.2383)
GCSEs Very Important	0.1318*	0.1209	0.3314**	0.3420**
	(0.0787)	(0.0787)	(0.1354)	(0.1374)
Eats: 1/2	0.2562*	0.2541*	0.4087*	0.4138*
	(0.1324)	(0.1319)	(0.2165)	(0.2167)
Eats: 3+	0.3870***	0.3806***	0.5928***	0.6052***
	(0.1192)	(0.1186)	(0.1963)	(0.1970)
Observations	2528	2528	2528	2528
Number of Households	2,267	2,267	2,267	2,267

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: Housework denotes whether the adolescent helps with the housework. All models control for the year of interview and LSOA of residence.

3.10 A3: Appendix 2: Estimating Equations

To investigate the effects of the mental health of parents on the ASB of adolescents we estimate equation (A3.1) using a random effects probit model. We estimate equation (A3.1) using Sample 1.

$$ASB_{ijt} = \beta_0 + \beta_1 ParGHQ_{ij(wave1/2)} + \boldsymbol{\gamma X^{d}_{ijt}} + \boldsymbol{\tau X^{f}_{ijt}} + \boldsymbol{\delta X^{s}_{ijt}} + \boldsymbol{\lambda Year_t} + \varphi LocalASB_{jt} + \boldsymbol{\xi_j} + u_i + v_{ijt} \qquad \text{(A3.1)}$$

Where $ParGHQ_{ij(wave1/2)}$ denotes the GHQ(36) score of the parent of individual i in LSOA j in wave 1 or wave 2 of Understanding Society. In the first specification, $ParGHQ_{ij(wave1/2)}$ indicates the GHQ(36) score of the father, and in the second specification $ParGHQ_{ij(wave1/2)}$ is the GHQ(36) of the mother. We use the first report of the mental health of parents in waves 1 or 2. For approximately two thirds of adolescents we measure the GHQ(36) of the parents in wave 1, and for a further third we measure the GHQ(36) of the parent in wave 2. The additional control variables are described in detail in Section 3.4.1. As previously outlined in Section 3.3, higher values of GHQ(36) denote poorer mental health. Hence, positive values of β_1 indicate that poorer paternal mental health may have an adverse effect on the ASB of adolescents.

We explore the effects of the mental health of adolescents on their harmful substance use using equation (A3.2). To lessen the risk of reverse causality, if harmful substance use affects mental health, we measure the mental health of adolescents in the previous wave. To investigate the effects of adolescent's mental health on harmful substance use we make use of Sample 2.

$$HSU_{ijt} = \beta_0 + \beta_1 SDQ_{ijt-1} + \boldsymbol{\gamma X^{d}_{ijt}} + \boldsymbol{\tau X^{f}_{ijt}} + \boldsymbol{\delta X^{s}_{ijt}} + \boldsymbol{\lambda Year_t} + \eta Drug_{jt} + \boldsymbol{\xi_j} + u_i + \varepsilon_{it} \qquad \text{(A3.2)}$$

HSU_{ijt} is a binary dependent variable equal to 1 if individual i in LSOA j and wave t reported to have used harmful substances, and 0 otherwise. We estimate equation (A3.2) using 3 models, each utilising a separate measure of harmful substance use, specifically, alcohol consumption, cigarettes smoking, or drug taking. SDQ_{ijt-1} denotes the SDQ total difficulties score of individual i in LSOA j in the previous wave. $Drug_{jt}$ indicates the rate of recorded drug offences per 1,000 in the local neighbourhood j in year t. We control for the number of drug offences in the local neighbourhood to account for neighbourhood level variables that may affect an adolescent's likelihood of drinking alcohol, smoking cigarettes, and taking drugs. The remaining control variables are described in detail in Section 3.4.1.

In a similar fashion to our core findings relating to ASB, we also explore whether the tendency of adolescents to internalise and externalise have differential effects on their harmful substance use. To explore this, we split the SDQ total difficulties score into its constituent parts: externalising problems, and internalising problems, as shown by equation (A3.3):

$$\begin{aligned} HSU_{ijt} = \alpha_0 + \alpha_1 EP_{ijt-1} + \alpha_2 IP_{ijt-1} + \boldsymbol{\gamma X^{d}_{ijt}} + \boldsymbol{\tau X^{f}_{ijt}} \\ + \boldsymbol{\delta X^{c}_{ijt}} + \boldsymbol{\lambda Year_t} + \eta Drug_{jt} + u_i + \xi_j + \varepsilon_{it} \end{aligned} \tag{A3.3}$$

Where EP_{ijt-1} (IP_{ijt-1}) denotes the externalising (internalising) problems subscale of individual i in LSOA j in the previous wave.

We investigate the effects of the mental health of adolescents on prosocial behaviour using equation (A3.4). If an adolescent's participation in prosocial behaviour affects their mental health, our estimates may be affected by reverse causality. For this reason, we lag the measures of the mental health of adolescents. We investigate the effects of the mental health of adolescents on their participation in prosocial behaviour using Sample 3.

$$\begin{aligned} PSB_{ijt} = \beta_0 + \beta_1 SDQ_{ijt-1} + \boldsymbol{\gamma X^{d}_{ijt}} + \boldsymbol{\tau X^{f}_{ijt}} + \boldsymbol{\delta X^{s}_{ijt}} + \boldsymbol{\lambda Year}_t + u_i + \xi_j \\ + \varepsilon_{it} \end{aligned} \tag{A3.4}$$

Where PSB_{ijt} denotes a binary variable equal to 1 if individual i in LSOA j and wave t reported to have participated in prosocial behaviour, and 0 otherwise. We estimate equation (A3.5) using 2 models for each of the dependent variables (volunteering and helping with housework). Note that we do not have access to data on the prevalence of volunteering in an individual's local neighbourhood and thus we are unable to control for such effects. The remaining control variables are described in detail in Section 3.4.1.

We also investigate whether the effects of externalising problems and internalising problems on prosocial behaviour differ by estimating equation (A3.5):

$$\begin{aligned} PSB_{ijt} = \alpha_0 + \alpha_1 EP_{ijt-1} + \alpha_2 IP_{ijt-1} + \boldsymbol{\gamma X^{d}_{ijt}} + \boldsymbol{\tau X^{f}_{ijt}} \\ + \boldsymbol{\delta X^{s}_{ijt}} + \boldsymbol{\lambda Year}_t + u_i + \xi_j + \varepsilon_{it} \end{aligned} \tag{A3.5}$$

Where EP_{ijt-1} (IP_{ijt-1}) denotes the externalising (internalising) problems subscale score of individual i in LSOA j during the previous wave.

3.11 A3: Appendix 3: Estimation Results

Table A3.1: Multivariate Probit Model Coefficients: The Effects of Adolescent Mental Health on Antisocial Behaviour: Sample 1 (Waves 3 and 5): Full Estimation Results from Table 3.10

	(1)	(2)
Dep. Var.: Fighting		
SDQ: Total Difficulties	0.0705***	
	(0.0055)	
Externalising Problems		0.1169***
		(0.0093)
Internalising Problems		0.0176*
		(0.0099)
Age	-0.1043***	-0.1024***
	(0.0179)	(0.0180)
Male	0.4840***	0.4108***
	(0.0610)	(0.0614)
Black	0.0654	0.0718
	(0.1077)	(0.1088)
Indian	0.1723*	0.1764*
	(0.0966)	(0.0979)
2nd Income Quartile	-0.0061	-0.0070
	(0.1088)	(0.1089)
3rd Income Quartile	0.1263	0.1163
	(0.1040)	(0.1043)
4th Income Quartile	0.0500	0.0404
	(0.1050)	(0.1056)
Parents Separated	-0.0292	-0.0665
	(0.1607)	(0.1621)
Number of Children	0.1130***	0.1097***
	(0.0290)	(0.0293)
1-5 Friends	-0.4296**	-0.5576**
	(0.2163)	(0.2226)
6+ Friends	-0.3904*	-0.5612**
	(0.2192)	(0.2262)
Once/ Twice Out Past 9pm	0.2196**	0.1791*
	(0.1031)	(0.1032)
3+ Times Out Past 9pm	0.7003***	0.6334***
	(0.1358)	(0.1375)
GCSEs Very Important	-0.1255*	-0.0771
	(0.0718)	(0.0724)
Eats: 1/2	0.1912	0.2346*
	(0.1383)	(0.1359)
Eats: 3+	0.1765	0.2231*
	(0.1274)	(0.1247)
Constant	-0.6286*	-0.5597
	(0.3786)	(0.3813)

Note: Table continues on the next page.

Table A3.1 (continued): Multivariate Probit Model Coefficients: The Effects of Adolescent Mental Health on Antisocial Behaviour: Sample 1: Full Estimation Results from Table 3.10 (Waves 3 and 5)

	(1)	(2)
Dep. Var.: Vandalising		
SDQ: Total Difficulties	0.0719***	
	(0.0061)	
Externalising Problems		0.1401***
		(0.0114)
Internalising Problems		-0.0058
		(0.0126)
Age	-0.0041	-0.0012
	(0.0214)	(0.0219)
Male	0.3962***	0.2859***
	(0.0753)	(0.0778)
Black	0.3000**	0.3353***
	(0.1259)	(0.1290)
Indian	0.2097*	0.2191*
	(0.1107)	(0.1152)
2nd Income Quartile	0.1006	0.1158
	(0.1328)	(0.1373)
3rd Income Quartile	0.1641	0.1542
	(0.1295)	(0.1339)
4th Income Quartile	0.2386*	0.2335*
	(0.1283)	(0.1327)
Parents Separated	0.3646**	0.3476*
	(0.1769)	(0.1823)
Number of Children	0.0292	0.0231
	(0.0335)	(0.0347)
1-5 Friends	-0.2654	-0.4350*
	(0.2603)	(0.2562)
6+ Friends	-0.1417	-0.3658
	(0.2624)	(0.2594)
Once/ Twice Out Past 9pm	0.3331***	0.2737**
	(0.1114)	(0.1130)
3+ Times Out Past 9pm	0.2189	0.1241
	(0.1571)	(0.1585)
GCSEs Very Important	-0.2620***	-0.1966**
	(0.0823)	(0.0846)
Eats: 1/2	0.0842	0.1566
	(0.1689)	(0.1771)
Eats: 3+	-0.0005	0.0685
	(0.1556)	(0.1654)
Constant	-3.1857***	-3.1972***
	(0.5036)	(0.5163)

Note: Table continues on the next page.

Table A3.1 (continued): Multivariate Probit Model Coefficients: The Effects of Adolescent Mental Health on Antisocial Behaviour: Sample 1 (Waves 3 and 5): Full Estimation Results from Table 3.10

	(1)	(2)
Dep. Var.: Shoplifting		
SDQ: Total Difficulties	0.0840***	
	(0.0117)	
Externalising Problems		0.1613***
		(0.0206)
Internalising Problems		-0.0017
		(0.0206)
Age	0.1043***	0.1040***
	(0.0340)	(0.0362)
Male	0.4552***	0.3176**
	(0.1292)	(0.1378)
Black	0.1849	0.2112
	(0.2146)	(0.2216)
Indian	-0.2685	-0.2649
	(0.2459)	(0.2541)
2nd Income Quartile	0.3680*	0.3649
	(0.2217)	(0.2311)
3rd Income Quartile	0.4135*	0.3954*
	(0.2159)	(0.2225)
4th Income Quartile	0.1124	0.0785
	(0.2077)	(0.2084)
Parents Separated	0.2943	0.3190
	(0.2090)	(0.2172)
Number of Children	0.0075	-0.0049
	(0.0647)	(0.0671)
1-5 Friends	-0.5728*	-0.8140**
	(0.3261)	(0.3571)
6+ Friends	-0.3430	-0.6494*
	(0.3218)	(0.3515)
Once/ Twice Out Past 9pm	0.4442***	0.3782**
	(0.1443)	(0.1483)
3+ Times Out Past 9pm	0.6950***	0.6181***
	(0.1909)	(0.1920)
GCSEs Very Important	0.1118	0.2249
	(0.1404)	(0.1457)
Eats: 1/2	-0.1833	-0.0885
	(0.2255)	(0.2416)
Eats: 3+	-0.1234	-0.0343
	(0.1876)	(0.2041)
Constant	-4.6801***	-4.6516***
	(0.6876)	(0.7357)

Note: Table continues on the next page.

Table A3.1 (continued): Multivariate Probit Model Coefficients: The Effects of Adolescent Mental Health on Antisocial Behaviour: Sample 1 (Waves 3 and 5): Full Estimation Results from Table 3.10

	(1)	(2)
Dep. Var.: Truancy		
SDQ: Total Difficulties	0.0667***	
	(0.0075)	
Externalising Problems		0.1029***
		(0.0122)
Internalising Problems		0.0249*
		(0.0130)
Age	0.1268***	0.1285***
	(0.0264)	(0.0267)
Male	0.1349	0.0706
	(0.0841)	(0.0866)
Black	-0.0146	-0.0034
	(0.1565)	(0.1586)
Indian	0.3007**	0.3020**
	(0.1292)	(0.1290)
2nd Income Quartile	0.0611	0.0597
	(0.1424)	(0.1428)
3rd Income Quartile	0.0463	0.0368
	(0.1411)	(0.1413)
4th Income Quartile	0.0108	0.0025
	(0.1415)	(0.1417)
Parents Separated	0.1352	0.1213
	(0.1693)	(0.1701)
Number of Children	0.0395	0.0351
	(0.0412)	(0.0412)
1-5 Friends	0.0604	-0.0295
	(0.3128)	(0.3189)
6+ Friends	0.1052	-0.0188
	(0.3152)	(0.3216)
Once/ Twice Out Past 9pm	0.3492***	0.3152**
	(0.1199)	(0.1225)
3+ Times Out Past 9pm	0.4407***	0.3894**
	(0.1589)	(0.1618)
GCSEs Very Important	-0.2067**	-0.1691*
	(0.0938)	(0.0961)
Eats: 1/2	-0.1376	-0.1042
	(0.1638)	(0.1636)
Eats: 3+	-0.3132**	-0.2799*
	(0.1507)	(0.1506)
Constant	-4.3792***	-4.3200***
	(0.5849)	(0.5875)
Observations	3249	3249
Number of Individuals	2495	2495
Chi-Squared Statistic	147.46	112.29

Note: Table continues on the next page.

Table A3.1 (continued): Multivariate Probit Model Coefficients: The Effects of Adolescent Mental Health on Antisocial Behaviour: Sample 1 (Waves 3 and 5): Full Estimation Results from Table 3.10

	(1)	(2)
Rho(Fighting-Vandalism)	0.3010***	0.2570***
	(0.0454)	(0.0469)
Rho(Shoplifting-Fighting)	0.2418***	0.1834***
	(0.0740)	(0.0782)
Rho(Truancy-Fighting)	0.2970***	0.2753***
	(0.0531)	(0.0538)
Rho(Shoplifting-Vandalism)	0.4702***	0.4130***
	(0.0699)	(0.0740)
Rho(Truancy-Vandalism)	0.3765***	0.3544***
	(0.0578)	(0.0589)
Rho(Truancy-Shoplifting)	0.3297***	0.3178***
	(0.0884)	(0.0913)

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: All models control for the year of interview.

Chapter 4: Subjective Well-being and Natural Disasters

4.1 Introduction

In comparison to Chapter 2 that explored "*what others do to you*", and Chapter 3 that looked at "*what you do to others*", in this chapter we investigate how "*what happens to others*" affects your own subjective well-being (SWB). The events under consideration are three large-scale natural disasters: the Indian Ocean tsunami on 26th December 2004, Hurricane Katrina on 23rd August 2005, and the Haiti earthquake on the 12th January 2010. We focus on the Indian Ocean tsunami and the Haiti earthquake because they were two of the most destructive natural disasters in modern history, (see Athukorala and Resosudarmo, 2005; Cavallo et al., 2010). To allow us to contrast the effects of natural disasters in the country of the disaster with the effects outside of the country of the disaster, we also explore the effects of Hurricane Katrina on the SWB of Americans. Hurricane Katrina was the deadliest natural disaster to affect the US since 1906, see Centre for Research on the Epidemiology of Disasters (2014a). We investigate how each of these disasters affected the SWB of Americans and how the effects of the disasters varied by proximity to the disaster areas.

4.1.1 Motivation

A relatively small literature from the economics discipline explores the effects of natural disasters on SWB in the disaster country. For example, Ohtake et al. (2016) and Rehdanz et al. (2015) investigate how the Great East Japan earthquake and the resulting Fukushima nuclear disaster in 2011 affected SWB in Japan. In a similar vein, Kimball et al. (2006) and Zahran et al. (2011) explore the effects of Hurricane Katrina on SWB in America, and Danzer and Danzer (2016) investigate the long-term effects of the 1986 Chernobyl nuclear disaster on SWB in Ukraine. In contrast, there is scarce literature exploring the effects of natural disasters on SWB in countries where the disaster did not take place. One exception is Shultz et al. (2012) who investigate the effect of the 2010 Haiti earthquake on the mental health of Haitian-Americans. In a similar fashion, Kimball et al. (2006) explore the effects of the 2005 Pakistan earthquake on American SWB. This study thus contributes to a small literature exploring the wider effects of natural disasters. In addition, this chapter contributes to a growing literature exploring how major world events such as terrorist attacks affect SWB, (see Frey et al., 2007; Metcalfe et al., 2011).

Economics typically assumes that utility is dependent initially upon the utility of the individual, and secondly upon the utility of family members, see Becker (1981). However, economics generally does not assume that own utility is dependent on that of strangers.[89] The Indian Ocean tsunami and the Haiti earthquake were large utility shocks for millions of people who live in Asia, Africa, and Haiti. Moreover, natural disasters are unanticipated and hence provide opportunities to investigate the interdependence of utility between strangers, by exploring their effects far from the disaster areas. Hence, by exploring the effects of these natural disasters on the SWB of Americans, we can cast light on the validity of the assumption that own utility is independent of that of strangers.

4.1.2 Summary of the Findings

Using a difference-in-difference approach and data from the Behavioural Risk Factor Surveillance System (BRFSS), we explore the effects of three large-scale natural disasters on American SWB, as measured by the number of days of poor self-reported mental health in the past 30 days. We also investigate how the effects of the natural disasters varied by geographical proximity to the areas that were directly affected. We present several interesting findings.

Firstly, in accordance with Zahran et al. (2011), the empirical analysis suggests that Hurricane Katrina had a detrimental effect on the SWB of Americans who were living in the states that were directly affected by the disaster. These estimated effects are large, up to 80% of the magnitude of the effect of being unemployed.

Secondly, the empirical analysis suggests that the Indian Ocean tsunami and the Haiti earthquake increased the SWB of Americans who lived in the states closest to the affected areas. In comparison, the effects of the Indian Ocean tsunami and the Haiti earthquake on SWB are less pronounced in states further from the disaster areas. The estimated effects of the Indian Ocean tsunami (Haiti earthquake) on SWB are large: up to, for example, 80% (40%) of the magnitude of the absolute size of the unemployment coefficient.

The Indian Ocean tsunami and the Haiti earthquake may have increased the SWB of Americans if Americans compared themselves to the disaster victims. In the US, the Indian Ocean tsunami and the Haiti earthquake attracted considerable media coverage in the aftermath of the disasters. For example, the Indian Ocean tsunami dominated

[89] One exception is the literature relating to charitable giving, which presents several explanations for why people give to charity. The first explanation, "pure altruism", states that people give to charity because they gain utility from the output of the charity, (see, for example Bergstrom et al., 1986; Andreoni, 1989). The second explanation, termed "impure altruism", states that individuals gain more utility from their own charitable giving than that of others because their own level of charitable giving enters their utility function directly, see Andreoni and Payne (2013). Andreoni (1990) present a number of explanations for how utility may be affected by an individual’s charitable giving such as social pressure, guilt, and the "warm-glow" effect (positive emotions experienced by helping others).

media headlines for a month after the disaster struck, longer than any disaster in modern history, see Wynter (2005)[90].

The extensive media coverage of the Indian Ocean tsunami and the Haiti earthquake may have led Americans to pay attention to how the disasters affected the lives of the disaster victims. For this reason, in the aftermath of the disasters, Americans may have compared themselves favourably to the disaster victims, making them feel grateful that they were not affected, and thereby increasing their SWB. Economic models generally assume that strangers have independent utility functions and thus that utility is unaffected by unanticipated utility shocks in other continents, such as natural disasters. However, the empirical evidence of this chapter suggests that these utility shocks had a positive effect on the SWB of Americans. Consequently, the findings suggest that the utility functions of strangers may be interdependent, rather than independent as is typically assumed in economics.

The effects of the Indian Ocean tsunami and the Haiti earthquake may be less pronounced for individuals who do not live close to the disaster area because they may not have compared themselves to the disaster victims. This may suggest that following natural disasters, an individual's reference group may be defined by geographical proximity. Brown et al. (2015) suggest that the effects of relative income comparisons on SWB are highly sensitive to whether the reference group is defined by individual characteristics ("*people like you*") or by geographical proximity ("*people near you*"). Hence, we explore the effects of the disasters by ethnicity to investigate whether the effects of the natural disasters were more pronounced for Americans who are similar to the disaster victims.[91] However, the empirical analysis does not suggest that the effects of the Indian Ocean tsunami and the Haiti earthquake were larger for individuals of the same ethnicity as the disaster victims. Consequently, the findings suggest that it is geographical proximity to the disaster area, rather than sharing similar individual characteristics to the disaster victims, which may determine the effects of natural disasters on SWB outside of the disaster country.

This chapter is structured as follows. Section 4.2 reviews the literature from the economics discipline exploring the effects of natural disasters on SWB in the areas that were directly affected by the disaster. Additionally, we review the literature from psychology and economics that explores how natural disasters affect people who do not live in the areas that were directly affected. Section 4.2 also analyses the literature exploring empathy between strangers, the effects of gratitude on SWB, and the effects of interpersonal comparisons on SWB. These literatures are relevant to the empirical analysis because they highlight the mechanisms via which natural disasters may affect SWB outside of the disaster country. What is more, the evidence from these literatures suggests that natural disasters may have either a positive, or a negative, effect on SWB

[90] We discuss the worldwide media coverage of each of the disasters in detail in Section 4.3.
[91] Section 4.8 offers a justification for why ethnicity, rather than age, education level, or gender is selected as the reference group.

in areas where the disaster did not take place. Section 4.3 defines a natural disaster, provides further detail concerning each of the natural disasters under investigation, and discusses the media coverage of the disasters. Section 4.4 outlines the data, the estimation samples, the dependent variable, and provides summary statistics. Section 4.5 presents the empirical specifications and outlines the rationale for the use of zero inflated negative binomial models. In addition, Section 4.5 discusses how the difference-in-difference approach can be extended to non-linear models and discusses the validity checks for common trends. Section 4.6 analyses the results and Section 4.7 examines the findings from the validity check for common trends. Section 4.8 discusses the results exploring the effects of the disaster by ethnicity and Section 4.9 concludes.

4.2 Literature Review

4.2.1 The Effects of Natural and Technological Disasters on Subjective Well-being in the Disaster Country: Evidence from Economics

A small literature from the economics discipline investigates the effects of natural disasters on SWB in the disaster country. For example, using a sample of 5,979 individuals from the Keio Household Panel Survey, Rehdanz et al. (2015) investigate the effects of the Japanese earthquake and the resulting Fukushima nuclear disaster on SWB in Japan. The Japanese earthquake and the resulting Fukushima nuclear disaster occurred on the 11th March 2011 in North-Eastern Japan. Using a difference-in-difference approach, the authors present evidence to suggest that the disaster reduced the SWB of individuals living less than 300 km from the Fukushima nuclear plant. They do not find a statistically significant effect of the disaster on individuals living more than 300 km from Fukushima. However, the authors do not test for common trends prior to the Fukushima nuclear disaster. Common trends is an important assumption underpinning difference-in-difference analysis, see Lechner (2010). Thus, the effects of the Fukushima nuclear disaster on SWB may be biased if SWB did not follow a common trend.

Another important contribution is Zahran et al. (2011) who investigate the effects of Hurricane Katrina on SWB in the US. To explore the effects of Hurricane Katrina, they use of a sample of 347,173 observations from the BRFSS dataset from 2005 to 2006. They measure SWB by the number of days of poor self-reported mental health in the past 30 days. Using a difference-in-difference approach, they provide evidence to suggest that Hurricane Katrina increased the number of days of poor mental health of individuals living in the areas that were directly affected by the disaster. The authors also show that the effect of Hurricane Katrina was greater for single mothers, and people who were living in areas that were more heavily damaged by the disaster.

The analysis of this chapter extends the work of Zahran et al. (2011) in a several ways. Firstly, unlike Zahran et al. (2011) who do not test for common trends, we investigate whether the number of days of poor mental health followed a common trend prior to the disasters, thus we are able to validate the assumptions underpinning our analysis.

Secondly, unlike Zahran et al. (2011), we control for the personal characteristics of the individual such as their labour force status, marital status, and ethnicity. If the date of interview of an individual is associated with their personal characteristics then the estimated effects of Hurricane Katrina on SWB may be biased. For this reason, it is important to condition upon the personal characteristics of the individual. Finally, they only explore the effects of Hurricane Katrina. As well as exploring the effects of Hurricane Katrina on SWB in the US, we investigate how the Indian Ocean tsunami and the Haiti earthquake affected SWB in the US. Hence, we are able to compare the effects of natural disasters on SWB in the country of the disaster with the effects far from the areas that were directly affected.

Danzer and Danzer (2016) use a sample of approximately 6,000 individuals from the Ukrainian Longitudinal Monitoring Study dataset to investigate the long-term effects of the 1986 Chernobyl nuclear disaster on life satisfaction in Ukraine 20 years later. To identify the effects of the disaster on life satisfaction, the authors match data on regional radiation levels in 1986 to an individual's place of residence in 1986. Danzer and Danzer (2016) suggest that individuals who lived in areas with higher levels of radiation after the Chernobyl disaster had lower SWB 20 years later.

Luechinger and Raschky (2009) explore the effects of flood disasters on SWB in the US. They utilise data on flooding from the Emergency Events Database of the Centre for Research on Epidemiological Studies. They merge the data on flooding with SWB data from the US General Social Survey and the Eurobarometer Survey. The authors use a sample of 328,610 (13,138) observations from Europe (the US) interviewed from 1973 to 2004 (1993 to 2004). Using ordered probit regression models, they present evidence to suggest that floods have a detrimental effect on SWB in a region.

Another recent addition is Berlemann (2016) who investigates the effects of hurricane risk on happiness and life satisfaction using data from the World Values Survey. They make use of a sample of 133,718 individuals, living in 100 countries, who were interviewed from 1995 to 2009. They use hurricane data from the Best Track Dataset of tropical cyclones provided by the National Oceanic and Atmospheric Administration in the US. Using ordered logit models, the analysis of Berlemann (2016) suggests that happiness is adversely affected by a greater frequency of hurricanes in the past year, but not in the past 5, 10, or 15 years. In contrast, they show that hurricane frequency in the past 10 years has a detrimental effect on life satisfaction.

4.2.2 The Effects of Natural and Technological Disasters on Subjective Well-being, Mental Health, and Other Outcomes Outside of the Disaster Country: Evidence from Psychology and Economics

In comparison to the small literature showing the effects of natural disasters on SWB in the disaster country, the literature exploring the effects of natural disasters outside of the disaster country is even smaller.

One exception from psychology is Shultz et al. (2012), who investigate the effect of the Haiti earthquake (12th January 2010) on the mental health of Haitian-Americans. They use cross-sectional, primary data on a small sample of 42 first and second-generation Haitian-American university students in Miami, who were interviewed within two months of the Haiti earthquake.

The measures of mental health used by the authors are the Patient Health Questionnaire (an index used to diagnose Major Depressive Disorder), the General Anxiety Disorder questionnaire, and the Complicated Grief index. In addition, they use the mental and physical health component summaries from the Short Form 12 (SF-12) general health questionnaire.

Shultz et al. (2012) use three indexes to measure the extent of an individual's indirect earthquake exposure: the Earthquake Reactions scale, the Indirect Exposure to Earthquake Consequences scale, and the Primary Family Member Earthquake Experiences scale. The Earthquake Reactions scale is a 10-item index measuring the emotional reactions to, and exposure to media coverage of, the Haiti earthquake.[92] The Indirect Exposure to Earthquake Consequences scale is a 10-item index indicating whether family members or close friends were killed, severely injured, displaced, or made missing by the earthquake. Finally, the Primary Family Member Earthquake Experiences scale is a 25-point scale indicating whether an individual's family suffered from 25 earthquake related experiences (such as seeing people hurt or killed).

Using bivariate regression models, they estimate the associations between the five mental health measures and the measures of indirect earthquake exposure. The authors find that all of the measures of indirect exposure are positively associated with Major Depressive Disorder. In addition, the Earthquake Reactions scale and Primary Family Member Earthquake Experiences scale are positively correlated with Generalized Anxiety Disorder. The authors find that the Primary Family Member Earthquake Experiences scale is positively associated with Complicated Grief. Likewise, Shultz et al. (2012) find a negative association between the SF-12 Mental Health Component Summary (SF-12-MCS) and the Primary Family Member Earthquake Experiences scale. This indicates that individuals whose family members were exposed

[92] These emotional reactions are helplessness, survivor guilt, stress, sadness, distraction, and sleep difficulties.

to the Haiti earthquake had poorer mental health two months after the earthquake. In a similar fashion, they show that individuals who reported higher values on the Earthquake Reactions scale and Indirect Exposure to Earthquake Consequences scale had poorer self-reported physical health, as measured by the SF-12 Physical Health Component Summary (SF-12-PCS). In summary, Shultz et al. (2012) find a negative association between indirect exposure to the Haiti earthquake and mental health.

However, note that the analysis of Shultz et al. (2012) suffers from a number of shortcomings. Firstly, they do not control for the confounding variables that may affect both mental health and indirect earthquake exposure, such as income. In comparison to less materially deprived Haitian-Americans, deprived Haitian-Americans may be more likely to have family and friends living in Haiti in crowded accommodation who may be more likely to be adversely affected by the earthquake, see Doocy et al. (2013). There is a large literature which finds a positive effect of income on SWB and mental health, (see, for example, Powdthavee, 2010; Frijters et al., 2004; Gardner and Oswald, 2007). Because of the omission of income, they may overestimate the effects of indirect earthquake exposure on the mental health of Haitian-Americans.

Secondly, Shultz et al. (2012) use retrospectively reported measures of indirect earthquake exposure, and hence their findings may suffer from reverse causality. For instance, individuals who are depressed may be more likely to remember, or may be more prone to exaggerating, the extent of their indirect exposure to the Haiti earthquake. Thirdly, they use cross-sectional data and are therefore unable to control for time-invariant, unobserved heterogeneity that may be correlated with both indirect earthquake exposure and mental health. For this reason, Shultz et al. (2012) may overestimate the effects of indirect exposure to the Haiti earthquake on mental health.

Fourthly, they use a very small sample of students with racial and familial ties to the disaster country. Thus, these effects may differ from the effects for the general population of Americans, or to the population of Haitian-Americans. However, despite these limitations, the analysis of Shultz et al. (2012) supports the notion that natural disasters may affect mental health outside of the country of the disaster.

In the economics discipline, Kimball et al. (2006) investigate the effects of Hurricane Katrina and the Pakistan earthquake on happiness using a sample of 1,105 Americans from the Monthly Survey of Consumers. Hurricane Katrina occurred between 23rd and 29th August 2005 and the Pakistan earthquake occurred on 8th October 2005. The Monthly Survey of Consumers is a representative telephone interview of American adults surveyed between August and October 2005. Kimball et al. (2006) measure happiness using an index, which is formed by summing the yes/ no responses to four questions relating to the individual's happiness in the past week.[93]

To investigate the effect of Hurricane Katrina on happiness, the authors compare the happiness of individuals interviewed before and after Hurricane Katrina. They find that individuals interviewed from 1st to 14th September 2005 report lower happiness relative to individuals interviewed from 29th July to 31st August 2005. However, Kimball et al. (2006) find no statistically significant effect of Hurricane Katrina on the happiness of individuals interviewed from 15th to 21st September 2005, relative to individuals interviewed from 29th July to 31st August 2005. Consequently, they argue that this may provide evidence of hedonic adaptation to Hurricane Katrina.

In addition, Kimball et al. (2006) do not find a greater reduction in happiness in the South Central region[94] between 1st and 7th September 2005, relative to the reduction in happiness in the rest of the US. However, the authors find a greater reduction in happiness for individuals living in the South Central region between 8th and 14th September 2005, relative to the fall in the rest of the US. There are several explanations for this effect. Firstly, individuals who lived in the South Central region may have worried that the disaster will affect them. Secondly, individuals who live in closer proximity to Hurricane Katrina may be more likely to have family or friends who were directly affected by the disaster.

As well as investigating the effects of Hurricane Katrina, they also explore the effect of the Pakistan earthquake (on 8th October 2005) on the happiness of Americans. Kimball et al. (2006) do not find that happiness is significantly lower between the 6th and 12th October 2005 relative to happiness between 29th July and 31st August 2005. However, between the 13th and 19th October 2005 there was substantially lower happiness, relative to between 29th July and 31st August. The authors argue that the lag in the effect of the Pakistan earthquake may be due to the phrasing of the happiness questions that ask about "much of the time during the past week". Thus, Kimball et al. (2006) offer evidence to support the view that the Pakistan earthquake may have reduced the happiness of Americans.

However, their analysis is subject to several shortcomings. Firstly, they do not control for the personal characteristics of the individual. If these characteristics are correlated with an individual's date of interview, the estimated effects of Hurricane Katrina and the Pakistan earthquake on happiness may be biased. Secondly, the authors note that fewer people are interviewed at the end of the month relative to the beginning of the month. This may bias the results if individuals interviewed at the end of the month are

[93] The questions are how much of the time during the past week you "felt you were happy?", "felt sad?", "enjoyed life?", and "felt depressed?".

[94] The South Central region of the US covers the states of Alabama, Arkansas, Kentucky, Louisiana, Mississippi, Oklahoma, Tennessee, and Texas.

more difficult to contact than individuals interviewed at the beginning of the month, see Heffetz and Rabin (2013).

Thirdly, the authors only use a single year of data and therefore cannot control for seasonal trends in happiness. Thus, arguably their results may be due to time of year effects, rather than the effects of the natural disasters, see Kavetsos et al. (2014). Fourthly, a further problem that arises from using only 1 year of data is that the authors cannot test whether happiness followed a common trend before September 8th in the South Central region, relative to the rest of the US. Finally, Kimball et al. (2006) use a relatively small sample of just 1,105 Americans.

In the economics literature, Goebel et al. (2015) investigate the effects of the Fukushima nuclear disaster on SWB, voting preferences, risk aversion, and environmental concerns in Germany, Switzerland, and the UK. The authors use data from the German Socioeconomic Panel for Germany (sample size (N) = 20,178), the Swiss Household Panel for Switzerland (N = 14,104), and Understanding Society for the UK (N = 46,406).

Using a difference-in-difference approach, Goebel et al. (2015) suggest that the Fukushima nuclear disaster increased environmental concerns, risk aversion, and support for the Green party in Germany. The authors also provide evidence to suggest that the Fukushima nuclear disaster increased the probability that Germans interviewed after the disaster reported feeling sad.

Their analysis further suggests that the Fukushima nuclear disaster increased environmental concerns in Switzerland. Their results also suggest that the Fukushima nuclear disaster increased support for the Green party for individuals in the UK and in Switzerland who live in close proximity to nuclear reactors. However, the authors present no evidence to suggest that the Fukushima nuclear disaster affected life satisfaction in Switzerland or the UK. Hence, the findings of Goebel et al. (2015) suggest that large-scale disasters in a country may affect political preferences, environmental concerns, and SWB in countries more than 5,000 miles distant.

Although the existing literature exploring the effects of natural disasters on SWB outside of the disaster country yields some interesting findings, it suffers from a number of shortcomings. Firstly, in some cases, the literature does not control for the personal characteristics of individuals and may therefore suffer from omitted variable bias if these characteristics are correlated with an individual's date of interview. Secondly, in some cases, due to a shortage of data, some of the existing studies use relatively small samples and short time periods. In Section 4.5, we outline the approach taken to address these issues.

4.2.3 Empathy Between Strangers: Evidence from Neuroscience

The empathy literature is relevant when exploring the effects of natural disasters on SWB in areas where the disaster did not take place because it explains why individuals who do not live in the area where the disaster took place may feel empathy towards the disaster victims. The neuroscience literature investigates empathy by showing subjects pictures of human suffering and measuring the responses in their brains using functional magnetic resonance imaging (fMRI) technology.

Decety et al. (2004) argue that empathy has three core components: affect (feeling another person's feelings), cognition (knowing how another person feels), and the intention to respond compassionately. Wynter (2005) argues that natural disasters, in particular the Indian Ocean tsunami, dominate worldwide media coverage in the months that follow. Because of the extensive media coverage of disasters, individuals living in countries where the disaster did not take place are exposed to large numbers of images of human suffering following the disasters. The exposure to these pictures of human suffering may lead them to feel empathy towards the disaster victims.

Using a sample of 15 subjects aged 19-29, Jackson et al. (2005) investigate how seeing pictures of strangers in painful positions affects brain activity. The subjects of their experiment wore an fMRI head coil and were shown pictures of hands and feet in neutral positions, painful positions (e.g. trapped in a door), and baseline pictures showing crosses. Jackson et al. (2005) show that viewing pictures of strangers in painful positions leads to the activation of the anterior cingulate cortex and anterior insula. These areas of the brain are activated when individuals experience pain themselves, (see Peyron and Laurent, 2000; Coghill et al., 1999).

In a similar vein, Simon-Thomas et al. (2012) investigate the effect of viewing compassion inducing images on brain activity using a sample of 20 students from the University of California. The students lay inside an fMRI scanner and were shown pictures which intended to induce feelings of compassion (e.g. a starving child), pride (e.g. a university graduation), and neutral pictures (e.g. a room with people inside). Simon-Thomas et al. (2012) found that seeing compassion inducing pictures activated the midbrain periaqueductal gray. Previous studies have found that the midbrain periaqueductal gray is activated when an individual experiences pain, (see Lovick and Adamec, 2009; Heinricher et al., 2009).

Thus, the neuroscience literature suggests that seeing pictures of the suffering of strangers activates regions of the brain activated when individuals experience pain themselves. Natural disasters generate substantial media coverage, leading individuals who live outside of the disaster country to view large numbers of images of human suffering, see Wynter (2005). Hence, the neuroscience literature suggests mechanisms via which natural disasters may affect SWB outside of the disaster country.

4.2.4 The Effect of Gratitude on Subjective Well-being: Evidence from Psychology

The psychology literature exploring the effect of gratitude on SWB highlights another possible pathway via which natural disasters may affect SWB outside of the disaster country. Natural disasters may increase gratitude outside of the disaster country if individuals feel thankful that the disaster did not affect them. Sansone and Sansone (2010) define gratitude as an "appreciation of what is valuable and meaningful to oneself". (p.1).

Using 3 experiments, Emmons and McCullough (2003) investigate the effect of gratitude on SWB. In study 1, the authors randomly assigned 192 students to one of three treatment conditions. In these conditions, students were either asked to write five things from the past week that they were grateful for (the gratitude condition), that hassled them (the hassles condition), or five events or circumstances that affected them (the events condition). The students completed these reports weekly for 10 weeks. In addition, every week, students in all of the conditions reported the frequency that they experienced 30 feelings[95], how they felt about their life overall, and whether they had optimistic expectations for the next week. The students who were assigned to the gratitude condition reported the highest optimism regarding their lives as a whole, and had more optimistic expectations for the future, relative to students assigned to the other conditions.

In study 2, Emmons and McCullough (2003) randomly assigned 157 students to one of 3 conditions. Conditions 1 and 2 were identical to the gratitude and hassles conditions in their first experiment. However, in condition 3 (the downward comparison condition), the students wrote ways in which they are better off than others.[96] Unlike the first experiment, the students were asked to report the 30 feelings on a daily, rather than weekly, basis. The gratitude of the students assigned to each of the three conditions was measured by summing their responses to three gratitude related questions.[97] The findings suggested that students assigned to the gratitude and downward comparison conditions reported higher levels of gratitude, relative to students assigned to the hassles condition. Additionally, students assigned to the

[95] These feelings were interested, distressed, excited, alert, irritable, sad, stressed, ashamed, happy, grateful, tired, upset, strong, nervous, guilty, joyful, determined, thankful, calm, attentive, forgiving, hostile, energetic, hopeful, enthusiastic, active, afraid, proud, appreciative, and angry. The students reported the number of times that they experienced these feelings on a scale from 1 (not at all) to 5 (extremely).

[96] The students assigned to the downward social comparison condition were told: "It is human nature to compare ourselves to others. We may be better off than others in some ways, and less fortunate than other people in other ways. Think about ways in which you are better off than others, things that you have that they don’t, and write these down in the spaces below."

[97] The questions related to whether the students were grateful, thankful, and appreciative.

gratitude condition reported higher positive affect[98] relative to students assigned to the social comparison and hassles, conditions. Furthermore, mediation analysis suggested that assignment to the gratitude condition increased positive affect via its indirect effect on gratitude.

In study 3, the authors randomly assigned 65 patients with neuromuscular diseases to two conditions: the gratitude condition, or a control condition. The gratitude condition was identical to the gratitude condition of studies 1 and 2, i.e. individuals assigned to the gratitude condition were asked to write five things from the past week they were grateful for. The individuals assigned to the control condition were not asked to write any of the experiences that they were grateful for. In common with studies 1 and 2, patients assigned to both of the conditions reported their SWB at the end of the day. Their findings indicate that the patients assigned to the gratitude condition reported higher life satisfaction, greater optimism about the upcoming week, higher positive effect, and lower negative affect.

Emmons and McCullough (2003) thus present a range of experimental evidence suggesting that feelings of gratitude increase SWB. Natural disasters may increase the feelings of gratitude of individuals who live outside of the disaster country because they feel lucky that the disaster did not affect them. If this is the case, natural disasters may SWB outside of the disaster country.

4.2.5 The Effects of Interpersonal Comparisons on Subjective Well-being: Evidence from Economics

A wide literature investigates the effects of interpersonal comparisons on SWB. This literature is relevant because individuals outside of the disaster country may compare their lives to the lives of the disaster victims, leading to an increase in their SWB. One early contribution to this literature is Clark and Oswald (1996), who show that employees who live in areas with a higher average income report lower job satisfaction relative to employees living in a region with a lower average income.

Another interesting contribution to the literature exploring the effects of relative income is Card et al. (2012). The authors use a randomised experiment to investigate how the disclosure of information about the salaries of colleagues affects job satisfaction. In their experiment, a randomly chosen subset of employees (the treatment group) of the University of California were informed by email of a database detailing the wages of their colleagues, and also received a web-link to the database. In comparison, the control group received a "placebo email" informing them of the existence of a website listing the pay of top administrators at the University of California, but did not receive a web-link to the database.

[98] The feelings of positive affect reported by the students are attentive, determined, energetic, enthusiastic, excited, interested, joyful, and strong.

The findings of Card et al. (2012) suggest that for workers with salaries below the median for their pay unit and occupation, the disclosure of information on the pay of colleagues adversely affected their pay satisfaction and job satisfaction. However, the disclosure of information on the pay of colleagues did not affect the pay satisfaction and job satisfaction of workers who have salaries above the median for their pay unit and occupation.

Using data from Understanding Society, Brown et al. (2015) show that the effects of relative income on SWB are highly sensitive to whether the reference group is defined by individual characteristics ("*people like you*") or geographical proximity ("*people near you*"). If an individual's reference group is defined by geographical proximity, then the effects of natural disasters on SWB outside of the disaster country may be most pronounced for those individuals who live closest to the disaster area. In contrast, if an individual's reference group is determined by personal characteristics, then the effects of natural disasters on SWB outside of the disaster country may be more pronounced for individuals with similar characteristics to the victims of the disaster.

4.3 The Natural Disasters Under Investigation

The Centre for Research on the Epidemiology of Disasters (2012) defines a disaster to be an "unforeseen and often sudden event that causes great damage, destruction and human suffering". Disasters can have two causes: technological (caused by humans) and natural (caused by nature).

The Centre for Research on the Epidemiology of Disasters (2014b) splits natural disasters into six distinct categories based on their root cause, which are: geophysical, meteorological, climatological, hydrological, biological, and extraterrestrial. The Centre for Research on the Epidemiology of Disasters (2014b) defines each of the categories of natural disasters as follows:

Firstly, a geophysical disaster is a hazard originating from solid earth such as an earthquake, volcano, or a mass movement of earth materials. Secondly, meteorological disasters such as storms, extreme temperatures, and fog are the result of changes in weather and atmospheric conditions lasting from minutes to days. Thirdly, climatological disasters (droughts, glacial lake outbursts, and wildfires) are due to long-lasting changes in atmospheric processes lasting from months to decades.

Fourthly, the movement of surface and subsurface water causes hydrological disasters (such as floods, landslides, and waves). Fifthly, biological disasters such as epidemics and insect infestations result from exposure to toxic substances from living organisms. Finally, asteroids, meteoroids, and comets colliding with the earth cause extraterrestrial disasters.

This section will now outline the three natural disasters under consideration and examine how they affected people living in the areas that were directly affected.

Section 4.3 will also discuss the media coverage of, and charitable giving associated with, each of the disasters. We discuss the charitable giving associated with each of the disasters because it indicates that Americans responded to the disasters and because it suggests that individual utility may be affected by that of strangers.

4.3.1 The Indian Ocean Tsunami

A tsunami (the Japanese for "wave in the port") is a series of waves generated by the displacement of water from an underwater earthquake. A tsunami is therefore a geophysical, rather than hydrological, disaster, because its root cause is an earthquake, see the Centre for Research on the Epidemiology of Disasters (2014b).

The Centre for Research on the Epidemiology of Disasters (2014a) reports that the earthquake that triggered the Indian Ocean tsunami occurred on 26th December 2004, approximately 250 km off the west coast of Northern Sumatra, Indonesia. The earthquake had a magnitude of approximately 9.1 on the moments magnitude scale, thus making it the 3rd largest earthquake in modern history[99], see United States Geological Society (2016a).

The Indian Ocean tsunami is estimated to have killed approximately 216,683 people and displaced a further 1.99 million, thus making it the deadliest natural disaster in recorded history, see Athukorala and Resosudarmo (2005). Data from the Centre for Research on the Epidemiology of Disasters (2014a) suggests that the Indian Ocean tsunami affected the countries of Indonesia, Sri Lanka, India, Thailand, Somalia, Myanmar, Maldives, Malaysia, Tanzania, Seychelles, Bangladesh, South Africa, Yemen, and Kenya. Figure 4.1 shows a map of the countries affected by the Indian Ocean tsunami. For a timeline detailing the development of the Indian Ocean tsunami, see the National Oceanic and Atmospheric Administration (2005).

The Indian Ocean tsunami attracted an unprecedented amount of media coverage in the US and worldwide in the aftermath of the disaster. For example, Cable News Network deployed 80 employees to provide 24-hour television coverage of the relief efforts, see Brown and Minty (2008). In addition to the media coverage in the immediate aftermath of the disaster, the Indian Ocean tsunami was heavily featured in worldwide media headlines into late January 2005: longer than any other disaster in modern history, see Wynter (2005). For example, in the months following the disaster, the Indian Ocean tsunami featured in numerous cover stories of the New York Times, Time, Newsweek, US News and World Report, and The Economist, see Brown and Minty (2008).

[99] The moment magnitude scale is a measure of the energy of an earthquake. A 1 unit increase in the moment magnitude scale indicates a $10^{3/2}$ (approximately 32) fold increase in the total energy generated by an earthquake, see United States Geological Society (2016b). The two most powerful earthquakes in modern history are the 1960 Valdivia earthquake in Southern Chile (magnitude = 9.5), and the 1964 Southern Alaskan earthquake (magnitude = 9.2), see United States Geological Society (2016a).

There are a number of explanations for why the Indian Ocean tsunami may have attracted such unprecedented media coverage in the US. Firstly, the disaster occurred in the final week of the year when the US congress was in recess and accordingly may have had little competition in the US media, see Brown and Minty (2008). Secondly, the Indian Ocean tsunami was an unanticipated crisis rather than an ongoing struggle (such as a war) and may thus have attracted more media coverage, see Wynter (2005). Finally, a number of westerners were killed by the Indian Ocean tsunami and thus it may have been deemed of further interest to the US population, see Suzanne (2006).

In addition to the extensive coverage of the Indian Ocean tsunami in the traditional media, data from the internet search engine, Google, illustrates the widespread attention given to the disaster in the immediate aftermath. Google (2016a) data suggests that in US in the fortnight following the disaster, the word "tsunami" was "*googled*" approximately fifty percent more than the word "weather".[100]

The Indian Ocean tsunami also attracted enormous sums in charitable donations from private donors. For example, Strom (2005) reports that Save the Children USA received $6 million in private donations within four days of the disaster, approximately twenty times the sum typically received within a month of other natural disasters. In total, US charities received approximately $1.6 billion in disaster relief following the Indian Ocean tsunami, see Wallace and Willhelm (2005).

4.3.2 Hurricane Katrina

Hurricanes, a form of meteorological disaster, are a large, circulation system above the western Atlantic ocean with a maximum wind speed of sixty-four knots or more, see the Centre for Research on the Epidemiology of Disasters (2012).

Hurricane Katrina occurred between the 23rd and 30th August 2005 and affected the US states of Alabama, Florida, Georgia, Louisiana, Mississippi, and Texas, see Centre for Research on the Epidemiology of Disasters (2014a). Figure 4.2 illustrates the US states affected by Hurricane Katrina. Peek and Erikson (2008) estimate that Hurricane Katrina killed approximately 1,800 people, displaced 1.5 million people, and caused approximately $90 billion in property damage. For a timeline detailing the development of Hurricane Katrina, see Brookings Institute (2009).

A month after Hurricane Katrina, on the 23rd September 2005, Hurricane Rita struck coastal communities in Texas, Louisiana, Alabama and Florida, see Knabb et al. (2006). Knabb et al. (2006) estimate that Hurricane Rita caused an additional $10 billion in property damage, killed 62 people, and forced the evacuation of 2 million people.

Hurricanes Katrina and Rita increased pre-existing socioeconomic inequalities in the Southern US because they were most damaging to the deprived areas of New Orleans

[100] Siege Media (2016) data shows that the term "weather" is the most popular non-branded search term, accounting for 45 million searches per month.

(Louisiana), Biloxi-Gulf-Port-Pascagoula (Mississippi), and Beaumont-Port Arthur (Texas), see Gault et al. (2005). The authors show that these areas had higher poverty, lower rates of health insurance coverage, lower educational attainment, a higher proportion of Black residents, and lower median income prior to the disaster relative to the US average.

Hurricanes Katrina and Rita also exacerbated racial inequalities because Blacks were more likely to lose their job due to Hurricane Katrina, less likely to evacuate, and suffered more property damage due to the disasters relative to Whites, (see Elliott and Pais, 2006; Dyson, 2007). For this reason, the following analysis will explore whether the effects of Hurricane Katrina on SWB were more pronounced for Black individuals by estimating the effects of the disaster by ethnicity.

Hurricane Katrina attracted large amounts of media coverage in the US. For instance, Boydstun (2013) show that in the 45 days following the Indian Ocean tsunami and Hurricane Katrina, sixteen major US news sources devoted substantially more media coverage to Hurricane Katrina relative to the Indian Ocean tsunami.

In common with the Indian Ocean tsunami, Hurricane Katrina was a regular topic of Google searches in the immediate aftermath of the disaster. Google (2016b) data suggests that in the US in the two weeks following the disaster, the term "Katrina" was "*googled*" approximately fifty percent more than the term "weather". Following Hurricane Katrina, US charities raised approximately $3.3 billion in disaster relief, approximately twice the sum raised for the Indian Ocean tsunami, see Chronicle of Philanthropy (2011).

4.3.3 The Haiti Earthquake

An earthquake, a geophysical natural disaster, is the sudden movement of the earth's crust along a geological fault line and the ensuing trembling of the ground, see the Centre for Research on the Epidemiology of Disasters (2012).

The Haiti earthquake occurred at 4:53pm local time on 12th January 2010. The epicentre of the earthquake was in the Haitian city of Léogâne, approximately 25 km southwest of Port-Au-Prince (the capital city of Haiti), see DesRoches et al. (2011). The Haiti earthquake is estimated to have a magnitude of approximately 7.0 on the moment magnitude scale and was therefore under one thousandth of the size of the Indian Ocean tsunami, see United States Geological Society (2010).

The Haiti earthquake killed approximately 222,570 people in Haiti and displaced a further 2.3 million people, see the United Nations General Assembly (2011). Also, when measured in terms of the proportion of the population of a country killed, the Haiti earthquake is the most destructive natural disaster in modern history, killing approximately two percent of the population of Haiti[101], see Cavallo et al. (2010). In addition to the enormous human cost associated with the Haiti earthquake, Cavallo et al. (2010) estimate that the disaster caused approximately $8bn in property damage. Figure 4.3 illustrates the location of Haiti relative to that of the US.

In common with the Indian Ocean tsunami, the Haiti earthquake attracted considerable media coverage in the US in the aftermath of the disaster. For example, Lobb et al. (2012) estimate that from the 12th to 19th January 2010, the Haiti earthquake was the subject of approximately 440 US newspaper stories per day, on average. In a similar fashion, they estimate that from 12th to 19th January 2010 approximately 6% of "tweets" on the social network Twitter were related to the Haiti earthquake, on average[102]. In common with the Indian Ocean tsunami and Hurricane Katrina, the Haiti earthquake was frequently "*googled*" in the immediate aftermath of the disaster. Google (2016c) data suggests that the term "Haiti" was "*googled*" approximately five percent more than the term "weather" in the US in the fortnight following the disaster.

As well as the enormous media interest, the Haiti earthquake attracted substantial sums in charitable donations. For instance, in the month following the disaster, US charities received approximately $0.78 billion in disaster relief from private donors, and a further $0.66 billion within the next 7 months, see Indiana University Centre for Philanthropy (2011).

To summarise, the Indian Ocean tsunami and the Haiti earthquake were unanticipated, negative shocks to the utility of millions of people living thousands of miles from the US. In the aftermath of the disasters, Americans donated large amounts of money towards disaster relief. As a result, Americans who donated money to the disasters may have experienced a "warm-glow", increasing their SWB. On top of the charitable giving associated with the Indian Ocean tsunami and the Haiti earthquake, the disasters attracted considerable media coverage and "*googling*" in relation to the disasters. Accordingly, in the immediate aftermath of the disasters, Americans may have reflected on how the disasters affected the lives of the victims. Consequently, they may have compared their lives to lives of the victims, thus affecting their utility. Economics assumes that utility is dependent principally upon the utility of that individual, and secondly upon the utility of family members, see Becker (1981), and generally assumes that utility is unaffected by that of complete strangers who live in

[101] For comparison, the second most destructive event was the 1972 Nicaragua earthquake killing 0.4% of the population of Nicaragua. The Indian Ocean tsunami killed 0.07% of the population of Indonesia, see Cavallo et al. (2010).

[102] The social network Twitter was founded in 2006, after the Indian Ocean tsunami and Hurricane Katrina, and thus we do not have any information on the number of "tweets" relating to these disasters.

other continents.[103] Thus, economic models typically predict that large-scale natural disasters such as the Indian Ocean tsunami and the Haiti earthquake should not affect the utility of Americans.

4.4 Data

This chapter analyses BRFSS data from 2001 to 2010 collected by the Centre for Disease Control and Prevention. The Centre for Disease Control and Prevention interviews approximately 400,000 Americans annually in all US states, and ensures that the BRFSS is representative of the US population by selecting the sample via the use of Random Digit Dialling techniques. For more information regarding the BRFSS, see Centre for Disease Control and Prevention (2014).

4.4.1 The Estimation Samples

This investigation utilises six estimation samples drawn from the BRFSS dataset. Sample 1, containing 440,066 individuals interviewed within a two year period from the 1st March 2003 to 28th February 2005, is used to explore the effects of the Indian Ocean tsunami on American SWB. Sample 2 is made up of 496,066 individuals who were interviewed over a two year period from 1st January 2004 to 31st December 2005. Sample 2 is used to explore the effects of Hurricane Katrina on American SWB. Sample 3 is used to explore the effects of the Haiti earthquake on American SWB, and contains 638,853 individuals who were interviewed within a two year period from 1st April 2008 to 31st March 2010.

We use a further three estimation samples to test the plausibility of the common trends assumption. Sample 4 is a sample of individuals interviewed in the two year period from 1st March 2001 to 28th February 2003 and contains 196,745 individuals. Sample 4 is used to test whether the number of days of poor mental health followed a common trend pre and post 26th December prior to the Indian Ocean tsunami.

Sample 5 is a sample containing individuals interviewed during 2001 and 2003, a total of 331,859 observations. Unfortunately, in 2002 there were 147,964 individuals who did not report the number of days of poor mental health, reducing the number of observations for 2002 to 32,719. The large number of missing values in 2002 results from a large number of states omitting this variable from the BRFSS questionnaire in that year. For this reason, as an alternative, we use a sample of 133,155 individuals who were interviewed in 2001. Sample 5 is used to test whether the number of days of poor mental health followed a common trend pre and post 23rd August prior to Hurricane Katrina.

[103] Telford et al. (2006) estimate that the Indian Ocean tsunami killed 18 Americans, and, the US Department of State (2010) estimates that the Haiti earthquake killed 24 Americans. Hence, relatively few Americans will have had family and friends who were directly affected by the Indian Ocean tsunami and Haiti Earthquake.

Finally, Sample 6 contains 605,570 individuals interviewed within a two year period from 1st April 2006 to 31st March 2008. We utilise Sample 6 to investigate whether the number of days of poor mental health followed a common trend pre and post 12th January prior to the Haiti earthquake.

4.4.2 The Dependent Variable

The measure of SWB used in this analysis is the number of days of self-reported poor mental health in the previous 30 days. In the BRFSS questionnaire, the respondents are asked the following: "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?". The individuals provide responses from 0 days (the highest SWB) to 30 days (the lowest SWB). This variable may be regarded as a measure of mental strain or depression over the past month, see Blanchflower and Oswald (2011). For a recent analysis of this variable, see Helliwell and Huang (2014) who explore how unemployment in the local area affects SWB.

The distribution of the number of days of poor mental health is illustrated in both Table 4.1 and Figures 4.4 to 4.6 for Samples 1 to 3. There are several notable characteristics regarding the distribution of the number of days of poor mental health in each of the samples. Firstly, the number of days of poor mental health is non-negative and assumes integer values from 0 to 30. Secondly, it is overdispersed because the mean (approximately 3 days) is less than the variance (approximately 50 days), see Hilbe (2007). Finally, approximately two thirds of individuals report 0 days of poor mental health. The implications of the large number of 0 values and overdispersion for the estimation method are discussed in Section 4.5.1.

4.4.3 Summary Statistics: The Mean Number of Days of Poor Mental Health: Pre and Post the Indian Ocean Tsunami

Table 4.2 presents summary statistics from Sample 1 of the number of days of poor mental health before and after the Indian Ocean tsunami (on 26th December 2004). We present the following statistics for the entire distribution of the number of days of poor mental health: the mean of all observations, sample size, and standard deviation. The number of days of poor mental health is overdispersed and has a large proportion of zero values. As a consequence, the following descriptive statistics are presented for individuals who report greater than 0 days of poor mental health: the percentage of non-zero observations, the mean, median, and the standard deviation.

We are interested in the following periods:

a) 1st March 2003 to 25th December 2003
b) 27th December 2003 to 29th February 2004
c) 1st March 2004 to 25th December 2004
d) 27th December 2004 to 28th February 2005 (the period after the disaster)

Figure 4.7 presents a timeline illustrating the four periods that relate to the Indian Ocean tsunami. Periods a) and b) relate to the 12 month period from 1st March 2003 to 29th February 2004 – the 12 month period prior to the Indian Ocean tsunami. Period a) relates to the control group and period b) relates to the treatment group. In contrast, period c) and d) relate to the 12 month period from 1st March 2004 to 28th February 2005 – the 12 month period of the Indian Ocean tsunami. Period c) denotes the control group and d) relates to the treatment group. Hence, period d) relates to the period after the Indian Ocean tsunami – the immediate aftermath of the disaster.

Columns 2-4 and 9-11 present summary statistics for the entire distribution of the number of days of poor mental health. Table 4.2 indicates that individuals interviewed from 1st March 2004 to 25th December 2004 reported 0.01 more days of poor mental health relative to individuals who were interviewed from 1st March 2003 to 25th December 2003. On average, individuals interviewed between 27th December 2004 to 28th February 2005 (the period after the disaster) reported 0.2 fewer days of poor mental health relative to individuals who were interviewed from 27th December 2003 to 29th February 2004. Hence, the summary statistics suggest that there was a 0.21 day fall in the average number of days of poor mental health following the Indian Ocean tsunami.

Columns 5-8 and 12-15 show summary statistics for individuals who report more than zero days of poor mental health. For individuals who report more than zero days of poor mental health, there was a 0.46 day reduction in the number of days of poor mental health following the Indian Ocean tsunami[104].

4.4.4 Summary Statistics: The Mean Number of Days of Poor Mental Health: Pre and Post Hurricane Katrina

Table 4.3 shows summary statistics from Sample 2 indicating the mean number of days of poor mental health before and after Hurricane Katrina (on 23rd August 2005). We are interested in four periods:

a) 1st January 2004 to 22nd August 2004
b) 24th August 2004 to 31st December 2004
c) 1st January 2005 to 22nd August 2005
d) 24th August 2005 to 31st December 2005 (the period after the disaster)

[104] $(9.18 - 9.47) - (9.52 - 9.35) = -0.46.$

These periods are shown by the timeline presented in Figure 4.8. Periods a) and b) relate to the 12 month period prior to Hurricane Katrina (2004). Period a) relates to the control group and b) denotes the treatment group. In contrast, periods c) and d) relate to the 12 month period in which Hurricane Katrina occurred (2005). Period c) relates to the control group and d) relates to the treatment group. Hence, period d) relates to the period after the disaster: the immediate aftermath of Hurricane Katrina.

In a similar vein to Table 4.2, columns 2-4 and 9-11 present summary statistics for the entire distribution of the number of days of poor mental health. On average, individuals interviewed from 1st January 2005 to 22nd August 2005 reported 0.15 fewer days of poor mental health relative to individuals interviewed from 1st January 2004 to 22nd August 2004. Additionally, individuals interviewed from 24th August 2005 to 31st December 2005 reported 0.12 fewer days of poor mental health relative to individuals who were interviewed from 24th August 2004 to 31st December 2004. Thus, it is evident that individuals interviewed after the disaster reported a 0.03 day greater increase in the number of days of poor mental health.

Columns 5-8 and 12-15 show summary statistics for individuals who report more than zero days of poor mental health. Amongst individuals reporting more than zero days of poor mental health, there was a 0.08 day increase in the average number of days of poor mental health following Hurricane Katrina[105].

4.4.5 Summary Statistics: The Mean Number of Days of Poor Mental Health: Pre and Post the Haiti Earthquake

Summary statistics are presented in Table 4.4 showing the mean number of days of poor mental health before and after the Haiti earthquake, which occurred on 12th January 2010. We are interested in four periods:

a) 1st April 2008 to 11th January 2009
b) 13th January 2009 to 31st March 2009
c) 1st April 2009 to 11th January 2010
d) 13th January 2010 to 31st March 2010 (the period after the disaster)

Figure 4.9 shows these time periods. In a similar vein to the other disasters, periods a) and b) relate to the 12 month period prior to the Haiti earthquake (1st April 2008 to 31st March 2009). Periods a) and b) denote the treatment and control groups, respectively. Periods c) and d) relate to the 12 month period of the Haiti earthquake (1st April 2009 to 31st March 2010) – period c) relates to the control group, d) the treatment group. Hence, period d) are interviewed in the period after the Haiti earthquake.

[105] $(9.38 - 9.50) - (9.31 - 9.51) = 0.08.$

Table 4.4 is presented in an identical fashion to Tables 4.2 and 4.3. Columns 2-4 and 9-11 present summary statistics for the entire distribution of the number of days of poor mental health. Individuals who were interviewed from 1st April 2009 to 11th January 2010 reported 0.05 fewer days of poor mental health relative to individuals interviewed from 1st April 2008 to 11th January 2009. In addition, individuals interviewed from 13th January 2010 to 31st March 2010 (the period after the disaster) reported 0.01 more days of poor mental health relative to individuals interviewed from 13th January 2009 to 31st March 2009. Hence, the summary statistics suggest that there was a 0.06 day greater increase in the number of days of poor mental health following the Haiti earthquake.

Columns 5-8 and 12-15 show summary statistics for individuals who report more than zero days of poor mental health. For individuals that reported more than zero days of poor mental health, there was a 0 day change in the number of days of poor mental health following the Haiti earthquake[106]. Section 4.6 will investigate whether the effects of the disasters varied over time and by proximity to the disaster area.

[106] $(9.79 - 9.66) - (9.68 - 9.55) = 0.$

4.5 Methodology

4.5.1 Econometric Specification

To estimate the effect of the natural disasters on the number of days of poor mental health, the following generalised difference-in-difference approach is used:

$$\begin{aligned} DAYS_{itj} = {} & \beta_0 + \beta_1(PostDis_i) + \beta_2(Disasterperiod_i) + \beta_3[(PostDis_i) \\ & \times (Disasterperiod_i)] + \boldsymbol{\gamma Month} + \boldsymbol{\lambda X}_{itj} + \tau Attempts_{itj} \\ & + \xi_j + \varepsilon_{itj} \end{aligned} \tag{4.1}$$

$DAYS_{itj}$ denotes the number of days of poor mental health of individual i at time t in state j. $PostDis_i$ is a binary variable equal to 1 if individual i was interviewed after the date of the disaster (the treatment group), and 0 if the individual was interviewed before the date of the disaster (the control group). For instance, in the case of Hurricane Katrina, $PostDis_i$ equals 1 if the individual was interviewed from 24th August to 31st December, and 0 if the individual was interviewed from 1st January to 22nd August.[107] $Disasterperiod_i$ equals 1 if individual i was interviewed in the 12 month period of the disaster, and 0 if the individual was interviewed in the 12 month period prior to the disaster. For Hurricane Katrina, $Disasterperiod_i$ equals 1 if the individual was interviewed in 2005, and 0 if the individual was interviewed in 2004.

$PostDis_i \times Disasterperiod_i$ is an interaction term that equals 1 if the individual was interviewed in the period after the disaster, and 0 otherwise. For Hurricane Katrina, $PostDis_i \times Disasterperiod_i$ equals 1 if the individual was interviewed from 24th August 2005 to 31st August 2005 (period d) in Figure 4.8); and 0 if the individual was interviewed in periods a), b), or c) of Figure 4.8. $\boldsymbol{Month}_i$ indicates a vector of binary variables denoting the month of interview.

A number of existing studies exploring the effects of natural disasters on SWB, such as Kimball et al. (2006) and Shultz et al. (2012), do not control for an individual's personal characteristics. In contrast, we condition upon $\boldsymbol{X}_{itj}$, a vector of the personal characteristics of individual i at time t in state j. The individual characteristics are gender, household income category, highest educational attainment, marital status, labour force status, disability status, ethnicity, age, and age squared. As previously discussed in Section 4.4, the BRFSS selects respondents using Random Digit Dialling techniques and interviews them throughout the year. Arguably, the date of interview is therefore likely to be exogenously determined. However, we control for the personal

[107] Individuals interviewed on the dates of the disasters are coded as missing and hence omitted from the analysis. On the day of the Indian Ocean tsunami (26th December 2004), a total of 167 individuals were interviewed (0.037% of the estimation sample). In addition, on the day of Hurricane Katrina (23rd August 2005), a total of 651 individuals were interviewed (0.131% of the estimation sample). Furthermore, on the day of the Haiti earthquake (12th January 2010) a total of 1,916 individuals were interviewed (0.3% of the estimation sample). It is thus evident that relatively few individuals were interviewed on the day of the natural disasters.

characteristics of the individual to account for the possibility that the personal characteristics of the individual may affect their date of interview.

Blanchflower and Oswald (2011) find that males report fewer days of poor mental health, relative to females. For this reason, a binary variable taking the value 1 if the individual is male, and 0 if female is included in the analysis. Likewise, Helliwell and Huang (2014) find that individuals who have a higher income report fewer days of poor mental health relative to individuals who have a lower income. Consequently, binary variables denoting the annual nominal household income category of the individual are included as control variables. The categories of household income are $10,000-$14,999, $15,000 to $19,999, $20,000 to $24,999, $25,000 to $34,999, $35,000 to $49,999, $50,000 to $74,999, and $75,000 or more. Individuals who have a household income of less than $10,000 per annum form the base category.

Likewise, using the BRFSS, Blanchflower and Oswald (2011) find that more educated individuals report fewer days of poor mental health, relative to individuals who did not graduate from high school. As a result, binary variables are included to indicate the highest educational attainment of the individual: graduation from high school, 1-3 years of college (university) education, or college graduation. Individuals without qualifications form the base category. In addition, Stutzer and Frey (2006) and Lucas and Clark (2006) suggest that married individuals have higher SWB, relative to unmarried individuals. For this reason, we condition on two binary variables indicating whether the individual is married or cohabiting; and separated, divorced, or widowed. Single individuals form the base category.

Additionally, unemployment is found by Clark and Oswald (1994) and Kassenboehmer and Haisken-DeNew (2009) to adversely affect SWB. Hence, we control for two binary variables indicating whether the individual is unemployed or out of the labour force; employees form the base category. Oswald and Powdthavee (2008) find that individuals who have health problems that limit their daily activities report lower SWB. Thus, a binary variable equal to 1 if the individual has health problems which limit their daily activities (0 if they do not) is included as a control variable.

Blanchflower and Oswald (2011) find that Blacks report lower SWB relative to Whites. Accordingly, binary variables indicating whether the individual is Black, Asian, Hawaiian, or American Indian are included as control variables; the base category is White. Finally, Blanchflower and Oswald (2008) suggest that SWB is "U-shaped" over the life-course and reaches a minimum in midlife. Hence, we control for the age and age-squared of the individual.

Heffetz and Rabin (2013) show that the number of attempts taken to contact an individual does not have a statistically significant effect on their happiness. However, to control for selection effects, we control for the number of call attempts taken to contact individual i at time t in state j. Table 4.5 provides full definitions of the variables used in this chapter and Tables 4.6 to 4.8 present summary statistics for Samples 1 to 3. ξ_j indicates a state fixed effect to control for the time invariant characteristics of the state in which an individual lives, such as culture and climate. ε_{itj} is an error term.

Under the following assumptions, the parameter β_3 in equation (4.1) is the causal effect of the natural disaster on the number of days of poor mental health of individuals interviewed in the period after the disaster. Firstly, conditioning on the individual's personal characteristics and the number of attempts taken to contact them, the date of interview of the individual is exogenously determined. As previously discussed, the Centre for Disease Control and Prevention selects survey respondents by means of Random Digit Dialling techniques and interviews them throughout the year. Arguably, therefore the date of interview of the individual is likely to be exogenously determined.

Secondly, in the absence of the disaster, the difference in the number of days of poor mental health between the pre and post disaster groups would have been the same in the 12 month period of the disaster as in the 12 month period before the disaster[108]. This assumption is called the common trends assumption, see Lechner (2010).

For clarity, Figure 4.10 shows a graphical representation of common trends assumption. The dotted blue line represents the control group who were interviewed before the disaster, and the red line indicates the treatment group who were interviewed after the disaster. For example, in the case of Hurricane Katrina, the control group were interviewed from January 1st to August 22nd and the treatment group were interviewed from 24th August to 31st December.

In the case of Hurricane Katrina, the coefficient β_1 shows the difference in the number of days of poor mental health between individuals interviewed from 1st January 2004 to 22nd August 2004 (the control group) and individuals interviewed from 24th August 2004 to 31st December 2004 (the treatment group). In other words, β_1 is the difference in the number of days of poor mental between individuals interviewed in periods a) and b) in Figure 4.8.

For Hurricane Katrina, the coefficient β_2 is the difference in the number of days of poor mental health between individuals interviewed from 1st January 2005 to 22nd August 2005 and individuals interviewed from 1st January 2004 to 22nd August 2004. Hence, β_2 denotes the difference in the number of days of poor mental health between individuals interviewed in periods c) and a) in Figure 4.8.

The coefficient β_3 shows how the difference in the number of days of poor mental health between the pre disaster (control) and post disaster (treatment) groups

[108] The assumption of common trends in the outcome variable relates to linear models. We discuss how the difference-in-difference approach extends to a non-linear framework in greater detail in Sections 4.5.2 to 4.5.4.

changed from the 12 month period before the disaster to the 12 month period of the disaster. In the case of Hurricane Katrina, the coefficient β_3 equals the difference in the number of days of poor mental health between the treatment group (post 23rd August) and control group (pre 23rd August) in 2005, minus the difference in the number of days of poor mental health between the treatment and control groups in 2004.

Under the assumption of common trends, the coefficient β_3 is the causal effect of the disaster on the number of days of poor mental health of individuals interviewed in the period after the disaster.

The common trends assumption states that in the absence of the disaster, the parameter β_3 would have been equal to 0. Hence, in the absence of the disaster, the number of days of poor mental health of the pre and post disaster groups in the period of the disaster is shown by the counterfactual (dotted green) line in Figure 4.10. In other words, in the absence of the disaster, the difference in the number of days of poor mental health between the pre disaster (control) and post disaster (treatment) groups in the 12 month period of the disaster would have been equal to β_1. The generalised approach outlined in equation (4.1) can be applied to the Indian Ocean tsunami, Hurricane Katrina, and the Haiti earthquake, as shown by equations (A4.1) to (A4.3) presented in Appendix 2.

4.5.2 Estimation Method

As previously revealed in Section 4.4.2, the distribution of the number of days of poor mental health is non-negative, overdispersed (the variance exceeds the mean), and has a large proportion of 0 values. The implications of these characteristics for the estimation method are now discussed.

The number of days of poor mental health assumes non-negative values. Thus, an estimator is required that provides non-negative expected values of the number of days of poor mental health for all values of the vector of explanatory variables ($\boldsymbol{X}$), as illustrated by equation (4.2):

$$E(DAYS|\boldsymbol{X}) \geq 0 \text{ for all } \boldsymbol{X}'\boldsymbol{\beta} \tag{4.2}$$

$E(DAYS|\boldsymbol{X})$ denotes the expected number of days of poor mental health given the values of the explanatory variables ($\boldsymbol{X}$), and $\boldsymbol{\beta}$ denotes a vector of coefficients. Wooldridge (2002) argues that ordinary least squares (OLS) models are unlikely to satisfy this condition. For this reason, as an alternative to OLS, we use count data models to estimate the effect of the natural disasters on the number of days of poor mental health. Count data models constrain the expected value of the dependent variable to be non-negative by modelling it as an exponential function, as shown by equation (4.3):

$$E(DAYS|\boldsymbol{X}) = \exp^{\boldsymbol{X}'\boldsymbol{\beta}} \tag{4.3}$$

Where exp indicates the exponential function. The standard count data model, the Poisson model, assumes equidispersion: the equality of the variance and the mean of the dependent variable, see Hilbe (2007). This assumption is stated by equation (4.4):

$$Variance\ (DAYS|\boldsymbol{X}) = E(Y|\boldsymbol{X}) = \mu \tag{4.4}$$

Where μ indicates the mean. However, as previously stated, the mean number of days of poor mental health is overdispersed, which means that the variance exceeds the mean. Hilbe (2007) argues that overdispersion may cause the Poisson model to underestimate the standard errors, leading to overconfidence in the results. For this reason, the negative binomial model is likely to provide more robust results relative to the Poisson model. The negative binomial model relaxes the assumption of equidispersion and thus allows the variance to exceed the mean. The variance of the negative binomial model is shown in equation (4.5):

$$Variance\ (DAYS|\boldsymbol{X}) = \mu + \alpha\mu^2 \tag{4.5}$$

Where α is the variance parameter of the gamma distribution, a measure of overdispersion. If α is positive (negative), there is evidence that the dependent variable is overdispersed (underdispersed). Note, if $\alpha = 0$ this implies equidispersion, and, hence the equivalence of the Poisson and negative binomial models.

As previously discussed in Section 4.4.2, the number of days of poor mental health has a large proportion of 0 values (approximately 65%). Consequently, a zero inflated negative binomial model will be used to estimate the effect of the natural disasters on the number of days of poor mental health. The zero inflated negative binomial model is a 2 step model that supplements the negative binomial model with a binary model which predicts 0 counts, typically a logit model. The expected value of the zero inflated negative binomial model is thus shown by equation (4.6):

$$E(DAYS|\boldsymbol{Z},\boldsymbol{X}) = (1 - \mathrm{f}_1(0|\boldsymbol{Z})) \times\ (\exp^{\boldsymbol{X}'\boldsymbol{\beta}}) \tag{4.6}$$

The first term $(1 - \mathrm{f}_1(0|\boldsymbol{Z}))$ denotes the probability that an individual reports zero days of poor mental health as predicted by the logit or probit model, where **Z** is a vector of explanatory variables from the logit model. The second term $\exp^{\boldsymbol{X}'\boldsymbol{\beta}}$ is the count density as given by the negative binomial model, where **X** is the vector of explanatory variables of the negative binomial model. Thus, in the case of the logit model the expected value is shown by equation (4.7):

$$E(DAYS|\boldsymbol{Z},\boldsymbol{X}) = (1 - \frac{(\exp^{\mathbf{Z}'\mathbf{G}})}{(1 + \exp^{\mathbf{Z}'\mathbf{G}})})\times\ (\exp^{\boldsymbol{X}'\boldsymbol{\beta}}) \tag{4.7}$$

Hilbe (2007) argues that the zero inflated negative binomial model predicts 0 counts in 2 ways. Firstly, 0 counts are predicted by the negative binomial model. Secondly, a binary ("inflate") model predicts the likelihood of a 0 count. Thus, the negative binomial model is used to model the number of days of poor mental health, and, the "inflate" model is used to model the probability of having 0 days of poor mental health.[109] As a result of these features of the zero inflated negative binomial model, Long and Freese (2006) argue that the same variables in the negative binomial and "inflate" models may often have coefficients with opposite signs. For example, unemployment may increase the number of days of poor mental health, and reduce the probability of having 0 days of poor mental health. As a result, unemployment may have positive (negative) coefficients in the negative binomial ("inflate") models.

4.5.3 The Extension of the Difference-in-Difference Approach to Non-Linear Models

This study utilises zero inflated negative binomial models to investigate the effects of natural disasters on the number of days of poor mental health. In both the negative binomial and inflate parts of the zero inflated negative binomial model, the difference-in-difference approach presented by equation (4.1) is utilised[110].

However, it is important to note that the extension of the difference-in-difference approach to non-linear models is more complicated than the linear case, see (Lechner, 2010). One departure from the linear model relates to the calculation of treatment (i.e. natural disaster) effects. In a linear difference-in-difference framework the coefficient of the interaction term (β_3 in equation (4.1)) denotes the effect of the treatment on the outcome variable, see Puhani (2012). However, in non-linear difference-in-difference models such as count data models the treatment effect cannot be constant across the population because the dependent variable is bounded (in this case the dependent variable is bounded between 0 and 30), see Athey and Imbens (2006).

To calculate the treatment effect in non-linear difference-in-difference models we must subtract the counterfactual outcome (if the disaster did not occur) from the observed outcome (i.e. in the event of the disaster). Equation (2) denotes the expected number of days of poor mental health of the observed outcome (i.e. in the event of the disaster). The left-hand term denotes the probability of a non-zero outcome (number of days of poor mental health > 0) as predicted by the logit model. The right hand term indicates the number of days of poor mental health as predicted by the negative binomial model.

[109] The "inflate model" uses a binary dependent variable equalling 1 if the individual reported 0 days of poor mental health, and 0 otherwise.

[110] However, for the purposes of identification, we exclude the number of call attempts taken to contact the individual from the negative binomial model.

$$E(DAYS|\boldsymbol{Z},\boldsymbol{X}) = (1 - \frac{(\exp^{\alpha_1+\alpha_2+\alpha_3+\boldsymbol{Z'G}})}{(1+\exp^{\alpha_1+\alpha_2+\alpha_3+\boldsymbol{Z'G}})}) \times \ (\exp^{\beta_1+\beta_2+\beta_3+\boldsymbol{R'}\mathbf{X}}) \tag{4.8}$$

Z denotes the control variables and **G** denotes the coefficients of the logit model. $\boldsymbol{R}$ denotes a vector of control variables and **X'** denotes the coefficients of the negative binomial model. β_1 (α_1) is the post-disaster effect (i.e. the effect of being in the treatment group) and β_2 (α_2) denotes the disaster period (time) effect. The coefficients of β_3 (α_3) indicate the coefficients of the interaction terms (disaster period times treatment group). The counterfactual outcome (i.e. if the disaster did not occur) is shown by equation (4.9):

$$E(DAYS|\boldsymbol{Z},\boldsymbol{X}) = (1 - \frac{(\exp^{\alpha_1+\alpha_2+\boldsymbol{Z'G}})}{(1+\exp^{\alpha_1+\alpha_2+\boldsymbol{Z'G}})}) \times \ (\exp^{\beta_1+\beta_2+\boldsymbol{\lambda}\mathbf{X}}) \tag{4.9}$$

The treatment effect is the conditional expectation of the observed outcome minus the conditional expectation of the counterfactual outcome. Thus, the treatment effect equals equation (4.8) minus equation (4.9):

$$\begin{aligned}&\left((1 - \frac{\left(\exp^{\alpha_1+\alpha_2+\alpha_3+\boldsymbol{Z'G}}\right)}{\left(1+\exp^{\alpha_1+\alpha_2+\alpha_3+\boldsymbol{Z'G}}\right)}) \times \ (\exp^{\beta_1+\beta_2+\beta_3+\boldsymbol{\lambda}\mathbf{X}})\right) \\ &- \left((1 - \frac{\left(\exp^{\alpha_1+\alpha_2+\boldsymbol{Z'G}}\right)}{\left(1+\exp^{\alpha_1+\alpha_2+\boldsymbol{Z'G}}\right)}) \times \ (\exp^{\beta_1+\beta_2+\boldsymbol{\lambda}\mathbf{X}})\right)\end{aligned} \tag{4.10}$$

Note that if $\alpha_3 = \beta_3 = 0$ then the treatment effect will equal zero. The treatment effect is thus the total incremental effect of the interaction terms (α_3 in the logit model and β_3 in the negative binomial model) on the number of days of poor self-reported mental health.

For other applications of the difference-in-difference approach using zero inflated negative binomial models, see Schreyögg and Grabka (2010) and Green and Navarro Paniagua (2012). The former investigate the effects of the introduction of copayments for ambulatory care in Germany on the demand for physician visits, and the latter investigates the effects of raising the school leaving age on teacher absenteeism in Spain.

4.5.4 Validity Check 1: Placebo Tests for Common Trends

As previously discussed in Section 4.5.1, causal inference using the linear difference-in-difference approach relies on the assumption of common trends, see Lechner (2010). The common trends assumption states that in the absence of the disaster, the number of days of poor mental health of the pre disaster (control) and post disaster (treatment) groups would have followed the same trend in the 12-month period of the disaster, relative to the 12-month period prior to the disaster[111].

However, in the case of non-linear models the common trends assumption is unlikely to hold, see Lechner (2010). For example, assume that the control (pre disaster) group in the post treatment period have a mean number of days of poor mental health of 25 days. In addition, assume that in the period before the disaster the treatment group reported 8 more days of poor mental health than the control group. Hence, for the common trends assumption to hold the counterfactual number of days of poor mental health for the treated group must equal 33. This is clearly outside of the support of the outcome variable, and thus violating the common trends assumption.

As an alternative to assuming common trends in the outcome variable (number of days of poor mental health), a more feasible assumption in is to assume common trends in a non-linear transformation of the outcome variable, (see Lechner, 2010). Thus, instead of assuming common trends in the number of days of poor mental health in the absence of the disaster, we assume common trends in the exponential of the number of days of poor mental health in the absence of the disasters.

We use placebo tests to test formally for common trends[112] by making use of data from before the disasters. Lechner (2010) argues that placebo tests may be used to test whether the treatment and control groups followed a common trend prior to the treatment, assuming that treatment was unanticipated (as in the case of natural disasters).

A number of recent empirical papers have tested for common trends using placebo tests. For instance, Boockmann et al. (2013) explore the effects of changes in the 1997 minimum wage on employment in the electrical industry in Germany, using the building industry as a control group. The authors test for common trends prior to the policy by estimating the effect of a 'pretend' change in the minimum wage in 1996 on employment, 1 year prior to the actual change. In a similar fashion, Havnes and Mogstad (2011) use a difference-in-difference approach to investigate the effects of subsidised childcare services on educational attainment in Norway. The authors use regions of Norway in which subsidised childcare was rapidly (slowly) expanded as

[111] The trends in the mean number of days of poor mental health in the pre and post disaster groups in the three periods prior to each of the disasters are plotted in Figures 4.11 to 4.13.
[112] In the remainder of this chapter, for brevity we will refer to the assumption of common trends in the number of days of poor mental health, rather than common trends in the exponential.

treatment (comparison) groups. To test whether educational attainment followed a common trend in the treatment and control groups prior to the expansion of subsidised childcare, they estimate the effect of a 'pretend' expansion of subsidised childcare in the pre reform period.

To test for common trends prior to the natural disasters, we utilise the placebo experiment illustrated by equation (4.11). Equation (4.11) replicates equation (4.1) but assumes that the natural disaster occurred 2 years prior to the real natural disaster:

$$\begin{aligned} DAYS_{itj} = \delta_0 + \delta_1(PostDis_i) + \delta_2(2PeriodsBefore) + \delta_3[(PostDis_i) \\ \times (2PeriodsBefore)] + \boldsymbol{\gamma Month} + \boldsymbol{\lambda X}_{itj} + \tau Attempts_{itj} \\ + \xi_j + \varepsilon_{itj} \end{aligned} \quad (4.11)$$

$PostDis_i$ is a binary variable equal to 1 if individual i was interviewed after the date of the disaster (the treatment group), and 0 if the individual was interviewed before the date of the disaster (the control group). $2PeriodsBefore$ is a binary variable which is equal to 1 if the individual was interviewed 2 periods prior to the disaster, and 0 if the individual was interviewed 3 periods prior to the disaster.

$(PostDis_i) \times (2PeriodsBefore)$ is an interaction term that equals 1 if the individual was interviewed in the period following the 'pretend' natural disaster, and 0 otherwise. For example, for Hurricane Katrina $(PostDis_i) \times (2PeriodsBefore)$ equals 1 if the individual was interviewed from 24th August 2003 to 31st August 2003, 0 otherwise. The parameter δ_3 indicates the effect of the 'pretend' natural disaster, exactly 2 years prior to the actual disaster, on the number of days of poor mental health. For example, in the case of Hurricane Katrina, the parameter δ_3 indicates the effect of the 'pretend' disaster on 23rd August 2003 (Hurricane Katrina occurred on 23rd August 2005).

If δ_3 is statistically insignificant, this provides evidence to suggest that the number of days of poor mental health followed a common trend in the periods prior to the disaster. In contrast, if δ_3 is statistically significant this suggests that in the periods prior to the disaster the number of days of poor mental health did not follow a common trend. The generalised approach presented by equation (4.11) can be applied to test for common trends prior to each of the natural disasters, as shown by equations (A4.4) to (A4.6) in Appendix 2.

4.6 Results

The effects of a natural disaster on the number of days of poor mental health may be more pronounced for individuals who live in close proximity to the disaster area. It is also interesting to test whether the effects of the natural disasters dissipated or heightened in the months that followed. As a result, the following analysis will explore whether the effects of the Indian Ocean tsunami, Hurricane Katrina, and the Haiti earthquake varied by proximity to the area that was affected as well as time.

4.6.1 The Effects of the Indian Ocean Tsunami on Subjective Well-being

Table 4.9 reveals the findings from estimating equation (A4.1) (see Appendix 2) using a zero inflated negative binomial model.[113] Equation (A4.1) estimates the effect of the Indian Ocean tsunami (on 26th December 2004) on the number of days of poor mental health of individuals interviewed from 27th December 2004 to 28th February 2005 (the period after the disaster – period d) presented in Figure 4.7). For all the tables of estimation results presented in this chapter, the upper and lower halves of the table specify the coefficients from the negative binomial and "inflate" models, respectively.

The estimation results for the US as a whole are shown in column (1). Under the assumptions outlined in Section 4.5.1, the Indian Ocean tsunami reduced the number of days of poor mental health of people interviewed from 27th December 2004 to 28th February 2005, holding the control variables constant. This effect is statistically significant at the 1% level. The "inflate" model has a coefficient of 0.0437 indicating that the Indian Ocean tsunami increased the probability that individuals who were interviewed from 27th December 2004 to 28th February 2005 reported 0 days of poor mental health. The coefficients of the "inflate" (logit) model indicate how a unit change in the explanatory variable affects the log odds of reporting zero days of poor mental health, see Long and Freese (2006). As a result, the coefficients of the "inflate" model do not have a direct meaningful interpretation, (see Long and Freese, 2006; Hilbe, 2007). In addition, note that the Vuong test of the preference of the zero inflated negative binomial model relative to the negative binomial model has a z-statistic of 33 or more, indicating the preference of the zero inflated negative binomial model relative to the negative binomial model[114].

[113] For presentational purposes, only the estimated effects of the natural disasters and the estimated effect of unemployment are presented in Tables 4.9 to 4.14. The effect of unemployment is used to illustrate the magnitude of the effects of the natural disasters, as unemployment is a heavily researched determinant of SWB, see Kassenboehmer and Haisken-DeNew (2009), for example. The key results for each disaster are presented in the Appendix.

[114] This is the case for all of the findings presented in this chapter.

The incremental effects (i.e. treatment effects) presented at the bottom of Table 4.9 allow a quantitative interpretation of the effects of the Indian Ocean tsunami on the expected number of days of poor mental health. For all US states (column 1), the findings indicate that the Indian Ocean tsunami reduced the expected number of days of poor mental health by 0.25 days. For the Pacific ocean states (those in closest proximity to East Asia), the Indian Ocean tsunami is estimated to have reduced the number of days of poor mental health by 0.51 days. The findings for the non-coastal, Atlantic, Gulf of Mexico, and Great Lake states are statistically significant and negative, though they are smaller in magnitude than for the Pacific Ocean states.

To investigate whether the effects of the Indian Ocean tsunami varied by geographical proximity to the affected areas we re-estimate equation (A4.1) using 5 subsamples: non-coastal, Atlantic Ocean, Pacific Ocean, Gulf of Mexico, and Great Lake states, see Environmental Systems Research Institute (2016). Figure 4.14 shows the locations of these states. Note that the states that are in closest geographical proximity to South-East Asia are the Pacific Ocean states, which are located on the East coast of the US.

The findings displayed in columns (2), (3), (5), and (6) show no evidence to suggest that the Indian Ocean tsunami affected the number of days of poor mental health of individuals living in non-coastal, Atlantic, Gulf of Mexico, and Great Lake, states. The effects for the Pacific Ocean states, the states closest to East Asia, are found in column (4). Under the previously stated assumptions, the Indian Ocean tsunami reduced the number of days of poor mental health of individuals interviewed from 27th December 2004 to 28th February 2005 by 17.27%. The estimated magnitude of this effect is approximately 3 times the magnitude of the effect for individuals living in all US states and is statistically significant at the 1% level. In addition, note that the estimated effect of the Indian Ocean tsunami is large, approximately 70% of the magnitude of the coefficient of the unemployment variable.[115] Thus, the empirical evidence presented in Table 4.9 suggests that the effect of the Indian Ocean tsunami was most pronounced in the Pacific Ocean states, which are the US states closest to East Asia.

In addition, the results revealed in column (5) suggest that the Indian Ocean tsunami increased the probability that individuals living in the Gulf of Mexico reported zero days of poor mental health. In contrast, the "inflate" models indicate no evidence that the Indian Ocean tsunami affected the number of days of poor mental health of individuals living in the Gulf of Mexico. Also, note that in all of the models, the coefficient of the ln(alpha) variable is statistically significant, indicating that alpha is significantly different from zero. Hence, the number of days of poor mental health is overdispersed, thus endorsing the use of zero inflated negative binomial models.

[115] Note that the effect of unemployment varies little across the models.

We split individuals interviewed from 27th December 2004 to 28th February 2005 (the period after the disaster) into 2 groups to investigate how the effects of the Indian Ocean tsunami varied over time. These groups are individuals interviewed from: 27th December 2004 to 31st January 2005 (a 0-1 month window of the disaster) and February 2005 (a 1-2 month window). The results are presented in Table 4.10. Column (1) indicates the findings for individuals from all US states. Note that the effect of the Indian Ocean tsunami was larger within a 1-2 month window than a 1 month window of the disaster. These effects are statistically significant at the 1% level.

The effect of the Indian Ocean tsunami is greater for individuals interviewed approximately 1-2 months after the Indian Ocean tsunami, relative to individuals interviewed within 1 month of the disaster. There are a number of explanations for this. Firstly, a 1 month window of the Indian Ocean tsunami covers the Christmas holiday period. However, if Christmas has a constant effect on the number of days of poor mental health in the 12 month period of the disaster (1st March 2004 to 28th February 2005) and the 12 month period prior to the disaster (1st March 2003 to 29th February 2004), the estimated effect of the Indian Ocean tsunami will be unaffected by Christmas.

Secondly, the effects of the Indian Ocean tsunami may be greater for individuals interviewed within a 1-2 month window of the disaster because the survey respondents are asked "for how many days during the past 30 days was your mental health not good". Hence, there may be a lag in the effect of the Indian Ocean tsunami on the number of days of poor mental health, see Kimball et al. (2006).

Thirdly, during February 2005, another event may have affected the number of days of poor mental health.[116] If this is the case, the common trends assumption may be violated, biasing the estimated effect of the Indian Ocean tsunami on the number of days of poor mental health. The empirical results from placebo tests of the plausibility of the common trends assumption are discussed in detail in Section 4.7.

Column (3) presents the findings for the Atlantic Ocean states. Under the previously stated assumptions, the Indian Ocean tsunami reduced the number of days of poor mental health of individuals interviewed from 1st to 28th February 2005. This effect is statistically significant at the 1% level. However, there is no effect of the Indian Ocean tsunami on the number of days of poor mental health of individuals interviewed within a month window of the disaster.

Column (4) contains the results for Pacific Ocean states, the US states closest to East Asia. Under the previously stated assumptions, the Indian Ocean tsunami reduced the number of days of poor mental health of individuals interviewed from 27th December 2004 to 31st January 2005. This effect is statistically significant at the 1% significance

[116] However, a search of an American news history website shows no evidence of any major world events in February 2005, see Infoplease (2005).

level and large in magnitude. In a similar fashion, under the previously stated assumptions, the Indian Ocean tsunami reduced the number of days of poor mental health of individuals interviewed in February 2005. This effect is statistically significant at the 1% significance level.

The estimation results displayed in Tables 4.9 and 4.10 suggest that the Indian Ocean tsunami led to the largest reduction in the number of days of poor mental health for individuals living in the Pacific Ocean states. Note that the Pacific Ocean states are those states within closest proximity to the East Asia. In the Pacific Ocean states (located in the South East of the US), the greatest reduction in the number of days of poor mental health occurred in a one month window of the disaster.

4.6.2 The Effects of Hurricane Katrina on Subjective Well-being

We investigate how Hurricane Katrina (on 23rd August 2005) affected the number of days of poor mental health of Americans interviewed from 24th August 2005 to 31st December 2005 (the period after the disaster - period d) presented in Figure 4.8) by estimating equation (A4.2), outlined in the Appendix.

The results displayed in column (1) of Table 4.11 cover all US states and indicate no statistically significant effect of Hurricane Katrina on the number of days of poor mental health of Americans interviewed from 24th August 2005 to 31st December 2005. To explore how the effect of Hurricane Katrina varied by proximity to the disaster area, we re-estimate equation (A4.2) using 3 subsamples of Sample 2: states that were directly affected by Hurricane Katrina; states that border the affected states; and the remaining unaffected states (see Figure 4.15). Interestingly, the findings presented in column (2) do not suggest that Hurricane Katrina affected the number of days of poor mental health of individuals living in affected states who were interviewed in the period after the disaster (24th August 2005 to 31st December 2005). This finding is inconsistent with the results of Rehdanz et al. (2015) who find an adverse effect of the Japanese tsunami and the Fukushima nuclear disaster on the happiness of individuals living in the affected areas. Table 4.11 shows no effect of Hurricane Katrina on the number of days of poor mental health of individuals living in the states that were unaffected by Hurricane Katrina.

The incremental effects are presented at the bottom of Table 4.11 and indicate the effect of Hurricane Katrina on the expected number of days of poor mental health. The findings for all US states (column (1)) suggest that Hurricane Katrina increased the expected number of days of poor mental health by 0.043 days. The findings presented in column (2) indicate that Hurricane Katrina increased the expected number of days of poor mental health by 0.32 days for individuals living in the affected states. The findings presented in column (3) indicate that Hurricane Katrina increased the expected number of days of poor mental health of individuals living in those states that border the affected states by 0.1 days. Finally, the findings for the remaining states indicate that Hurricane Katrina increased the expected number of days of poor mental health by approximately 0.0042 days. It is therefore evident that the adverse effects of Hurricane Katrina are more pronounced in the areas closest to the disaster and declined with proximity to the affected area.

We investigate whether the effects of Hurricane Katrina varied over time by splitting the individuals interviewed from 24th August 2005 to 31st December 2005 (the period after the disaster) into 4 groups. The groups are as follows: individuals interviewed from 24th August 2005 to 30th September 2005 (a 0-1 month window of the disaster), October 2005 (1-2 month window), November 2005 (2-3 month window), and December 2005 (3-4 month window).

Column (1) of Table 4.12 presents the findings relating to all US states. Under the previously stated assumptions, Hurricane Katrina increased the number of days of poor mental health of individuals interviewed from 24th August 2005 to 30th September 2005. This coefficient is large, approximately 20% of the magnitude of the unemployment coefficient and statistically significant at the 5% level. Thus, the findings presented in column (1) suggest that Hurricane Katrina increased the number of days of poor mental health of individuals interviewed within a month of the disaster. Furthermore, under the previously stated assumptions, the "inflate" model results suggest that Hurricane Katrina reduced the likelihood that individuals interviewed 1-2 months after the disaster reported 0 days of poor mental health. However, column (1) shows no evidence to suggest that Hurricane Katrina affected the number of days of poor mental health of individuals interviewed 2-3 months or 3-4 months after the disaster.

Column (2) displays the results for the states that were directly affected by Hurricane Katrina. The findings show no statistically significant effect of Hurricane Katrina on the number of days of poor mental health of individuals interviewed from 24th August 2005 to 30th September 2005, in November 2005, or in December 2005. The empirical evidence in column (2) suggests that Hurricane Katrina increased the number of days of poor mental health of individuals interviewed in October 2005. The evidence suggests that Hurricane Katrina increased the number of days of poor mental health of individuals interviewed in a 1-2 month window of the disaster. However, the findings show no evidence to suggest that the disaster affected the number of days of poor mental health of individuals interviewed within a month window of the disaster. There are a number of explanations for this.

Firstly, in the states that were directly affected by Hurricane Katrina, the sampling of the BRFSS may have been disrupted during the months following the disaster, thus leading to a violation of the assumption of the exogeneity of the date of interview. This assumption may be violated if disruptions due to Hurricane Katrina caused an under-sampling of individuals in the areas that were worst affected by the disaster. Email correspondence with BRFSS state coordinators suggests that BRFSS sampling was disrupted in the six coastal counties of Mississippi for a month following Hurricane Katrina because of cuts to electricity and telephone services. In contrast, telephone and electricity services in Texas and Florida were not affected.[117] If individuals living in the coastal counties of Mississippi were more adversely affected by the disaster than individuals living in non-coastal counties, this may cause the effects of Hurricane Katrina to be biased towards zero, underestimating the psychological harm caused by the disaster.

Secondly, the survey respondents are asked about their number of days of poor mental health during the past 30 days. As a result, there may be a delay in the effect of Hurricane Katrina on the number of days of poor mental health. Thirdly, Hurricane Katrina had a detrimental effect on physical health in the disaster areas due to damage to housing, electricity and water supplies, and shortages of healthcare services, see Rhodes et al. (2010). Accordingly, in the immediate aftermath of Hurricane Katrina, physical health may have been more of a concern in the disaster areas, rather than mental health.

Finally, the effect of Hurricane Katrina may be more pronounced a month after the disaster than in the immediate aftermath because Hurricane Rita struck the states of Texas, Louisiana, Alabama, and Florida on 23rd September 2005, a month after Hurricane Katrina. Hurricane Rita, though less damaging than Hurricane Katrina, may have exacerbated the damage already caused by Hurricane Katrina, thus leading to a greater reduction in the number of days of poor mental health.

Column (3) reveals the results for individuals living in the states that border the states that were directly affected. Under the previously stated assumptions, the empirical results suggest that Hurricane Katrina increased the number of days of poor mental health of individuals interviewed within a 1 month window of the disaster. However, this finding is statistically significant at the 10%, but not the 5%, level. The findings suggest that Hurricane Katrina had no effect on the number of days of poor mental health of individuals interviewed 2-3 or 3-4 months after the disaster.

The results presented in column (4) show no evidence to suggest that Hurricane Katrina affected the number of days of poor mental health of individuals living in the remaining states (i.e. states that were not affected and do not border the affected states). This indicates that Hurricane Katrina did not affect the SWB of those Americans who lived furthest from the disaster area.

The findings presented in the previous section suggest that the Indian Ocean tsunami had a positive effect on the SWB of Americans who lived closest to the areas that were directly affected by the disaster. In contrast, the results relating to Hurricane Katrina suggest that natural disasters may have an adverse effect on the SWB of Americans

[117] There was no response received from email correspondence with the BRFSS state coordinators for Alabama, Georgia, and Louisiana.

living in the areas that were directly affected by the disaster. To further investigate how natural disasters affect the SWB of people who live far from the areas that were directly affected, we will now explore the effects of the Haiti earthquake on the SWB of Americans.

4.6.3 The Effects of the Haiti Earthquake on Subjective Well-being

We estimate equation (A4.3) to investigate the effects of the Haiti earthquake (on 12th January 2010) on the number of days of poor mental health of individuals interviewed from 13th January 2010 to 31st March 2010 (the period after the disaster - period d) presented in Figure 4.9).

Column (1) of Table 4.13 demonstrates the findings relating to all US states. Under the assumptions that were previously discussed, the Haiti earthquake reduced the number of days of poor mental health of individuals interviewed from 13th January 2010 to 31st March 2010. This effect is statistically significant at the 5% level. This suggests that the Haiti earthquake increased the SWB of Americans who were interviewed in a 2 month window of the disaster.

We split Sample 3 into 4 subsamples to explore how the effects of the earthquake varied by geographical proximity to the disaster area. These subsamples are states that are 951-1,501, 1,502-1,825, 1,826-2,552, and 2,553-5,368 miles from Haiti. These ranges are (approximate) quartiles and are calculated using geodesic (i.e. "as the crow flies") distances from Haiti, see Google (2015). Figure 4.16 illustrates the location of these groups of states.

The findings for individuals who were living in the states that are closest to Haiti may be seen in column (2) of Table 4.13. Under the previously stated assumptions, the results suggest that the Haiti earthquake reduced the number of days of poor mental health of individuals interviewed in the period after the disaster (13th January 2010 to 31st March 2010). This effect is statistically significant at the 5% level and sizeable, approximately 30% of the magnitude of the unemployment coefficient. The findings presented in columns (3) to (5) indicate no statistically significant effect of the Haiti earthquake on the number of days of poor mental health of Americans living more than 1,502 miles from Haiti.

Whether the effects of the Haiti earthquake dissipated or heightened over time is also investigated. To do so, we split individuals interviewed from 13th January 2010 to 31st March 2010 (the period after the disaster) into 2 groups: individuals interviewed from 13th January 2010 to 28th February 2010 and individuals interviewed in March 2010. Column (1) of Table 4.14 displays the findings for all US states. Under the previously stated assumptions, the Haiti earthquake reduced the number of days of poor mental health of individuals interviewed from 13th January to 28th February 2010. In contrast, the results indicate no effect of the Haiti earthquake on the number of days of poor mental health of individuals interviewed in March 2010.

Column (2) presents the estimation results for individuals living in the states located 951 to 1,501 miles from Haiti (the states that are closest to Haiti). Under the previously stated assumptions, the Haiti earthquake reduced the number of days of poor mental health of individuals interviewed from 13th January 2010 to 28th February 2010. This effect is large in magnitude, over 40% of the magnitude of the unemployment coefficient, and statistically significant at the 1% level. Thus, the empirical results suggest that the Haiti earthquake reduced the number of days of poor mental health of individuals interviewed within approximately a month and a half window of the earthquake. In contrast, the results show no effect of the Haiti earthquake on the number of days of poor mental health of individuals interviewed from 1st to 31st March 2010. The findings also indicate no effect of the disaster on individuals who were living in the states that are more than 1,502 miles from Haiti (see columns (3) to (5)).

The incremental effects presented at the bottom of Table 4.13 allow a quantitative interpretation of the effects of the Haiti earthquake. The findings for all US states indicate that the Haiti earthquake reduced the expected number of days of poor mental health by 0.093 days. Additionally, the incremental effects presented in column (2) for the US states closest to Haiti suggest that the Haiti earthquake reduce the number of days of poor mental health in these states by 0.11 days. The effects for the states that are further from Haiti are also negative and statistically significant, though they are smaller in magnitude (in common with the findings for the Indian Ocean tsunami).

The results presented in the previous subsection indicate that Hurricane Katrina had an adverse effect on the SWB of individuals who live in the states that were directly affected. In contrast to the findings relating to Hurricane Katrina, the findings presented in this subsection suggest that the Haiti earthquake had a positive effect on the SWB of Americans living in the states closest to the area that was directly affected by the disaster.

4.7 Validity Check 1: Placebo Tests for Common Trends

The evidence presented in Tables 4.9 to 4.14 supports the case that the effects of the natural disasters on SWB were most pronounced for individuals living within closest proximity to the disaster areas. However, causal inference using the difference-in-difference approach relies on the assumption of common trends, see Lechner (2010). The common trends assumption states that in the absence of the disaster, the difference in the number of days of poor mental health between the pre disaster (control) and post disaster (treatment) groups would have been the same in the 12 month period of the disaster as the 12 month period before the disaster[118]. This section makes use of placebo tests to test whether the number of days of poor mental health followed a common trend before the disasters.[119]

4.7.1 Placebo Tests for Common Trends Prior to the Indian Ocean Tsunami

To test for common trends prior to the Indian Ocean tsunami we estimate equation (A4.4) outlined in Appendix 2. Equation (A4.4) estimates the effect of a 'pretend' natural disaster on the 26th December 2002 (two years before the Indian Ocean tsunami) on the number of days of poor mental health of individuals interviewed from 27th December 2002 to 28th February 2003. The analysis contained in columns (1) and (2) of Table 4.15 shows no statistically significant effect of the 'pretend' natural disaster on the number of days of poor mental health of individuals living in all US states and Pacific Ocean states (the US states that are closest to East Asia). Thus, the placebo tests suggest that the number of days of poor mental health followed a common trend pre and post 26th December prior to the Indian Ocean tsunami.

4.7.2 Placebo Tests for Common Trends Prior to Hurricane Katrina

We estimate equation (A4.5) in Appendix 2 to test for common trends prior to Hurricane Katrina.[120] Equation (A4.5) estimates the effect of a 'pretend' Hurricane Katrina on 23rd August 2003 (two years in advance of Hurricane Katrina) on the number of days of poor mental health of individuals interviewed from 24th August 2003 to 31st December 2003. Column (1) of Table 4.16 illustrates the findings for all US states. The negative binomial and "inflate" models indicate no significant effect of the 'pretend' natural disaster on the number of days of poor mental health. Similarly, column (2) shows no statistically significant effect of a 'pretend' natural disaster on the number of days of poor mental health of individuals living in the states that were directly affected by Hurricane Katrina. Hence, the empirical results displayed in Table 4.16 suggest that the number of days of poor mental health followed a common trend in the periods prior to Hurricane Katrina.

[118] As previously discussed, common trends are assumed in the exponential of the expected number of days of poor mental health. However, for brevity, in the remainder of this chapter we will refer to the assumption of common trends in the number of days of poor mental health, rather than common trends in the exponential.

[119] The results of placebo experiments are not presented for individuals who were living in the states that are not in close proximity to the disaster areas because the analysis of Tables 4.9 to 4.14 suggests that the effects of the disasters were less pronounced in these areas.

[120] As previously discussed in Section 3.4, the number of days of poor mental health variable has a large number of missing values in 2002, thus reducing the available sample size to 32,719. For this reason, we test whether the SWB of the pre and post disaster groups followed a common trend using data from 2001 and 2003.

4.7.3 Placebo Tests for Common Trends Prior to the Haiti Earthquake

Equation (A4.6) in Appendix 2 is used to estimate the effect of a 'pretend' natural disaster on 12th January 2008 (two years prior to the Haiti earthquake) on the number of days of poor mental health of individuals from 13th January 2008 to 31st March 2008. Column (1) of Table 4.17 displays the results for all US states. The empirical evidence shows no statistically significant effect of the 'pretend' natural disaster on the number of days of poor mental health of individuals interviewed from 13th January 2008 to 31st March 2008. Column (2) reveals the findings for the US states that are closest to Haiti (states located 951-1,501 miles from Haiti). In common with column (1), column (2) shows no statistically significant effect of the 'pretend' natural disaster on the number of days of poor mental health of individuals interviewed from 13th January 2008 to 31st March 2008. Hence, the analysis supports the case that the number of days of poor mental health in the periods prior to the Haiti earthquake.

The evidence in Tables 4.15 to 4.17 suggests that the number of days of poor mental health followed a common trend before the disasters, thus supporting a causal interpretation of the findings.

4.8 Robustness Check 1: The Effects of the Disasters by Ethnicity

Sections 4.6 and 4.7 suggest that the Indian Ocean tsunami and the Haiti earthquake increased the SWB of Americans who were living in the states closest to the disaster areas. The Indian Ocean tsunami and the Haiti earthquake attracted substantial media coverage globally (see Section 4.3 for further details). Thus, one possible explanation is that Americans viewed the media coverage of the disasters, and compared their lives to the lives of the disaster victims, thereby increasing their SWB. Note that the effects of the Indian Ocean tsunami and the Haiti earthquake were less pronounced for Americans who did not live within the closest proximity to the disaster areas. This may suggest that natural disasters in other countries may lead individuals living closest to the disaster areas to compare themselves favourably to the disaster victims, thus increasing their SWB. In contrast, individuals who do not live close to the disaster area may not compare themselves to the disaster victims, leading their SWB to be unaffected. One explanation for this finding is that following natural disasters in other countries, an individual's reference group may be defined by geographical proximity. In other words, people living in the states that are closest to the disasters may feel lucky to have missed being affected by the disaster, whereas people who live further away may not feel this.

As previously discussed in Section 4.2.5, Brown et al. (2015) suggest that the effects of relative income comparisons on SWB are highly sensitive to the definition of the reference group used. The authors suggest that the conclusions regarding the effects of relative income on SWB depend on whether the reference group is defined by individual characteristics ("*people like you*" in terms of gender, age, and education) or defined by geographical proximity ("*people near you*"). For this reason, it may be argued that natural disasters in other countries may affect an individual’s SWB if the individual shares similar characteristics to the disaster victims, rather than if individuals live close to the disaster area. To explore this possibility further, the following analysis will investigate whether the effects of the Indian Ocean tsunami and the Haiti earthquake on SWB were most pronounced for individuals of the same ethnicity as the disaster victims.

Ethnicity has been chosen as the potential reference group partly because the majority of the victims of the Indian Ocean tsunami and the Haiti earthquake were Asian and Black, respectively. Data from the United Nations Office for the Coordination of Humanitarian Affairs (2005) shows that the Indian Ocean tsunami caused approximately 157,000 (153) casualties in Asia (Africa). A substantial majority of those killed by the Indian Ocean tsunami were Asian; but of all ages, levels of education, and genders. The Haiti earthquake killed relatively few foreigners including just 24

Americans, see the US Department of State (2010).[121] In addition, data from the Central Intelligence Agency (2015) suggests that 95% of the population of Haiti is Black. Hence, it is likely that the vast majority of the victims of the Haiti earthquake were Black.

Using a sample of 6,151 individuals from the Study of the Tsunami Aftermath and Recovery dataset, Frankenberg et al. (2011) investigate the predictors of mortality due to the Indian Ocean tsunami in Northern Sumatra, Indonesia. They suggest that socioeconomic status prior to the Indian Ocean tsunami had a small effect on the probability of mortality due to the disaster. They also show that females living in Northern Sumatra had a mortality risk due to the Indian Ocean tsunami of 31.1%, 7.6% points higher than men. Individuals aged 15-44 were found to have a probability of mortality due to the Indian Ocean tsunami of 24%, 10% points lower than individuals aged 45 or older.

Doocy et al. (2013) offer empirical evidence to suggest that in Port-au-Prince, educational attainment and gender had no statistically significant effect on the risk of mortality due to the Haiti earthquake. In addition, they show that individuals aged 18-49 had a probability of being killed by the Haiti earthquake of 2.49%, 1.4% points lower than individuals aged 50 years or older.

The empirical evidence of Frankenberg et al. (2011) and Doocy et al. (2013) suggests that the Indian Ocean tsunami and the Haiti earthquake killed individuals of all ages, levels of educational attainment, and genders but not a variety of ethnicities.[122] For this reason, the following analysis will explore whether the effects of the Indian Ocean tsunami and the Haiti earthquake were more pronounced for individuals of the same ethnicity as the disaster victims.

4.8.1 The Effects of the Indian Ocean Tsunami by Ethnicity

Table 4.18 illustrates the results from estimating the effects of the Indian Ocean tsunami on the number of days of poor mental health using equation (A4.1), revealed in Appendix 2. The findings displayed in columns (3) to (5) show no statistically significant effect of the Indian Ocean tsunami on the number of days of poor mental health of Asians, Hawaiians or Pacific Islanders, or American Indians and Alaskan natives living in the US states surveyed. In comparison, the Indian Ocean tsunami had statistically significant effects on the SWB of Whites and Blacks. Thus, these results support the case that it may be geographical proximity to the disaster area, rather than sharing similar characteristics to the disaster victims, that determines the effect of natural disasters on SWB outside of the disaster country.

[121] Note that there are no official figures showing the total foreign death toll from the Haiti earthquake because the death tolls for each country are collected by their individual embassies.
[122] Individuals may compare themselves to the disaster victims on the basis of having a shared religious affiliation. However, it is not possible to investigate this hypothesis because the BRFSS contains no data detailing an individual's religion.

4.8.2 The Effects of Hurricane Katrina by Ethnicity

Following Hurricane Katrina, Blacks were more likely to lose their job, suffered more property damage, and were less likely to evacuate from the disaster area (see Section 4.3.2). For this reason, we investigate whether the effects of Hurricane Katrina on the number of days of poor mental health were more pronounced for Blacks by estimating equation (A4.2), outlined in Appendix 2, by ethnicity. For each of the ethnicities, the empirical evidence revealed in Table 4.19 shows no statistically significant effects of Hurricane Katrina on the number of days of poor mental health of individuals interviewed in a 4 month window of the disaster. The estimation results found in Table 4.19 control for an individual's household income category and labour market status. As previously discussed, Hurricane Katrina had a particularly detrimental effect on the employment prospects of Blacks. Accordingly, by controlling for household income and labour market status, we may underestimate the effect of Hurricane Katrina on the number of days of poor mental health of Blacks.[123]

4.8.3 The Effects of the Haiti Earthquake by Ethnicity

Finally, we investigate whether the effects of the Haiti earthquake varied by ethnicity by estimating equation (A4.3) in Appendix 2. As previously argued, if natural disasters lead Americans to compare their lives to the lives of disaster victims with similar characteristics to them, the effect of the Haiti earthquake may be more pronounced for Blacks. The findings displayed in columns (1) to (5) of Table 4.20 show no statistically significant effect of the Haiti earthquake on the number of days of poor mental health for each of the ethnicities.

The results presented in Tables 4.18 and 4.20 do not suggest that the effects of the Indian Ocean tsunami and the Haiti earthquake were more pronounced for individuals of the same ethnicity as the disaster victims. Hence, this analysis suggests that it may be geographical proximity to the disaster area, rather than sharing similar individual characteristics to the disaster victims, which determines the effects of natural disasters on SWB outside of the disaster country.

[123] However, re-estimating the models after removing the household income and labour market status variables does not increase the magnitude of the effects of Hurricane Katrina on the employment prospects of Blacks. Thus, the findings do not support this hypothesis.

4.9 Conclusion

This chapter explored the effects of the Indian Ocean tsunami, Hurricane Katrina and the Haiti earthquake on the SWB of Americans. In addition, it investigated whether the effects of the natural disasters were dependent upon geographical proximity to the disaster area. This hypothesis was supported, in contrast to any dependence of the effects on being of the same ethnicity as the disaster victims, where no evidence was found.

The results suggest that Hurricane Katrina had an adverse effect on the SWB of individuals who were living in the states that were directly affected by the disaster. This effect was found to be approximately 80% of the magnitude of the effect of the unemployment coefficient, a large effect. The findings correspond with those of Rehdanz et al. (2015) who suggest that the Japanese tsunami and the Fukushima nuclear disaster reduced the SWB of individuals living in close proximity to Fukushima. Hence, the analysis of this chapter supports the case for government intervention in the aftermath of disasters to alleviate the adverse effects of disasters on the SWB of people who live in the directly affected areas. For instance, where appropriate, mental health services and counselling could be offered to people suffering distress or unhappiness in the wake of natural disasters.

The empirical evidence suggests that the Indian Ocean tsunami had a positive effect on the SWB of Americans living in the Pacific Ocean states, the states closest to East Asia. The effect was found to be large in magnitude, approximately 80% of the absolute magnitude of the coefficient of the unemployment variable. Similarly, the analysis suggests that the Haiti earthquake increased the SWB of individuals living in the US states that are closest to Haiti. In common with the effects of the Indian Ocean tsunami, the effects of the Haiti earthquake were found to be large, roughly 40% of the absolute magnitude of the unemployed coefficient. Thus, the evidence suggests that the two natural disasters that did not occur in the US (the Indian Ocean tsunami and the Haiti earthquake) increased the SWB of Americans living in closest proximity to the disaster area.

The finding that the Indian Ocean tsunami and the Haiti earthquake increased the SWB of Americans who were living in the states closest to the affected areas may reflect Americans comparing themselves to the disaster victims. The Indian Ocean tsunami and the Haiti earthquake led to a large amount of media coverage, social media usage, and Google searching with respect to the disasters (see Section 4.3). As a result, in the immediate aftermath of the disasters, Americans may have reflected on the devastating effects of the disasters on the lives of the disaster victims. Consequently, Americans living closest to the affected areas may have compared themselves to the disaster victims, leading them to feel thankful that they were not affected by the disaster, thus increasing their SWB.

Disasters such as the Indian Ocean tsunami and the Haiti earthquake were unanticipated negative shocks to people living in the disaster areas, see Rehdanz et al. (2015). Economic models typically assume that an individual's utility is unaffected by the utility of strangers. In contrast with this view, the analysis illustrates that utility shocks such as natural disasters in one country may affect the utility of strangers farther afield. For this reason, the findings challenge the assumption of independent utility functions in this regard, suggesting that strangers may have interdependent utility.

To explore whether the effects of the Indian Ocean tsunami and the Haiti earthquake were greater for individuals with similar characteristics to the disaster victims, the effects of the disasters were estimated by ethnicity. There was no evidence to suggest that the effects of the Indian Ocean tsunami and the Haiti earthquake were more pronounced for individuals of the same ethnicity as the disaster victims. This supports the case that it may be geographical proximity to the disaster area that determines the effect of natural disasters on SWB outside of the disaster country, rather than sharing similar characteristics to the disaster victims. Hence, the empirical analysis suggests that an individual's reference group may extend beyond their peers and neighbours to individuals living much farther afield.

The findings suggest that the Indian Ocean tsunami and the Haiti earthquake had a positive effect on the SWB of Americans who were living in the states closest to the affected areas. In contrast, the analysis suggests that Hurricane Katrina did not affect the SWB of individuals who were living in the states closest to the states that were directly affected. There are a number of explanations for this. Firstly, Hurricane Katrina occurred in the US whilst the Indian Ocean tsunami and the Haiti earthquake did not occur in the US. Arguably, therefore Hurricane Katrina may affect the SWB of Americans via different channels to the Indian Ocean tsunami and the Haiti earthquake.

Secondly, natural disasters in nearby areas may have 2 opposing effects on SWB. Natural disasters may lead individuals who live close to the affected areas to compare themselves favourably to the disaster victims, leading them to feel grateful that they were unaffected, thus increasing their SWB. Natural disasters in nearby areas may also lead to feelings of worry and distress because family members and friends may be directly affected by the disaster, see Rehdanz et al. (2015).

Hurricane Katrina killed approximately 1,800 Americans and may therefore have caused worry and distress in the states close to the disaster area. In comparison to Hurricane Katrina, the Indian Ocean tsunami and the Haiti earthquake killed relatively few Americans. For instance, Telford et al. (2006) estimate that the Indian Ocean tsunami killed approximately 18 Americans, and, the US Department of State (2010) estimates that the Haiti earthquake killed just 24 Americans. As a result, the Indian Ocean tsunami and the Haiti earthquake are unlikely to cause worry and distress for

Americans living closest to the disaster area. Hurricane Katrina may have had no statistically significant effect on the SWB of individuals who were living in the states close to the disaster area because the effects of worry and distress about whether friends and family were affected may have offset the effects of interpersonal comparison. In contrast, the Indian Ocean tsunami and the Haiti earthquake may have increased the SWB of Americans living in the states closest to the disaster area because the effects of comparison may have outweighed the effects of fear and worry regarding the safety of family and friends.

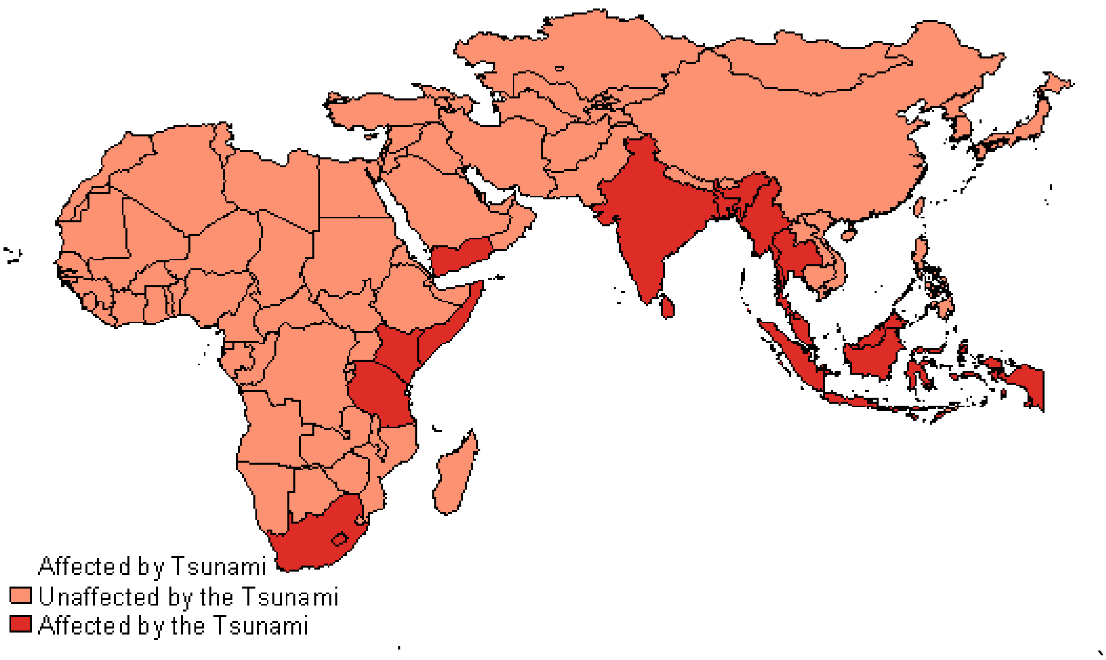
However, note that the analysis used a difference-in-difference approach and therefore relies on the assumption of common trends. As a result, arguably one shortcoming is that the assumption of common trends may not hold if another event affected the SWB of individuals interviewed after the natural disasters. Nevertheless, in comparison to Kimball et al. (2006) and Zahran et al. (2011) who do not test for common trends, we show that SWB followed a common seasonal trend prior to the disasters, therefore supporting a causal interpretation of the findings.

The analysis of this chapter investigated the effects of natural disasters on the SWB of people who live outside the disaster area, i.e. how "*what happens to others*" may affect your own SWB. We presented some early evidence to suggest that the SWB of individuals living in a country may be affected by natural disasters farther afield. Economic analysis typically assumes that the utility functions of strangers are independent and therefore that utility is unaffected by that of individuals living in other continents. In conflict with this assumption, our analysis suggests that utility shocks in one country may affect the utility of strangers living in others. For this reason, the findings suggest that in this regard, the utility functions of strangers may be interdependent, rather than independent.

Future research in this area could investigate the sensitivity of our findings to the institutional context of the area where an individual lives. For instance, by exploring how the SWB of people who live in developing countries is affected by natural disasters farther afield.

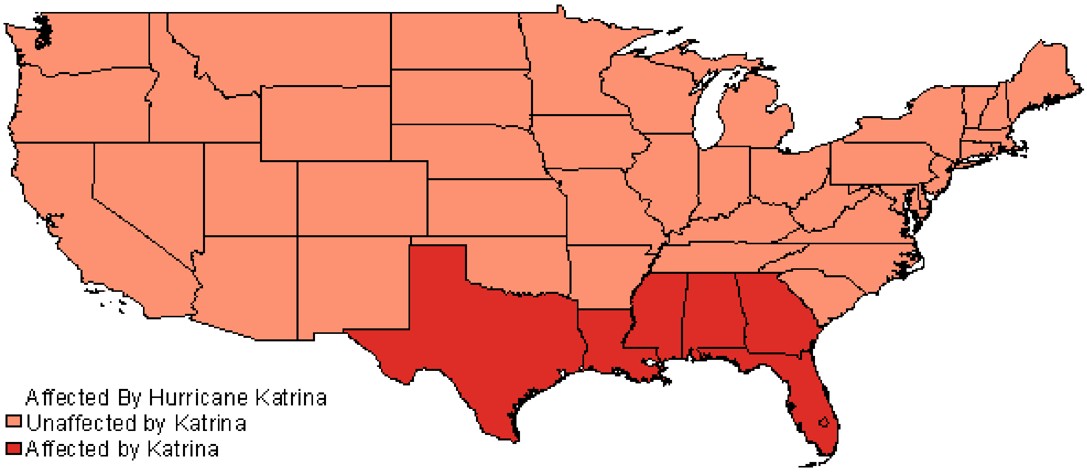
4.10 A4: Appendix 1: Figures and Tables

Figure 4.1: A Map of the Countries Affected by the Indian Ocean Tsunami



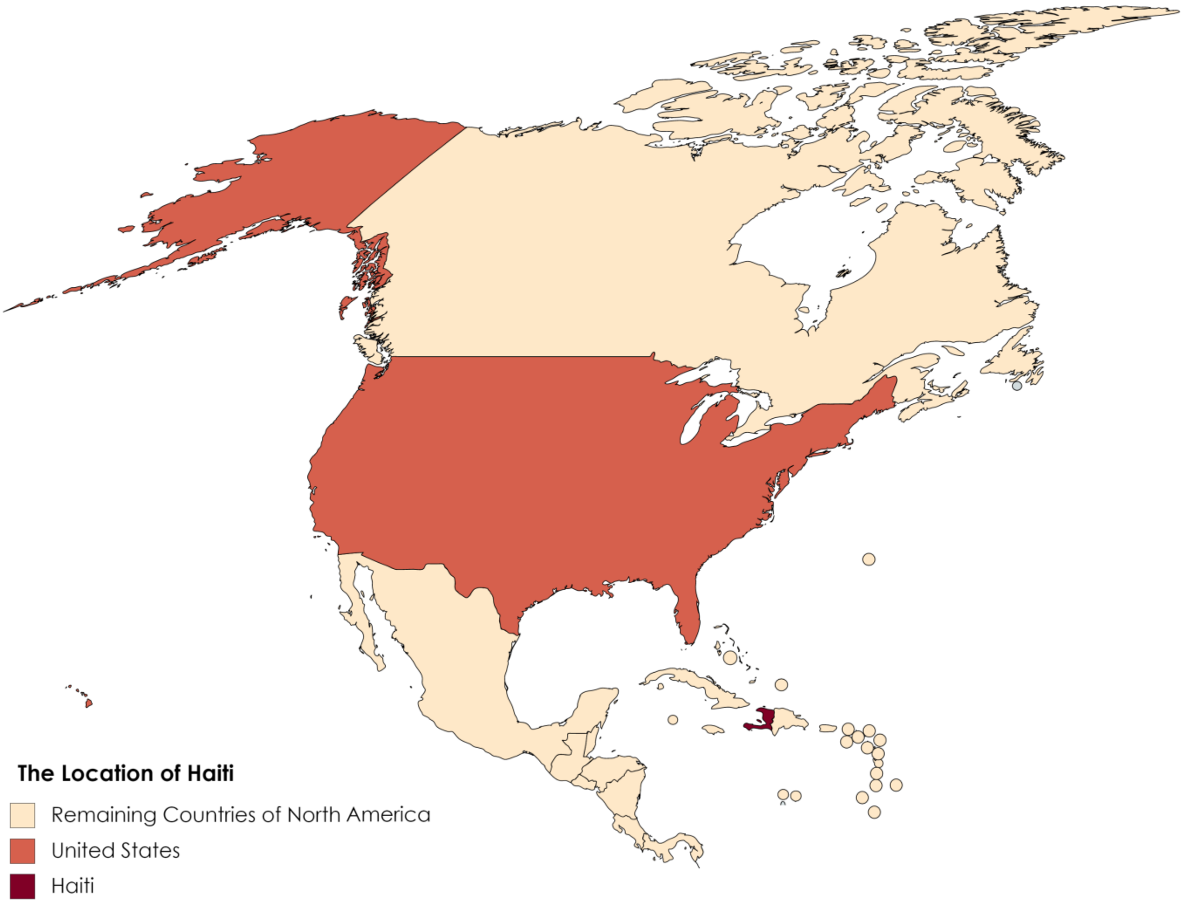
The Indian Ocean tsunami affected the countries of Indonesia, Sri Lanka, India, Thailand, Somalia, Myanmar, Maldives, Malaysia, Tanzania, Seychelles, Bangladesh, South Africa, Yemen, and Kenya.

Figure 4.2: A Map of the US States Affected by Hurricane Katrina



Note: For presentational purposes Alaska and Hawaii are excluded from Figure 3. Alaska and Hawaii were unaffected by Hurricane Katrina. Hurricane Katrina affected the US states of Alabama, Florida, Georgia, Louisiana, Mississippi, and Texas. The states unaffected by Hurricane Katrina are Arkansas, New Mexico, North Carolina, Oklahoma, South Carolina, Tennessee, Alaska, Arizona, California, Colorado, Connecticut, Delaware, Hawaii, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Maine, Maryland, Massachusetts, Michigan, Minnesota, Missouri, Montana, Nebraska, Nevada, New Hampshire, New Jersey, New York, North Dakota, Ohio, Oregon, Pennsylvania, Rhode Island, South Dakota, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin, and Wyoming.

Figure 4.3: A Map of North America showing the Location of Haiti and the United States



Source: Mapchart.net

Figure 4.4: The Distribution of the Number of Days of Poor Mental Health in Sample 1

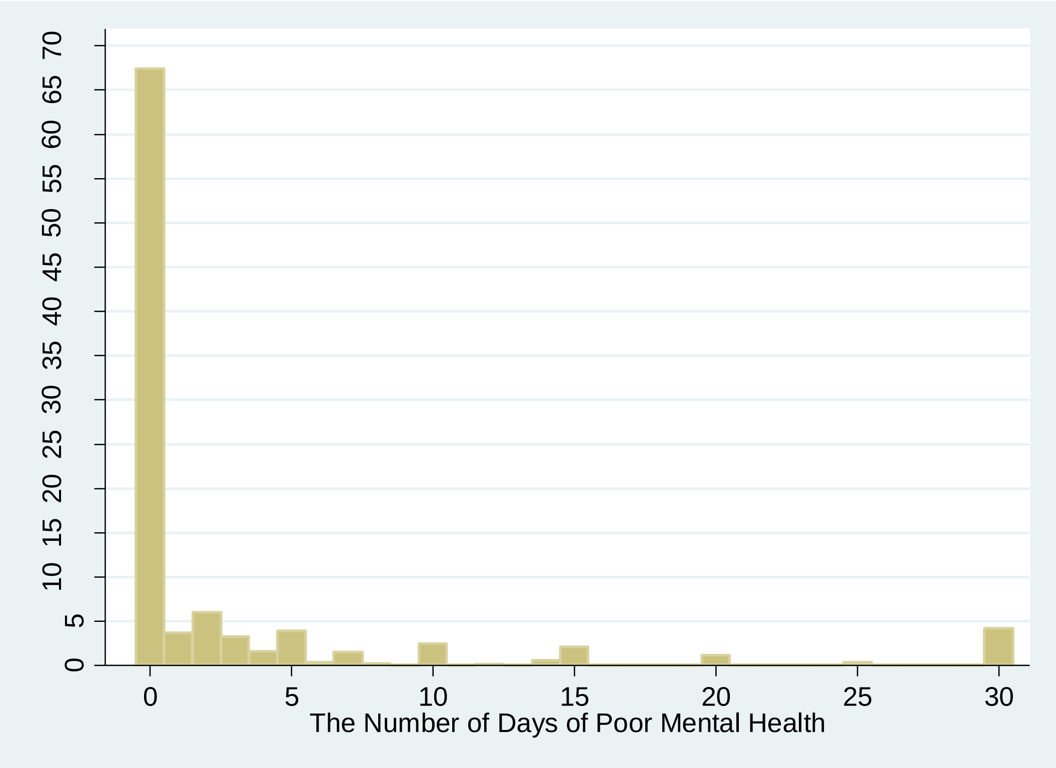


Figure 4.5: The Distribution of the Number of Days of Poor Mental Health in Sample 2

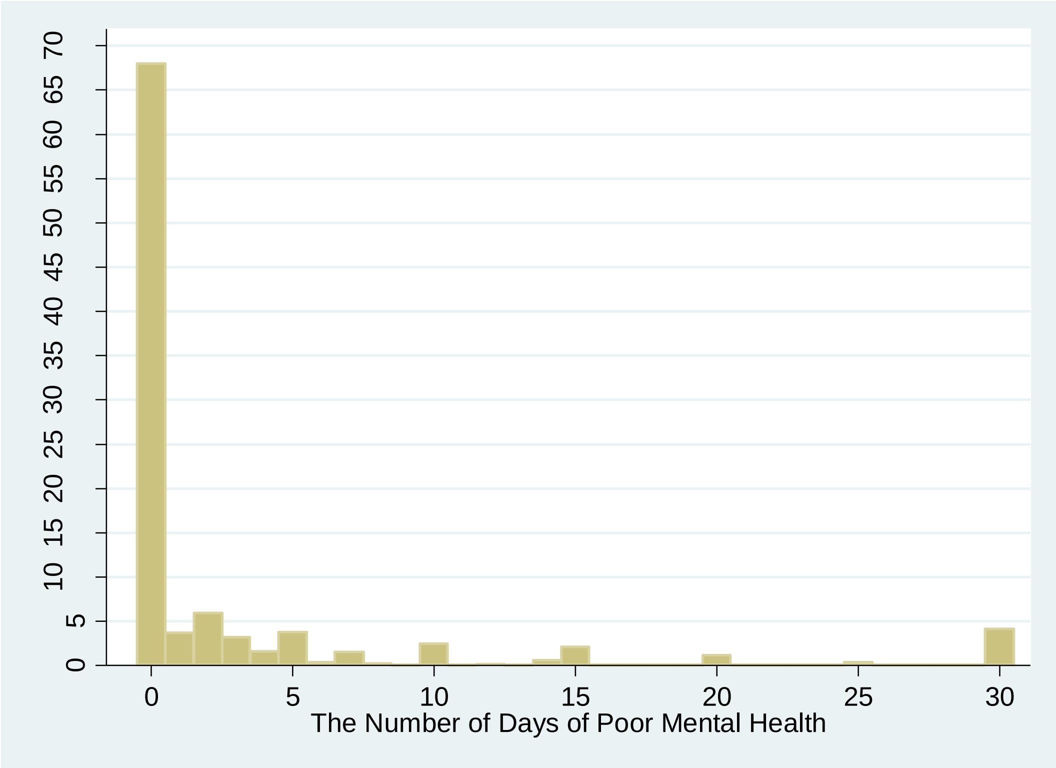


Figure 4.6: The Distribution of the Number of Days of Poor Mental Health in Sample 3

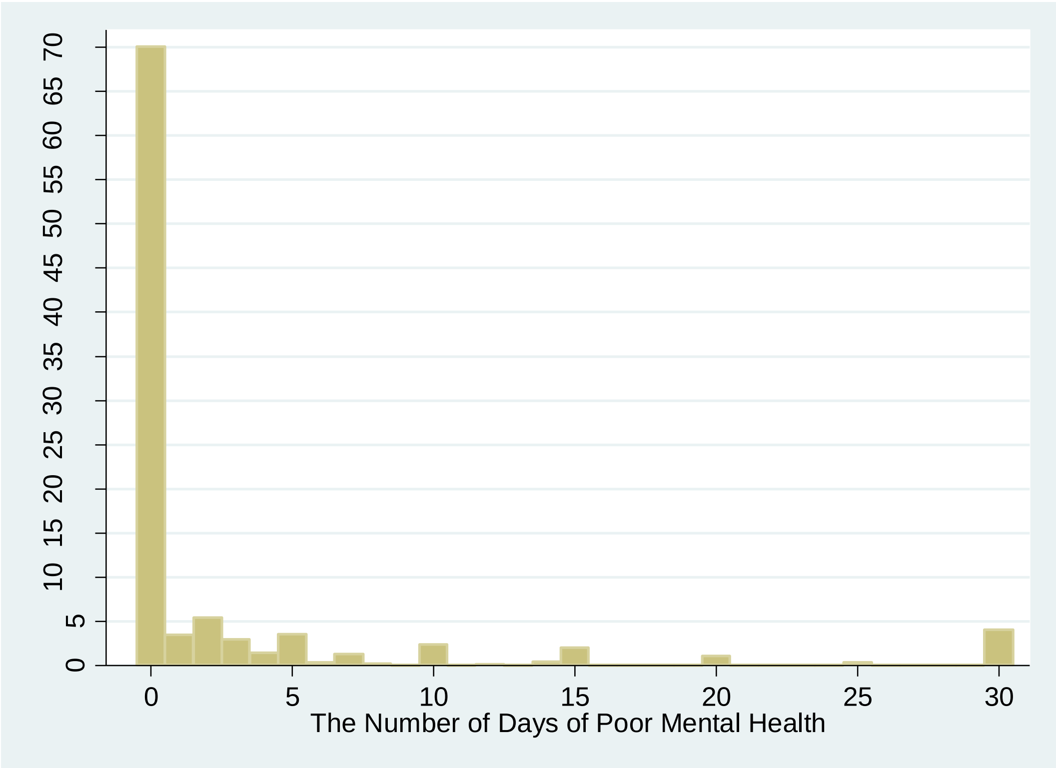


Figure 4.7: Timeline Indicating the Periods Relating to the Indian Ocean Tsunami

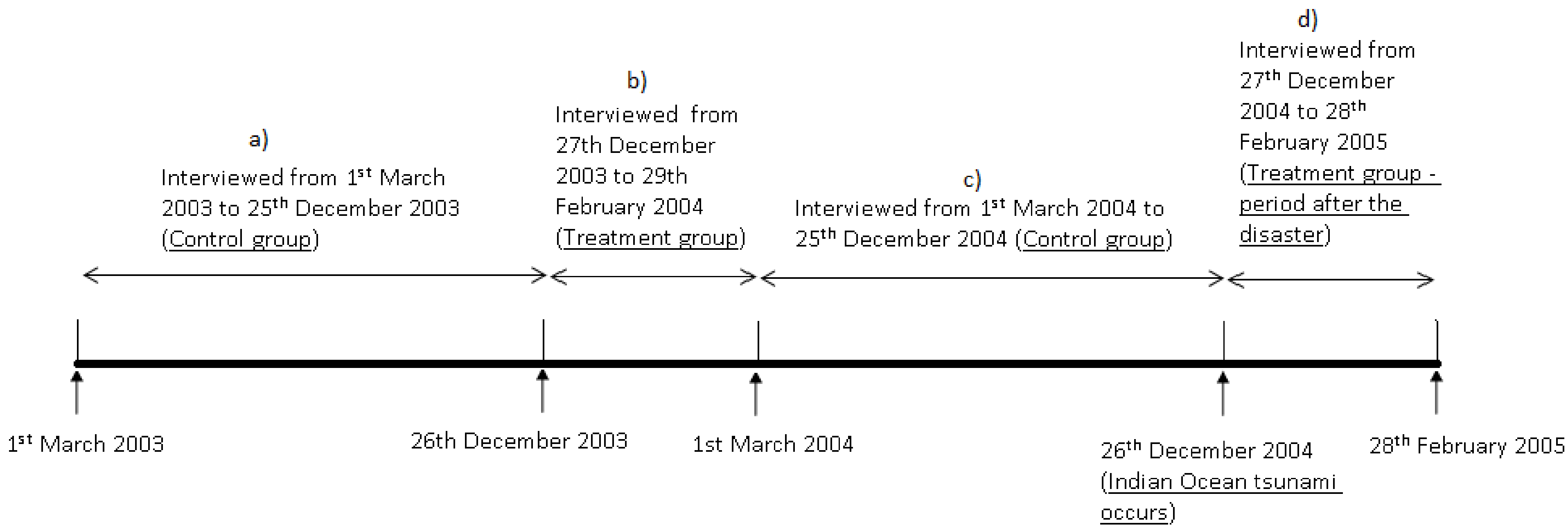


Figure 4.8: Timeline Indicating the Periods Relating to Hurricane Katrina

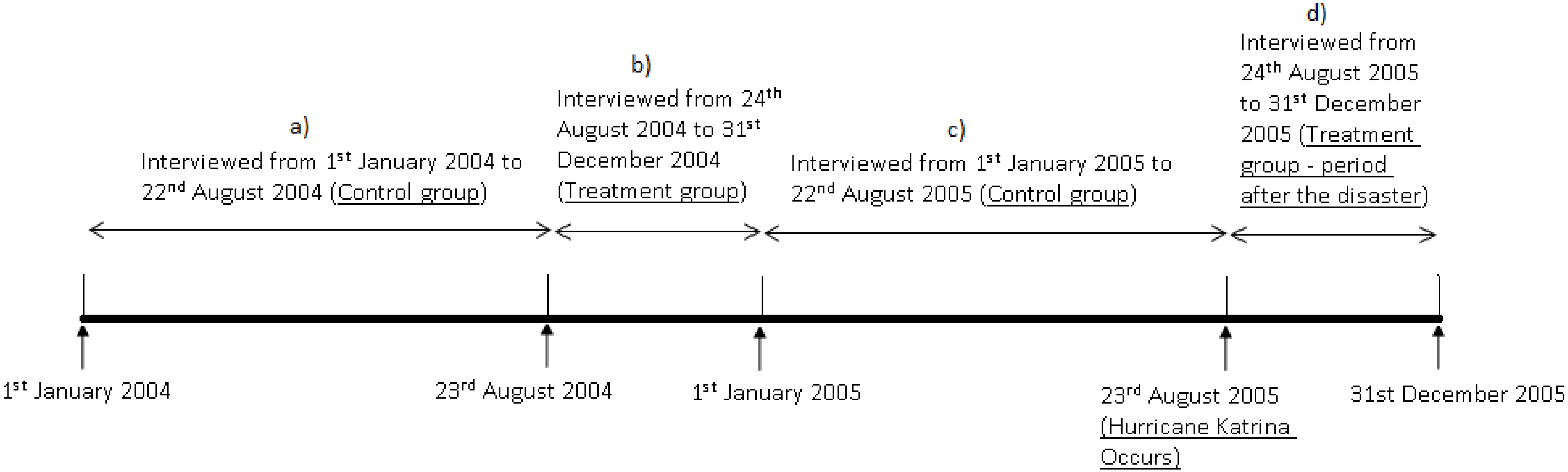


Figure 4.9: Timeline Indicating the Periods Relating to the Haiti Earthquake

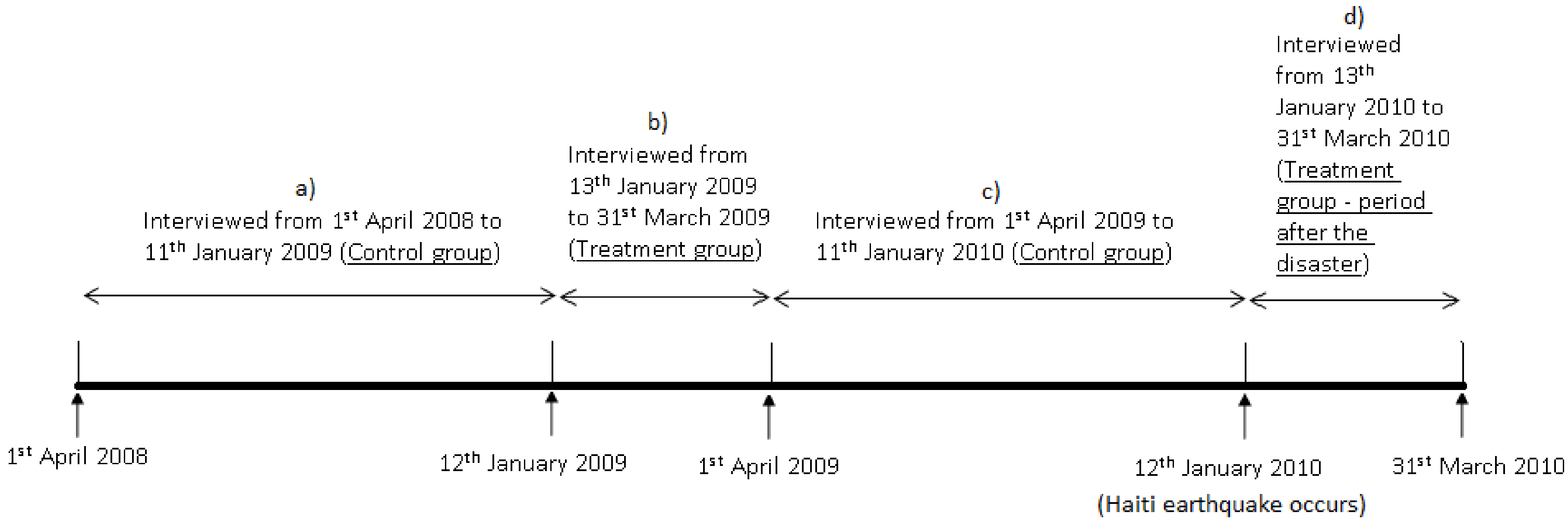


Figure 4.10: Common Trends Diagram

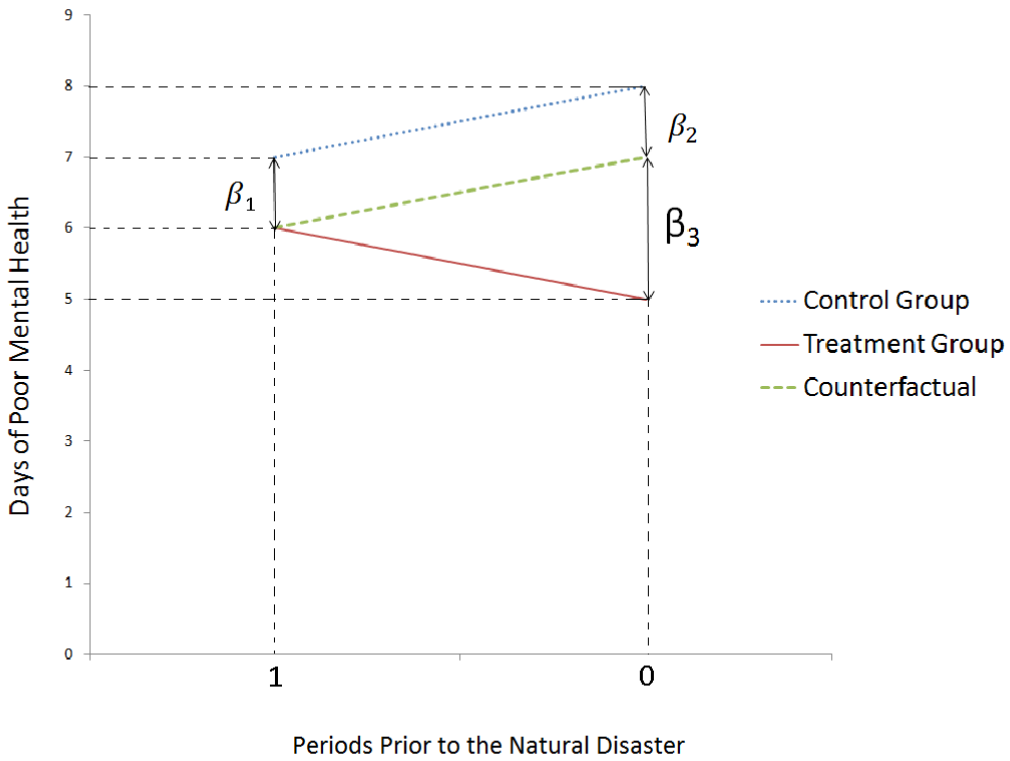
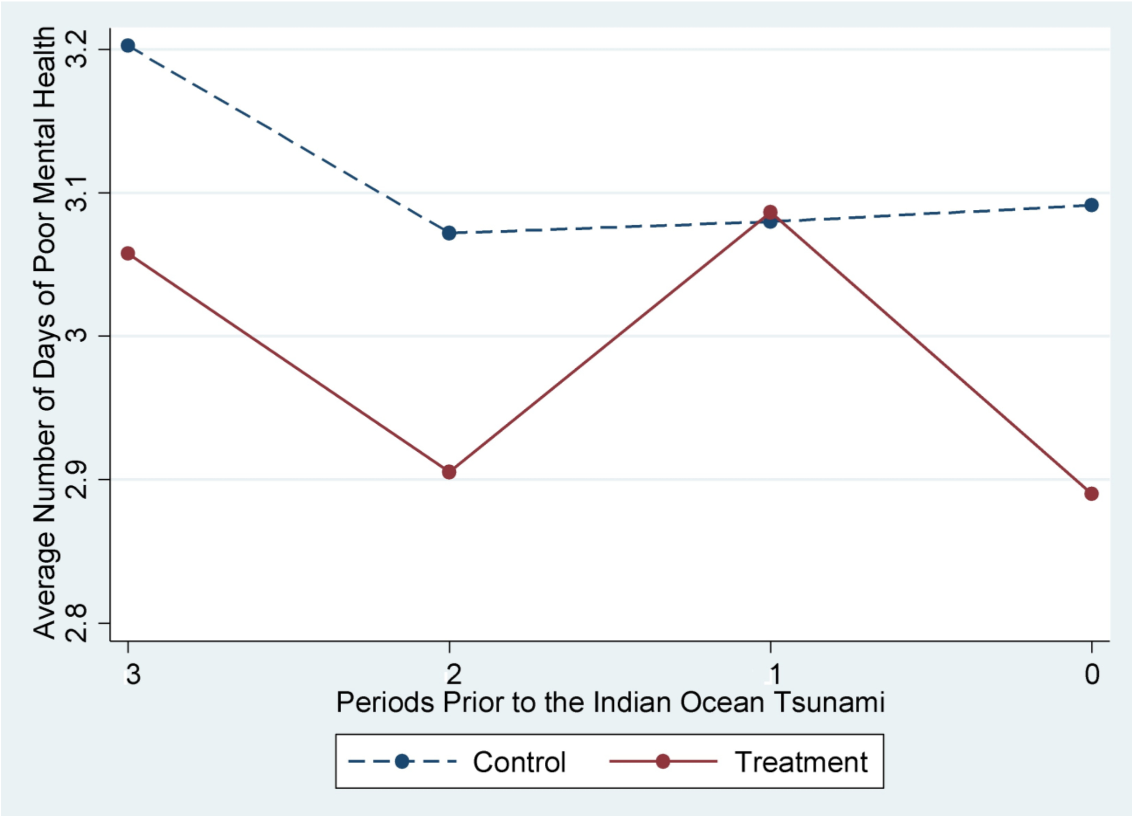
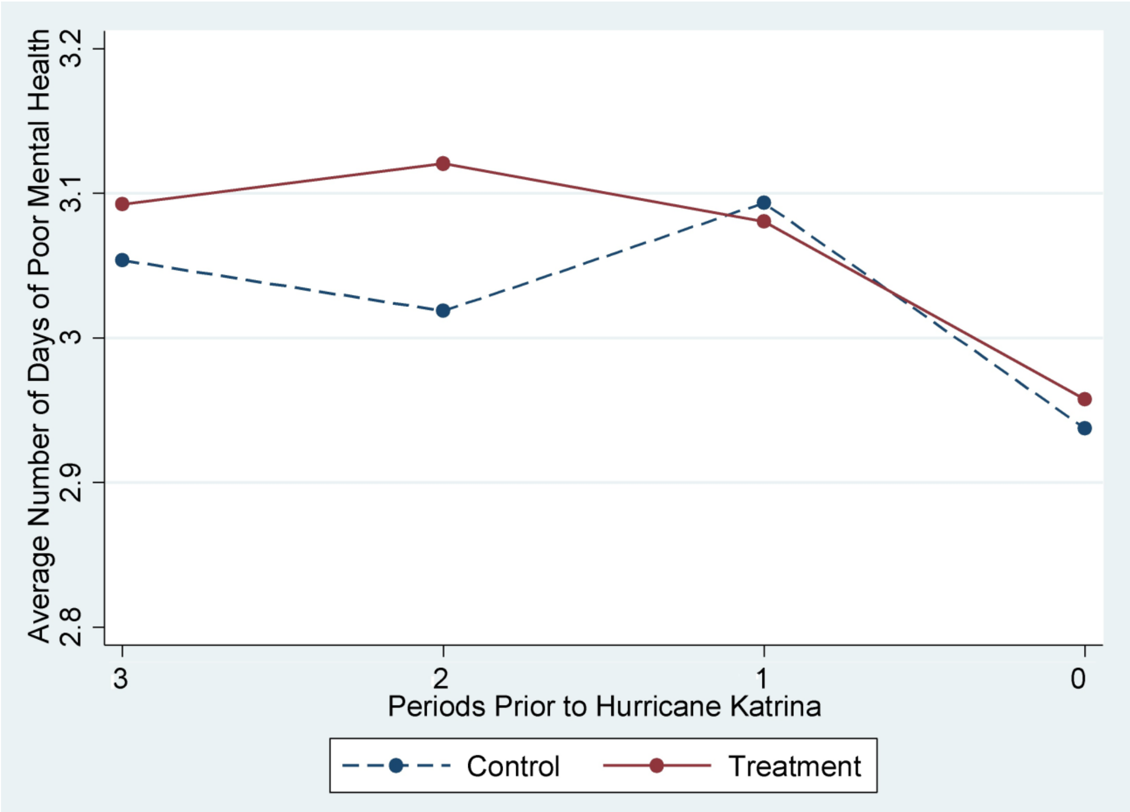


Figure 4.11: The Average Number of Days of Poor Mental Health Before and After the Indian Ocean Tsunami



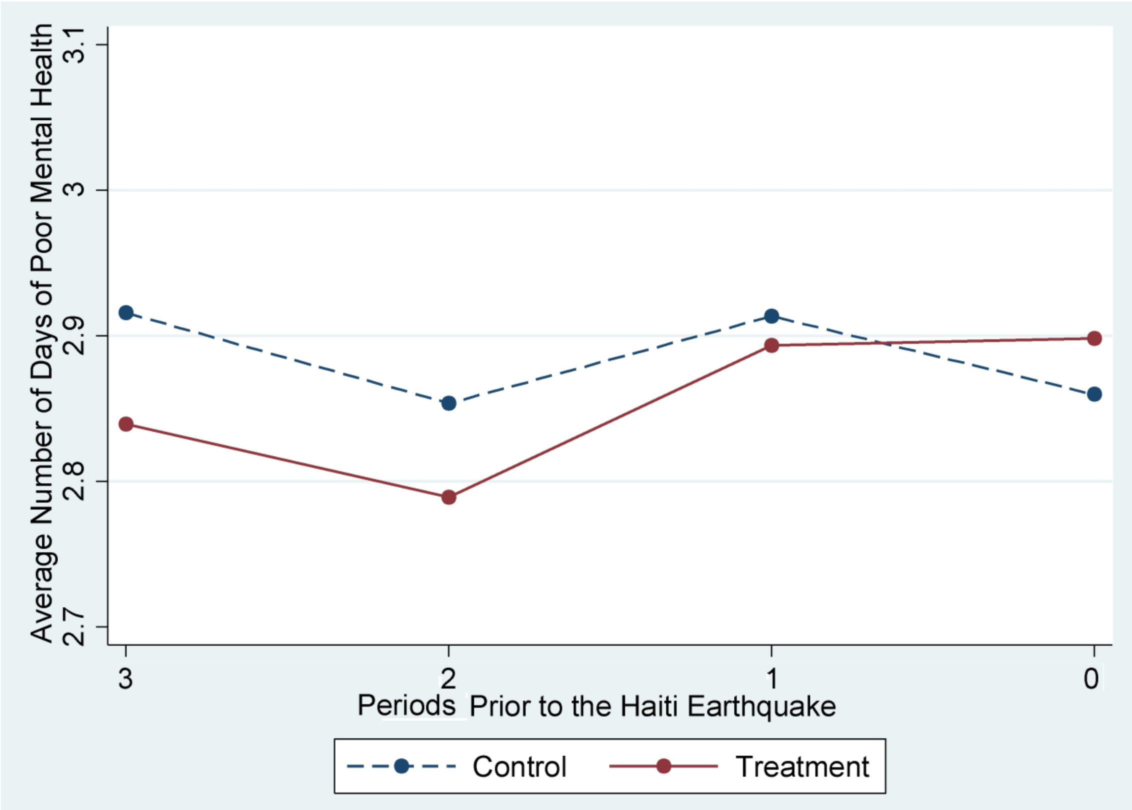
Note: The control group (pre disaster group) is individuals interviewed from 1st March to 25th December and the treatment group (post disaster group) is individuals interviewed from 27th December to 29th February. 0 periods = interviewed from 1st March 2004 to 28th February 2005, 1 period = interviewed from 1st March 2003 to 29th February 2004, 2 periods = interviewed from 1st March 2002 to 28th February 2003, and 3 periods = interviewed from 1st March 2001 to 28th February 2002. The Indian Ocean tsunami occurred on 26th December 2004.

Figure 4.12: The Average Number of Days of Poor Mental Health Before and After Hurricane Katrina



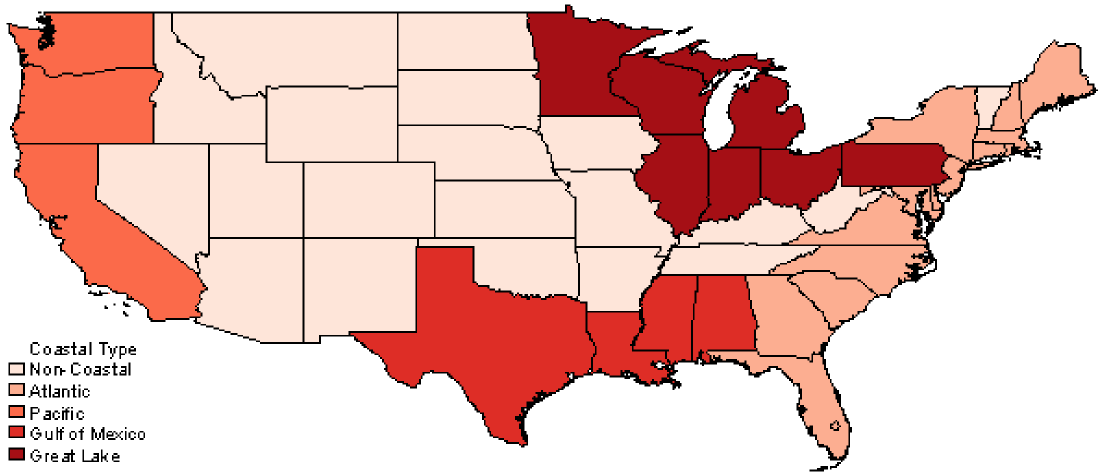
Note: The control group (pre disaster group) is individuals interviewed from 1st January to 22nd August and the treatment group (post disaster group) are individuals interviewed from 24th August to 31st December. 0 periods = individuals interviewed in 2005, 1 period = interviewed in 2004, 2 periods = interviewed in 2003, and 3 periods = interviewed in 2002. Hurricane Katrina occurred on 23rd August 2005.

Figure 4.13: The Average Number of Days of Poor Mental Health Before and After the Haiti Earthquake



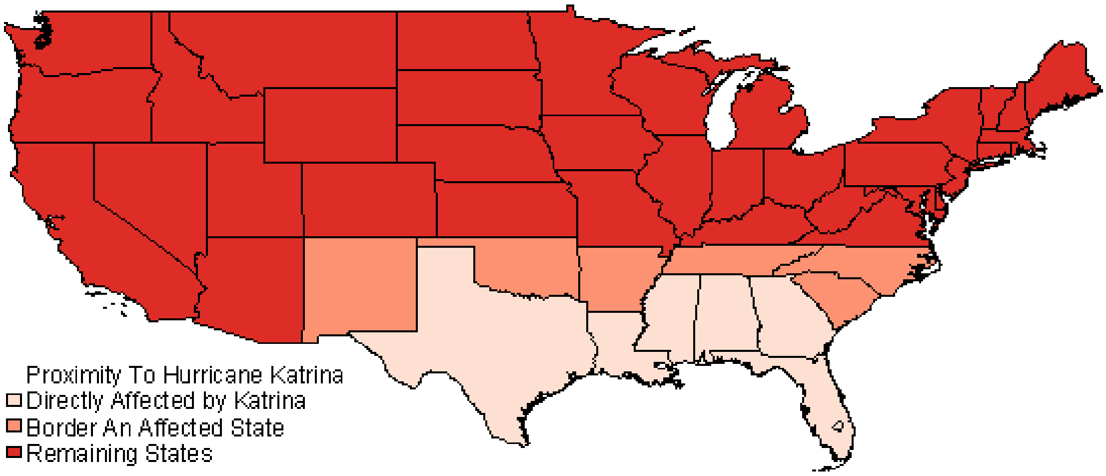
Note: The control group (pre disaster group) is individuals interviewed from 1st April to 11th January and the treatment group (post disaster group) is individuals interviewed from 13th January to 31st March. 0 Period = individuals interviewed from 1st April 2009 to 31st March 2010, 1 = 1st April 2008 to 31st March 2009, 2 periods = 1st April 2007 to 31st March 2008, and 3 periods prior to the earthquake relates to individuals interviewed from 1st April 2006 to 31st March 2007. The Haiti earthquake occurred on 12th January 2010.

Figure 4.14: A Map of the Coastal Regions of the United States



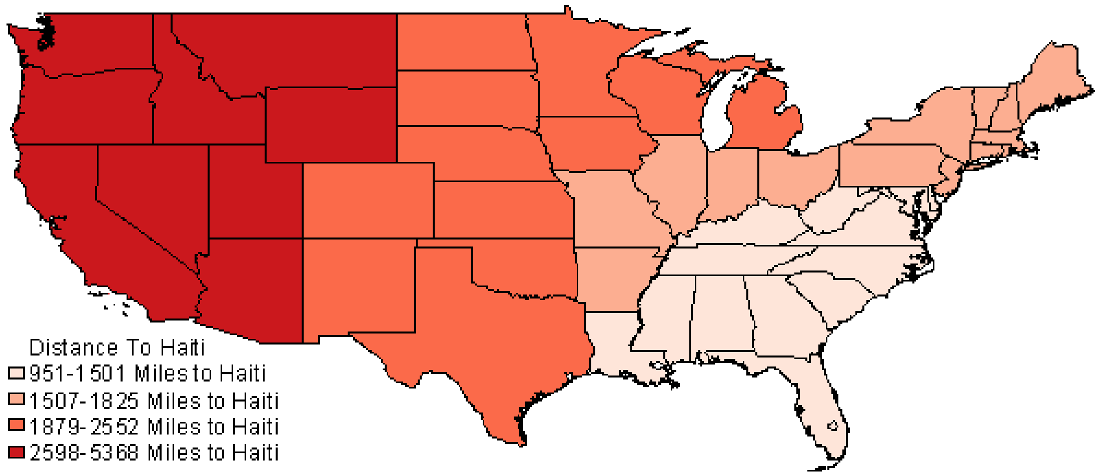
Note: For presentational purposes Alaska and Hawaii are excluded from Figure 2. Alaska and Hawaii are Pacific Ocean states. The non-coastal states are Arizona, Arkansas, Colorado, Idaho, Iowa, Kansas, Kentucky, Missouri, Montana, Nebraska, Nevada, New Mexico, North Dakota, Oklahoma, South Dakota, Tennessee, Utah, Vermont, West Virginia, and Wyoming. The Atlantic Ocean states are Connecticut, Delaware, Florida, Georgia, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, North Carolina, Rhode Island, South Carolina, and Virginia. The Pacific Ocean states are Alaska, California, Hawaii, Oregon, and Washington. The Gulf of Mexico states are Alabama, Louisiana, Mississippi, and Texas. The Great Lake states are Illinois, Indiana, Michigan, Minnesota, Ohio, Pennsylvania, and Wisconsin.

Figure 4.15: A Map of the US States in Proximity to Hurricane Katrina



Note: For presentational purposes Alaska and Hawaii are excluded from Figure 4. Alaska and Hawaii are remaining states (states which did not share a border with the states affected by Hurricane Katrina). The states that border the states affected by Hurricane Katrina are Arkansas, New Mexico, North Carolina, Oklahoma, South Carolina, and Tennessee. The remaining states are Alaska, Arizona, California, Colorado, Connecticut, Delaware, Hawaii, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Maine, Maryland, Massachusetts, Michigan, Minnesota, Missouri, Montana, Nebraska, Nevada, New Hampshire, New Jersey, New York, North Dakota, Ohio, Oregon, Pennsylvania, Rhode Island, South Dakota, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin, and Wyoming.

Figure 4.16: A Map of the US States in Proximity to Haiti



Note: For presentational purposes Alaska and Hawaii are excluded from Figure 6. Alaska and Hawaii are located between 2,598 and 5,368 miles from Haiti. The states located 951 to 1,501 miles from Haiti are Alabama, Delaware, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia. The states located 1,507 to 1,825 miles from Haiti are Arkansas, Connecticut, Illinois, Indiana, Maine, Massachusetts, Missouri, New Hampshire, New Jersey, New York, Ohio, Pennsylvania, Rhode Island, and Vermont. The states located 1,879 to 2,552 miles from Haiti are Colorado, Iowa, Kansas, Michigan, Minnesota, Nebraska, New Mexico, North Dakota, Oklahoma, South Dakota, Texas, and Wisconsin. The states located 2,598 to 5,368 miles from Haiti are Alaska, Arizona, California, Hawaii, Idaho, Montana, Nevada, Oregon, Utah, Washington, and Wyoming.

Table 4.1: The Distribution of the Number of Days of Poor Mental Health: Samples 1 to 3

	Sample 1 (Tsunami)			Sample 2 (Katrina)			Sample 3 (Haiti)		
Days	Freq.	%	Cum.	Freq.	%	Cum.	Freq.	%	Cum.
0	29679	67.44	67.44	33741	68.02	68.02	44739	70.03	70.03
1	16284	3.70	71.14	18303	3.69	71.71	22130	3.46	73.50
2	26665	6.06	77.20	29618	5.97	77.68	34597	5.42	78.91
3	14546	3.31	80.51	15943	3.21	80.89	19169	3.00	81.91
4	7187	1.63	82.14	7945	1.60	82.49	9422	1.47	83.39
5	17424	3.96	86.10	18919	3.81	86.31	22577	3.53	86.92
6	1765	0.40	86.50	1921	0.39	86.70	2390	0.37	87.29
7	6856	1.56	88.06	7502	1.51	88.21	8312	1.30	88.60
8	1140	0.26	88.32	1277	0.26	88.46	1590	0.25	88.84
9	141	0.03	88.35	175	0.04	88.50	238	0.04	88.88
10	10949	2.49	90.84	12270	2.47	90.97	15365	2.41	91.29
11	63	0.01	90.85	63	0.01	90.99	58	0.01	91.30
12	640	0.15	91.00	693	0.14	91.13	928	0.15	91.44
13	63	0.01	91.01	70	0.01	91.14	81	0.01	91.45
14	2600	0.59	91.60	2870	0.58	91.72	3084	0.48	91.94
15	9452	2.15	93.75	10691	2.16	93.87	13113	2.05	93.99
16	101	0.02	93.78	112	0.02	93.90	144	0.02	94.01
17	81	0.02	93.79	86	0.02	93.91	115	0.02	94.03
18	103	0.02	93.82	133	0.03	93.94	194	0.03	94.06
19	22	0.00	93.82	27	0.01	93.95	40	0.01	94.07
20	5116	1.16	94.98	5784	1.17	95.11	7227	1.13	95.20
21	442	0.10	95.08	458	0.09	95.20	548	0.09	95.28
22	88	0.02	95.10	83	0.02	95.22	107	0.02	95.30
23	51	0.01	95.12	49	0.01	95.23	73	0.01	95.31
24	57	0.01	95.13	63	0.01	95.24	74	0.01	95.32
25	1602	0.36	95.49	1775	0.36	95.60	2382	0.37	95.70
26	77	0.02	95.51	72	0.01	95.62	78	0.01	95.71
27	128	0.03	95.54	118	0.02	95.64	162	0.03	95.73
28	537	0.12	95.66	584	0.12	95.76	755	0.12	95.85
29	375	0.09	95.75	411	0.08	95.84	497	0.08	95.93
30	18715	4.25	100.0	20635	4.16	100.0	26004	4.07	100.00
Mean		3.06			3.01			2.88	
Var.		50.34			49.53			48.63	
Obs.		440066			496066			638853	

Table 4.2: Summary Statistics of the Number of Days of Poor Mental Health Before and After the Indian Ocean Tsunami: Sample 1

	2003/2004							2004/2005							
	All Observations			Non-Zero Observations				All Observations			Non-Zero Observations				
	Mean	Obs.	S.D	% (N)	Mean	Med.	S.D	Mean	Obs.	S.D	% (N)	Mean	Med.	S.D	Difference (Mean)
Pre Tsunami	3.08	166998	7.09	32.9 (54995)	9.35	5	9.70	3.09	189920	7.14	32.5 (61686)	9.52	5	9.80	0.01
Post Tsunami	3.09	37908	7.11	32.6 (12353)	9.47	5	9.74	2.89	45240	6.88	31.5 (14236)	9.18	5	9.62	-0.20
Total	3.08	204906	7.10	32.9 (67348)	9.37	5	9.71	3.05	235160	7.09	32.3 (75922)	9.45	5	9.76	

Note: The Indian Ocean tsunami occurred on 26th December 2004. Sample 1 includes individuals Interviewed From 1st March 2003 to 28th February 2005. 2003/2004 denotes individuals interviewed from 1st March 2003 to 29th February 2004 (the 12 month period prior to the Indian Ocean tsunami) and 2004/2005 indicates the dates of 1st March 2004 to 28th February 2005 (the 12 month period of the Indian Ocean tsunami). Pre Tsunami denotes individuals interviewed from 1st March to 25th December (the control group) and Post Tsunami denotes individuals interviewed from 27th December to 29th February (the treatment group). The final column shows the difference in the mean number of days of poor mental health between 2004/2005 and 2003/2004 for the Pre and Post Tsunami groups. Obs. denotes the number of observations, med. denotes the median, and S.D indicates the standard deviation. Columns 2-4 and 8-10 relate to the entire distribution of the number of days of poor mental health. Columns 5-7 and 11-13 relate to the number of days of poor mental health for individuals reporting more than 0 days of poor mental health.

Table 4.3: Summary Statistics of the Number of Days of Poor Mental Health Before and After Hurricane Katrina: Sample 2

	2004							2005							
	All Observations			Non-Zero Observations				All Observations			Non-Zero Observations				
	Mean	Obs.	S.D	% (N)	Mean	Med.	S.D	Mean	Obs.	S.D	% (N)	Mean	Med.	S.D	Difference (Mean)
Pre Katrina	3.09	149305	7.13	32.6 (48550)	9.51	5	9.76	2.94	179271	6.94	31.6 (56573)	9.31	5	9.65	-0.15
Post Katrina	3.08	78485	7.15	32.4 (25459)	9.50	5	9.84	2.96	89005	6.99	31.5 (28068)	9.38	5	9.72	-0.12
Total	3.09	227790	7.14	32.5 (74009)	9.51	5	9.79	2.94	268276	6.95	31.5 (86641)	9.33	5	9.68	

Note: Hurricane Katrina occurred on 23rd August 2005. Sample 2 includes individuals interviewed in 2004 (the 12 month period prior to Hurricane Katrina) and 2005 (the 12 month period of Hurricane Katrina). Pre Katrina denotes the dates from 1st January to 22nd August (the control group) and Post Katrina indicates the dates from 24th August to 31st December (the treatment group). Obs. denotes the number of observations, med. denotes the median, and S.D indicates the standard deviation. Columns 2-4 and 8-10 relate to the entire distribution of the number of days of poor mental health. Columns 5-7 and 11-13 relate to the number of days of poor mental health for individuals reporting more than 0 days of poor mental health. The final column shows the difference in the mean number of days of poor mental health between 2005 and 2004 for the Pre and Post Katrina groups.

Table 4.4: Summary Statistics of the Number of Days of Poor Mental Health Before and After the Haiti Earthquake: Sample 3

	2008/2009							2009/2010							
	All Observations			Non-Zero Observations				All Observations			Non-Zero Observations				
	Mean	Obs.	S.D	% (N)	Mean	Med.	S.D	Mean	Obs.	S.D	% (N)	Mean	Med.	S.D	Difference (Mean)
Pre Haiti	2.91	243704	6.99	30.5 (74359)	9.55	5	9.83	2.86	250147	6.94	29.5 (73921)	9.68	5	9.85	-0.05
Post Haiti	2.89	74032	6.99	29.9 (22175)	9.66	5	9.89	2.90	70970	7.01	29.6 (20999)	9.79	5	9.93	0.01
Total	2.91	317736	6.99	30.4 (96534)	9.57	5	9.85	2.87	321117	6.96	29.6 (94920)	9.70	5	9.86	

Note: The Haiti earthquake occurred on 12th January 2010. Sample 3 includes individuals Interviewed From 1st April 2008 to 31st March 2010. 2008/2009 denotes individuals interviewed from 1st April 2008 to 31st March 2009 (the 12 month period prior to the Haiti earthquake) and 2009/2010 indicates the dates of 1st April 2009 to 31st March 2010 (the 12 month period of the Haiti earthquake). Pre Haiti represents the dates from 1st April to 11th January (the control group) and Post Haiti denotes the dates from 13th January to 31st March (the treatment group). Obs. denotes the number of observations, med. denotes the median, and S.D indicates the standard deviation. Columns 2-4 and 8-10 relate to the entire distribution of the number of days of poor mental health. Columns 5-7 and 11-13 relate to the number of days of poor mental health for individuals reporting more than 0 days of poor mental health. The final column shows the difference in the mean number of days of poor mental health between 2009/2010 and 2008/2009 for the Pre and Post Haiti groups.

Table 4.5: Variable Definitions for Variables included in the Analysis

Variable	Definition
Outcome Variable	
Poor Mental Health Days	Number of days of poor mental health in the past 30 days. The respondents are asked "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?". The respondents report an integer value between 0 and 30.
Date Variables	
Post26/12	Binary variable equals 1 if individual i was interviewed from December 27th to 29th February (treatment group), and 0 if individual i was interviewed from March 1st to December 25th (control group) Individuals interviewed on December 26th are coded as missing and omitted from the estimation sample. The Indian Ocean tsunami occurred on 26th December 2004.
Post23/8	Binary variable equals 1 if the individual was interviewed from 24th August to 31st December (treatment group), and 0 if the individual was interviewed from 1st January to 22nd August (control group). Individuals interviewed on 23rd August are coded as missing and omitted from the estimation sample. Hurricane Katrina occurred on 23rd August 2005.
Post12/1	Binary variable equals 1 if the individual was interviewed from 13th January to 31st March (treatment group), and 0 if individual i was interviewed from 1st April to 11th January (control group). Individuals interviewed on 12th January are coded as missing and omitted from the estimation sample. The Haiti earthquake occurred on 12th January 2010.
Year = 2004/2005	Binary variable equals 1 if the individual was interviewed from 1st March 2004 to 28th February 2005, and 0 if interviewed from 1st March 2003 to 29th February 2004.
Year = 2005	Binary variable equals 1 if the individual was interviewed in 2005, and 0 if interviewed in 2004.
Year = 2009/2010	Binary variable equals 1 if the individual was interviewed from 1st April 2009 to 31st March 2010, and 0 if interviewed from 1st April 2008 to 31st March 2009.
Year = 2002/2003	Binary variable equals 1 if the individual was interviewed from 1st March 2002 to 28th February 2003, and 0 if interviewed between 1st March 2001 to 28th February 2002.
Year = 2003	Binary variable equals 1 if the individual was interviewed in 2003, and 0 if interviewed in 2001.
Year = 2007/2008	Binary variable equals 1 if the individual was interviewed from 1st April 2007 to 31st March 2008, and 0 if interviewed from 1st April 2006 to 31st March 2007.

Note: Table continues on the next page.

Table 4.5 (continued): Variable Definitions for Variables included in the Analysis

Individual Characteristics	
Male	Binary variable equals 1 if the individual is male, and 0 if female.
Labour Force Status	
Out of Labour Force	Binary variable takes the value 1 if the individual is not in the labour force.
Unemployed	Binary variable takes the value 1 if the individual is unemployed.
Employed	Base category denotes that the individual is employed.
Household Income	Categorical variable indicates the individual's nominal annual household income category. The income categories are \$10,000-\$14,999, \$15,000 to \$19,999, \$20,000 to \$24,999, \$25,000 to \$34,999, \$35,000 to \$49,999, \$50,000 to \$74,999, and \$75,000 or more. Individuals who have a household income of less than \$10,000 form the base category.
Marital Status	
Married or Cohabiting	Binary variable takes the value 1 if the individual is married or cohabiting.
Separated, Divorced, or Wid	Binary variable takes the value 1 if the individual is separated, divorced, or widowed.
Never Married	Base category indicates that the individual has never been married.
Ethnicity	
Black	Binary variable takes the value 1 if the individual is Black or African American.
Asian	Binary variable takes the value 1 if the individual is Asian.
Hawaiian	Binary variable takes the value 1 if the individual is Hawaiian, a Pacific Islander, or another ethnicity.
American Indian	Binary variable takes the value 1 if the individual is an American Indian or Alaskan Native.
White	Base category are Whites.
Highest Educational Attainment	
University Degree	Binary variable takes the value 1 if the individual's highest educational attainment is a university degree.
1-3 Years of University	Binary variable takes the value 1 if the individual's highest educational attainment is 1-3 years of university education.
High School Graduate	Binary variable takes the value 1 if the individual's highest educational attainment is graduation from high school.
No Qual.	Base category indicates that the individual has no qualifications.
Age	The age of the individual in years.
Disabled	Binary variable takes the value 1 if the individual has their activities limited due to health problems.
Number of Attempts	The number of attempts required to contact the individual.

Note: Table continues on the next page.

Table 4.6: Summary Statistics for Pre and Post 26th December (The Indian Ocean Tsunami): Sample 1

	Pre 26th December				Post 26th December			
Continuous Variables	Mean	S.D	Min.	Max.	Mean	S.D	Min.	Max.
Poor M.H Days	3.09	7.12	0	30	2.98	6.99	0	30
Age	48.83	16.75	18	99	49.18	16.64	18	99
Number of Attempts	4.92	4.22	1	61	4.68	4.11	0	51
Binary Variables	*Percent* (N)				*Percent* (N)			
Male	40 (144173)				40 (34122)			
Not in Labour Force	30 (107730)				31 (24962)			
Unemployed	5 (16578)				4 (3876)			
Employed	65 (232610)				64 (54310)			
Income < $10,000	4 (15678)				4 (3535)			
$10,000-$14,999	5 (19312)				5 (4400)			
$15,000 to $19,999	8 (28033)				8 (6349)			
$20,000 to $24,999	10 (36112)				10 (8415)			
$25,000 to $34,999	15 (52347)				14 (12028)			
$35,000 to $49,999	18 (65610)				18 (15187)			
$50,000 to $74,999	18 (63351)				18 (15137)			
> $75,000	21 (76475)				22 (18097)			
Married/ Cohabiting	60 (213599)				60 (50129)			
Separated, Div, or Wid	26 (92759)				26 (21697)			
Unmarried	14 (50560)				13 (11322)			
White	86 (306787)				86 (71536)			
Black	8 (26881)				8 (6432)			
Asian	1 (5235)				2 (1297)			
Hawaiian	3 (11416)				3 (2351)			
American Indian	2 (6599)				2 (1532)			
University Degree	34 (122376)				34 (28475)			
1-3 Years College	28 (98645)				27 (22965)			
High School Grad.	30 (105826)				30 (24986)			
No Qualifications	8 (30071)				8 (6722)			
Disabled	17 (62075)				18 (13970)			
Observations	356918				83148			

Note: Sample 1 contains individuals Interviewed From 1st March 2003 to 28th February 2005. Income denotes the individual's nominal household income band. S.D (M.H) indicates the standard deviation (mental health). Pre 26th December indicates individuals interviewed from 1st March to 25th December. Post 26th December indicates individuals interviewed from 27th December to 29th February.

Table 4.7: Summary Statistics for Pre and Post Hurricane Katrina: Sample 2

	Pre 23rd August				Post 23rd August			
Continuous	Mean	S.D	Min.	Max.	Mean	S.D	Min.	Max.
Poor M.H Days	3.01	7.03	0	30	3.01	7.06	0	30
Age	49.78	16.80	18	99	52.01	16.65	18	99
Number of Attempts	4.80	4.10	1	71	5.00	4.25	1	60
Binary Variables	*Percent (N)*				*Percent (N)*			
Male	40 (131605)				40 (67492)			
Not in Labour Force	31 (103278)				31 (52701)			
Unemployed	4 (14728)				4 (6844)			
Employed	64 (210570)				64 (107945)			
Income < $10,000	4 (14085)				4 (6778)			
$10,000-$14,999	5 (17820)				5 (9048)			
$15,000 to $19,999	8 (25661)				8 (12591)			
$20,000 to $24,999	10 (33242)				10 (16650)			
$25,000 to $34,999	14 (47153)				14 (23771)			
$35,000 to $49,999	18 (58950)				18 (30032)			
$50,000 to $74,999	18 (59040)				18 (29867)			
> $75,000	22 (72625)				23 (38753)			
Married/ Cohabiting	60 (197522)				61 (101726)			
Sep, Div or Wid	26 (86716)				26 (44249)			
Unmarried	13 (44338)				13 (21515)			
White	86 (281630)				86 (144324)			
Black	8 (24932)				7 (12019)			
Asian	2 (5251)				2 (2594)			
Hawaiian	3 (10624)				3 (5476)			
American Indian	2 (6139)				2 (3077)			
University Degree	34 (113084)				35 (58368)			
1-3 Years College	27 (89587)				27 (45757)			
High School Grad.	30 (98212)				30 (49661)			
No Qualifications	8 (27693)				8 (13704)			
Disabled	18 (57756)				17 (29093)			
Observations	328576				167490			

Note: Sample 2 includes individuals interviewed in 2004 and 2005. Income denotes the individual's nominal household income band. S.D (M.H) indicates the standard deviation (mental health). Pre 23rd August represents individuals who were interviewed from 1st January to 22nd August. Post 23rd August indicates individuals interviewed from 24th August to 31st December.

Table 4.8: Summary Statistics for Pre and Post the Haiti Earthquake: Sample 3

	Pre 12th January				Post 12th January			
Continuous Variables	Mean	S.D	Min.	Max.	Mean	S.D	Min.	Max.
Poor M.H Days	2.89	6.97	0	30	2.9	7	0	30
Age	54.79	16.42	18	99	54.77	16.22	18	99
Number of Attempts	4.74	4.24	1	71	4.89	4.17	1	43
Binary Variables	*Percent (N)*				*Percent (N)*			
Male	39 (194273)				40 (58299)			
Not in Labour Force	37 (182078)				36 (51998)			
Unemployed	5 (26136)				6 (8998)			
Employed	58 (285637)				58 (84006)			
Income < $10,000	4 (17633)				4 (5256)			
$10,000-$14,999	5 (23577)				5 (6828)			
$15,000 to $19,999	7 (34748)				7 (10413)			
$20,000 to $24,999	9 (46872)				9 (13555)			
$25,000 to $34,999	12 (61523)				12 (17804)			
$35,000 to $49,999	16 (80368)				16 (23307)			
$50,000 to $74,999	18 (86977)				18 (25480)			
> $75,000	29 (142153)				29 (42359)			
Married/ Cohabiting	61 (303040)				62 (89397)			
Sep, Div, or Wid	28 (137505)				28 (40055)			
Unmarried	11 (53306)				11 (15550)			
White	86 (426973)				86 (125239)			
Black	7 (35893)				8 (10992)			
Asian	2 (9410)				2 (2845)			
Hawaiian	3 (13493)				2 (3430)			
American Indian	2 (8082)				2 (2496)			
University Degree	36 (180157)				37 (52955)			
1-3 Years College	27 (135154)				27 (39567)			
High School Grad.	29 (142287)				29 (41896)			
No Qualifications	7 (36253)				7 (10584)			
Disabled	21 (104476)				20 (29458)			
Observations	493851				145002			

Note: Sample 3 includes individuals Interviewed From 1st April 2008 to 31st March 2010. Income denotes the individual's nominal household income category. S.D (M.H) indicates the standard deviation (mental health). Pre 12th January represents individuals interviewed from 1st April to 11th January. Post 12th January indicates individuals interviewed from 13th January to 31st March.

Table 4.9: Zero Inflated Negative Binomial Model Coefficients: The Effects of the Indian Ocean Tsunami on the Number of Days of Poor Mental Health: Sample 1

	(1) All States	(2) Non-coastal	(3) Atlantic	(4) Pacific	(5) Gulf of Mexico	(6) Great Lake
Dep. Var.	Days of Poor Mental Health					
Negative Binomial Model						
2 Month Window	-0.0653***	-0.0361	-0.0465	-0.1895***	-0.0128	-0.0643
	(0.0172)	(0.0289)	(0.0321)	(0.0471)	(0.0709)	(0.0449)
Unemployed	0.2497***	0.2564***	0.2462***	0.2698***	0.2287***	0.2390***
	(0.0136)	(0.0249)	(0.0240)	(0.0349)	(0.0465)	(0.0357)
Inflate Model						
2 Month Window	0.0437**	0.0393	0.0102	-0.1058*	0.2662***	0.0833
	(0.0211)	(0.0349)	(0.0384)	(0.0620)	(0.0814)	(0.0585)
Incremental Effect	-0.2529***	-0.1509***	-0.1399***	-0.5147***	-0.3401***	-0.2706***
	0.01156	0.0115	0.0164	0.0519	0.1856	0.0269
Ln(Alpha)	0.4302***	0.4228***	0.4352***	0.4935***	0.3252***	0.4106***
	(0.0077)	(0.0128)	(0.0138)	(0.0215)	(0.0271)	(0.0210)
Observations	440066	160028	138067	54634	32441	54896
Vuong Test	118.7401	72.6302	65.0283	41.0925	33.9594	41.0131

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Sample 1 contains all individuals interviewed from 1st March 2003 to 28th February 2005. All estimation results control for the following individual characteristics: age, age squared, the number of attempts taken to contact the individual, gender, employment status, nominal income category, marital status, ethnicity, highest educational attainment, the month of interview, disability, the state of residence, and the year of interview. In addition, the estimation results include a binary variable whether the individual was interviewed from 27th December to the end of February. The coefficient "2 Month Window" is an estimate of the effect of the Indian Ocean tsunami on the number of days of poor mental health of individuals interviewed from 27th December 2004 to 28th February 2005. Column (1) uses a sample of individuals from all states. Columns (2) to (6) investigate whether the effect of the Indian Ocean tsunami varies depending on the individual's proximity to the Indian Ocean tsunami (see Figure 4.14).

Table 4.10: Zero Inflated Negative Binomial Model Coefficients: The Effects Of the Indian Ocean Tsunami on the Number of Days of Poor Mental Health: Sample 1: By Time

	(1) All States	(2) Non-coastal	(3) Atlantic	(4) Pacific	(5) Gulf of Mexico	(6) Great Lake
Dep. Var.			Days of Poor Mental Health			
Negative Binomial Model						
0-1 Month Window	-0.0532**	-0.0581	0.0442	-0.2010***	0.0267	-0.0828
	(0.0236)	(0.0392)	(0.0455)	(0.0621)	(0.0950)	(0.0633)
1-2 Month Window	-0.0766***	-0.0149	-0.1194***	-0.1773***	-0.0580	-0.0494
	(0.0227)	(0.0387)	(0.0413)	(0.0635)	(0.0974)	(0.0576)
Unemployed	0.2498***	0.2561***	0.2471***	0.2699***	0.2294***	0.2386***
	(0.0136)	(0.0249)	(0.0240)	(0.0349)	(0.0465)	(0.0357)
Inflate Model						
0-1 Month Window	0.0234	0.0217	-0.0242	-0.0906	0.3678***	0.0449
	(0.0291)	(0.0476)	(0.0545)	(0.0817)	(0.1111)	(0.0820)
1-2 Month Window	0.0620**	0.0560	0.0391	-0.1219	0.5612***	0.1149
	(0.0277)	(0.0464)	(0.0495)	(0.0834)	(0.1095)	(0.0753)
Ln(Alpha)	0.4302***	0.4228***	0.4347***	0.4934***	0.3251***	0.4106***
	(0.0077)	(0.0128)	(0.0138)	(0.0215)	(0.0271)	(0.0210)
Observations	440066	160028	138067	54634	32441	54896
Vuong Test	118.7407	72.6337	65.0321	41.1014	33.9604	41.0187

Standard errors in parentheses.
* p < 0.10, ** p < 0.05, *** p < 0.01.
Note: Sample 1 contains all individuals interviewed from 1st March 2003 to 28th February 2005. All estimation results include control variables as for Table 4.9. Additionally, binary variables are included to denote that the individual was interviewed from 27th December to 31st January and 1st February to 29th February. The coefficient "0-1 month window" is an estimate of the effect of the Indian Ocean tsunami on the number of days of poor mental health of individuals interviewed from 27th December 2004 to 31st January 2005. The coefficient "1-2 month window" is an estimate of the effect of the Indian Ocean tsunami on the number of days of poor mental health of individuals interviewed from 1st to 28th February 2005. Column (1) utilises a sample of individuals from all states. Columns (2) to (6) investigate whether the effect of the Indian Ocean tsunami varies depending on the individual's proximity to the Indian Ocean tsunami (see Figure 4.14).

Table 4.11: Zero Inflated Negative Binomial Model Coefficients: The Effects of Hurricane Katrina on the Number of Days of Poor Mental Health: Sample 2

	(1) All States	(2) Affected by Katrina	(3) Border an Affected State	(4) Remaining States
Dep. Var.		Days of Poor Mental Health		
Negative Binomial Model				
4 Month Window	0.0069	0.0695	0.0335	-0.0038
	(0.0134)	(0.0442)	(0.0350)	(0.0155)
Unemployed	0.2345***	0.1881***	0.2342***	0.2403***
	(0.0133)	(0.0398)	(0.0334)	(0.0156)
Inflate Model				
4 Month Window	-0.0150	-0.0712	-0.0014	-0.0106
	(0.0164)	(0.0521)	(0.0412)	(0.0191)
Incremental Effect	0.0430***	0.3253***	0.1064***	0.0042***
	0.0011	(0.0284)	(0.0079)	(0.0002)
Ln(Alpha)	0.4404***	0.3419***	0.3354***	0.4731***
	(0.0073)	(0.0221)	(0.0183)	(0.0085)
Observations	496066	50348	73928	371790
Vuong Test	123.45	40.94	49.33	104.67

Standard errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Note: Sample 2 contains all individuals interviewed from 1st January 2004 to 31st December 2005. All estimation results include control variables as for Table 4.9. We also include a binary variable denoting that the individual was interviewed from 24th August to 31st December. The coefficient "4 Month Window" is an estimate of the effect of Hurricane Katrina on the number of days of poor mental health of individuals interviewed from 24th August 2005 to 31st December 2005. Column (1) uses a sample of individuals from all states and columns (2) to (4) investigate whether the effect of Hurricane Katrina is dependent on the individual's proximity to the disaster area (see Figure 4.15).

Table 4.12: Zero Inflated Negative Binomial Model Coefficients: The Effects of Hurricane Katrina on the Number of Days of Poor Mental Health: Sample 2: By Time

	(1) All States	(2) Affected by Katrina	(3) Border an Affected State	(4) Remaining States
Dep. Var	Days of Poor Mental Health			
Negative Binomial Model				
0-1 Month Window	0.0517**	0.0648	0.0963*	0.0423
	(0.0226)	(0.0801)	(0.0578)	(0.0260)
1-2 Month Window	0.0028	0.1581*	0.0449	-0.0208
	(0.0236)	(0.0813)	(0.0613)	(0.0270)
2-3 Month Window	0.0004	0.0938	-0.0285	-0.0046
	(0.0233)	(0.0773)	(0.0618)	(0.0268)
3-4 Month Window	-0.0306	-0.0239	0.0108	-0.0359
	(0.0232)	(0.0748)	(0.0616)	(0.0268)
Unemployed	0.2346***	0.1876***	0.2350***	0.2403***
	(0.0133)	(0.0398)	(0.0334)	(0.0156)
Inflate Model				
0-1 Month Window	-0.0336	-0.0887	-0.0108	-0.0289
	(0.0279)	(0.0944)	(0.0696)	(0.0324)
1-2 Month Window	-0.0585**	-0.0810	-0.0646	-0.0544
	(0.0288)	(0.0963)	(0.0716)	(0.0335)
2-3 Month Window	0.0293	-0.0238	0.0587	0.0293
	(0.0283)	(0.0902)	(0.0720)	(0.0330)
3-4 Month Window	0.0012	-0.0933	0.0126	0.0105
	(0.0282)	(0.0886)	(0.0723)	(0.0328)
Ln(Alpha)	0.4403***	0.3415***	0.3352***	0.4729***
	(0.0073)	(0.0221)	(0.0183)	(0.0085)
Observations	496066	50348	73928	371790
Vuong Test	123.4610	40.9463	49.3475	104.6791

Standard errors in parentheses

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

Note: Sample 2 contains all individuals interviewed from 1st January 2004 to 31st December 2005. All estimation results include control variables as for Table 4.9. In addition, binary variables are included denoting that the individual was interviewed from 24th August to 30th September, 1st to 31st October, 1st to 30th November, and 1st to 31st December. The coefficient "0-1 Month Window" is an estimate of the effect of Hurricane Katrina on the number of days of poor mental health of individuals interviewed from 24th August to 30th September 2005. The coefficient "1-2 Month Window" is an estimate of the effect of Hurricane Katrina on the number of days of poor mental health of individuals interviewed from 1st to 31st October 2005. The coefficient "2-3 Month Window" is an estimate of the effect of Hurricane Katrina on the number of days of poor mental health of individuals interviewed from 1st to 30th November 2005. The coefficient "3-4 Month Window" is an estimate of the effect of Hurricane Katrina on the number of days of poor mental health of individuals interviewed from 1st December to 31st December 2005. Column (1) uses a sample of individuals from all states and columns (2) to (4) investigate whether the effect of Hurricane Katrina is dependent on the individual's proximity to the disaster area (see Figure 4.15).

Table 4.13: Zero Inflated Negative Binomial Model Coefficients: The Effects of the Haiti Earthquake on the Number of Days of Poor Mental Health: Sample 3

	(1) All States	(2) 951-1,501 Miles from Haiti	(3) 1,502-1,825 Miles from Haiti	(4) 1,826-2,552 Miles from Haiti	(5) 2,553-5,368 Miles from Haiti
Dep. Var.	Days of Poor Mental Health				
Negative Binomial Model					
2 Month Window	-0.0313**	-0.0677**	-0.0152	-0.0245	-0.0129
	(0.0138)	(0.0263)	(0.0257)	(0.0284)	(0.0306)
Unemployed	0.2434***	0.2042***	0.2370***	0.2567***	0.2784***
	(0.0108)	(0.0205)	(0.0197)	(0.0238)	(0.0234)
Inflate Model					
2 Month Window	0.0021	-0.0515*	0.0144	0.0181	0.0412
	(0.0162)	(0.0306)	(0.0305)	(0.0327)	(0.0371)
Incremental Effect	-0.0936***	-0.1109***	-0.0711***	-0.0877***	-0.0957***
	0.0018	0.0048	0.0026	0.0033	0.0037
Ln(Alpha)	0.4262***	0.2826***	0.4230***	0.4936***	0.5086***
	(0.0066)	(0.0124)	(0.0123)	(0.0137)	(0.0145)
Observations	638853	156142	177160	168372	137179
Vuong Test	134.4803	71.5567	69.0820	65.9520	61.2362

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Sample 3 contains all individuals interviewed from 1st April 2008 to 31st March 2010. All estimation results include control variables as for Table 4.9. In addition, a binary variable is included denoting that the individual was interviewed from 13th January to 31st March. The coefficient "2 Month Window" denotes the effect of the Haiti earthquake on the number of days of poor mental health of individuals interviewed in from 13th January to 31st March 2010. Column (1) uses a sample of individuals from all states. Additionally, columns (2) to (4) investigate whether the effect of the Haiti earthquake is dependent on the individual's proximity to the disaster area (see Figure 4.16).

Table 4.14: Zero Inflated Negative Binomial Model Coefficients: The Effects of the Haiti Earthquake on the Number of Days of Poor Mental Health: Sample 3: By Time

	(1) All States	(2) 951 to 1,501 Miles from Haiti	(3) 1,502-1,825 Miles from Haiti	(4) 1,826-2,552 Miles from Haiti	(5) 2,553-5,368 Miles from Haiti
Dep. Var	Days of Poor Mental Health				
Negative Binomial Model					
0-1 Month Window	-0.0345**	-0.0923***	-0.0126	-0.0250	-0.0055
	(0.0170)	(0.0320)	(0.0317)	(0.0351)	(0.0384)
1-2 Month Window	-0.0266	-0.0294	-0.0189	-0.0237	-0.0236
	(0.0201)	(0.0387)	(0.0376)	(0.0413)	(0.0439)
Unemployed	0.2434***	0.2042***	0.2370***	0.2567***	0.2784***
	(0.0108)	(0.0205)	(0.0197)	(0.0238)	(0.0234)
Inflate Model					
0-1 Month Window	0.0104	-0.0362	0.0272	0.0416	0.0144
	(0.0200)	(0.0373)	(0.0376)	(0.0403)	(0.0468)
1-2 Month Window	-0.0100	-0.0751*	-0.0047	-0.0167	0.0768
	(0.0236)	(0.0450)	(0.0447)	(0.0478)	(0.0529)
Ln(Alpha)	0.4263***	0.2827***	0.4230***	0.4938***	0.5089***
	(0.0066)	(0.0124)	(0.0123)	(0.0137)	(0.0145)
Observations	638853	156142	177160	168372	137179
Vuong Test	134.4798	71.5599	69.0833	65.9452	61.2359

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Sample 3 contains all individuals interviewed from 1st April 2008 to 31st March 2010. All estimation results include control variables as for Table 4.9. In addition, binary variables are included to denote that the individual was interviewed from 13th January to 29th February and from 1st to 31st March. The coefficient "0-1 Month Window" denotes the effect of the Haiti earthquake on the number of days of poor mental health of individuals interviewed from 13th January to 28th February 2010. The coefficient "1-2 Month Window" indicates the effect of the Haiti earthquake on the number of days of poor mental health of individuals interviewed from 1st March to 31st March 2010. Column (1) uses a sample of individuals from all states. Columns (2) to (5) investigate whether the effect of the Haiti earthquake is dependent on the individual's proximity to the disaster area (see Figure 4.16).

Table 4.15: Zero Inflated Negative Binomial Model Coefficients: Placebo Tests For Common Trends Prior to the Indian Ocean Tsunami: Sample 4

	(1)	(2)
	All States	Pacific
Dep. Var.	Days of Poor Mental Health	
Negative Binomial Model		
2 Month Window	-0.0384	0.1267
	(0.0417)	(0.0923)
Inflate Model		
2 Month Window	-0.0585	0.0471
	(0.0512)	(0.1161)
Ln(Alpha)	0.4025***	0.4197***
	(0.0111)	(0.0322)
Observations	196745	24359
Vuong Test	82.7675	30.0297

Standard errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Note: Sample 4 contains all individuals interviewed from 1st March 2001 to 28th February 2003. All estimation results include control variables as for Table 4.9. All estimation results include a binary variable denoting that the individual was interviewed from 27th December to the end of February. The coefficient "2 Month Window" is an estimate of the effect of a 'pretend' natural disaster on the 26th December 2002 on the number of days of poor mental health of individuals interviewed from 27th December 2002 to 28th February 2003. Column (1) and (2) use a sample of individuals from all US states and Pacific Ocean states, respectively.

Table 4.16: Zero Inflated Negative Binomial Model Coefficients: Placebo Tests For Common Trends Prior to Hurricane Katrina: Sample 5

	(1) All States	(2) Affected by Katrina
Dep. Var.	Days of Poor Mental Health	
Negative Binomial Model		
4 Month Window	0.0098	0.0756*
	(0.0162)	(0.0458)
Inflate Model		
4 Month Window	0.0268	-0.0357
	(0.0213)	(0.0412)
Ln(Alpha)	0.4224***	0.3621***
	(0.0087)	(0.0241)
Observations	331859	41206

Standard errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Note: Sample 5 contains all individuals interviewed in 2001 and 2003. All estimation results include control variables as for Table 4.9. In addition, a binary variable is included denoting that the individual was interviewed from 24th August to 31st December. The coefficient "4 Month Window" is an estimate of the effect of a 'pretend' natural disaster on the 23rd August 2003 on the number of days of poor mental health of individuals interviewed from 23rd August 2003 to 31st December 2003. Columns (1) and (2) use a sample of individuals from all US states and those states that were directly affected by Hurricane Katrina (see Figure 4.15), respectively.

Table 4.17: Zero Inflated Negative Binomial Model Coefficients: Placebo Tests For Common Trends Prior to the Haiti Earthquake: Sample 6

	(1) All States	(2) 951 to 1,501 Miles from Haiti
Dep. Var.	Days of Poor Mental Health	
Negative Binomial Model		
2 Month Window	-0.0242	-0.0182
	(0.0226)	(0.0286)
Inflate Model		
2 Month Window	0.0298	-0.0166
	(0.0254)	(0.0332)
Ln(Alpha)	0.4458***	0.3515***
	(0.0068)	(0.0124)
Observations	605570	166843
Vuong Test	130.61	72.36

Standard errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.0

Note: Sample 6 contains all individuals interviewed from 1st April 2006 to 31st March 2008. All estimation results include control variables as for Table 4.9. Additionally, all results include a binary variable denoting whether the individual was interviewed from 13th January to 31st March. The coefficient "2 Month Window" is an estimate of the effect of a 'pretend' natural disaster on 23rd August 2003 on the number of days of poor mental health of individuals interviewed from 24rd August 2003 to 31st December 2003. Columns (1) and (2) use a sample of individuals from all US states and the states that were closest to Haiti (see Figure 4.16), respectively.

Table 4.18: Zero Inflated Negative Binomial Model Coefficients: The Effects of the Indian Ocean Tsunami on the Number of Days of Poor Mental Health: Sample 1: By Ethnicity

	(1) White	(2) Black	(3) Asian	(4) Hawaiian	(5) American Indian
Dep. Var.	Days of Poor Mental Health				
Negative Binomial Model					
2 Month Window	-0.0541***	-0.1298**	0.0523	-0.0243	-0.0429
	(0.0187)	(0.0574)	(0.1838)	(0.1001)	(0.1167)
Unemployed	0.2711***	0.1692***	0.4260***	0.1606**	0.1893***
	(0.0155)	(0.0362)	(0.1338)	(0.0630)	(0.0673)
Inflate Model					
2 Month Window	0.0448	0.0939	-0.1017	0.0456	0.2079
	(0.0401)	(0.0704)	(0.2059)	(0.1176)	(0.1439)
Ln(Alpha)	0.4511***	0.2464***	0.5241***	0.3055***	0.2037***
	(0.0084)	(0.0243)	(0.0772)	(0.0397)	(0.0455)
Observations	378323	33313	6532	13767	8131
Vuong Test	110.5232	34.6088	12.5785	21.1391	18.7327

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Sample 1 contains all individuals interviewed from 1st March 2003 to 28th February 2005. All estimation results include control variables as for Table 4.9, though ethnicity is excluded from the analysis. In addition, a binary variable is included denoting that the individual was interviewed from 27th December to the end of February. The coefficient "2 Month Window" is an estimate of the effect of the Indian Ocean tsunami on the number of days of poor mental health of individuals interviewed from 27th December 2004 to 28th February 2005). Hawaiian denotes that the individual is Hawaiian, a Pacific Islander, or another ethnicity and American Indian indicates that the individual is an American Indian or Alaskan Native.

Table 4.19: Zero Inflated Negative Binomial Model Coefficients: The Effects of Hurricane Katrina on the Number of Days of Poor Mental Health: Sample 2: By Ethnicity

	(1) White	(2) Black	(3) Asian	(4) Hawaiian	(5) American Indian
Dep. Var.	Days of Poor Mental Health				
Negative Binomial Model					
4 Month Window	0.0050	0.0059	-0.1713	0.0573	0.0754
	(0.0146)	(0.0454)	(0.1408)	(0.0735)	(0.0845)
Unemployed	0.2523***	0.1650***	0.3684**	0.2576***	0.0763
	(0.0152)	(0.0353)	(0.1452)	(0.0644)	(0.0634)
Inflate Model					
4 Month Window	-0.0180	-0.0856	-0.0698	0.1240	0.1188
	(0.0179)	(0.0557)	(0.1567)	(0.0870)	(0.1113)
Ln(Alpha)	0.4596***	0.2627***	0.6984***	0.3276***	0.2166***
	(0.0080)	(0.0234)	(0.0767)	(0.0386)	(0.0431)
Observations	425954	36951	7845	16100	9216
Vuong Test	115.07	35.42	12.23	22.04	19.58

Standard errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Note: Sample 2 contains all individuals interviewed from 1st January 2004 to 31st December 2005. All estimation results include control variables as for Table 4.9, though ethnicity is excluded from the analysis. In addition, we include a binary variable denoting that the individual was interviewed from 24th August to 31st December. The coefficient "4 Month Window" is an estimate of the effect of Hurricane Katrina on the number of days of poor mental health of individuals interviewed from 24th August 2005 to 31st December 2005.

Table 4.20: Zero Inflated Negative Binomial Model Coefficients: The Effects of the Haiti Earthquake on the Number of Days of Poor Mental Health: Sample 3: By Ethnicity

	(1) White	(2) Black	(3) Asian	(4) Hawaiian	(5) American Indian
Dep. Var.	Days of Poor Mental Health				
Negative Binomial Model					
2 Month Window	-0.0223	-0.0560	-0.1634	-0.1288	-0.1073
	(0.0151)	(0.0447)	(0.1208)	(0.0822)	(0.0855)
Unemployed	0.2656***	0.1296***	0.2386**	0.1985***	0.2395***
	(0.0123)	(0.0285)	(0.0981)	(0.0529)	(0.0549)
Inflate Model					
2 Month Window	0.0061	-0.0300	-0.0302	0.0785	-0.1898*
	(0.0177)	(0.0543)	(0.1287)	(0.0972)	(0.1127)
Ln(Alpha)	0.4556***	0.1884***	0.5986***	0.2637***	0.1479***
	(0.0073)	(0.0203)	(0.0615)	(0.0356)	(0.0390)
Observations	552212	46885	12255	16923	10578
Vuong Test	124.61	40.77	14.62	23.26	20.95

Standard errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Note: Sample 3 contains all individuals interviewed from 1st April 2008 to 31st March 2010. All estimation results include control variables as for Table 4.9, though ethnicity is excluded from the analysis. In addition, a binary variable is included denoting that the individual was interviewed from 13th January to 31st March. The coefficient "2 Month Window" denotes the effect of the Haiti earthquake on the number of days of poor mental health of individuals interviewed in period from 13th January to 31st March 2010.

4.11 A4: Appendix 2: Estimating Equations

The effect of the Indian Ocean tsunami (on 26th December 2004) on the number of days of poor mental health is estimated using equation (A4.1). Equation (A4.1) is estimated using Sample 1.

$$\begin{aligned} DAYS_{itj} = \beta_0 + \beta_1(Post26/12_{i(2MonthsAfter)}) + \beta_2(Yer \\ = 2004/2005_i) + \beta_3[(Post26/12_{i(2MonthsAfter)}) \times (Year \\ = 2004/2005_i)] + \boldsymbol{\gamma Month} + \boldsymbol{\lambda X}_{itj} + \tau Attempts_{itj} + \xi_j \\ + \varepsilon_{itj} \end{aligned} \quad \text{(A4.1)}$$

$Post26/12_{i(2MonthsAfter)}$ is a binary variable equal to 1 if individual i was interviewed from 27th December to 29th February (the treatment group), the 2 month period following the time of year of the Indian Ocean tsunami[124]. $Post26/12_{i(2MonthsAfter)}$ is equal to 0 if individual i was interviewed from March 1st to 25th December (control group). Hence, $Post26/12_{i(2MonthsAfter)}$ equals 1 if the individual was interviewed in periods b) and d) in Figure 4.7, and 0 if the individual was interviewed in periods a) and c).

$Year = 2004/2005_i$ equals 1 if individual i was interviewed from 1st March 2004 to 28th February 2005, the 12 month period during which the Indian Ocean tsunami occurred. $Year = 2004/2005_i$ is equal to 0 if individual i was interviewed from 1st March 2003 to 29th February 2004. Thus, $Year = 2004/2005_i$ equals 1 if the individual was interviewed in periods c) and d) in Figure 4.7, and 0 if the individual was interviewed in periods a) and b).

$Post26/12_{i(2MonthsAfter)} \times Year = 2004/2005_i$ is an interaction term between the time of year following the Indian Ocean tsunami and the 12 month period during which the Indian Ocean tsunami occurred. In other words, $Post26/12_{i(2MonthsAfter)} \times Year = 2004/2005_i$ equals 1 if the individual was interviewed in period d) in Figure 4.7, and 0 if the individual was interviewed in periods a), b), or c). Thus, the parameter β_3 indicates the effect of the Indian Ocean tsunami on the number of days of poor mental health of individuals interviewed from 27th December 2004 to 28th February 2005 (after the disaster – period d) in Figure 4.7).

[124] For all of the zero inflated negative binomial models presented in this chapter we exclude the number of attempts taken to contact the individual from the negative binomial model to aid the identification.

Equation (A4.2) is used to investigate the effect of Hurricane Katrina (on 23rd August 2005) on the number of days of poor mental health. Equation (A4.2) is estimated using Sample 2.

$$DAYS_{itj} = \beta_0 + \beta_1(Post23/8_{i(4MonthsAfter)}) + \beta_2(Year = 2005_i) + \beta_3[(Post23/8_{i(4MonthsAfter)}) \times (Year = 2005_i)] + \boldsymbol{\gamma Month}_i + \boldsymbol{\lambda X}_{itj} + \tau Attempts_{itj} + \xi_j + \varepsilon_{itj} \quad \text{(A4.2)}$$

$Post23/8_{i(4MonthsAfter)}$ is a binary variable taking the value 1 if individual i was interviewed from 24th August to 31st December (the treatment group – periods b) and d) in Figure 4.8). $Post23/8_{i(4MonthsAfter)}$ equals 0 if the individual was interviewed from 1st January to 22nd August (the control group – periods a) and c) in Figure 4.8).

$Year = 2005_i$ equals 1 if individual i was interviewed in 2005 - the 12 month period of Hurricane Katrina (periods c) and d) in Figure 4.8). $Year = 2005_i$ equals 0 if the individual was interviewed in 2004 – periods a) and b) in Figure 4.8.

$Post23/8_{i(4MonthsAfter)} \times Year = 2005_i$ is an interaction term between the time of year following Hurricane Katrina and 2005, the 12 month period of Hurricane Katrina. Hence, $Post23/8_{i(4MonthsAfter)} \times Year = 2005_i$ is equal to 1 if the individual was interviewed in period d) in Figure 4.8, and 0 if the individual was interviewed in periods a), b), or c). The coefficient β_3 represents the effect of Hurricane Katrina on the number of days of poor mental health of individuals interviewed from 24th August 2005 to 31st December 2005 (the period after the disaster).

We make use of Equation (A4.3) to investigate the effect of the Haiti earthquake (on 12th January 2010) on the number of days of poor mental health. Equation (A4.3) is estimated using Sample 3.

$$\begin{aligned} DAYS_{itj} &= \beta_0 + \beta_1(Post12/1_{i(2MonthsAfter)}) + \beta_2(Year \\ &= 2009/2010_i) + \beta_3[(Post12/1_{i2MonthsAfter}) \times (Year \\ &= 2009/2010_i)] + \boldsymbol{\gamma Month}_i + \boldsymbol{\lambda X}_i + \tau Attempts_{itj} + \xi_j \\ &+ \varepsilon_{itj} \end{aligned} \qquad \text{(A4.3)}$$

$Post12/1_{i2MonthsAfter}$ is a binary variable taking the value 1 if individual i was interviewed from 13th January to 31st March (the treatment group – periods b) and d) in Figure 4.9). $Post12/1_{i2MonthsAfter}$ equals 0 if the individual was interviewed from 1st April to 11th January (the control group – periods a) and c) in Figure 4.9).

$Year = 2009/2010_i$ equals 1 if individual i was interviewed from 1st April 2009 to 31st March 2010, the 12 month period in which the Haiti earthquake occurred (periods c) and d) in Figure 4.9). $Year = 2009/2010_i$ equals 0 if the individual was interviewed from 1st April 2008 to 31st March 2009 – periods a) and b) in Figure 4.9.

$Post12/1_i \times Year = 2009/2010_i$ is an interaction term between the time of year of the Haiti earthquake and the 12 month period during which the Haiti earthquake took place. Thus, $Post12/1_i \times Year = 2009/2010_i$ equals 1 if the individual was interviewed in period d) of Figure 4.9, and 0 if the individual was interviewed in periods a), b), or c). The parameter β_3 indicates the effect of the Haiti earthquake on the number of days of poor mental health of individuals interviewed from 13th January to 31st March 2010 (the period after the disaster).

Equation (A4.4) is estimated using Sample 4 to test whether the number of days of poor mental health followed a common trend pre and post 26th December in the period prior to the Indian Ocean tsunami. Equation (A4.4) estimates the effect of a 'pretend' natural disaster on 26th December 2002, 2 years before the Indian Ocean tsunami, on the number of days of poor mental health.

$$\begin{aligned} DAYS_{itj} = \delta_0 + \delta_1(Post26/12_{i(2MonthsAfter)}) \ + \delta_2(Year \\ = 2002/2003_i) \ + \delta_3[Post26/12_{i(2MonthsAfter)} \times (Year \\ = 2002/2003_i)] + \boldsymbol{\gamma Month}_i + \boldsymbol{\lambda X}_{itj} + \tau Attempts_{itj} + \xi_j \\ + \varepsilon_{itj} \end{aligned} \quad \text{(A4.4)}$$

$Year = 2002/2003_i$ equals 1 if individual i was interviewed from 1st March 2002 to 28th February 2003, and 0 if interviewed from 1st March 2001 to 28th February 2002.

The coefficient of interest is δ_3 which indicates the effect of a 'pretend' Indian Ocean tsunami on the number of days of poor mental health of individuals interviewed from 27th December 2002 to 28th February 2003.

Equation (A4.5) tests for common trends pre and post 23rd August in the periods prior to Hurricane Katrina making use of Sample 5. Equation (A4.5) estimates the effect of a 'pretend' natural disaster on 23rd August 2003, 2 years prior to Hurricane Katrina, on the number of days of poor mental health.

$$\begin{aligned} DAYS_{itj} = \delta_0 + \delta_1(Post23/8_{i(4MonthsAfter)}) \ + \delta_2(Year \\ = 2003_i) + \delta_3[(Post23/8_{i(4MonthsAfter)}) \times (Year \\ = 2003_i)] + \boldsymbol{\gamma Month}_i + \boldsymbol{\lambda X}_{itj} + \tau Attempts_{itj} + \xi_j + \varepsilon_{itj} \end{aligned} \quad \text{(A4.5)}$$

$Year = 2003_i$ equals 1 if individual i was interviewed in 2003, and 0 if the individual was interviewed in 2001. The parameter δ_3 denotes the effect of the 'pretend' disaster on the number of days of poor mental health of individuals interviewed from 24th August 2003 to 31st December 2003.

Equation (A4.6) tests for common trends pre and post 12th January in the periods prior to the Haiti earthquake using Sample 6. Equation (A4.6) estimates the effect of a 'pretend' natural disaster on 12th January 2008, 2 years prior to the Haiti earthquake, on the number of days of poor mental health.

$$DAYS_{itj} = \delta_0 + \delta_1(Post12/1_{i(2MonthsAfter)}) + \delta_2(Year = 2007/2008_i) + \delta_3[(Post12/1_{i(2MonthsAfter)}) \times (Year = 2007/2008_i)] + \boldsymbol{\gamma Month}_i + \boldsymbol{\lambda X}_i + \tau Attempts_{itj} + \xi_j + \varepsilon_{itj} \quad \text{(A4.6)}$$

$(Year = 2007/2008_i)$ equals 1 if individual i was interviewed from 1st April 2007 to 31st March 2008, and 0 if the individual was interviewed from 1st April 2006 to 31st March 2007. The parameter δ_3 denotes the effect of the 'pretend' disaster on the number of days of poor mental health of individuals interviewed from 13th January 2008 to 31st March 2008.

4.12 A4: Appendix 3: Estimation Results

Table A4.1: Zero Inflated Negative Binomial Model Coefficients: The Effect of the Indian Ocean Tsunami on the Number of Days of Poor Mental Health (Sample 1): Full Estimation Results from Table 4.9

	(1) All States	(2) Non-coastal	(3) Atlantic	(4) Pacific	(5) Gulf of Mexico	(6) Great Lake
Dep. Var.			Days of Poor Mental Health			
Negative Binomial Model						
2 Month Window	-0.0653***	-0.0361	-0.0465	-0.1895***	-0.0128	-0.0643
	(0.0172)	(0.0289)	(0.0321)	(0.0471)	(0.0709)	(0.0449)
2004/2005	0.0284***	0.0214*	0.0126	0.0683***	0.0444*	0.0413**
	(0.0074)	(0.0125)	(0.0133)	(0.0213)	(0.0267)	(0.0204)
Post 26/12	-0.0345	-0.1162	-0.0791	0.1879*	-0.1527	-0.2086
	(0.0559)	(0.0934)	(0.1396)	(0.1080)	(0.3425)	(0.1402)
Male	-0.0328***	-0.0572***	-0.0257**	-0.0105	-0.0216	-0.0156
	(0.0073)	(0.0123)	(0.0130)	(0.0202)	(0.0277)	(0.0194)
Unemployed	0.2497***	0.2564***	0.2462***	0.2698***	0.2287***	0.2390***
	(0.0136)	(0.0249)	(0.0240)	(0.0349)	(0.0465)	(0.0357)
Not in Labour Force	0.0117	0.0206	0.0011	0.0181	-0.0199	0.0185
	(0.0094)	(0.0157)	(0.0175)	(0.0254)	(0.0334)	(0.0256)
Separated, Divorced, or Wid	0.1381***	0.1604***	0.1177***	0.1193***	0.2240***	0.1226***
	(0.0114)	(0.0201)	(0.0200)	(0.0318)	(0.0418)	(0.0298)
Married/ Cohab	-0.0182*	-0.0073	-0.0094	-0.0628**	0.0871**	-0.0430
	(0.0102)	(0.0182)	(0.0178)	(0.0279)	(0.0380)	(0.0265)

Note: Table continues on the next page.

Table A4.1 (continued): Zero Inflated Negative Binomial Model Coefficients: The Effect of the Indian Ocean Tsunami on the Number of Days of Poor Mental Health (Sample 1): Full Estimation Results From Table 4.9

	(1) All States	(2) Non-coastal	(3) Atlantic	(4) Pacific	(5) Gulf of Mexico	(6) Great Lake
Dep. Var.			Days of Poor Mental Health			
\$10,000 to \$14,999	-0.0519***	-0.0655**	-0.0460	-0.0311	-0.0610	-0.0529
	(0.0195)	(0.0318)	(0.0374)	(0.0551)	(0.0610)	(0.0544)
\$15,000 to \$19,999	-0.0563***	-0.0557*	-0.0766**	0.0295	-0.0270	-0.1213**
	(0.0183)	(0.0299)	(0.0348)	(0.0529)	(0.0572)	(0.0502)
\$20,000 to \$24,999	-0.1137***	-0.1169***	-0.1410***	-0.0447	-0.1263**	-0.1311***
	(0.0177)	(0.0291)	(0.0341)	(0.0486)	(0.0582)	(0.0483)
\$25,000 to \$34,999	-0.1726***	-0.1964***	-0.1680***	-0.1038**	-0.1788***	-0.1955***
	(0.0171)	(0.0282)	(0.0328)	(0.0475)	(0.0565)	(0.0469)
\$35,000 to \$49,999	-0.2295***	-0.2568***	-0.2223***	-0.1855***	-0.2089***	-0.2472***
	(0.0171)	(0.0282)	(0.0325)	(0.0470)	(0.0573)	(0.0468)
\$50,000 to \$74,999	-0.2933***	-0.3300***	-0.2926***	-0.2031***	-0.2491***	-0.3364***
	(0.0176)	(0.0295)	(0.0332)	(0.0483)	(0.0609)	(0.0482)
\$75,000 or More	-0.3514***	-0.3762***	-0.3585***	-0.2790***	-0.2758***	-0.4086***
	(0.0180)	(0.0305)	(0.0335)	(0.0493)	(0.0621)	(0.0492)
Black	0.0130	0.0452	0.0026	0.1276**	-0.0260	0.0311
	(0.0130)	(0.0344)	(0.0196)	(0.0601)	(0.0321)	(0.0303)
Asian	0.0080	0.0441	-0.0957*	0.0591	0.0232	0.1326
	(0.0312)	(0.0767)	(0.0533)	(0.0540)	(0.1460)	(0.0986)
Hawaiian	0.0748***	0.0819**	0.0556*	0.1667***	0.0092	0.1030
	(0.0193)	(0.0318)	(0.0334)	(0.0547)	(0.0626)	(0.0688)
American Indian	0.0735***	0.0588*	0.1254**	-0.0063	0.2126**	0.1937**
	(0.0232)	(0.0317)	(0.0580)	(0.0535)	(0.1078)	(0.0927)

Note: Table continues on the next page.

Table A4.1 (continued): Zero Inflated Negative Binomial Model Coefficients: The Effect of the Indian Ocean Tsunami on the Number of Days of Poor Mental Health (Sample 1): Full Estimation Results From Table 4.9

	(1) All States	(2) Non-coastal	(3) Atlantic	(4) Pacific	(5) Gulf of Mexico	(6) Great Lake
Dep. Var.	Days of Poor Mental Health					
High School Grad.	-0.0969***	-0.1072***	-0.0695***	-0.1424***	-0.0999**	-0.1189***
	(0.0134)	(0.0224)	(0.0243)	(0.0402)	(0.0417)	(0.0373)
1-3 Years University	-0.1766***	-0.1979***	-0.1277***	-0.2545***	-0.1363***	-0.2177***
	(0.0135)	(0.0227)	(0.0249)	(0.0393)	(0.0429)	(0.0382)
University Graduate	-0.3846***	-0.3787***	-0.3696***	-0.4553***	-0.3084***	-0.4325***
	(0.0139)	(0.0236)	(0.0251)	(0.0409)	(0.0452)	(0.0393)
Age	0.0074***	0.0087***	0.0069***	0.0069**	0.0013	0.0112***
	(0.0013)	(0.0022)	(0.0023)	(0.0035)	(0.0048)	(0.0033)
Age-Squared	-0.0001***	-0.0001***	-0.0001**	-0.0001*	-0.0000	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Disabled	0.4001***	0.4071***	0.3834***	0.4005***	0.4020***	0.4185***
	(0.0082)	(0.0137)	(0.0151)	(0.0220)	(0.0303)	(0.0223)
Constant	2.1842***	2.1299***	2.1446***	1.7939***	2.2433***	2.3742***
	(0.0711)	(0.1118)	(0.1540)	(0.1473)	(0.3652)	(0.1653)
Inflate Model						
2 Month Window	0.0437**	0.0393	0.0102	-0.1058*	0.4662***	0.0833
	(0.0211)	(0.0349)	(0.0384)	(0.0620)	(0.0814)	(0.0585)
2004/2005	-0.0184**	-0.0065	-0.0494***	0.0413	-0.0107	-0.0146
	(0.0092)	(0.0152)	(0.0162)	(0.0278)	(0.0321)	(0.0265)
Post 26/12	0.0423	0.0103	0.1536	-0.0532	0.2484	0.1312
	(0.0700)	(0.1130)	(0.1723)	(0.1457)	(0.3812)	(0.1828)
Male	0.6490***	0.7049***	0.5696***	0.6794***	0.6171***	0.6911***
	(0.0087)	(0.0146)	(0.0154)	(0.0256)	(0.0318)	(0.0246)

Note: Table continues on the next page.

Table A4.1 (continued): Zero Inflated Negative Binomial Model Coefficients: The Effect of the Indian Ocean Tsunami on the Number of Days of Poor Mental Health (Sample 1): Full Estimation Results From Table 4.9

	(1) All States	(2) Non-coastal	(3) Atlantic	(4) Pacific	(5) Gulf of Mexico	(6) Great Lake
Dep. Var.			Days of Poor Mental Health			
Unemployed	-0.3831***	-0.4438***	-0.4137***	-0.2977***	-0.2374***	-0.3839***
	(0.0201)	(0.0373)	(0.0348)	(0.0530)	(0.0625)	(0.0565)
Not in Labour Force	0.0893***	0.0704***	0.1076***	0.1319***	0.0225	0.1125***
	(0.0116)	(0.0192)	(0.0210)	(0.0332)	(0.0403)	(0.0333)
$10,000 to $14,999	0.0304	0.0830**	-0.0037	0.0059	-0.1203	0.1375*
	(0.0260)	(0.0424)	(0.0482)	(0.0768)	(0.0782)	(0.0793)
$15,000 to $19,999	0.1312***	0.2120***	0.0908**	0.0445	0.0508	0.1664**
	(0.0242)	(0.0395)	(0.0449)	(0.0734)	(0.0723)	(0.0741)
$20,000 to $24,999	0.1622***	0.2174***	0.1627***	-0.0216	0.0668	0.2945***
	(0.0236)	(0.0386)	(0.0440)	(0.0685)	(0.0729)	(0.0713)
$25,000 to $34,999	0.2388***	0.3259***	0.1576***	0.0952	0.1357*	0.4102***
	(0.0229)	(0.0377)	(0.0425)	(0.0668)	(0.0709)	(0.0694)
$35,000 to $49,999	0.2766***	0.3368***	0.2139***	0.1566**	0.2390***	0.4340***
	(0.0230)	(0.0380)	(0.0423)	(0.0664)	(0.0721)	(0.0697)
$50,000 to $74,999	0.3165***	0.3762***	0.2639***	0.2148***	0.2574***	0.4523***
	(0.0237)	(0.0394)	(0.0433)	(0.0679)	(0.0760)	(0.0716)
$75,000 or More	0.4315***	0.5036***	0.3983***	0.3080***	0.3698***	0.5140***
	(0.0242)	(0.0406)	(0.0438)	(0.0692)	(0.0777)	(0.0732)

Note: Table continues on the next page.

Table A4.1 (continued): Zero Inflated Negative Binomial Model Coefficients: The Effect of the Indian Ocean Tsunami on the Number of Days of Poor Mental Health (Sample 1): Full Estimation Results from Table 4.9

	(1) All States	(2) Non-coastal	(3) Atlantic	(4) Pacific	(5) Gulf of Mexico	(6) Great Lake
Dep. Var.			Days of Poor Mental Health			
Separated, Divorced, or Wid	-0.0802***	-0.0282	-0.1229***	-0.0655	-0.1025*	-0.1029**
	(0.0152)	(0.0267)	(0.0259)	(0.0452)	(0.0527)	(0.0420)
Married/ Cohab	0.1388***	0.1768***	0.1113***	0.1805***	0.0521	0.1137***
	(0.0137)	(0.0242)	(0.0233)	(0.0402)	(0.0481)	(0.0376)
Black	0.2156***	0.1841***	0.2951***	0.0832	0.1268***	0.0995**
	(0.0163)	(0.0420)	(0.0240)	(0.0852)	(0.0391)	(0.0416)
Asian	0.4763***	0.5681***	0.5296***	0.4274***	0.2255	0.6237***
	(0.0360)	(0.0861)	(0.0610)	(0.0645)	(0.1705)	(0.1144)
Hawaiian	0.3672***	0.2435***	0.4034***	0.7740***	0.1237	0.1584*
	(0.0237)	(0.0397)	(0.0410)	(0.0619)	(0.0780)	(0.0922)
American Indian	0.0036	-0.0735*	0.0713	0.0889	0.0254	0.1294
	(0.0303)	(0.0418)	(0.0718)	(0.0724)	(0.1327)	(0.1242)
High School Grad.	0.0769***	0.0609**	0.1461***	-0.1630***	0.1208**	0.1342***
	(0.0163)	(0.0269)	(0.0292)	(0.0501)	(0.0506)	(0.0484)
1-3 Years University	-0.0722***	-0.0591**	0.0040	-0.4308***	-0.0027	-0.0157
	(0.0168)	(0.0278)	(0.0303)	(0.0502)	(0.0530)	(0.0505)
University Graduate	-0.1041***	-0.1004***	-0.0437	-0.4199***	0.0127	-0.0582
	(0.0173)	(0.0289)	(0.0308)	(0.0522)	(0.0560)	(0.0520)
Age	0.0078***	-0.0008	0.0168***	0.0137***	-0.0121**	0.0202***
	(0.0016)	(0.0027)	(0.0029)	(0.0046)	(0.0058)	(0.0045)
Age-Squared	0.0003***	0.0004***	0.0002***	0.0003***	0.0005***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)

Note: Table continues on the next page.

Table A4.1 (continued): Zero Inflated Negative Binomial Model Coefficients: The Effect of the Indian Ocean Tsunami on the Number of Days of Poor Mental Health (Sample 1): Full Estimation Results from Table 4.9

	(1) All States	(2) Non-coastal	(3) Atlantic	(4) Pacific	(5) Gulf of Mexico	(6) Great Lake
Dep. Var.			Days of Poor Mental Health			
Disabled	-0.8679***	-0.8438***	-0.8978***	-0.8487***	-0.9804***	-0.8121***
	(0.0112)	(0.0183)	(0.0205)	(0.0317)	(0.0403)	(0.0320)
Number of Attempts	-0.0016	-0.0014	0.0005	-0.0021	-0.0022	-0.0082***
	(0.0010)	(0.0019)	(0.0016)	(0.0027)	(0.0039)	(0.0027)
Constant	-1.2777***	-1.1797***	-1.6512***	-0.9907***	-1.0443**	-1.9339***
	(0.0902)	(0.1385)	(0.1926)	(0.2007)	(0.4109)	(0.2256)
Ln(Alpha)	0.4302***	0.4228***	0.4352***	0.4935***	0.3252***	0.4106***
	(0.0077)	(0.0128)	(0.0138)	(0.0215)	(0.0271)	(0.0210)
State Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	440066	160028	138067	54634	32441	54896
Vuong Test	118.7401	72.6302	65.0283	41.0925	33.9594	41.0131

Standard errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Note: Sample 1 contains all individuals interviewed from 1st March 2003 to 28th February 2005. All models include state and month fixed effects. The coefficient "2 Month Window" is an estimate of the effect of the Indian Ocean tsunami on the number of days of poor mental health of individuals interviewed from 27th December 2004 to 28th February 2005. Column (1) uses a sample of individuals from all states. Columns (2) to (6) investigate whether the effect of the Indian Ocean tsunami varies depending on the individual's proximity to the disaster area.

Table A4.2: Zero Inflated Negative Binomial Model Coefficients: The Effect of Hurricane Katrina on the Number of Days of Poor Mental Health (Sample 2): Full Estimation Results from Table 4.11

	(1) All States	(2) Affected by Katrina	(3) Border an Affected State	(4) Remaining States
Dep. Var.	Days of Poor Mental Health			
Negative Binomial Model				
4 Month Window	0.0069	0.0695	0.0335	-0.0038
	(0.0134)	(0.0442)	(0.0350)	(0.0155)
2005	-0.0248***	-0.0172	-0.0407**	-0.0237***
	(0.0079)	(0.0242)	(0.0203)	(0.0092)
Post 23/8	-0.0152	-0.1048	-0.0152	-0.0021
	(0.0375)	(0.1201)	(0.1035)	(0.0427)
Male	-0.0293***	-0.0047	-0.0394**	-0.0310***
	(0.0070)	(0.0226)	(0.0183)	(0.0080)
Unemployed	0.2345***	0.1881***	0.2342***	0.2403***
	(0.0133)	(0.0398)	(0.0334)	(0.0156)
Not in Labour Force	0.0090	0.0027	0.0054	0.0087
	(0.0089)	(0.0274)	(0.0228)	(0.0103)
$10,000 to $14,999	-0.0665***	-0.0410	-0.0409	-0.0790***
	(0.0188)	(0.0516)	(0.0441)	(0.0225)
$15,000 to $19,999	-0.0807***	-0.0726	-0.0910**	-0.0809***
	(0.0176)	(0.0486)	(0.0414)	(0.0211)
$20,000 to $24,999	-0.1180***	-0.1093**	-0.1566***	-0.1139***
	(0.0170)	(0.0488)	(0.0410)	(0.0202)
$25,000 to $34,999	-0.1849***	-0.1808***	-0.1815***	-0.1886***
	(0.0165)	(0.0473)	(0.0398)	(0.0196)
$35,000 to $49,999	-0.2323***	-0.1913***	-0.2383***	-0.2395***
	(0.0165)	(0.0480)	(0.0403)	(0.0195)
$50,000 to $74,999	-0.3081***	-0.2721***	-0.2931***	-0.3184***
	(0.0169)	(0.0501)	(0.0423)	(0.0200)
$75,000 or More	-0.3517***	-0.3170***	-0.3487***	-0.3585***
	(0.0173)	(0.0513)	(0.0439)	(0.0203)
Separated, Div or Wid	0.1388***	0.1873***	0.1716***	0.1311***
	(0.0110)	(0.0348)	(0.0296)	(0.0126)
Married/ Cohab	-0.0157	0.0438	0.0709***	-0.0344***
	(0.0099)	(0.0318)	(0.0275)	(0.0112)
Black	0.0189	-0.0199	-0.0280	0.0602***
	(0.0125)	(0.0270)	(0.0269)	(0.0166)
Asian	-0.0121	0.0778	-0.2134*	-0.0025
	(0.0290)	(0.1232)	(0.1112)	(0.0311)
Hawaiian	0.0374**	0.0556	0.0022	0.0410*
	(0.0185)	(0.0478)	(0.0490)	(0.0220)
American Indian	0.0936***	0.2324**	0.1352***	0.0619**
	(0.0220)	(0.0929)	(0.0405)	(0.0271)

Note: Table continues on the next page.

Table A4.2 (continued): Zero Inflated Negative Binomial Model Coefficients: The Effect of Hurricane Katrina on the Number of Days of Poor Mental Health (Sample 2): Full Estimation Results from Table 4.11

	(1) All States	(2) Affected by Katrina	(3) Border an Affected State	(4) Remaining States
Dep. Var.		Days of Poor Mental Health		
High School Grad.	-0.1127***	-0.1093***	-0.0872***	-0.1192***
	(0.0127)	(0.0343)	(0.0295)	(0.0155)
1-3 Years University	-0.1756***	-0.1570***	-0.1559***	-0.1840***
	(0.0129)	(0.0351)	(0.0305)	(0.0156)
University Graduate	-0.3902***	-0.3455***	-0.3703***	-0.4013***
	(0.0133)	(0.0368)	(0.0318)	(0.0160)
Age	0.0068***	0.0050	-0.0004	0.0083***
	(0.0012)	(0.0038)	(0.0032)	(0.0014)
Age-Squared	-0.0001***	-0.0000	0.0000	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Disabled	0.3994***	0.3685***	0.4090***	0.4018***
	(0.0078)	(0.0244)	(0.0201)	(0.0090)
Constant	2.1979***	2.1207***	2.2305***	2.0524***
	(0.0452)	(0.1039)	(0.0875)	(0.0520)
Inflate Model				
4 Month Window	-0.0150	-0.0712	-0.0014	-0.0106
	(0.0164)	(0.0521)	(0.0412)	(0.0191)
2005	0.0273***	0.1018***	-0.0196	0.0271**
	(0.0096)	(0.0283)	(0.0239)	(0.0114)
Post 23/8	-0.0208	-0.1029	-0.0603	-0.0032
	(0.0473)	(0.1477)	(0.1257)	(0.0546)
Male	0.6422***	0.6174***	0.6352***	0.6487***
	(0.0082)	(0.0255)	(0.0207)	(0.0096)
Unemployed	-0.3659***	-0.2745***	-0.4152***	-0.3721***
	(0.0195)	(0.0541)	(0.0471)	(0.0234)
Not in Labour Force	0.0814***	0.0829**	0.0641**	0.0860***
	(0.0109)	(0.0322)	(0.0268)	(0.0128)

Table A4.2 (continued): Zero Inflated Negative Binomial Model Coefficients: The Effect of Hurricane Katrina on the Number of Days of Poor Mental Health (Sample 2): Full Estimation Results from Table 4.11

	(1) All States	(2) Affected by Katrina	(3) Border an Affected State	(4) Remaining States
Dep. Var.		Days of Poor Mental Health		
\$10,000 to \$14,999	0.0874***	-0.0723	0.1239**	0.1093***
	(0.0247)	(0.0649)	(0.0557)	(0.0304)
\$15,000 to \$19,999	0.1414***	0.0812	0.2029***	0.1359***
	(0.0232)	(0.0606)	(0.0524)	(0.0286)
\$20,000 to \$24,999	0.1845***	0.1006*	0.2003***	0.1967***
	(0.0225)	(0.0606)	(0.0520)	(0.0275)
\$25,000 to \$34,999	0.2624***	0.1393**	0.2848***	0.2784***
	(0.0219)	(0.0591)	(0.0508)	(0.0268)
\$35,000 to \$49,999	0.2981***	0.2371***	0.3290***	0.3030***
	(0.0220)	(0.0600)	(0.0515)	(0.0267)
\$50,000 to \$74,999	0.3427***	0.2344***	0.3618***	0.3561***
	(0.0226)	(0.0626)	(0.0537)	(0.0273)
\$75,000 or More	0.4697***	0.3733***	0.5513***	0.4715***
	(0.0230)	(0.0639)	(0.0554)	(0.0278)
Separated, Div or Wid	-0.0561***	-0.0819*	-0.0649*	-0.0516***
	(0.0144)	(0.0434)	(0.0372)	(0.0169)
Married/ Cohab	0.1428***	0.0585	0.1334***	0.1556***
	(0.0131)	(0.0398)	(0.0343)	(0.0152)
Black	0.2318***	0.1302***	0.2166***	0.2703***
	(0.0155)	(0.0327)	(0.0320)	(0.0210)
Asian	0.4605***	0.3944***	0.3490***	0.4804***
	(0.0336)	(0.1369)	(0.1258)	(0.0365)
Hawaiian	0.4240***	0.2306***	0.5433***	0.4326***
	(0.0222)	(0.0570)	(0.0552)	(0.0268)
American Indian	0.0033	0.0831	0.0196	-0.0132
	(0.0285)	(0.1117)	(0.0506)	(0.0362)
High School Grad.	0.0534***	0.1350***	0.0186	0.0453**
	(0.0153)	(0.0408)	(0.0347)	(0.0189)
1-3 Years University	-0.0914***	-0.0068	-0.1027***	-0.1059***
	(0.0159)	(0.0427)	(0.0364)	(0.0195)
University Graduate	-0.1208***	0.0063	-0.1610***	-0.1350***
	(0.0163)	(0.0450)	(0.0382)	(0.0199)

Note: Table continues on the next page.

Table A4.2 (continued): Zero Inflated Negative Binomial Model Coefficients: The Effect of Hurricane Katrina on the Number of Days of Poor Mental Health (Sample 2): Full Estimation Results from Table 4.11

	(1) All States	(2) Affected by Katrina	(3) Border an Affected State	(4) Remaining States
Dep. Var.	Days of Poor Mental Health			
Age	0.0029*	-0.0044	-0.0116***	0.0077***
	(0.0015)	(0.0046)	(0.0038)	(0.0018)
Age-Squared	0.0003***	0.0004***	0.0005***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Disabled	-0.8885***	-0.9940***	-0.8592***	-0.8802***
	(0.0105)	(0.0321)	(0.0259)	(0.0124)
Number of Attempts	-0.0010	0.0016	0.0012	-0.0016
	(0.0009)	(0.0029)	(0.0027)	(0.0011)
Constant	-1.1268***	-0.8528***	-0.6505***	-1.1388***
	(0.0578)	(0.1295)	(0.1094)	(0.0674)
Ln(Alpha)	0.4404***	0.3419***	0.3354***	0.4731***
	(0.0073)	(0.0221)	(0.0183)	(0.0085)
State Controls	Yes	Yes	Yes	Yes
Month Controls	Yes	Yes	Yes	Yes
Observations	496066	50348	73928	371790
Vuong Test	123.4514	40.9358	49.3337	104.6722

Standard errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Note: Sample 2 contains all individuals interviewed from 1st January 2004 to 31st December 2005. All models include state and month fixed effects. The coefficient "4 Month Window" is an estimate of the effect of Hurricane Katrina on the number of days of poor mental health of individuals interviewed from 24th August 2005 to 31st December 2005. Column (1) uses a sample of individuals from all states and columns (2) to (4) investigate whether the effect of Hurricane Katrina is dependent on the individual's proximity to the disaster area.

Table A4.3: Zero Inflated Negative Binomial Model Coefficients: The Effect of the Haiti Earthquake on the Number of Days of Poor Mental Health (Sample 3): Full Estimation Results from Table 4.13

	(1) All States	(2) < 1,501 Miles from Haiti	(3) 1,502 to 1825 Miles from Haiti	(4) 1,826 to 2,552 Miles from Haiti	(5) 2,553 to 5,368 Miles from Haiti
Dep. Var.	Days of Poor Mental Health				
Negative Binomial Model					
2 Month Window	-0.0313**	-0.0677**	-0.0152	-0.0245	-0.0313**
	(0.0138)	(0.0263)	(0.0257)	(0.0284)	(0.0138)
Post 12/1	0.0155	0.0200	0.0841*	-0.0606	0.0043
	(0.0231)	(0.0446)	(0.0440)	(0.0477)	(0.0496)
2009/2010	0.0153**	0.0270**	0.0090	0.0125	0.0125
	(0.0066)	(0.0130)	(0.0123)	(0.0134)	(0.0143)
Male	0.0119*	0.0214*	-0.0011	0.0247*	0.0035
	(0.0063)	(0.0127)	(0.0117)	(0.0129)	(0.0136)
Unemployed	0.2434***	0.2042***	0.2370***	0.2567***	0.2784***
	(0.0108)	(0.0205)	(0.0197)	(0.0238)	(0.0234)
Not in Labour Force	0.0126	0.0115	-0.0050	0.0311*	0.0127
	(0.0080)	(0.0154)	(0.0154)	(0.0163)	(0.0166)
$10,000 to $14,999	-0.0378**	-0.0528*	-0.0292	0.0126	-0.0834**
	(0.0177)	(0.0317)	(0.0338)	(0.0378)	(0.0392)
$15,000 to $19,999	-0.0757***	-0.0917***	-0.0624**	-0.0603*	-0.0881**
	(0.0165)	(0.0294)	(0.0313)	(0.0350)	(0.0373)
$20,000 to $24,999	-0.1003***	-0.1238***	-0.0920***	-0.0857**	-0.1030***
	(0.0160)	(0.0291)	(0.0306)	(0.0336)	(0.0353)
$25,000 to $34,999	-0.1697***	-0.1887***	-0.1820***	-0.1395***	-0.1762***
	(0.0157)	(0.0287)	(0.0300)	(0.0330)	(0.0345)
$35,000 to $49,999	-0.2235***	-0.2491***	-0.2223***	-0.1917***	-0.2414***
	(0.0155)	(0.0285)	(0.0295)	(0.0327)	(0.0336)
$50,000 to $74,999	-0.2938***	-0.3219***	-0.2973***	-0.2812***	-0.2821***
	(0.0157)	(0.0294)	(0.0300)	(0.0333)	(0.0339)
$75,000 or More	-0.3751***	-0.4129***	-0.3964***	-0.3411***	-0.3582***
	(0.0158)	(0.0296)	(0.0301)	(0.0335)	(0.0338)
Separated, Div or Wid	0.1397***	0.1588***	0.0938***	0.1532***	0.1804***
	(0.0103)	(0.0205)	(0.0183)	(0.0218)	(0.0230)
Married/ Cohab	0.0077	0.0468**	-0.0149	0.0099	0.0139
	(0.0095)	(0.0193)	(0.0167)	(0.0202)	(0.0207)
Black	0.0295***	-0.0414***	0.0738***	0.0781***	0.2103***
	(0.0113)	(0.0159)	(0.0208)	(0.0287)	(0.0481)
Asian	-0.0562**	-0.0695	-0.1934***	-0.0518	0.0051
	(0.0248)	(0.0720)	(0.0506)	(0.0714)	(0.0351)
Hawaiian	0.0892***	0.0462	0.0851**	0.0711**	0.1387***
	(0.0179)	(0.0426)	(0.0341)	(0.0353)	(0.0341)
American Indian	0.0634***	0.0963*	0.0408	0.1046***	0.0217
	(0.0205)	(0.0535)	(0.0591)	(0.0336)	(0.0357)

Note: Table continues on the next page.

Table A4.3 (continued): Zero Inflated Negative Binomial Model Coefficients: The Effect of the Haiti Earthquake on the Number of Days of Poor Mental Health (Sample 3): Full Estimation Results from Table 4.13

	(1) All States	(2) < 1,501 Miles from Haiti	(3) 1,502 to 1825 Miles from Haiti	(4) 1,826 to 2,552 Miles from Haiti	(5) 2,553 to 5,368 Miles from Haiti
Dep. Var.			Days of Poor Mental Health		
High School Grad.	-0.0985***	-0.1158***	-0.0909***	-0.1070***	-0.0893***
	(0.0119)	(0.0209)	(0.0231)	(0.0256)	(0.0267)
1-3 Years University	-0.1478***	-0.1557***	-0.1452***	-0.1429***	-0.1623***
	(0.0121)	(0.0216)	(0.0237)	(0.0257)	(0.0265)
University Graduate	-0.3656***	-0.3604***	-0.3597***	-0.3767***	-0.3759***
	(0.0124)	(0.0226)	(0.0239)	(0.0264)	(0.0270)
Age	0.0096***	0.0069***	0.0127***	0.0095***	0.0082***
	(0.0011)	(0.0022)	(0.0021)	(0.0023)	(0.0024)
Age-Squared	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Disabled	0.3843***	0.3534***	0.3883***	0.4068***	0.3882***
	(0.0066)	(0.0127)	(0.0125)	(0.0135)	(0.0141)
Constant	2.1351***	2.2932***	1.9508***	1.9459***	1.8840***
	(0.0425)	(0.0723)	(0.0717)	(0.0752)	(0.0831)
Inflate Model					
2 Month Window	0.0021	-0.0515*	0.0144	0.0181	0.0412
	(0.0162)	(0.0306)	(0.0305)	(0.0327)	(0.0371)
Post 12/1	0.0175	0.0988*	0.0260	-0.0357	-0.0329
	(0.0271)	(0.0524)	(0.0524)	(0.0540)	(0.0604)
2009/2010	0.0112	0.0518***	0.0056	-0.0373**	0.0259
	(0.0077)	(0.0152)	(0.0147)	(0.0155)	(0.0172)
Male	0.6080***	0.5903***	0.5612***	0.6394***	0.6633***
	(0.0072)	(0.0143)	(0.0135)	(0.0144)	(0.0160)
Unemployed	-0.4321***	-0.4517***	-0.3948***	-0.4606***	-0.4314***
	(0.0152)	(0.0283)	(0.0275)	(0.0335)	(0.0343)
Not in Labour Force	0.0748***	0.0422**	0.0950***	0.0884***	0.0834***
	(0.0093)	(0.0177)	(0.0181)	(0.0187)	(0.0202)

Note: Table continues on the next page.

Table A4.3 (continued): Zero Inflated Negative Binomial Model Coefficients: The Effect of the Haiti Earthquake on the Number of Days of Poor Mental Health (Sample 3): Full Estimation Results from Table 4.13

	(1) All States	(2) < 1,501 Miles from Haiti	(3) 1,502 to 1825 Miles from Haiti	(4) 1,826 to 2,552 Miles from Haiti	(5) 2,553 to 5,368 Miles from Haiti
Dep. Var.	Days of Poor Mental Health				
\$10,000 to \$14,999	0.0818***	0.0232	0.1573***	0.1283***	0.0317
	(0.0229)	(0.0400)	(0.0452)	(0.0480)	(0.0537)
\$15,000 to \$19,999	0.1185***	0.0303	0.1903***	0.1669***	0.1207**
	(0.0214)	(0.0373)	(0.0422)	(0.0447)	(0.0506)
\$20,000 to \$24,999	0.1784***	0.1125***	0.2861***	0.1659***	0.1671***
	(0.0207)	(0.0367)	(0.0409)	(0.0431)	(0.0480)
\$25,000 to \$34,999	0.2471***	0.1856***	0.3426***	0.2720***	0.1969***
	(0.0203)	(0.0361)	(0.0403)	(0.0422)	(0.0468)
\$35,000 to \$49,999	0.2972***	0.2604***	0.3832***	0.3241***	0.2316***
	(0.0202)	(0.0361)	(0.0399)	(0.0421)	(0.0462)
\$50,000 to \$74,999	0.3576***	0.3147***	0.4584***	0.3558***	0.3210***
	(0.0205)	(0.0371)	(0.0405)	(0.0430)	(0.0466)
\$75,000 or More	0.5019***	0.4668***	0.5683***	0.5384***	0.4597***
	(0.0207)	(0.0375)	(0.0407)	(0.0432)	(0.0465)
Separated, Div or Wid	-0.0837***	-0.1214***	-0.0900***	-0.0845***	-0.0186
	(0.0131)	(0.0254)	(0.0233)	(0.0273)	(0.0309)
Married/ Cohab	0.0976***	0.0446*	0.0913***	0.0920***	0.1864***
	(0.0121)	(0.0238)	(0.0215)	(0.0253)	(0.0282)
Black	0.1896***	0.1902***	0.1904***	0.1761***	0.1116*
	(0.0136)	(0.0189)	(0.0256)	(0.0348)	(0.0612)
Asian	0.3964***	0.4002***	0.4672***	0.4504***	0.3500***
	(0.0278)	(0.0795)	(0.0573)	(0.0783)	(0.0402)
Hawaiian	0.3390***	0.2589***	0.4038***	0.3295***	0.3283***
	(0.0212)	(0.0505)	(0.0413)	(0.0406)	(0.0409)
American Indian	-0.0449*	-0.0562	-0.1562**	0.0014	-0.0762
	(0.0264)	(0.0668)	(0.0787)	(0.0419)	(0.0481)
High School Grad.	0.0821***	0.1201***	0.1372***	0.0827***	-0.0605*
	(0.0141)	(0.0248)	(0.0277)	(0.0294)	(0.0329)
1-3 Years University	-0.0386***	-0.0012	0.0327	-0.0605**	-0.1710***
	(0.0145)	(0.0259)	(0.0289)	(0.0301)	(0.0330)
University Graduate	-0.0954***	-0.0424	-0.0364	-0.1290***	-0.2248***
	(0.0149)	(0.0271)	(0.0292)	(0.0310)	(0.0338)

Note: Table continues on the next page.

Table A4.3 (continued): Zero Inflated Negative Binomial Model Coefficients: The Effect of the Haiti Earthquake on the Number of Days of Poor Mental Health (Sample 3): Full Estimation Results from Table 4.13

	(1)	(2)	(3)	(4)	(5)
	All States	< 1,501 Miles from Haiti	1,502 to 1825 Miles from Haiti	1,826 to 2,552 Miles from Haiti	2,553 to 5,368 Miles from Haiti
Dep. Var.	Days of Poor Mental Health				
Age	-0.0003	-0.0110***	0.0134***	-0.0078***	0.0043
	(0.0014)	(0.0027)	(0.0026)	(0.0027)	(0.0030)
Age-Squared	0.0003***	0.0004***	0.0002***	0.0004***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Disabled	-0.8849***	-0.8989***	-0.8929***	-0.8331***	-0.9179***
	(0.0085)	(0.0162)	(0.0164)	(0.0170)	(0.0188)
Number of Attempts	-0.0027***	-0.0007	-0.0051***	-0.0006	-0.0039**
	(0.0008)	(0.0017)	(0.0015)	(0.0017)	(0.0016)
Constant	-0.8822***	-0.5564***	-1.2175***	-0.7918***	-0.9816***
	(0.0526)	(0.0886)	(0.0923)	(0.0930)	(0.1090)
Ln(Alpha)					
	0.4263***	0.2828***	0.4230***	0.4938***	0.5088***
State Controls	Yes	Yes	Yes	Yes	Yes
Month Controls	Yes	Yes	Yes	Yes	Yes
Observations	638853	156142	177160	168372	137179
Vuong Test	134.4803	71.5567	69.0820	65.9520	61.2362

Standard errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01

Note: Sample 3 contains all individuals interviewed from 1st April 2008 to 31st March 2010. All models include state and month fixed effects. The coefficient "2 Month Window" denotes the effect of the Haiti earthquake on the number of days of poor mental health of individuals interviewed from 13th January to 31st March 2010. Column (1) uses a sample of individuals from all states. Furthermore, columns (2) to (4) investigate whether the effect of the Haiti earthquake is dependent on the individual's proximity to the disaster area.

Chapter 5: Conclusions

This thesis presented three related, yet independent empirical chapters, each exploring important topics in the areas of subjective well-being (SWB) and mental health. Each of the chapters investigated "negative" areas relating to the determinants and consequences of SWB and mental health. To summarise, Chapter 2 explored how "*what others do to you*" as a child affects SWB in later life, Chapter 3 investigated how mental health affects "*what you do to others*", and Chapter 4 explored how "*what happens to others*" affects your own SWB.

5.1 Thesis Summary

5.1.1 Summary of Chapter 2

Chapter 2 investigated the long-term effects of being bullied on SWB as an adult using cohort data from the UK 1958 National Child Development Study (NCDS). The analysis made use of two indicators of SWB, namely, life satisfaction and total malaise. Life satisfaction was self-reported at ages 33, 42, 46, and 50; and total malaise was self-reported at ages 33, 42, and 50. The indicator of whether the child was bullied was reported when the child was age 11.

We contributed to the existing literature exploring the effects of bullying victimisation in several ways. Firstly, we did not rely on retrospectively reported measures of being bullied and therefore the findings cannot suffer from reverse causality. Secondly, we investigated the effects of bullying victimisation on two measures of adult SWB.

Thirdly, we show that the effect of being bullied on adult SWB exists after controlling for the marital status, employment status, and income. Fourthly, we utilised 2SRI models and Hausman tests to test for omitted variable bias, (see Terza et al., 2008; Hausman, 1978). Finally, we adjusted for non-response using Heckman selection models, see Heckman (1979).

The empirical analysis explored the effects of being bullied on adult SWB using random effects ordered probit models, random effects models that treat SWB as continuous, 2SRI models, and Heckman selection models. The evidence suggested that bullying victimisation at age 11 has a large, adverse effect on life satisfaction, approximately 30% of the magnitude of the effect of being unemployed. Additionally, individuals who were bullied report approximately 0.18 points lower total malaise, which is approximately 12% of a standard deviation lower SWB. We also used linear Heckman selection models to adjust for sample selection bias, though the findings did not change substantively. Finally, Hausman tests indicated no evidence of omitted variable bias supporting a causal interpretation of our results.

5.1.2 Summary of Chapter 3

Chapter 3 investigated the effects of the mental health of adolescents on their antisocial behaviour (ASB) using panel data from Understanding Society. The core analysis of Chapter 3 utilised four dependent variables denoting an adolescent's involvement in fighting, vandalism, shoplifting, and truancy. We measured the mental health of adolescents using the Strengths and Difficulties Questionnaire (SDQ), which is a measure of children's overall mental health, see Goodman et al. (2010). Likewise, we explored whether internalising and externalising mental health problems differ in their effects on ASB. As a further extension to our analysis, we investigated the predictive power of the mental health of adolescents on their participation in harmful substance use and prosocial behaviour in the next wave.[125]

The empirical analysis contributed to the existing literature exploring the effects of mental health on ASB in a number of ways. Firstly, we controlled for the social characteristics of adolescents such as the frequency that they eat evening meals with their family and stay out late. It is important to control for these social characteristics because they affect both the ASB of adolescents and their mental health, (see Iacovou, 2012; Sen, 2010). Secondly, we used multivariate probit models to improve the efficiency of our estimates.

We made use of several methodological approaches to investigate the effects of the mental health of adolescents on ASB, specifically: random effects probit models, multivariate probit models, and conditional logit models. Our results suggest several conclusions. Firstly, poorer overall mental health of adolescents positively predicts participation in ASB. Secondly, greater externalising problems of adolescents are positively associated with whether they engage in ASB. Thirdly, the results from random effects probit and multivariate probit models show that the tendency of adolescents to internalise is positively associated with whether adolescents fight, but has no statistically significant effect on whether they vandalise, shoplift, or truant. Finally, externalising problems of adolescents are positively (inversely) associated with the probability of harmful substance use (volunteering) in the next wave.

[125] The measures of harmful substance use were drinking alcohol, cigarette smoking, and taking drugs; and the measures of prosocial behaviour were volunteering and helping with housework.

5.1.3 Summary of Chapter 4

In comparison to the previous chapters, Chapter 4 explored how the wider context of world events affect SWB. The world events considered were three large-scale natural disasters: the 2004 Indian Ocean tsunami, Hurricane Katrina in 2005, and the Haiti earthquake in 2010. We investigated the effects of the natural disasters on the SWB of Americans using the Behavioural Risk Factor Surveillance System (BRFSS) dataset. The measure of SWB utilised was the number of days of poor self-reported mental health in the past 30 days. We further investigated how the effects of the disasters varied by proximity to the disaster areas.

We contributed to the existing literature exploring the effects of natural disasters on SWB in some ways. Firstly, we controlled for a wide range of individual level variables, state fixed effects, the number of attempts taken to contact the individual, and the month and year of interview. Secondly, we tested for common seasonal trends prior to the disasters using placebo tests.

To investigate the effects of the natural disasters on SWB we made use of zero inflated negative binomial models and a difference-in-difference approach. We used zero inflated negative binomial models to account for two characteristics of the dependent variable: the high proportion of individuals who reported 0 days of poor mental health, and overdispersion.

The analysis presented several findings. Firstly, Hurricane Katrina adversely affected the SWB of Americans who lived in the states that were directly affected by the disaster. Secondly, in contrast to the effect of Hurricane Katrina, the Indian Ocean tsunami and the Haiti earthquake had a positive effect on the SWB of Americans who lived closest to the disaster areas. Americans living closest to the disaster area may have compared themselves to the victims of the disasters, leading them to feel grateful that the disasters did not affect them, thus increasing their SWB. Finally, the results from placebo tests suggested that SWB followed a common trend prior to the disasters, supporting a causal interpretation of the findings.

5.2 Policy Implications and Avenues for Future Research

We discuss the policy implications of our findings and recommend some important areas for future research below:

The findings of Chapter 2 suggested that bullying victimisation at age 11 has a large, adverse effect on SWB as an adult. Recent estimates suggest that approximately 20-30% of children are bullied by other children, (see Understanding Society, 2013; Cawson et al., 2000). Consequently, our analysis supports the case that preventing children bullying in schools may have a positive effect on the SWB of a large percentage of the adult population. We acknowledge that, at present, there is little understanding of the specific channels via which bullying victimisation may reduce adult SWB. However, the findings indicate that maternal reports of children's experiences of bullying victimisation may be a useful "red flag" for policymakers. In other words, policymakers could use being bullied as an early predictor of low adult SWB.

Future research in this area should investigate the mechanisms via which bullying victimisation may affect adult SWB. Additionally, in order to clarify the importance of the institutional context in which bullying occurs, this research could investigate the robustness of our findings, using longitudinal data from countries other than the UK to take a comparative perspective.

The evidence provided in Chapter 3 indicated that greater externalising problems of adolescents are positively associated with the likelihood that they engage in ASB. Previous research has suggested that adolescents who commit ASB have an increased probability of committing crime as adults, see Bergman and Andershed (2009). Consequently, the findings suggest that mental health interventions to target the externalising problems of adolescents may reduce future crime. In addition, the results support the case that the money spent on the *"Troubled Families"* programme may be spent more cost-effectively in reducing ASB by expanding access to mental health interventions for adolescents, such as via the Improving Access to Psychological Therapies programme. Additionally, the findings indicate no consistent effect of family income on ASB and therefore support the notion that direct mental health interventions may be needed, rather than interventions to improve material well-being.

Future research in this area could investigate the effects of mental health on a wider range of measures of ASB such as car theft and drug dealing; and how different types of ASB as a child relate to adult behaviour. Additionally, as previously discussed in Chapter 1, Lee and Oguzoglu (2007) suggest that SWB and mental health problems such as depression are distinct constructs, rather than opposite ends of the same continuum. Consequently, future research could explore the distinctions and the relationships between SWB and mental health.

The analysis of Chapter 4 indicated two important findings. Firstly, Hurricane Katrina had a negative effect on the SWB of individuals living in the states that were directly affected by the disaster. As a result, the findings suggest that government intervention in the aftermath of disasters is needed to help mitigate the adverse effects of natural disasters on the SWB of people who live in the directly affected areas. For example, appropriate mental health services and counselling could be offered to people suffering unhappiness or distress because of natural disasters.

Secondly, the analysis suggested that the Indian Ocean tsunami and the Haiti earthquake increased the SWB of Americans living closest to the affected areas. This somewhat surprising finding may be explained by the interdependence of utility functions. Following the disasters, Americans were exposed to the widespread coverage of the disasters via social and traditional media sources. Because of the extensive media coverage, they may therefore have thought about the catastrophic repercussions of the disasters for the victims. Consequently, Americans who lived closest to the affected areas may have compared themselves to the disaster victims, leading them to feel thankful that the disaster did not affect them, thus increasing their SWB.

The empirical results support the case that the utility functions of strangers may be interdependent, rather than independent, an assumption generally made in economics. Furthermore, the findings indicated no evidence that the effects of the disasters were more pronounced for individuals of the same ethnicity as the disaster victims. The results therefore suggest that geographical proximity to the affected areas, rather than sharing similar characteristics with the disaster victims, may determine the effects of natural disasters on SWB outside of the areas that were directly affected. The findings support the case that large, unanticipated utility shocks in one country may affect the utility of strangers many thousands of miles distant.

Future research in this area could further explore the causal mechanisms of how natural disasters affect the SWB of people who live in other countries. Another avenue for future research is to explore the sensitivity of comparison effects following natural disasters to the institutional context of where an individual lives. For instance, by investigating how SWB in developing countries is affected by natural disasters that happen farther afield.

The empirical studies of this thesis each investigated topics relating to the areas of SWB and mental health. Due to the growing interest of policymakers in SWB, we call for further research to investigate how policymakers may intervene to increase SWB. We hope that the analyses presented in this thesis will help to provide a number of important suggestions for future avenues of research and will stimulate research in this highly policy-relevant area of economics.

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