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The Impact of Victimisation on Subjective Well-Being

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The Impact of Victimisation on Subjective Well-Being

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September, 2021

Abstract

This paper uses the UK Household Longitudinal Study to explore the relationship between victimisation and several measures of subjective well-being. Using person fixed effects models, I find that being attacked or insulted both significantly reduce well-being at the mean, with no significant differences between men and women in the effect size. Next, using unconditional quantile regression with fixed effects models, I identify the highly heterogeneous effects of victimisation along the unconditional well-being distribution. The effect of victimisation on subjective well-being is monotonically decreasing, with those at 'worse' quantiles of the well-being distribution experiencing the largest falls in well-being, and those at the 'better' quantiles of the distribution experiencing the smallest falls.

JEL Classification: I31, J00, J17, C21

Keywords: Victimisation, Subjective Well-Being

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1 Introduction

According to the Crime Survey for England and Wales (CSEW, 2019), 1 in 5 adults experienced a crime in the previous year. There were an estimated 1.3 million incidents of violence in 2019, and Britons consistently rank crime among the most important issues facing their country (YouGov, 2019). Estimating the costs of these victimisation incidents is of concern for policy makers in determining appropriate political responses. Since Becker (1968) launched the economics of crime literature, a significant body of work has developed measuring the pecuniary costs of crime victimisation which include medical expenses, lost labour market activity and the expenses incurred in funding police and legal responses. However, the impact of victimisation goes far beyond such financial costs and can have long lasting non-pecuniary negative effects on the mental health, well-being and subjective feelings of safety of the victimised. Any holistic estimate of the cost of victimisation should take such factors into account.

Economists now frequently incorporate psychometric measures of mental health and well-being into their analyses when evaluating the consequences of various life events and shocks. For example, adverse labour market events like underemployment and unemployment have been linked to large decreases in subjective well-being measures (Blanchflower and Oswald, 2004; Drydakis, 2015; Mousteri et al., 2020; Ahn et al., 2004; Mousteri et al., 2018), while noise pollution reduces individuals life satisfaction (van Praag and Baarsma, 2005).

The current 'happiness economics' literature has documented a negative relationship between victimisation and a wide array of subjective well-being and life satisfaction measures. However, Hope (2013) points out that many of these studies are limited by their use of cross-sectional analysis which cannot account for unobserved individual heterogeneity. Personality traits, which are moderately stable within individuals over time, are correlated with victimisation rates and measures of subjective well-being (Cawvey et al., 2018; Lucas et al., 2008). Given that many social surveys do not include personality trait data, cross-sectional analysis may be particularly problematic in the context of studying victimisation and well-being. When comparing victims and non-victims in cross-sectional analysis, these groups may differ systematically from one another and lead to biased estimates.

The majority of this literature has focused on regression methods which estimate the average effect of victimisation on individual well-being, with limited research accounting for the potentially heterogeneous effects of victimisation along the well-being distribution. However, those already at the bottom of the well-being distribution may have less of an ability to cope with adverse life shocks and so may be impacted more severely by victimisation. We ought to be more concerned about the psychological effect of victimisation when it leads to significant distress. Therefore, it is important to account for these differences by going beyond an analysis of the mean relationship of victimisation.

This paper contributes to the economics of crime literature and the growing literature on the determinants of subjective well-being in a number of ways. I use the UK Household Longitudinal Study

(UKHLS) to quantify the impact of victimisation (being harassed/insulted, and being physically attacked) on several cognitive and affective measures of subjective well-being. I use panel fixed effects methods to estimate the association of victimisation at the mean, and unconditional quantile regression with fixed effects methods to identify the heterogeneous association of victimisation along the unconditional distribution of well-being.[1]

Across subjective well-being measures, I find that victimisation is associated with significant decreases in well-being levels at the mean. When looking at the heterogeneous negative effect of victimisation on well-being, I find that it is monotonically decreasing over the distribution of subjective well-being.

2 Subjective Well-Being

Although 'happiness' is one part of subjective well-being (SWB), these concepts should not be conflated with one another. Diener (2006) defines SWB as being an "umbrella term for the different valuations people make regarding their lives, the events happening to them, their bodies and minds, and the circumstances in which they live". By definition, SWB measures rely upon an individual's subjective evaluation of various states and aspects of their lives. These measures exclude objective components of overall human well-being like one's state of physical health, or income. SWB is a broad concept and various distinctions between its constituent parts have been suggested (Kahneman and Riis, 2005; Waldron, 2010; Dolan et al., 2006). For this paper, I distinguish between three core domains of SWB: (1) life evaluation; (2) affect; and (3) eudaemonia.

Life evaluation is measured using questionnaires which ask respondents to reflect on how satisfied or dissatisfied they are with their lives as a whole, or with a specific domain of their lives (e.g. health or income satisfaction). Surveys usually pose these questions using a Likert scale going from 'completely dissatisfied' to 'completely satisfied'. When answering life evaluation questions, respondents make conscious judgement calls about how their lives measure up to a standard that they deem appropriate for themselves (Pavot and Diener, 1993). As a result, life evaluation measures of SWB lead to individuals making more cognitive judgements about their lives, rather than specific emotional states. Within the life evaluation domain, SWB increases when a person evaluates their life more positively.

Affect is a term that relates to the experience of emotions. There are positive and negative dimensions to affect. Positive affect captures the experience of feeling emotions like happiness and contentment whereas negative affect captures the experience of feeling negative emotions like anger and guilt. Kahneman et al., eds (1999) argues that individuals can aggregate their positive and negative affective states, at a given point in time, into a single net affective balance measure (Kahneman and Krueger, 2006). Within the affect domain, SWB increases when a person experiences more positive affect and/or less negative affect.

[1]For ease of comparison with much of the existing literature which relies on cross-sectional analysis, I also estimate the relationship between victimisation and subjective well-being using pooled OLS regression methods.

The evaluative and affective elements of SWB are similar in that they both focus on the life experiences of an individual. In contrast, the eudaemonic conception of well-being sees humans as having psychological capabilities which are needed in order to live a meaningful and purposeful life. These capabilities include autonomy, competence, interest in learning, goal orientation, sense of purpose, resilience, social engagement, caring, and altruism (Huppert, 2009). Eudaemonia is concerned with the degree to which a person has the capabilities to reach these universal 'goals' which characterise living a meaningful life. Possessing these capabilities increases well-being independently of any positive affect they may or may not bring (Hurka, 1996). Eudaemonic well-being focuses on the good psychological functioning of the individual and the realisation of one's potential. Eudaomonia can be seen as a subjective measure of well-being in that it is sometimes measured by asking respondents various questions evaluating the degree to which they feel their lives are meaningful or purposeful.

It is important to distinguish between the different domains of SWB because life events and shocks can impact them differently. For example, spending time with one's children is relatively more rewarding from a eudamonic perspective than it is pleasurable, watching television yields relatively more positive affect (Kahneman and Krueger, 2006), and increases in income are associated with improvements in life evaluation but not emotional well-being measures (Kahneman and Deaton, 2010).

However, unlike the evaluative and affective domains of SWB, there is no single agreed upon approach in the literature which captures the essence of eudaemonic well-being. For example, questions asking respondents to rate their overall life satisfaction are usually seen as being apart of the evaluative domain of SWB, but some view it as being a eudaemonic measure of living a good life (Kashdan et al., 2008). Therefore, in this paper, I test for differences in the relationship between victimisation and different (1) life evaluation/cognitive and (2) affective domains of well-being. Under the evaluative/cognitive measures of well-being, I explore the relationship between victimisation and satisfaction with (1) Health; (2) Income; (3) Leisure Time; and (4) Life Overall. For the affective domains of well-being, I use measures from the 12 item General Health Questionnaire (GHQ-12) and 12 item Short-Form questionnaire (SF-12).

There is some evidence to suggest that negative life events or shocks affect the evaluative domains of well-being more persistently than daily affective measures Luhmann et al. (2012). For example, Knabe et al. (2010) find that, compared with their employed counterparts, unemployed people report similar daily affective well-being but significantly lower life satisfaction. Given the existing literature, I would expect that being victimised would impact general cognitive evaluations of life satisfaction more severely than affective measures of well-being.

In addition, I test for differences in the relationship between victimisation and each domain measure of cognitive/evaluative well-being. I would posit that being victimised has a more direct effect on one's satisfaction with health and life overall, and only an indirect relationship with one's satisfaction with income and leisure time. Therefore, I expect that being victimised will be associated with larger reductions in health and overall life satisfaction compared with income and leisure time satisfaction.

3 Literature Review

A number of consistent findings on the correlates of well-being have been well documented in the literature. The impact of age is U-shaped in well-being (Blanchflower and Oswald, 2004). Women tend to report higher levels of life satisfaction than men within the evaluative domain, but higher levels of stress within the affective domain of well-being (Nolen-Hoeksema and Rusting, 1999). This gender difference is reflected in higher average Caseness and Likert scores among women in my sample. Racial well-being gaps have been documented in the UK with Black and Minority Ethnic groups reporting lower levels of well-being than White groups (Stevenson and Rao, 2014).

Although marriage is positively correlated with well-being, a large portion of this marriage happiness premium may come from happier people being more likely to select into marriage (Stutzer and Frey, 2006). The evidence on the relationship between children and well-being is mixed and varies across countries, cultures, and income levels as well as domains of SWB. In general, having children is associated with decreases in affective measures of well-being but increases in life evaluation/satisfaction measures (Luhmann et al., 2012). Education tends to be positively correlated with SWB, particularly through its relationship with increased earnings (Oreopoulos and Salvanes, 2011). However, those with higher education also tend to report higher values on scales asking how happy they 'should' be, indicating that the overall net effect of education on SWB could be ambiguous in some contexts.

In general, increases in absolute and/or relative income are correlated with increased SWB (Sacks et al., 2012; Headey and Wooden, 2004). Deaton (2008) finds that richer countries report higher average well-being scores as measured using the Cantril Ladder.[2]. At a macroeconomic level, aggregate unemployment, inflation and pollution levels are all negatively correlated with SWB (Ouardighi and Munier, 2019; Macculloch et al., 2001; Zhang et al., 2019; Ochsen, 2011).

3.1 Hedonic Adaptation / Set-Point Theory

Set-point theory posits that people have a natural equilibrium level of well-being around which they fluctuate even in the face of major life events and shocks (Headey and Wearing, 1989). Life shocks may result in increases or decreases in SWB, but these changes are predicted to be short-lived, and a return to equilibrium levels of SWB occurs relatively quickly. Empirical research testing the validity of set-point theory is mixed. In support, Lykken and Tellegen (1996) use Twin Study methods to show that lifetime average SWB has strong heritablity. Others have found that increases in income lead to only short term increases in SWB, with 'hedonic adaptation' back to pre-increase levels occurring relatively quickly (Wunder, 2009; Grund and Sliwka, 2007; Di Tella et al., 2010). Similar 'hedonic adaptation' has been documented for marriage, with a return to baseline SWB occurring after an average of two years (Lucas et al., 2003). However, divorce is associated with

[2]The Cantril Ladder or Self-Anchoring Scale is a life evaluation measure of SWB which asks respondents to think of a ladder and rate their current lives on a scale from 0 (the worst possible life for them) to 10 (the best possible life for them)

significant decreases in SWB that are longer-lasting, with any adaptation back to baseline being much slower.

Others argue that a well-being set-point can be permanently adjusted up or down as a result of significant life events. The impact of unemployment is among the most studied of these. Across studies, unemployment is associated with significant reductions in SWB, with these effects remaining significantly negative for long periods of time (Clark et al., 2008; Lucas et al., 2004; Clark, 2006; Kassenboehmer and Haisken-DeNew, 2009). The effect of unemployment on SWB is comparable to other life events like separating from a partner (Lucas et al., 2003). Even after re-employment, the scarring well-being effects of having once been unemployed persist (Mousteri et al., 2018). The death of a child, the death of a spouse, and becoming disabled are other negative life events which are associated with significant negative and long lasting effects on SWB (Moor and de Graaf, 2016; Lucas, 2016). Long-term positive increases in SWB have been documented in those who successfully underwent aesthetic surgery (Wengle, 1986; Frederick and Loewenstein, 1999). Luhmann et al. (2012) conduct an extensive meta-analyses which explores the heterogeneous impact of various life events on different domains of SWB. They find that bereavement impacts cognitive well-being more negatively than affective well-being and unemployment results in long-term negative effects on cognitive measures of SWB but not on affective measures.

For health policy makers, it is important to know if the impact of victimisation on SWB fades quickly or if it persists for a meaningful length of time afterwards. These mixed findings on set-point theory indicate that 'hedonic adaptation' likely occurs to at least some extent after various domain-specific life events, but this adaptation may be limited and is by no means inevitable. Within the current literature on SWB, gaps exist around the types of moderator variables which might lead to different adaptation rates in response to adverse life events. Luhmann et al. (2012) points to psychological, demographic, and methodological moderators as areas which need further research. I explore how gender, and different scales of SWB all act as moderators on the estimated relationship between victimisation and SWB.

3.2 Subjective Well-Being and Victimisation

Becker (1968) launched the economics of crime literature, arguing that the social cost of crime consists of the sum of the direct costs to victims and the costs of policing and prevention policies. If a society wants to minimise the social cost of crime, there is an 'optimal' quantity of crime where the marginal cost of additional crime prevention equals the marginal benefit from an additional prevention in crime. Within Becker's normative framework, policy makers ought to trade-off the costs of policing programmes against the benefits from deterring crime. Using Becker's framework, a number of cost-benefit analyses have been conducted to determine the cost-effectiveness of various crime prevention policies (Levitt and Miles, 2006; Marie, 2005).

The crime-costings literature often excludes the non-pecuniary psychological costs of victimisation. However, a number of studies have estimated large psychological costs from victimisation (Dolan et al., 2005; McCollister et al., 2010). Crime has been related to increased incidence of mental health problems, including depression and anxiety as well as fear of crime going forward (Ellis et al., 1982; Davis and Friedman, 1985; Kaniasty and Norris, 1992). There is a strong correlation between mental health issues like depression and reduced feelings of happiness and SWB (Staubli et al., 2014).

There have been relatively few studies looking at the relationship between SWB and victimisation. Kuroki (2013) uses Japanese repeated cross-sectional social surveys to look at the relationship between crime on a five-point happiness scale and concludes that burglary/robbery is associated with significant reductions in average happiness levels. Home-owners were impacted more than renters by burglary, while the wealthy experienced no negative reductions in happiness. These results point towards the need for a heterogeneous analysis of the effects of victimisation on SWB. Using repeated cross-sections from the US General Social Survey, Cohen (2008) finds a significant adverse impact on life satisfaction from home burglary with a compensating income equivalent of approximately $85,000 per burglary. Several studies have found differences in the relationship between victimisation and well-being by gender. Compared with men, women usually report higher rates of fear of crime and perceived vulnerability to victimisation (Snedker, 2012; Pantazis, 2000). In addition, crime victimisation tends to be correlated with larger decreases in well-being for women than for men (Sulemana, 2015). Given the existing literature, I test for gender differences in the relationship between victimisation and subjective well-being in this paper, and would predict that the subjective well-being of women will be affected by victimisation more than the well-being of men.

A number of other papers have also used cross-sectional survey data to compare the SWB outcomes of those who have experienced some form of victimisation to those who have not, with all reporting lower SWB for the victimised group (Bunch et al., 2013; Powdthavee, 2005; Davies and Hinks, 2010; Bunch et al., 2013; Hope, 2013; Michalos and Zumbo, 2000).

Cross-sectional analyses may be impacted by problems of unobserved heterogeneity, omitted variable, and selection biases. Other factors which are correlated with being victimised may explain the adverse relationship between victimisation and SWB found in these cross-sectional analyses. For example, the Victim Precipitation Theory of victimisation argues that perpetrators single out victims based on demographic characteristics (gender, race etc.), while the Lifestyle Theory of victimisation posits that the probability of being victimised depends on the lifestyle of the individual (Madero-Hernandez, 2019). Both of these theories predict that individuals are not randomly selected into victim and non-victim groups. The Symptoms-Driven Model of depression posits that lower levels of well-being lead to a distinctive pattern of social behaviour which may increase the target vulnerability of individuals and thus cause an increase in the probability of being victimised (Kochel et al., 2012). According to this model, the causal direction is from SWB levels towards victimisation.

To address these issues, studies have begun using panel data to explore if being victimised between two time points is related to a change in SWB. Mahuteau and Zhu (2016) estimate the impact of physical violence and property crimes on SWB in Australia using longitudinal household survey data. Both effects are negative, but physical violence has a larger average negative effect on SWB than property crime. Using unconditional quantile regression with fixed effects methods, the authors find that victimisation results in very heterogeneous effects on SWB along the well-being distribution. Those who were already on the lower part of the SWB distribution are impacted more negatively by a victimisation event compared with those who were already on the upper end of the distribution. The authors also find that the magnitude of the relationship more than halves in the fixed effects regression compared to the standard OLS regression models. This decrease indicates that unobserved individual heterogeneity is particularly important in estimating the adverse association of victimisation on SWB. Frijters et al. (2011) also find that the estimated negative impact of life events, including property crime victimisation, on life satisfaction was significantly smaller when controlling for selection bias. A number of others have used longitudinal survey data and fixed effects estimation methods to show that physical assault significantly reduces SWB (Ambrey et al., 2014; Cornaglia et al., 2014).

Powdthavee (2005) and Hanslmaier (2013) both argue that a major channel through which victimisation impacts individuals is not from the direct victimisation, but rather from the increased fear and anxiety people experience from increases in their perceived risk of future victimisation. This effect transmits to peers of the victim with local community and household members experiencing decreases in perceived quality of life, and increases in their perceived subjective risk of victimisation also. This fear transmission channel has been studied in greater detail in the unemployment literature where past unemployment periods significantly reduce current SWB. This scarring effect is long-lasting and comes from an increase in fear and anxiety around possible future unemployment (Clark et al., 2001; Knabe and Rätzel, 2011).

This paper makes contributions to the existing literature in a number of ways. First, I use panel regression methods and data from a large UK household longitudinal survey to present new evidence on the relationship between victimisation and SWB. In particular, I focus on two types of victimisation – being physically attacked, and being insulted/harassed. Previous work in this area by Mahuteau and Zhu (2016) among others have focused on physical assault and property crime. Therefore, studying the effect of being insulted and harassed on SWB is a contribution of this paper. Second, I use a wider variety of measures for SWB to explore how victimisation relates to different parts of well-being. Third, I use unconditional quantile regression with fixed effects methods to identify the highly heterogeneous relationship of victimisation along the unconditional distribution of SWB. Finally, I address recent concerns relating to the appropriateness of treating ordinal SWB data as cardinal and linear in regression analysis, and test for the robustness of my findings to alternative cardinalisations of the ordinal SWB measures.

4 Data

The data source is the UK Household Longitudinal Study (UKHLS) (commonly referred to as 'Understanding Society'), covering the geographical areas of England, Scotland, Wales, and Northern Ireland. The UKHLS collects detailed information on the demographic and socioeconomic characteristics of respondents and is one of the largest panel surveys in the world, beginning with a nationally representative sample of approximately 50,000 individuals across 40,000 households. I use the first 9 waves of the UKHLS which cover the period 2009-2018. Each household is interviewed face-to-face by a trained interviewer on an annual basis. Households are interviewed at approximately the same time each year with each wave taking approximately 24 months to complete. Beginning in Wave 3, a small fraction of responses are gathered via phone interview to capture adults who could not be contacted in person during each sample month fieldwork period. From Wave 7 onward, some respondents completed online web interviews.

4.1 Victimisation Measures

Victimisation status is derived from the following two questions: (Q1) In the last 12 months, have you been physically attacked in any of these places? If so, which ones? (Q2) In the last 12 months, have you been insulted, called names, threatened or shouted at, in any of these places? If so, which ones? Both questions then go on to list 11 possible locations (e.g. at work, or on public transport) and an additional 'other places' option from which respondents can indicate where they were victimised.

Table 1: Number of Victimisation Incidents in UKHLS Sample, Waves 1-9

		Q1	
		Attacked	**Not Attacked**
Q2	**Insulted**	580	3,449
	Not Insulted	171	22,979

I create two victimisation indicator variables: 'Attacked' and 'Insulted Only'. 'Attacked' is an indicator assigned a value of 1 for any respondent who reports being physically attacked (anywhere) in the last 12 months ($n = 580 + 171 = 751$). 'Insulted Only' is an indicator for anyone who reports *not* being physically attacked but does report being insulted, called names, threatened or shouted at (anywhere) in the last 12 months ($n = 3,449$). The reasoning behind restricting this second victim status variable to those who have not been attacked comes from the fact that these two victimisation statuses are not otherwise mutually exclusive. 85.6% of those reporting being attacked also report being insulted, while just 14.4% of those who report being insulted also report being attacked. The impact of being physically assaulted compared with being insulted are likely to be significantly different. As a result, it is important to disentangle the effects of these different victimisation indicators.

These victimisation questions are included in the 'Harassment' module of the UKHLS which is collected on an biennial basis.[3] As a result, my sample panel consists of five consecutive biennial

[3]The Harassment module is included in an 'extra 5 minutes' questionnaire which is given to the General Population

periods (Waves 1, 3, 5, 7, and 9). I restrict this sample to adults aged 18 years and older and drop any observation with missing data on the core variables used for my analysis as discussed in Section 6. The final sample used in my analysis consists of 27,179 observations across 13,747 individual respondents.

4.2 Subjective Well-Being Measures

4.2.1 12 Item General Health Questionnaire

The General Health Questionnaire was developed as a psychometric screening tool aimed at identifying those experiencing psychological distress or mental health morbidity. As a simple questionnaire which can be carried out in a non-clinical environment, it is widely used to identify those who are in possible need of psychiatric care. The 12-item version of the General Health Questionnaire (GHQ-12) was collected in each wave of the UKHLS. It is one of the most widely used measures of psychological distress and morbidity, and has been widely applied as a measure of SWB within the economics and psychology literature. In particular, the UKHLS GHQ-12 questionnaire proceeds as follows:

> 'the next questions are about how you have been feeling over the last few weeks. Have you recently...; (1) been able to concentrate on whatever you're doing? (2) lost much sleep over worry? (3) felt that you were playing a useful part in things? (4) felt capable of making decisions about things? (5) felt constantly under strain? (6) felt you couldn't overcome your difficulties? (7) been able to enjoy your normal day-to-day activities? (8) been able to face up to problems? (9) been feeling unhappy or depressed? (10) been losing confidence in yourself? (11) been thinking of yourself as a worthless person? (12) been feeling reasonably happy, all things considered?'

The sub-items of the GHQ-12 are designed to detect various symptoms of psychological distress, and the intensity of moods relative to individuals perceptions of their usual frequency or intensity of the given state. The GHQ-12 comprises six positively framed items (GHQ 1, 3, 4, 7, 8, and 12) and six negatively framed items (GHQ 2, 5, 6, 9, 10, and 11). Each item has four possible responses. The scale for positive items is: 'more so than usual'; 'same as usual'; 'less so than usual'; and 'much less than usual', whereas the scale for negative items is: 'not at all'; 'no more than usual'; 'rather more than usual'; and 'much more than usual'. These responses are coded 1 to 4, with higher values indicating a decreasing state of mental well-being.

There are two different scoring methods commonly applied to the GHQ-12 items in the literature. First, a binary indicator can be assigned to each item, scored in a [0-0-1-1] fashion for each of the four possible responses. These binary indicators are then summed up to create a 'Caseness' score which indicates how many of the 12 symptoms measured by the GHQ-12 are present. The Caseness

Comparison (GPC) sample, and to the Ethnic Minority Boost (EMB) sample. The EMB sample was designed to boost the general population sample to ensure that at least 1,000 adults from each of five communities were included in the UKHLS: Indians, Pakistanis, Bangladeshis, Caribbeans and Africans. The GPC sample is a sub-sample of the entire UKHLS general population sample, who are given the same 'extra 5 minutes' questionnaire as the EMB sample.

score ranges from 0 (least distressed) to 12 (most distressed). Another common approach is to score each item on a four point scale in a [0-1-2-3] fashion. The scores from each item are then summed to create a 'Likert' score which ranges from 0 (least distressed) to 36 (most distressed). These summary scores are widely used as measures of SWB, and of how respondents assess their lives overall (Peasgood et al., 2014). The GHQ-12 Caseness and Likert scoring methods demonstrate levels of validity and reliability/internal consistency which are high enough for psychometrically robust tests (Kline, 2013).[4]

The Caseness score is among the most widely used measures of SWB within this literature, and has been demonstrated to be valid in identifying 'cases' of psychological distress from 'non-cases' within the general population (Goldberg et al., 1997, 1998; Martucci et al., 1999; Donath, 2001). Various Caseness score cut-off points have been suggested to identify psychiatric morbidity. The most commonly used Caseness cut-offs identifying psychiatric distress range from 2-to-4 in the literature, with higher cut-offs indicating a greater bar which must be met in order to qualify as a 'case' (Goldberg et al., 1998; Jacob et al., 1997; Plummer et al., 2000).

For the purposes of this paper, the Likert scoring method has a number of potential advantages over the Caseness method. First, the Likert score is better able to capture the intensity of respondents feelings by assigning larger values to stronger responses. Generally, Likert scoring of the GHQ-12 produces less skewed data with a more consistent distribution of total GHQ cases (Goldberg and Williams, 1988; Jomeen and Martin, 2004), both of which are important in using it as a continuous variable, especially for unconditional quantile regression methods (discussed in Section 6). The most commonly used Likert cut-offs identifying psychiatric distress range from 10-to-12 in the literature (Politi et al., 1994; Goldberg et al., 1997; Lundin et al., 2016).

Affective domains of subjective well-being capture the positive and negative moods and emotions of individuals. Measuring affective well-being is quite similar to assessing mental health. For example, measures of depressive symptoms are often used to measure negative affect. As a result, the GHQ-12 can be seen as measuring the affective domains of SWB (Vanhoutte and Nazroo, 2014). Given that the GHQ-12 is one of the most widely used measures of SWB in the happiness economics literature, and given the advantages of the GHQ-12 Likert scoring method over the Caseness scoring method, the primary SWB outcome measure used in this paper is the Likert score.

4.2.2 Short-Form 12 Item Health Survey

The Short Form 12-item Health Survey (SF-12) is a health-related quality-of-life questionnaire which has been used extensively within the health, psychology and economics literature. The SF-12 is used to assess a respondent's subjective general, mental and physical health across eight domains. The physical health domains are General Health (GH), Physical Functioning (PF), Role Physical (RP),

[4] Reliability refers to the overall consistency of the measurement instrument (e.g. SWB measure). The Caseness score has high reliability if it produces consistent and reproducible scores when the measurement is taken by the same people, many times, under the same conditions. Validity refers to how well the measurement instrument (e.g. SWB measure) actually measures the phenomenon that it is designed to measure. The Caseness score has high validity if it can accurately identify cases of psychiatric morbidity.

and Body Pain (BP). The mental health domains are Vitality (VT), Social Functioning (SF), Role Emotional (RE), and Mental Health (MH).

Quality Metrics licensed the use of their SF-12 instrument and proprietary scoring algorithm to the UKHLS. Using their scoring methods (Ware et al., 2002), the UKHLS converts valid answers to each of the SF-12 items into two summary scores: 1) a Mental Component Summary (MCS) score; and 2) a Physical Component Summary (PCS) score. I focus on the SF-12 MCS score. The MCS score was designed to capture a wide number of mental health domains including feelings of depression and anxiety, social activity, amount accomplished, and carelessness. The psychometric properties of the SF-12 have been widely studied, and researchers have demonstrated its reliability and validity as a health-related quality-of-life questionnaire and screening tool for mental health disorders for the general population (Huo et al., 2018; Cheak-Zamora et al., 2009; Ware et al., 2002). Given the MCS' usefulness in screening for affective disorders, it can be seen as a measure of affective well-being.

The MCS score used in this paper is expressed as a single continuous variable ranging from a score of 0 (high functioning) to 100 (low functioning).[5] The MCS score is generated using norm-based methods, and transformed to have a mean score of 50 with a standard deviation of 10. An MCS score of $\geq$ 55 ($\geq$ 0.5 SD above the UK population mean) is often used as a cut-off to screen for possible depression. When screening for those with severe mental health issues, a cut-off score of $\geq$ 64 (approximately $\geq$ 1.5 SD above the UK population mean) has been used in the literature. Sanderson and Andrews (2002) find that those at or above this $\geq$ 64 cut-off have moderate to severe disability/impairment.[6]

5 Descriptive Statistics

Table 2 reports the summary statistics for (1) the 'Full Sample' used in my analysis, and then by victimisation status: (2) 'Attacked', and (3) 'Insulted Only'. These samples contain only those UKHLS respondents who are aged $\geq$ 18 years of age and who answered all questions used in this analysis. The mean and standard deviation of each variable, for each sample, are reported. I also report the results from each two sample t-test, testing for the difference in means between victims and non-victims for the 'Attacked' and 'Insulted Only' samples, respectively.

The full sample contains 27,179 observations, of whom 751 observations (3%) reported being physically 'Attacked' and 3,449 observations (13%) reported being 'Insulted Only' (i.e. insulted or harassed, but not attacked), in the prior 12 months. Of the 13,747 unique observations in my sample, 685 individuals report being 'Attacked' at least once across the five consecutive biennial panels with 53 individuals reporting multiple incidents. 2,755 individuals report being 'Insulted Only' at least

[5]Note that originally, an MCS score of 0 indicated low functioning and a score of 100 indicated high functioning. I have reversed the scale of the MCS for ease of interpretation with models using the GHQ-12 measures so that higher values of each SWB measure indicate worse SWB.

[6]Note that I have reversed the scale of the MCS used in this paper, so these cut-offs are reinterpreted to be consistent with this rescaling.

once, with 543 individuals reporting multiple incidents across the panels.

I report three measures of SWB in Table 2: the SF-12 Mental Component Summary (MCS); the GHQ-12 Likert score; and the GHQ-12 Caseness score. Higher values of each of these measures indicate worse SWB. From Section 2, common cut-off scores used to indicate psychological distress/morbidity were ≥ 55 for the MCS, ≥ 12 for the Likert score, and ≥ 3 for the Caseness score. The average MCS, Likert and Caseness scores for those who have been victimised all surpass these thresholds needed to indicate psychological distress, with all non-victims, on average, falling under these distress thresholds. I estimate two-sample t-tests for the differences in the mean SWB scores between victims and non-victims for both victimisation measures. Across SWB measures, those who have been victimised report statistically significantly worse average SWB than those who have not been victimised. This difference provides initial descriptive evidence for the link between victimisation and SWB. Additionally, across each SWB measure, those who have been 'Attacked' report worse average levels of SWB than those who have been 'Insulted Only'. These differences are not statistically different from one another, and I will further test if these two victimisation types impact SWB to different degrees later.

Those who report being 'Attacked' are significantly younger than those who have not been attacked. They are also less likely to be female, have a degree or be married, but are more likely to be single, unemployed, have a lower household income, and living in an urban area. Those who report being 'Insulted Only' are significantly younger but are better educated than those who have not been. They are also less likely to be married and more likely to be single, employed and have children living in their household.

Table 2: Summary Statistics by Victimisation Status

	Full Sample		Attacked				Insulted Only			
			Yes		No		Yes		No	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Subjective Well-Being Measures										
MCS Score	51.18	10.29	55.23***	12.04	51.06	10.21	54.27***	11.25	50.73	10.06
Likert Score	11.08	5.76	13.50***	7.20	11.01	5.70	12.77***	6.53	10.83	5.59
Caseness Score	1.88	3.04	3.25***	3.74	1.84	3.00	2.77***	3.57	1.75	2.93
Victimisation Indicators										
Attacked	.03	.16	1.00	.00	.00	.00	.00	.00	.03	.18
Insulted Only	.13	.33	.00	.00	.13	.34	1.00	.00	.00	.00
Socioeconomic Indicators										
Age	42.71	15.94	37.21***	13.70	42.86	15.97	39.25***	13.46	43.21	16.21
Female	.56	.50	.48***	.50	.56	.50	.56	.50	.56	.50
Urban	.92	.27	.94*	.24	.92	.27	.93	.26	.92	.27
White	.30	.46	.29	.46	.30	.46	.31	.46	.30	.46
LT GCSE etc.	.32	.47	.30	.46	.32	.47	.24***	.43	.33	.47
Degree	.35	.48	.32*	.47	.35	.48	.39***	.49	.35	.48
Chilren HH	.38	.49	.37	.48	.38	.49	.40**	.49	.38	.48
Single (Never Married)	.33	.47	.46***	.50	.33	.47	.40***	.49	.32	.47
Married/CP	.55	.50	.40***	.49	.55	.50	.49***	.50	.56	.50
HH Monthly Income	4012	3006	3540***	2582	4026	3016	4011	2954	4012	3013
Employed (FT)	.38	.49	.40	.49	.38	.49	.45***	.50	.37	.48
Unemployed	.08	.26	.12***	.32	.07	.26	.07	.26	.08	.26
England	.95	.23	.95	.21	.94	.23	.94	.23	.95	.23
No. of Observations	27,179		751		26,428		3,449		23,730	

Notes: * p<0.10, ** p<0.05, *** p<0.01 (two-sample t-test by victim status)

5.1 Raw Differences in SWB by Victim Status

In Figure 1, I present differences in average SWB Likert scores by victimisation status (with 90% confidence intervals) for the male and female samples, respectively. Although victimised women have significantly higher Likert scores (i.e. worse SWB) than victimised men, women report higher average Likert scores than men anyway (be they victims or non-victims).[7] For a given victimisation category, the average Likert score for women is approximately 10% higher than men. Thus, I see no descriptive evidence suggesting gender differences in SWB by victimisation status, at the mean. Rather, there appears to be a level shift in SWB between victim groups for men and women, respectively.[8]

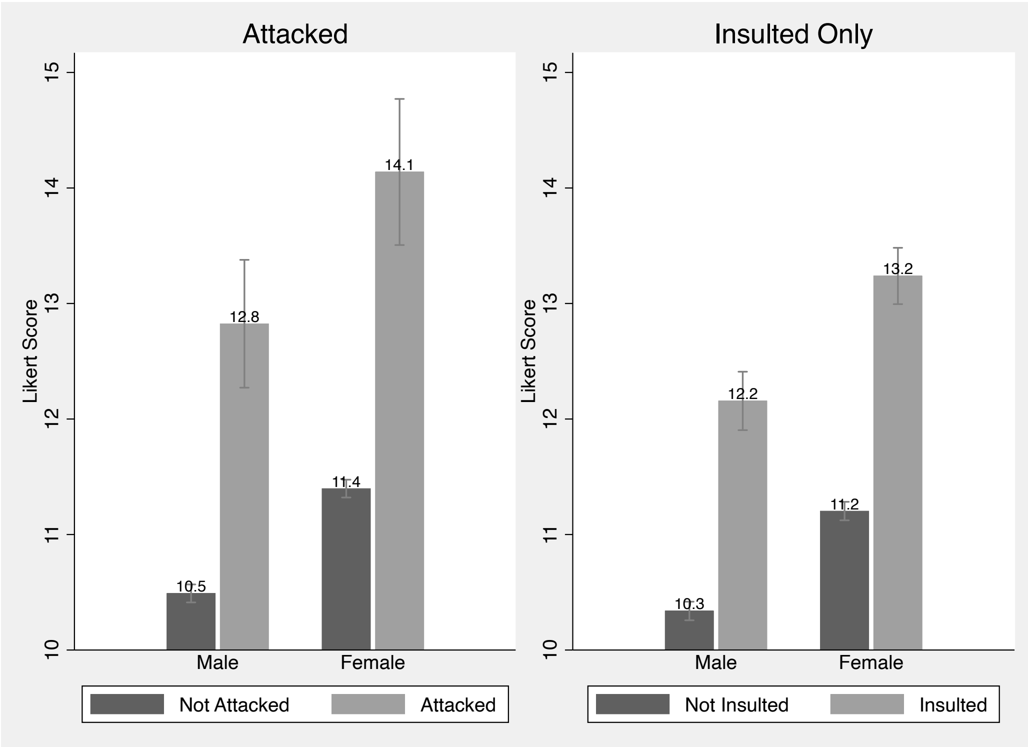


Figure 1: Likert Score by Victim Status and Gender

In Figure 2, I plot the cumulative density functions of Likert scores for the full sample by victim/non-victim status for both measures of victimisation. The CDFs for victims are statistically significantly different from their non-victim counterparts within the 'Attacked' and 'Insulted Only' groups, respectively.[9]

Differences in Likert scores between victims and non-victims persists across the distribution, with

[7] Such gender differences in average SWB scores are consistent with findings from the wider SWB literature which I discuss in Section 3

[8] In Appendix A.10.A, I present equivalent bar chart plots using the Caseness, MCS, and single-item measures of SWB. All results are qualitatively identical to those presented in Figure 1.

[9] Two-sample Kolmogorov-Smirnov equality-of-distributions test: p-value=0.00 for each 'Attacked' and 'Insulted Only' tests where the null hypotheses were: (1) $CDF_{attacked} = CDF_{notattacked}$; and (2) $CDF_{insulted} = CDF_{notinsulted}$, respectively.

the greatest differences occurring at higher levels of Likert score (i.e. at worse levels of SWB).[10] In addition, the size of the difference between victims and non-victims at the upper percentiles of the CDF appears to be larger for the 'Attacked' measure of victimisation when compared with the 'Insulted Only' measure. This descriptive evidence is consistent with victimisation having a heterogeneous impact on people with different levels of SWB. I will use quantile regression methods later to provide more robust evidence which supports the hypothesis that those who are at worse parts of the SWB distribution are impacted more severely by victimisation.

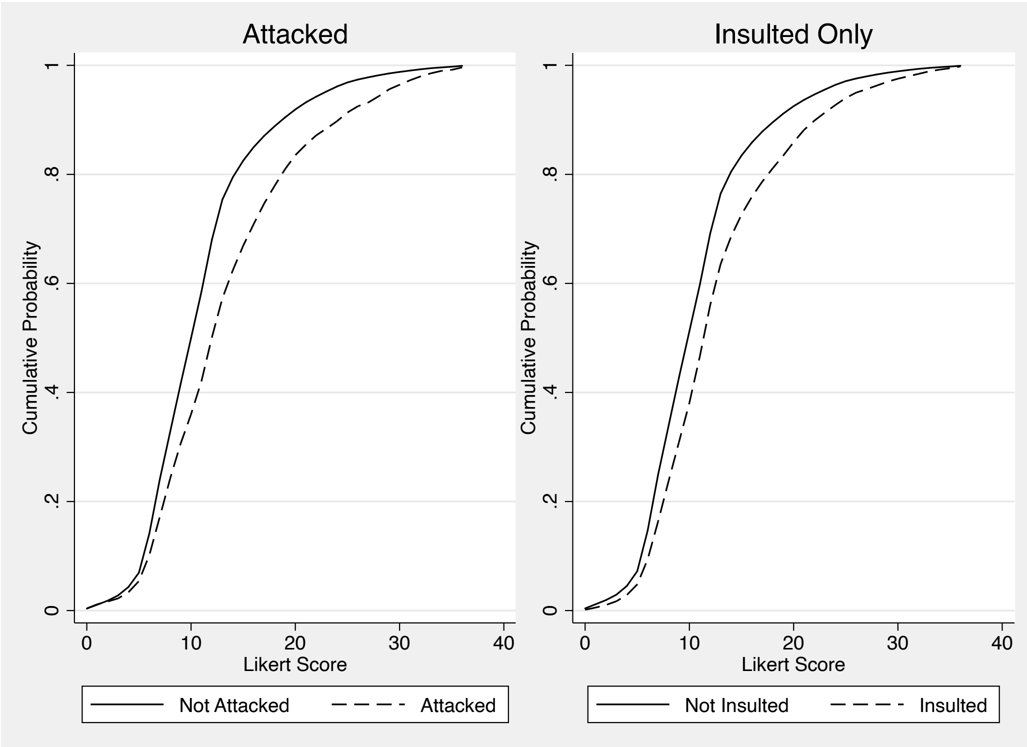


Figure 2: CDF Likert Score by Victim Status

6 Methods

I begin by estimating the following fixed effects model:

$$SWB_{it} = \beta_1 Attacked_{it} + \beta_2 Insulted_{it} + X_{it}\gamma + \alpha_i + \delta_t + \epsilon_{it}$$

where SWB_{it} is the subjective well-being of respondent 'i' in period 't' (as measured by the Likert, Caseness or MCS scores, or Single Item questions). $Attacked_{it}$ is a dummy indicating if a respondent reported being physically attacked in the prior 12 months. $Insulted_{it}$ is a dummy indicating if a respondent reported being insulted/harassed (but not physically attacked) in the prior 12 months.

X_{it} is a vector of control variables which are commonly included on the right-hand side of well-being equations including age (in years), age-squared, education level, marital status, labour market

[10] In Appendix A.10.B, I present equivalent CDF plots using the Caseness, MCS, and single-item measures of SWB. All results are qualitatively similar to those presented in Figure 2.

status, an indicator for children in the household, an urban/rural indicator, region indicators and the logarithm of gross household monthly income. For education level, I include four indicators for having ≤GCSE (reference group), A Levels, Other Higher and ≥University Degree. The five marital status indicators include Single, Never Married (reference group), Married/Civil Partnered, Divorced/Dissolved, Separated, Widowed. Labour market status is captured with six indicators including Full-Time Employed (reference group), Part-Time Employed, Self-Employed, Unemployed, Retired and Other. A full set of twelve UK region indicators are used including London (reference group), North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, South East, South West, Wales, Scotland and Northern Ireland.

δ_t are wave/time dummies and α_i are individual fixed effects controlling for unobserved time-invariant individual characteristics. ϵ_{it} is a standard error term. I estimate these models using standard fixed effects (FE) regression methods. β_1 and β_2 are the coefficients of interest for this paper, capturing the estimated within person average impact of victimisation (being 'Attacked' or 'Insulted Only') on SWB.

Fixed effects models have several advantages for estimating the relationship between victimisation and SWB. First, the subjective nature of SWB measures may lead to problems of interpersonal comparability. FE models address this problem by relying on within-person variation in covariates to estimate their effect. Individual fixed effects models also account for unobserved time-invariant factors like personality traits and temperament which are important in determining an individuals SWB. I discuss these benefits in more detail in Section 6.2.

In order to compare the results of this paper with others in the literature which relied on repeated cross-sectional data to estimate the relationship between victimisation and SWB, I also estimate a pooled OLS version of this model which drops the individual fixed effects, but includes a male/female gender indicator, and four racial indicators for being white (reference group), Black, Asian and other.

6.1 Distributional Analysis

There are a number of limitations to focusing on regression methods which estimate the average relationship between victimisation and SWB. First, if the magnitude or direction of effect of a treatment variable differs along the distribution of the dependent variable, then average effects estimates may significantly underestimate, overestimate, or fail to identify the true relationship (Cade and Noon, 2003). Second, policymakers are particularly concerned about small decreases in SWB experienced by those at lower deciles of the SWB distribution in response to victimisation, especially if these decreases in SWB result in them passing over a threshold into psychological distress. In contrast, larger decreases in SWB experienced by those in the upper deciles of SWB may be less important from a health policy maker perspective if these individuals remain above the societal average. Quantile regression methods can be used to address the limitations of focusing on the average relationship.

Conditional Quantile Regression

Koenker and Bassett (1978) first introduced conditional quantile regression (CQR) estimation for cross-sectional data, which was later expanded to the panel context (Koenker, 2004; Canay, 2011). CQRs are estimated with reference to the dependent variable *conditional* on explanatory variables (i.e. quantiles of the residual). $\beta_{1\tau}$ indicates the amount of change in the conditional quantile, τ, of Y associated with a one unit change in X_1. Generally, one cannot causally interpret $\beta_{1\tau}$ as the treatment effect for an individual of a given rank in the distribution of observables (Firpo et al., 2009). Such statements about the marginal impact of a variable on observations within a given quantile can only be made if one makes a rather strong rank invariance or rank similarity assumption (Angrist and Pischke, 2009; Chernozhukov and Hansen, 2005). Consequently, the interpretation of CQRs is of limited usefulness from a policy perspective because it is usually not possible to interpret a CQR coefficient as being the impact of a change in an explanatory variable on the marginal (unconditional) quantiles of the dependent variable (Wenz, 2019).

Despite the limitations of CQR, it has been the most pervasive method used to measure the differential impact of variables across the distribution of an outcome in empirical economics (Borah and Basu, 2013). Much of the literature which explores the heterogeneous impact of explanatory variables along the SWB distribution have used CQR also (Binder and Coad, 2015; Binder and Freytag, 2013; Yuan and Golpelwar, 2013; Binder and Coad, 2011). For ease of comparison with these earlier studies, I include pooled CQR estimates in Appendix A.18.A.[11]

Unconditional Quantile Regression

In contrast to conditional quantile regression methods, unconditional quantile regression (UQR) coefficients directly estimate the impact of changes in explanatory variables on observations in the quantile of the unconditional distribution of the dependent variable. For this reason, I use UQR as my primary estimation methodology to analyse the heterogeneous relationship between victimisation and SWB, along the SWB distribution.

Introduced by Firpo et al. (2009), the authors provide a two-step procedure to calculate UQRs. First, estimate the recentered influence function (RIF) of the unconditional quantile of the dependent variable of interest, which is defined as:

$$RIF(y;q_\tau) = q_\tau + IF(y;q_\tau) = q_\tau + \frac{\tau - \mathbb{1}(y \leq q_\tau)}{f_Y(q_\tau)}$$

where q_τ is the value of the outcome variable, Y, at quantile, τ. F_Y is the cumulative distribution function of F_Y. $\mathbb{1}(Y \leq q_\tau)$ is an indicator function that equals 1 if the y value for a given observation is at or below the value of the dependent variable at quantile τ (and 0 otherwise). $f_Y(q_\tau)$ is the probability density function of the dependent variable y evaluated at the quantile, τ.

To estimate a RIF at the τ^{th} quantile, first estimate the value of Y, at the τ^{th} quantile. Next, estimate

[11] I also apply Koenker and Bassett's (1978) original method for conditional quantile regression of cross-sectional data to estimate CQRs for each cross-section of the UKHLS. These results are presented in Appendix A.18.B and complement the cross-sectional OLS results.

$f_Y(q_\tau)$ (the density of the variable, Y, at quantile, τ) using kernel methods and generate the RIF variable for that quantile. RIFs are dummy variables taking on a value for all observations above the τ^{th} quantile, and a value for all observations below the τ^{th} quantile.

A potential problem in generating RIFs lies in estimating the density of Y using non-parametric kernel estimators. These estimates are sensitive to the choice of kernel and selection of bandwidth, the latter of which can greatly influence resulting estimates. I use the Gaussian kernel and the optimal bandwidth selection suggested by Silverman (1986) for all UQR estimates in this paper.

A separate RIF indicator variable is generated for each quantile of interest. In a linear model specification, these RIFs then serve as the outcome variable in an OLS regression, with $\beta_1\tau$ providing a consistent estimate of the marginal impact of X_1 on the unconditional quantile of Y. These UQR coefficients have an easier and more policy relevant interpretation compared with CQR estimates in that they are interpreted in much the same way as linear OLS estimates. For example, for an UQR on a SWB equation, coefficients are interpreted as the impact of the variable on individuals within a given quantile of the SWB distribution.[12]

UQR has become popular in many areas of economics research including inequality (Sakellariou, 2012; Fang and Sakellariou, 2013; Le and Booth, 2014), gender wage-gaps (Adireksombat et al., 2016), education (Messinis, 2013), and trade economics (Powell and Wagner, 2014). However, only a handful of papers have applied this method within the SWB literature (Mahuteau and Zhu, 2016; Fang and Sakellariou, 2016).

6.2 SWB and Estimation Methodology

The psychometric and sociology literatures usually treat measures of SWB as cardinal when conducting quantitative analysis. Economists have viewed the assumption of cardinal comparability of subjective states like SWB with more scepticism. In this section, I discuss and address the concerns of using measures of SWB in econometric analyses.

In contrast to more objective outcome measures like income, 'true' underlying well-being is an abstract psychological concept which cannot be directly observed. The most basic assumption for cardinal comparability to hold is that the underlying (latent) subjective well-being state is perceived in units of intensity ('phenomenal cardinality'). If latent well-being was not perceived in units of intensity, then it could not, even in principle, be measured cardinally.[13] Accepting this primitive condition, there is a consensus among psychologists that self-reported measures of well-being, life satisfaction, and happiness convey real information regarding underlying emotional states. Given that psychologists accept the 'construct validity' of SWB measures, we can infer latent well-being from self-reported answers to questions which ask respondents to rank their own well-being or happiness.[14]

[12]See Porter (2015) for a detailed explanation of the interpretation of CQRs and UQRs

[13]See Plant (2020) for a defence of the 'phenomenal cardinality' condition.

[14]The construct validity of SWB measures have been tested by looking at their relation to objective measures, physiological measures, and neurological measures of well-being. See Clark et al. (2008) or Layard et al. (2008) for a summary

Oswald (2008) argues that there is a missing information problem where we do not know the form of the reporting function which maps reported well-being to the true latent well-being of an individual. To operationalise SWB measures, we must make assumptions about the reporting function linking measured and actual well-being. For example, take the UKHLS question on life satisfaction with seven responses ranging from "completely dissatisfied" to "completely satisfied". The majority of the happiness economics literature operationalises these types of measures using a rank-order scale.[15] The scale used is important when treating the variable as cardinal and estimating linear regression models. Rank-order scaling implicitly assumes a linear reporting function, that the relationship between reported and true well-being maps in a linear fashion. Therefore, we assume that the difference in life satisfaction between a score of 1-to-2, equals the difference in life satisfaction between 2-to-3, 3-to-4, and so on. Given that underlying well-being is continuous, inferring it from the limited discrete response categories available in life satisfaction measures means that the linear reporting function is approximated by a step wise reporting function (see Figure 3).

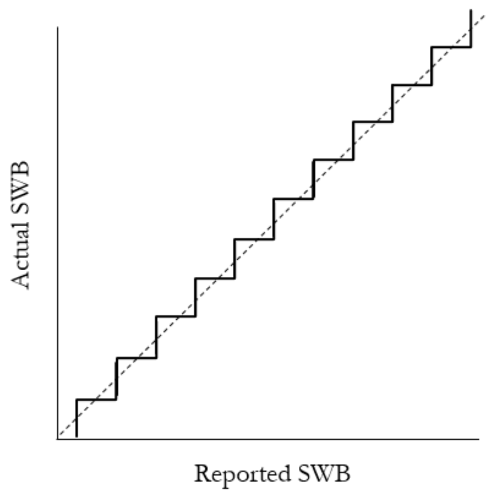


Figure 3: Linear Reporting Function (Plant, 2020)

Whether a linear reporting function is assumed or not, strict cardinality also assumes that the reporting function is common across individuals, and across time (Kahneman et al., eds, 1999). Therefore, estimating SWB regression models requires that I make and justify three assumptions: (1) linearity of the reporting function linking reported and true well-being; (2) interpersonal cardinal comparability; and (3) inter-temporal cardinal comparability.

Linearity

Johnson et al. (2002) reviews the neuroscience literature which studied the neural mechanisms un-

of the social science evidence, and Kahneman and Krueger (2006) or Layard (2011) for neuroscience studies supporting validity.

[15] Rank-order scaling gives a value of 1 to response option one, a value of 2 to response option two, and so on to the final response option.

derlying subjective reports of stimulus intensity. The authors conclude that the relationship between neural activity and subjective reports of texture is linear. Layard et al. (2008) argue that if there is a linear relationship between neural activity and subjective reporting, *and* if we assume a linear relationship between neural activity and actual subjective experience, then the neuroscience evidence implies a linear relationship between reported and actual experience.

Additional evidence in support of linearity comes from experiments which attempt to identify the functional form of the reporting function by looking at the relationship between objective and subjective measurements of the same variable. For example, Oswald (2008) asked respondents to rate their height relative to their gender, on a horizontal line with ten equally spaced dashed lines from 'very short' to 'very tall'. The author finds that the reporting function describing the relationship between objective and subjective feelings of height, is approximately linear (or slightly concave when male/female responses are grouped).[16]

In contrast, Ng (2008) posits that, for a bounded scale, an increase in reported SWB score requires larger increases in actual well-being toward the extremes of the scale.[17] In this case, an arc-tangent reporting function form is appropriate. Given the uncertainty around the reporting functions form, I relax the linearity assumption as a robustness test in Section 8 to ensure that my estimates are robust to a range of reasonable concave, convex and arc-tangent transformation of the SWB variable.

Interpersonal Cardinal Comparability

Interpersonal cardinal comparability requires that individuals interpret SWB scales similarly so that those experiencing the same underlying well-being, give the same reported well-being, on average. Suppose certain individuals are predisposed to having a negative temperament because of their personality. Relative to their more positively tempered peers, they may answer life satisfaction questions more negatively, thus violating the interpersonal comparability assumption. The degree to which SWB is interpersonally comparable can be debated. However, I largely side-step this issue by applying individual fixed effects (FE) models where SWB measures do not have to be fully interpersonally comparable to estimate the impact of victimisation on SWB. The coefficients from a FE model are estimated using within-person variation, estimating how SWB changes at the margin as a person switches between victim/non-victim status. The FE model also accounts for unobserved individual heterogeneity that is time invariant, like a person's temperament or disposition.

Intertemporal Cardinal Comparability

Whereas FE models address the problem of interpersonal comparability, one still assumes that the same individual interprets the SWB question identically through time. Does a person with the same SWB score at two different times have the same well-being? Ng (2008) posits that we may re-scale

[16]In another experiment, van Praag (1991) found that respondents translate ordinal verbal labels, approximately linearly, into cardinal quantities.

[17]For example, on an 11 point cantrill ladder from 0 (worst life) to 10 (best life), moving from a 5 to a 6 is a smaller increase in true well-being than moving from an 8 to a 9.

or change our interpretation of the endpoints on a SWB question. Suppose I report a '9/10' on a cantril ladder question today. I then get married and, later, report a '9/10' on the cantril ladder. This is consistent with hedonic adaptation where the impact of life events on well-being are transitory so that I am equally as happy at both time points. An alternative explanation is that I am far happier after marriage, and have re-scaled what a 10/10 represents to me on the cantril ladder.

Few papers discuss this intertemporal cardinal comparability assumption, and even fewer have attempted to test it. Prati and Senik (2020) are a recent exception. The authors use ten years of the German Socio-Economic Panel to compare how individuals recall past well-being with observed past reported well-being levels. From a list of picture patterns, respondents choose the one which best represents the evolution of their well-being over the previous years. Despite this cognitively demanding task, respondents were able to map their remembered past well-being to observed past well-being, over the same life satisfaction scale. Assuming there is consistency between remembered and observed past well-being, this is a strong piece of evidence in support of the stability of subjective well-being scales over time.[18]

Plant (2020) argues that if re-scaling were to occur, it would be in response to new evidence from relatively extreme and unexpected events or life shocks, which cause individuals to reinterpret the meaning of the well-being scale endpoints. If victimisation is one of these negative shocks, it would lead to a shrinking in the SWB scale, so that the level of happiness represented by the endpoint is lower. In other words, such 'rescaling bias' would work against my finding significant effects of victimisation on SWB. However, given that it is difficult to fully reject these re-scaling concerns, I acknowledge that intertemporal cardinal comparability of SWB scores is an assumption I make when interpreting my results of the relationship between victimisation and SWB.

7 Results

7.1 Baseline OLS Results

Table 3 contains three pooled cross-sectional SWB linear regressions on the full sample of UKHLS respondents. The dependent variable in the first two columns is the MCS score from the SF-12 questionnaire. For ease of interpretation I have standardised the MCS score to have a mean of 0 and a standard deviation of 1.[19] Coefficients from linear models using this standardised MCS score should be interpreted as standard deviational changes, with higher MCS scores corresponding with worse SWB. Positive coefficients indicate worse than average SWB with MCS scores above the mean, and negative values indicate better than average SWB with MCS scores below the mean. The dependent variable in the middle and final two sets of results columns both use the Likert score

[18] Plant (2020) points out that an alternative explanation of these results is that individuals may re-scale over time *and* have bad memories. However, he shows that this explanation also requires that re-scaling (i.e. stretching or shrinking of the well-being scale) be associated with a particular direction of memory failure which is unlikely. He concludes that the most plausible explanation is that individuals use the same scale over time.

[19] The MCS was constructed as a standardised measure for the UK population with a mean of 50 and standard deviation of 10.

from the GHQ-12 questionnaire. Possible values range from 0-to-36 with higher values indicating worse SWB. For ease of comparison with the MCS results, the middle two results columns also use a standardised version of the Likert score, with a mean of 0 and a standard deviation of 1. The final results columns use the unstandardised Likert score.

Overall, the significance and direction of effect on each control variable is the same across SWB measures used. The relationship between each control variable and SWB are consistent with findings from the wider literature. Ageing, being female, living in an urban area, and being unemployed are all associated with significantly worse SWB. Higher household monthly income, higher levels of education, being married, and being in full-time employment are all associated with improved SWB.[20]

Being 'Attacked' is associated with a 0.46 standard deviation increase in the MCS score, and an increase of 0.50 standard deviations or 2.76 units in Likert score. Being Insulted is also associated with decreased SWB but to a smaller degree with a 0.37 standard deviation increase in MCS, and a 0.38 standard deviation or 2.09 unit increase in Likert score. The magnitude of the coefficients on Attacked are significantly larger than the coefficients on being Insulted in each of these models.

[20] I have re-run these models using all measures of SWB discussed previously, on the male and female samples separately, as well as on individual cross-sections of each UKHLS wave. The relationship between SWB and each of the controls are qualitatively similar across all of these specifications.

Table 3: Mean Effects of Victimisation on SWB – Pooled OLS, Full Sample

	Standardised MCS		Standardised Likert		Likert	
	β	SE	β	SE	β	SE
Attacked	.46***	(.045)	.50***	(.049)	2.76***	(.27)
Insulted Only	.37***	(.021)	.38***	(.023)	2.09***	(.13)
Age	.020***	(.0034)	.027***	(.0035)	.15***	(.019)
Age^2	-.00021***	(.000038)	-.00021***	(.000039)	-.0012***	(.00021)
Female	.12***	(.016)	.099***	(.017)	.55***	(.093)
Children in HH	.027	(.018)	-.010	(.019)	-.057	(.11)
Urban	.083***	(.031)	.049	(.032)	.27	(.18)
Log HH Mnth Inc	-.062***	(.010)	-.059***	(.011)	-.32***	(.060)
Race (ref: White)						
Black	-.10***	(.025)	-.16***	(.026)	-.90***	(.14)
Asian	.061***	(.021)	.033	(.021)	.18	(.12)
Other	.13***	(.030)	.092***	(.032)	.51***	(.18)
Education (ref: ≤ GCSE)						
A Level	-.063***	(.024)	-.014	(.025)	-.079	(.14)
Other Higher	-.076***	(.027)	-.034	(.028)	-.19	(.15)
Degree	-.13***	(.019)	-.094***	(.020)	-.52***	(.11)
Marital Status (ref: Single)						
Married	-.14***	(.022)	-.14***	(.023)	-.75***	(.13)
Divorced	.045	(.039)	.033	(.042)	.18	(.23)
Separated	.068	(.052)	.061	(.058)	.34	(.32)
Widowed	.012	(.053)	-.011	(.055)	-.060	(.30)
Emp. Status (ref: FT Emp.)						
PT Employed	.054**	(.023)	.059**	(.024)	.33**	(.13)
Self-Employed	-.011	(.024)	-.027	(.023)	-.15	(.13)
Unemployed	.35***	(.031)	.40***	(.033)	2.18***	(.18)
Retired	-.046	(.039)	-.029	(.040)	-.16	(.22)
Other	.28***	(.023)	.32***	(.025)	1.75***	(.14)
Region Dummies	Yes		Yes		Yes	
Wave Dummies	Yes		Yes		Yes	
$H_0 : Attacked = Insulted$ *p-value*	.053		.019		.019	
No. of Observations	27,013		27,013		27,013	

Notes: Standard errors clustered at the individual level in parenthesis. * p<0.10, ** p<0.05, *** p<0.01.

7.2 Average Relationship by Gender

In Table 4, I report the results from pooled OLS and fixed effects models, using the Likert score as the dependent variable, for the Full Sample (columns 1 and 5); Male Sample (columns 2 and 6); and Female Sample (column 3 and 7). A number of differences are immediately apparent when comparing the pooled OLS coefficients with those from fixed effects models. Although victimisation is still significantly associated with higher Likert scores across the samples used, the FE estimates for the association between victimisation and SWB are significantly smaller than their pooled OLS equivalents, ranging from 1/4 to 2/3 the size. I test for the difference in coefficients on the victim indicators across male/female models (columns 4 and 8). I find no statistically significant differences in each of the victimisation coefficients by gender across pooled OLS and FE models, indicating that the relationship between victimisation and SWB is similar for men and women.

For men and women in the pooled OLS models, being 'Attacked' is associated with significantly larger increases in Likert scores than being 'Insulted'. However, when controlling for individual level fixed effects, the significant difference between the two victimisation coefficients disappears for all samples. In other words, being attacked may not be significantly worse for one's SWB than being insulted, on average. The similarity of coefficients in the FE model highlights the importance that unobserved individual heterogeneity (e.g. personality) plays in explaining SWB in this sample. Ignoring this heterogeneity in pooled OLS methods significantly overestimates the relationship between victimisation and SWB. The empirical literature, discussed in Section 3, which has explored the impact of victimisation on SWB using cross-sectional OLS methods should be viewed in light of this fact. These findings also contribute to the wider SWB literature using panel methods which has consistently found that effect sizes are significantly reduced when accounting for this heterogeneity in fixed effect models.[21]

[21] In Appendix A.11, I estimate the equivalent pooled OLS and fixed effects regression models using the Caseness, MCS, and single-item measures of SWB. All results are qualitatively identical to those presented in Table 4.

Table 4: Mean Effects of Victimisation on SWB, by Gender (Pooled OLS and FE)

	Pooled OLS (Likert)				Fixed Effects (Likert)			
	(1) Full	(2) Male	(3) Female	(4) p-value	(5) Full	(6) Male	(7) Female	(8) p-value
Attacked	2.76*** (.27)	2.67*** (.36)	2.86*** (.40)	.72	.82*** (.30)	.89** (.40)	.75* (.44)	.82
Insulted Only	2.09*** (.13)	1.95*** (.17)	2.16*** (.18)	.40	.59*** (.14)	.65*** (.20)	.54*** (.19)	.71
Additional Controls	Yes	Yes	Yes		Yes	Yes	Yes	
$H_0: Attacked = Insulted$ $p\text{-}value$	.019	.063	.096		.456	.564	.658	
No. of Observations	27013	11968	15045		27013	11968	15045	

Notes: All models control for age, age-squared, educational attainment indicators, marital status indicators, employment status indicators, an indicator for children in the household, an urban/rural indicator, log of household income, region of residence indicators, and survey wave indicators. The pooled OLS models include gender and race indicators. The fixed effects models include individual fixed effects. Standard errors clustered at the individual level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

7.3 Life Evaluation Domains of SWB

The UKHLS contains four single-item SWB life-evaluation type questions. Respondents are asked to evaluate how satisfied they are with their (1) Health, (2) Income, (3) Leisure Time, and (4) Life Overall. Each of these items are scored on a seven-point Likert scale from 1 (completely dissatisfied) to 7 (completely satisfied). In results columns (1)-(4) of Table 5, I use the responses to each of these questions as dependent variable measures of SWB to capture the heterogeneous relationship between victimisation and different evaluative domains of life satisfaction. For comparison with previous sections, I include the MCS and Likert scores in results columns (5) and (6), respectively. For ease of coefficient interpretation, all dependent variables in Table 5 have been standardised to have a mean of 0 and standard deviation of 1.[22]

For the satisfaction with Leisure Time domain, being attacked has no significant association, but being insulted/harassed is associated with significant decreases in well-being. Both measures of victimisation are associated with statistically significant decreases in well-being across the Health, Income, and Life Overall evaluative domains of SWB.

Of the four evaluation-type measures of SWB, satisfaction with Life Overall is the most general, and requires individuals to evaluate all sub-domains of satisfaction which influence their perceptions of their quality of life. In contrast, the three questions on satisfaction with health, income, and leisure time ask respondents to evaluate their satisfaction with a specific sub-domain of well-being.

Being 'Attacked' is associated with larger decreases in well-being among the Health and Life Overall domains compared with the Income and Leisure Time domains. It is unsurprising that victimisation

[22]Note that worsening SWB is indicated by decreases in the life-evaluation type question scores, and increases in the Likert and MCS scores.

is associated with worse holistic evaluations of one's overall life compared with income and leisure time satisfaction. In addition, compared with those who were 'Insulted Only', being 'Attacked' is associated with significantly larger reductions in the Health satisfaction domain. Being attacked likely resulted in some physical injury for a portion of respondents. Therefore, it is unsurprising that being physically attacked has a larger negative effect on health satisfaction than being insulted.

Satisfaction with one's leisure time captures, in part, the well-being which we derive from social activities. The significantly negative association between leisure time satisfaction and being insulted (but not being attacked) is consistent with this form of non-physical victimisation affecting individuals' social lives more negatively. Being insulted, threatened, and harassed likely lowers one's feelings of self-worth and confidence. These feelings can lead to increased social withdrawal and isolation, which would significantly reduce the satisfaction one experiences in one's leisure time.

In Section 2, I mentioned existing research which suggested that life shocks may have larger effects on cognitive/evaluative measures of well-being compared with affective measures of well-being. In Table 5, I find that the magnitude of the victimisation coefficients on the affective measures of well-being in columns (5)-(6) are always at least as large as the magnitude of the coefficients on the cognitive/evaluative domain measures of well-being in columns (1)-(4). Therefore, I find no evidence to support the hypothesis that cognitive measures of SWB are impacted more than affective measures in the context of victimisation.

Table 5: FE Estimates: Impact of Victimisation on Satisfaction Domains of SWB

Satisfaction with...:	(1) Health	(2) Income	(3) Leisure Time	(4) Life Overall	(5) MCS Score	(6) Likert Score
Attacked	-.14***	-.078*	-.0016	-.15***	.21***	.15***
	(.046)	(.046)	(.049)	(.049)	(.050)	(.054)
Insulted Only	-.055**	-.061***	-.084***	-.10***	.12***	.11***
	(.023)	(.022)	(.023)	(.024)	(.023)	(.025)
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes
P-value (victim diff)	.08	.73	.10	.376	.10	.46
No. of Observations	26861	26815	26830	26835	27013	27013

Notes: See Table 4 for a list of the additional controls used. Standard errors clustered at the individual level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

7.4 Distributional Analysis

Next I test for the heterogeneous relationship of victimisation along the SWB distribution of the Likert and MCS scores.[23] In Table 6 and Figure 4, I present the coefficients on the victimisation indicators from unconditional quantile regressions with fixed effects. RIF's estimated from the Likert

[23]For the quantile regression analyses, I focus on the Likert and MCS scores because they have the widest range of possible outcomes.

score are the dependent variable. For a given quantile, each coefficient is interpreted as the change in the unconditional distribution of the Likert score that is associated with being 'Attacked' or 'Insulted'. Those in higher quantiles of the unconditional Likert score distribution represent those with worse SWB (more symptoms of psychological distress/morbidity).

I find significant heterogeneity in the relationship between victimisation and SWB across the distribution of the Likert score. At lower quantiles of the distribution (i.e. those with better SWB), the coefficients on being attacked or insulted are small or statistically insignificant. At the 20th quantile of the SWB (Likert score) distribution, being insulted is associated with a 0.20 point increase in Likert score, and being attacked has no significant association. In contrast, those in the upper quantiles of the SWB distribution (i.e. those with worse SWB) are impacted far more severely by victimisation incidents. At the 80th quantile, being attacked and insulted are both associated with a 2.33 point and 1.02 point increase in Likert score, respectively. In general, the magnitude of the association of victimisation on SWB increases monotonically as one moves up the unconditional quantiles of the SWB (Likert score) distribution. These findings suggest that those with better SWB and those who are furthest away from having mental health issues are the ones who face the least negative impact on their SWB following a victimisation incident. In contrast, those with worse SWB are impacted most severely by victimisation incidents.

In comparison to the average FE estimates from Table 4 for Attacked (.82) and Insulted (.59), it is clear that much information is lost when one ignores the heterogeneous association of victimisation along the SWB distribution. These results support the hypothesis that those with better levels of SWB have a greater ability to absorb negative life events compared with their poorer SWB counterparts. Table 6 shows that the coefficient estimates on being Attacked are significantly larger (at the 5% level) than the coefficient on being Insulted, for the 60th and 80th quantiles of the SWB distribution. Therefore, these results are consistent with the hypothesis that being physically attacked has a stronger negative relationship with SWB than being insulted among those in the upper quantiles of the SWB distribution. The distributional results are qualitatively similar when conducting the same UQR-FE analysis using the MCS score as the dependent variable (see Figure 5 and Table 7).

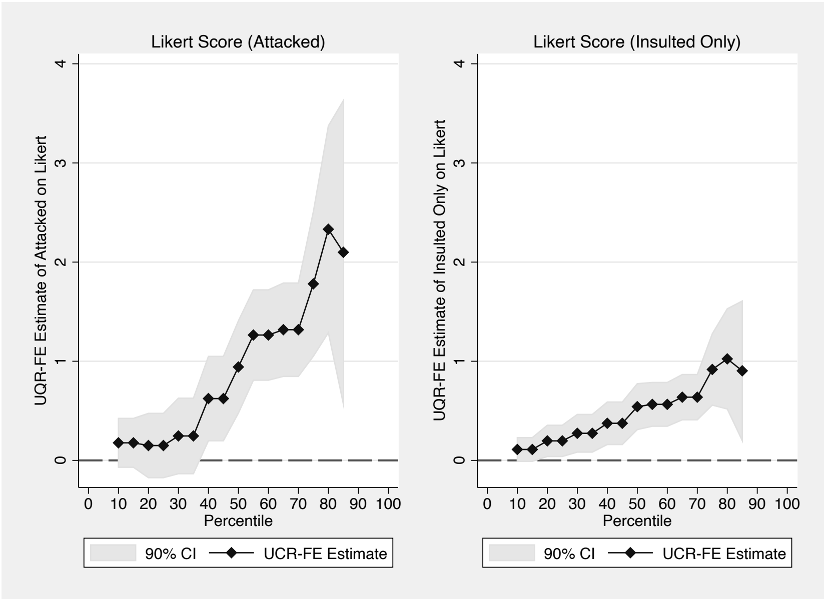


Figure 4: Unconditional Quantile Regression with Fixed Effects: Impact of Victimisation on the Unconditional Likert Score Distribution

Table 6: Unconditional Quantile Regression with Fixed Effects: Full Sample (Likert)

	Likert Score				
	q20	q40	q50	q60	q80
Attacked	.15	.62**	.94***	1.26***	2.33***
	(.19)	(.25)	(.32)	(.31)	(.63)
Insulted Only	.20**	.37***	.54***	.56***	1.02***
	(.096)	(.14)	(.14)	(.13)	(.29)
Additional Controls	Yes	Yes	Yes	Yes	Yes
P-value (victim diff)	.826	.341	.248	.019	.043
No. of Observations	27013	27013	27013	27013	27013

Notes: See Table 4 for a list of the additional controls used. Bootstrapped standard errors, clustered at the individual level. 200 replications per decile. * p<0.10, ** p<0.05, *** p<0.01.

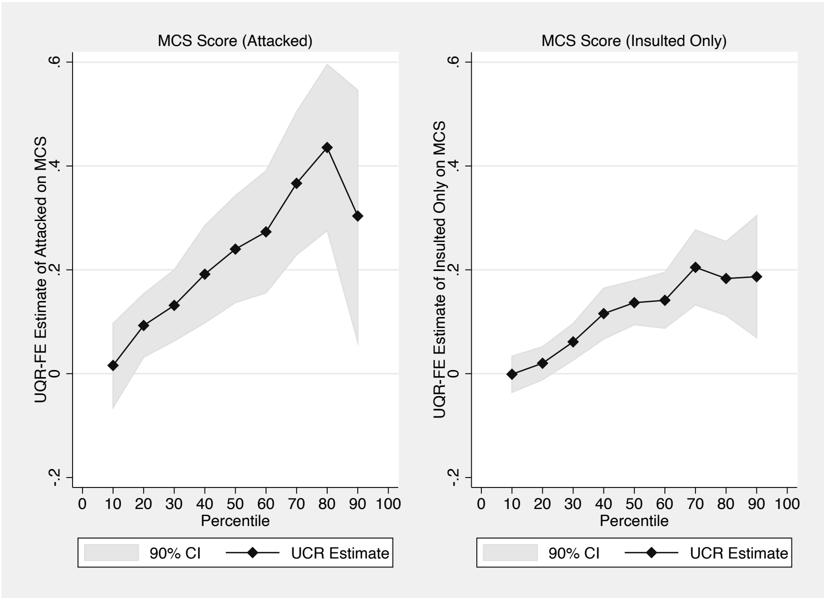


Figure 5: Unconditional Quantile Regression with Fixed Effects: Impact of Victimisation on the Unconditional MCS Score Distribution

Table 7: Unconditional Quantile Regression with Fixed Effects: Full Sample (MCS)

	MCS Score				
	q20	q40	q50	q60	q80
Attacked	.09***	.19***	.24***	.27***	.44***
	(.035)	(.053)	(.052)	(.065)	(.096)
Insulted Only	.020	.12***	.14***	.14***	.18***
	(.020)	(.028)	(.035)	(.038)	(.046)
Additional Controls	Yes	Yes	Yes	Yes	Yes
P-value (victim diff)	.037	.164	.051	.066	.0080
No. of Observations	27013	27013	27013	27013	27013

Notes: See Table 4 for a list of the additional controls used. Bootstrapped standard errors, clustered at the individual level. 200 replications per decile. * p<0.10, ** p<0.05, *** p<0.01.

7.5 Dynamics – Reverse Causality and Adaptation Effects

The causal direction between SWB and various life shocks is a topic of debate within the happiness economics literature. For example, there is a positive correlation between marriage and SWB, but happiness also increases one's chances of becoming married which makes disentangling the causal pathway difficult (Stutzer and Frey, 2006).

I have identified a significant association between victimisation and SWB, but it is possible that these victimisation incidents are also correlated with individual's past SWB levels. For example, according to the Symptom Driven Model of Depression, lower SWB can lead to social behaviour which increases the risk of becoming victimised (Kochel et al., 2012). This model would suggest that there may be reverse causality concerns, where reduced SWB leads to increased probability of being victimised rather than victimisation leading to reduced SWB levels. In addition, set-point theory predicts that the negative effect of life shocks like victimisation on SWB are short-lived, and a return to natural equilibrium levels of SWB occurs relatively quickly.

I test for these adaptation effects and reverse causality concerns in two ways. First, I run similar FE regression models on each SWB measure as previously, with the addition of a set of lead/lag dummies indicating one and two waves before, and one and two waves after the victimisation incident. I am limited in the time horizon of this dynamics analysis by the victimised sample sizes, and only having five biennial waves of the UKHLS which collected victimisation data. In Appendix A.12 (Tables 13-18), I present these results on each of the main measures of SWB (Likert score, MCS score, and each of the satisfaction domains). Second, in Appendix A.13, I present a series of event study coefficient plots, further looking at the anticipation and adaptation effects of victimisation on SWB. I include two lagged periods in Figures 14-15; two leading periods in Figures 16-17; and one leading and one lagged period in Figures 18-19. The reference period in all figures is the wave prior to the victimisation incident, and I restrict the sample to those who reported a single victimisation incident over the course of the UKHLS sampling period.

Across both sets of results, I find little evidence of any anticipation effects leading up to the victimisation period. Therefore, I find no evidence that SWB changes significantly in the waves prior to victimisation incidents. These results suggest that incidents of victimisation precedes reductions in well-being, indicating that reverse causality is not a concern. Similarly, when looking at the lagged effect of victimisation on SWB in the waves which follow on from victimisation incidents, adaptation back to pre-victimisation levels of SWB is seen across most specifications, although there is some evidence that the effect of being 'Attacked' persists for an additional biennial period for the Health and Life Overall Satisfaction domains. Overall, these results indicate that the reductions in well-being which are associated with being victimised are significant in the wave in which the incident occurred and are transitory. Those who were victimised generally return to pre-victimisation levels of SWB by the following biennial wave.[24]

[24] It is possible that the effect of victimisation lasts for more than one year, but I am unable to test for this because my data is biennial.

7.6 Sensitivity Analysis

7.6.1 Disaggregating GHQ-12 Domains

The between-item validity of the GHQ-12 is high in the sample used in this analysis with a Cronbach's alpha score of 0.9007, indicating high levels of reliability or internal consistency. However, there has been some debate around treating the GHQ-12 as a uni-dimensional measure of well-being in generating single Caseness or Likert scores. To test for the robustness of the FE estimates of the relationship between victimisation and well-being, I disaggregate the items used to generate the main single-factor GHQ-12 Likert and Caseness scores, into alternative multidimensional scales.

Using factor analysis methods, Graetz (1991) argued that the GHQ-12 is a multidimensional measure of well-being which captures three different constructs or factors – (i) Anxiety and Depression (4-items), (ii) Social Dysfunction (6-items), and (iii) Confidence (2-items). I apply the [0-1-2-3] scoring and aggregation procedure used in the standard Likert score previously, to the items in each of the three factors, to create three SWB variables.[25] Alternatively, Andrich and Schoubroeck (1989) argue that the positively and negatively worded questions form separate constructs which warrant being treated as different scales in a two-factor model. I follow Huppert and Whittington (2003) in applying the same [0-1-2-3] scoring and aggregation procedure used in the standard Likert score previously, to the positively and negatively framed questions respectively, to generate a GHQ+ and a GHQ– measure of well-being.

The items used in each factor model are detailed in Table 9. For ease of comparison, I normalise each of these factors to share the same scale as the Likert score used previously so that each factor ranges from 0 (Least Distressed) to 36 (Most Distressed). In Table 8, I re-run the linear FE baseline specification from Table 4 on the two-factor measures (columns 2-3), and three factor measures (columns 4-6). For comparison, the results of the single-factor Likert score measure are reproduced in column 1. Decomposing the GHQ-12 into two factors, I find that being Attacked has a significant impact on GHQ– but not on GHQ+, while being Insulted is associated with significantly larger decreases in well-being for the GHQ– factor compared with the GHQ+ factor, at the 10% level. Therefore, I find that victimisation is associated with larger decreases in the GHQ– dimension of well-being, when compared with the GHQ+ dimension. When decomposing the GHQ-12 into a three factor structure, I find that victimisation is associated with larger decreases in well-being for the 'Anxiety & Depression' and 'Loss of Confidence' domains of well-being, when compared with the 'Social Dysfunction' domain.

[25] Gao et al. (2004) and Shevlin and Adamson (2005) argue that going from a uni-dimensional instrument (Caseness/Likert scores) to a three-dimensional instrument offers no practical advantages given that these factors are highly correlated.

Table 8: Mean Effects of Victimisation on SWB – Alternative GHQ Factor Models

	One Factor	Two Factors		Three Factors		
	Likert	GHQ+	GHQ−	Anxiety & Depression	Social Dysfunction	Loss of Confidence
Attacked	.82***	.42	1.22***	1.28***	.42	1.10**
	(.29)	(.27)	(.38)	(.40)	(.27)	(.46)
Insulted Only	.59***	.32**	.85***	.87***	.32**	.82***
	(.14)	(.13)	(.17)	(.18)	(.13)	(.21)
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes
P-value (victim diff)	0.456	0.732	0.356	0.325	0.732	0.563
No. of Observations	27013	27013	27013	27013	27013	27013

Notes: See Table 4 for a list of the additional controls used. Standard errors clustered at the individual level.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 9: Factor Models of the GHQ-12

Two Factor Structure	Item	Question
GHQ+	GHQ-1	Been able to concentrate on whatever you are doing?
	GHQ-3	Felt that you were playing a useful part in things?
	GHQ-4	Felt capable of making decisions about things?
	GHQ-7	Been able to enjoy your normal day-to-day activities?
	GHQ-8	Been able to face up to your problems?
	GHQ-12	Been feeling reasonably happy, all things considered?
GHQ–	GHQ-2	Lost much sleep over worry?
	GHQ-5	Felt constantly under strain?
	GHQ-6	Felt that you could not overcome your difficulties?
	GHQ-9	Been feeling unhappy and depressed?
	GHQ-10	Been losing self-confidence in yourself?
	GHQ-11	Been thinking of yourself as a worthless person?
Three Factor Structure	**Item**	**Question**
GHQ - Anxiety and Depression	GHQ-2	Lost much sleep over worry?
	GHQ-5	Felt constantly under strain?
	GHQ-6	Felt that you could not overcome your difficulties?
	GHQ-9	Been feeling unhappy and depressed?
GHQ - Social Dysfunction	GHQ-1	Been able to concentrate on whatever you are doing?
	GHQ-3	Felt that you were playing a useful part in things?
	GHQ-4	Felt capable of making decisions about things?
	GHQ-7	Been able to enjoy your normal day-to-day activities?
	GHQ-8	Been able to face up to your problems?
	GHQ-12	Been feeling reasonably happy, all things considered?
GHQ - Loss of Confidence	GHQ-10	Been losing self-confidence in yourself?
	GHQ-11	Been thinking of yourself as a worthless person?

8 Robustness Checks

In Appendix A.19, I re-estimate the relationship between victimisation and SWB (Caseness, and Life Evaluation measures) using ordered probit, and ordered logit methods. Across these econometric models, I consistently find that victimisation is associated with a decrease in well-being levels.

However, it is not sufficient to investigate the robustness of an empirical relationship between an explanatory variable and the same well-being scale across different estimators. Mathematically, any monotonic increasing transformation of a reported ordinal SWB scale is a theoretically valid representation. Therefore, we must ensure the robustness of SWB regression model results to monotonic increasing transformations of the well-being scale (Schröder and Yitzhaki, 2017).

In related work by Bond and Lang (2019), the authors argue that treating ordinal reports of SWB as cardinal is inappropriate and that the signs of coefficients in many SWB regression models can be reversed with a suitable monotonic increasing transformation of the SWB dependent variable. In response, Kaiser and Vendrik (2020) argue that, for the reversal of signs on coefficients in SWB regressions to occur, one must assume that respondents interpret the SWB response scales in a highly non-linear way.[26] Given that existing evidence within the economics and psychological literature is that respondents interpret these scales in an approximately linear fashion when responding, the authors argue that the work of Bond and Lang (2019) is not a serious concern when estimating the direction of effects of explanatory variables on SWB.

Kaiser and Vendrik (2020) recommend that future work using SWB as an outcome ought to ensure that findings are robust to a range of plausible transformations of SWB. In the following sections, I relax the linear reporting function assumption and present several robustness analyses related to the cardinalisation of the SWB variable.

8.1 Robustness of Mean Group Differences in SWB

Schröder and Yitzhaki (2017) provide a proof showing that if the cumulative distribution functions of two mutually exclusive groups do not intersect (i.e. if they first-order stochastically dominate one another), then there exists no monotonic increasing transformation of the SWB variable scale that can change which group has a larger mean SWB. Kaiser and Vendrik (2020) show that a weaker condition – first order stochastic dominance (FOSD) of the cumulative response categories – is sufficient to ensure that the mean SWB of one group is always larger than another for all monotonic increasing transformations of the well-being scale.

In Section 5, I presented descriptive evidence showing that the mean Caseness and Likert scores for those who had been victimised was higher than those who had never been victimised. In Appendix A.14, I present comparisons of SWB cumulative density functions (CDFs) by victim and non-victim status, to test for FOSD. Across SWB measures, I find that the CDFs of 'Insulted' and 'Not Insulted'

[26] In Section 6.2, I presented arguments for the linear relationship between actual and reported SWB. There was limited experimental evidence for some mildly concave or convex deviations from linearity, and speculation around an arc-tangent reporting function, functional form.

groups never cross. The CDFs for 'Attacked' and 'Not Attacked' groups do not cross for any of the evaluative/satisfaction well-being domains in Figure 21, or for the Caseness score measure in Figure 20. Therefore, with the exception of the 'Attacked' and 'Not Attacked' Likert score CDFs where there is cross over, these results show that the finding that victimised groups have worse mean SWB than their non-victimised counterparts is robust to all monotonic increasing transformation of the well-being scale.

8.2 LMA Curves

There are an infinite number of ways to transform an ordinal variable when testing for the robustness of victimisation estimates to monotonic increasing transformations of SWB. To tackle this problem, Schröder and Yitzhaki (2017) introduce the line of independence minus absolute concentration (LMA) curve. The LMA curve is related to the concept of second-order stochastic dominance and the absolute Lorenz curve, where if the Lorenz curves of two mutually exclusive groups do not intersect, then you can say which group second-order stochastically dominates the other. Similarly, if the LMA curve of the SWB dependent variable (Y) with respect to a victimisation explanatory variable (X), does not cross the x-axis, then the absolute Lorenz curve does not intersect the line of independence, and there exists no monotonic increasing transformation which will change the sign of the victimisation coefficient in an OLS regression (Bloem, 2020).

In Appendix A.15, I estimate LMA curves for each of the main SWB measures, and each of the victimisation indicators of interest ('Attacked' and 'Insulted'). Across SWB measures and victimisation indicators in Figure 22 and Figure 23, the LMA curves never cross the x-axis. The LMA curve results provide some evidence in support of the robustness of my victimisation estimates to monotonic increasing transformations.

The main advantage of using the LMA curve method is that it ensures robustness to all of the nearly infinite number of monotonic transformations that we can apply to the SWB variable. However, the LMA curve method has several disadvantages: it only ensures robustness of the point estimate sign within a univariate OLS regression; says nothing of changes to statistical significance or effect size; and, even if the LMA curve test fails, this does not mean that the transformations which cause the failure are plausible in the real-world.

8.3 Estimating Plausible Bounds to Estimates

To address the limitations of the LMA curve robustness test, I follow Bloem's (2020) three-step procedure to calculate plausible bounds around the effect sizes of victimisation on SWB. First, I limit the infinite number of possible monotonic increasing transformations by defining a parameterised function which allow for a wide range of convex and concave transformations, as suggested by Bloem (2020). Second, I estimate a set of estimates for victimisation, across this range of transformations. Third, I graphically access how sensitive and robust the victimisation estimates are across the range of concave/convex transformations.

Concave and Convex Transformations

To test the robustness of my estimates to concave and convex reporting functions, I use the following parameterised function:

$$T(Y) = Y_{max} \cdot (\frac{Y}{Y_{max}})^{\sigma} \qquad \forall \quad \sigma > 0$$

Y is a rank order (linear) SWB scale ranging from Y_{min} to Y_{max} – the minimum and maximum values of the SWB ordinal scale. For values of $0 < \sigma < 1$, $T(Y)$ is variously concave. A concave reporting function describes reporting behaviour where distances between lower score levels represent a larger change in SWB than distances between higher score levels. When $\sigma = 1$, $T(Y)$ is linear and will reproduce the main estimates of this paper. When $\sigma > 1$, $T(Y)$ is variously convex. A convex reporting function describes reporting behaviour where distances between lower score levels represent a smaller change in SWB than distances between higher score levels.

Mathematically, σ can be infinity large. To test for deviations from linearity, I assume that σ lies in the range $[0.2, 5]$, which allows for a relatively extreme/wide range of concave and convex transformations of the SWB variables (see Figure 6 for a graphical representation of how highly non-linear the reporting functions are at the extrema of the σ range for the Caseness score). A transformation at the extrema of the σ range implies large changes in underlying (latent) well-being associated with either only the lower scores, or only the higher scores, of reported SWB.[27]

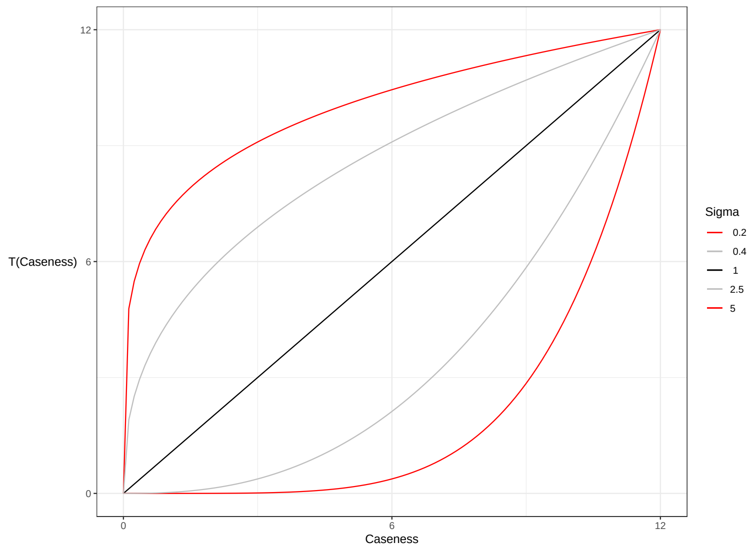


Figure 6: Concave and Convex Transformations of the Caseness Score

I re-estimate a set of coefficient estimates for victimisation, across the range of σ, on each of the SWB measures. I present these results graphically in Appendix A.16. Previously, I found that being 'Insulted' was associated with worse SWB across all measures. The 'Insulted' result persists across

[27]For example, take the Caseness Score: a $\sigma = 0.2$ means that the difference between the top two Caseness scores is 0.21. However, the difference between the bottom two Caseness scores is 7.3, which is more than 34 times larger. A $\sigma = 5$ means that the difference between the bottom two Caseness scores is 0.00005. However, the difference between the top two Caseness scores is 4.23, which is more than 84,000 times larger.

the entire range of concave/convex transformations estimated for the Caseness score; the Likert score; Overall Life Satisfaction; and Leisure Time Satisfaction.[28]

Previously, I found that being 'Attacked' was, with the exception of 'Leisure Time Satisfaction', associated with worse SWB across all measures. The 'Attacked' estimates are a little less robust across the extreme range of smooth concave/convex transformations. Therefore, it is necessary to assess if these estimates are robust across a plausibly wide range of possible transformations. The significance of the 'Attacked' result persists across the range of concave/convex transformations estimated for the Caseness score up to a $\sigma \approx 1.4$; and the Likert score up to a $\sigma \approx 2.2$. Therefore, these estimates are robust to all concave transformations (i.e. $\sigma < 1$) and for a reasonably wide range of convex transformations, particularly for the Likert score.[29] The estimated effect of being 'Attacked' is robust across the entire range of σ for 'Overall Life Satisfaction' and 'Health Satisfaction'. The previous finding that being 'Attacked' reduced Income Satisfaction is only robust to convex transformations of $2.2 \leq \sigma \geq 1$. The estimated impact of being 'Attacked' on 'Leisure Time Satisfaction' remains insignificant across the range of transformations.

Overall, the main finding of this paper – that victimisation is associated with a reduction in subjective well-being – is robust to even relatively extreme concave/convex transformations of the SWB measures. A limitation of testing the robustness of my estimates in this way is that the function is only one of many options I can choose from to define monotonically increasing transformations. In Appendix A.17, I test the robustness of the victimisation estimates to a range of transformations of SWB with an inflection point. I find that the estimated relationship between victimisation and SWB measures are robust to this class of transformations with an inflection point.

9 Conclusion

This paper presents new evidence on the relationship between victimisation and subjective well-being (SWB) using data from the UK Household Longitudinal Study (UKHLS). Using panel fixed effects regression methods, I find that being physically attacked and being insulted/harassed are both associated with significant reductions in SWB. Compared with the existing literature, I show that these findings are consistent across a wider variety of measures for SWB including the Likert, Caseness, and multidimensional scoring methods of the 12-item general health questionnaire (GHQ-12); as well as the Mental Component Summary measure from the 12-item short form questionnaire (SF-12); and the single-item health and overall life satisfaction measures of well-being. Addressing recent debate within the economics of happiness literature on the appropriateness of cardinalising ordinal measures of well-being, I show that the substantive findings of this paper are robust to a wide variety of concave, convex, and arc-tangent transformations of the reporting function, which maps reported ordinal subjective well-being onto latent well-being.

[28] The 'Insulted' estimates are robust for all $\sigma > 0.27$ for Health Satisfaction; and $\sigma > 0.43$ for Income Satisfaction.

[29] A transformed Caseness score where $\sigma > 1.4$ describes a reporting function where the difference between the top two points on the scale are > 3.72 times larger than the bottom two. For a transformed Likert score with $\sigma > 2.2$, this difference is even greater at > 159 times.

Much of the current literature on victimisation and SWB has relied on cross-sectional samples. The use of longitudinal survey data and panel methods is a contribution of this paper. In particular, I find that once individual fixed effects are controlled for in the well-being regression models, there are no significant differences in the average relationship between subjective well-being and being physically attacked or insulted/harassed. These findings highlight the importance of controlling for time invariant individual heterogeneity in well-being regression models. I also find no difference in the magnitude of the impact of victimisation on SWB between men and women.

Several papers have relied on conditional quantile regression methods to explore the relationship between victimisation and SWB along the well-being distribution. A contribution of this paper is the use of unconditional quantile regression with fixed effects methods to test for the heterogeneous association of victimisation along the SWB distribution. I find that victimisation has an approximately monotonic relationship across the unconditional SWB distribution, where victimisation is associated with smaller decreases in well-being for those at the 'better' end of the distribution, and larger decreases in well-being for those at the 'worse' end of the distribution. These results indicate that an analysis which focuses on the average impact of victimisation on SWB understates the magnitude of the relationship for those who are of most importance from the perspective of policy makers. An incident of victimisation is associated with a larger fall in SWB for those who are already experiencing more psychological symptoms of distress. Overall, this paper highlights the significance of the non-pecuniary costs of crime in the form of reduced well-being. In addition to crime prevention spending and financial remediation following victimisation, policy makers ought to consider health policies which adequately support the psychological health and well-being of individuals following a victimisation incident.

*Appendix A: Chapter 2

A.10 Additional Descriptive Statistics

A.10.A Bar Charts – Alternative SWB Measures, by Victim Status and Gender

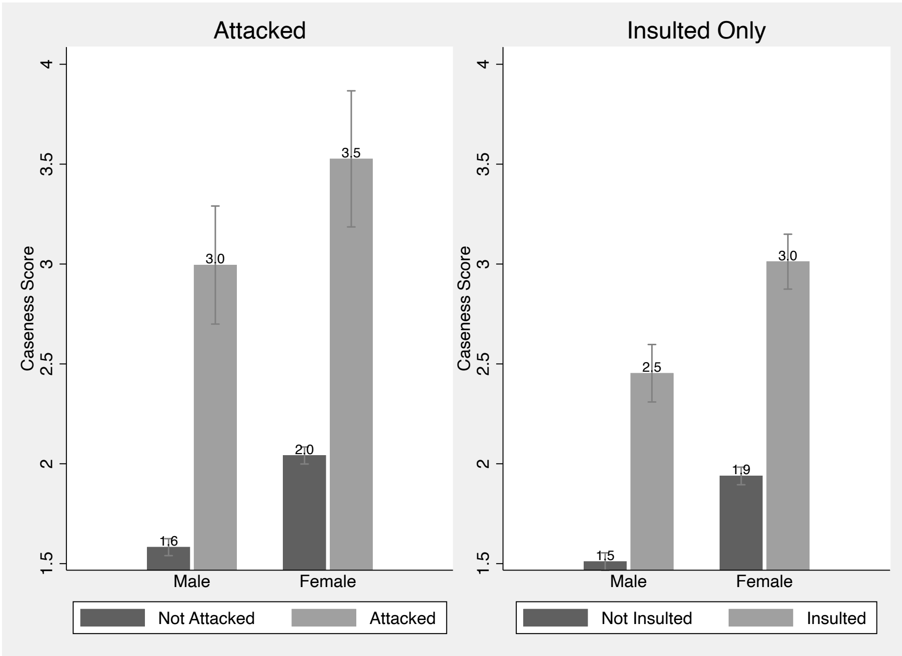


Figure 7: Caseness Score by Victim Status and Gender

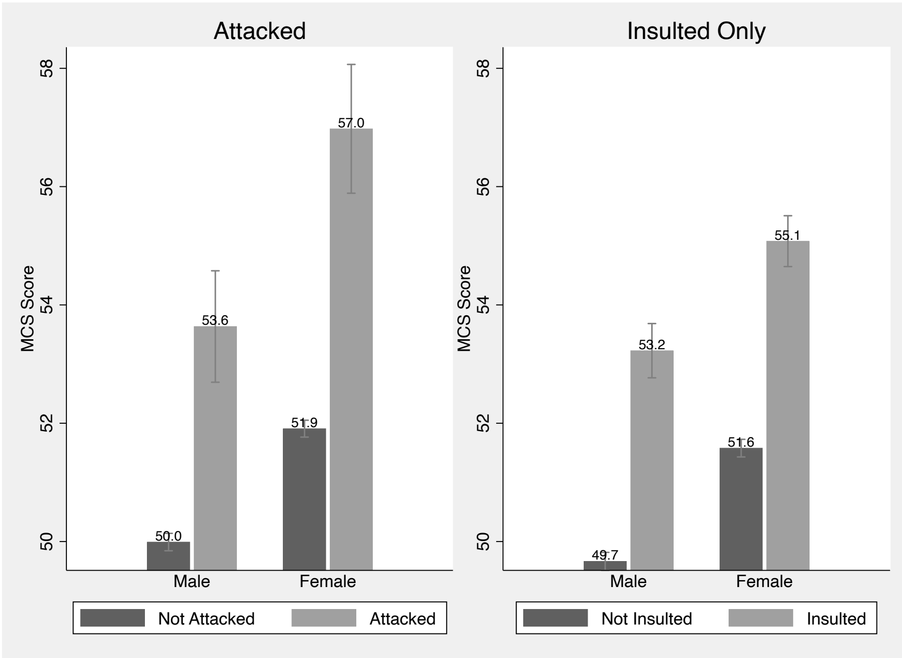


Figure 8: MCS Score by Victim Status and Gender

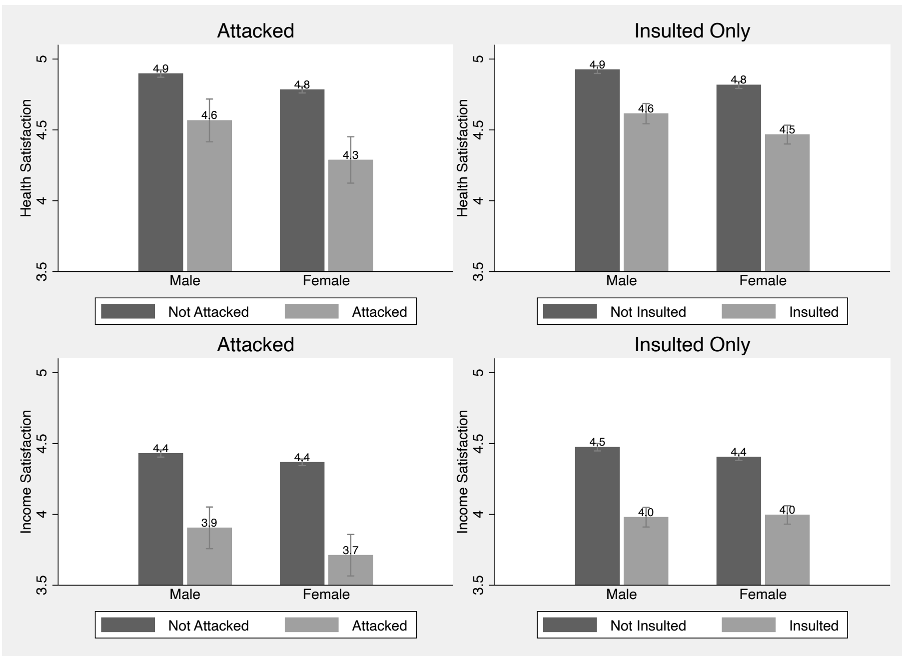


Figure 9: Satisfaction Domains of SWB by Victim Status and Gender (1 of 2)

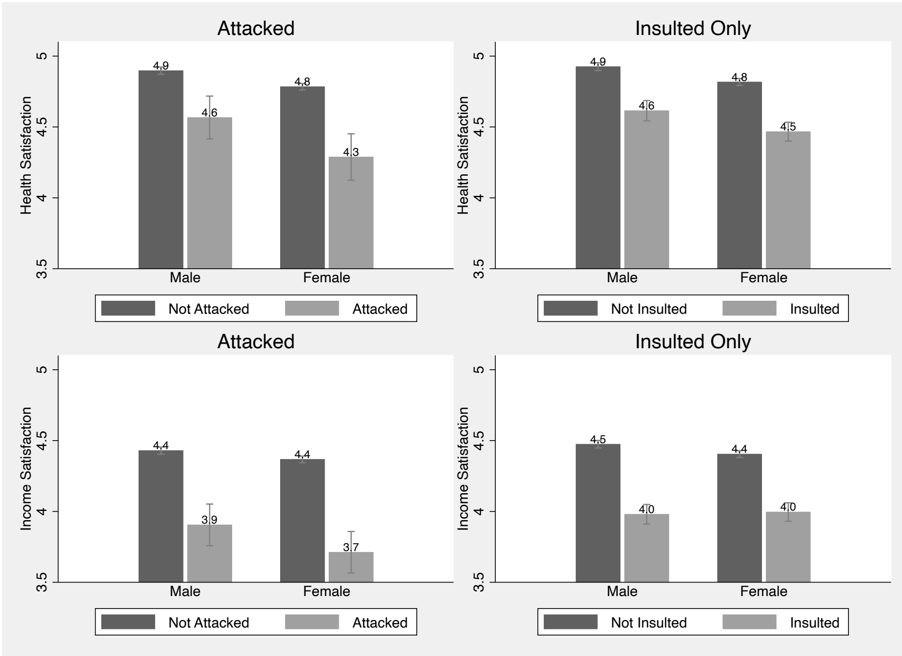


Figure 10: Satisfaction Domains of SWB by Victim Status and Gender (2 of 2)

A.10.B CDF Plots – Alternative SWB Measures, by Victim Status and Gender

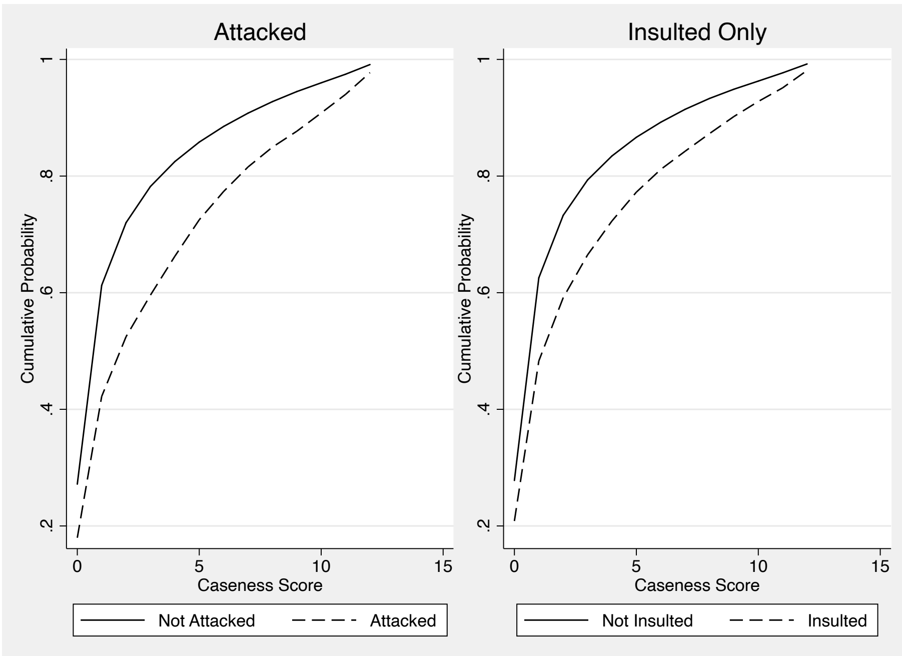


Figure 11: CDF Caseness Score by Victim Status

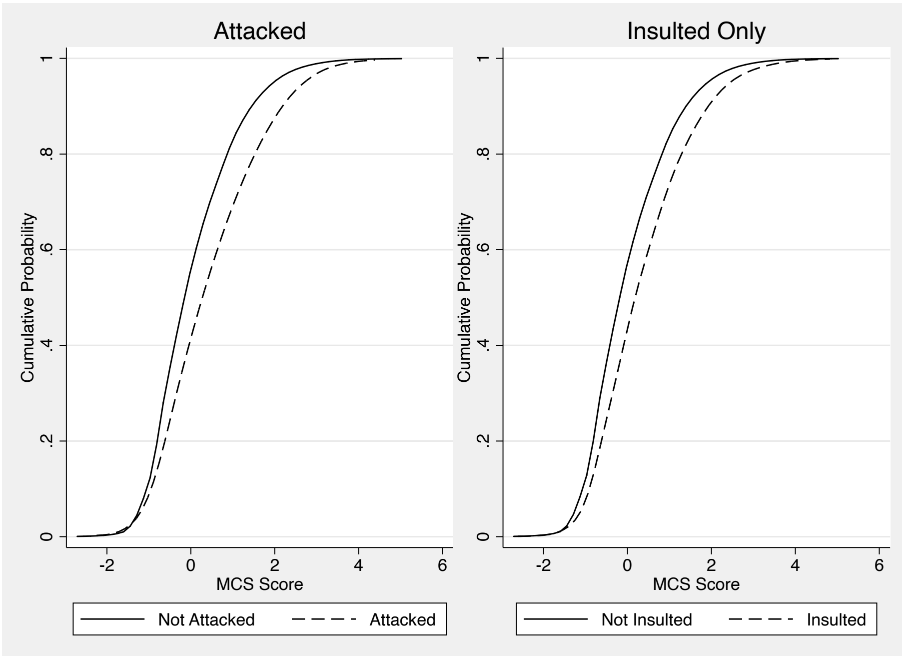


Figure 12: CDF MCS Score by Victim Status

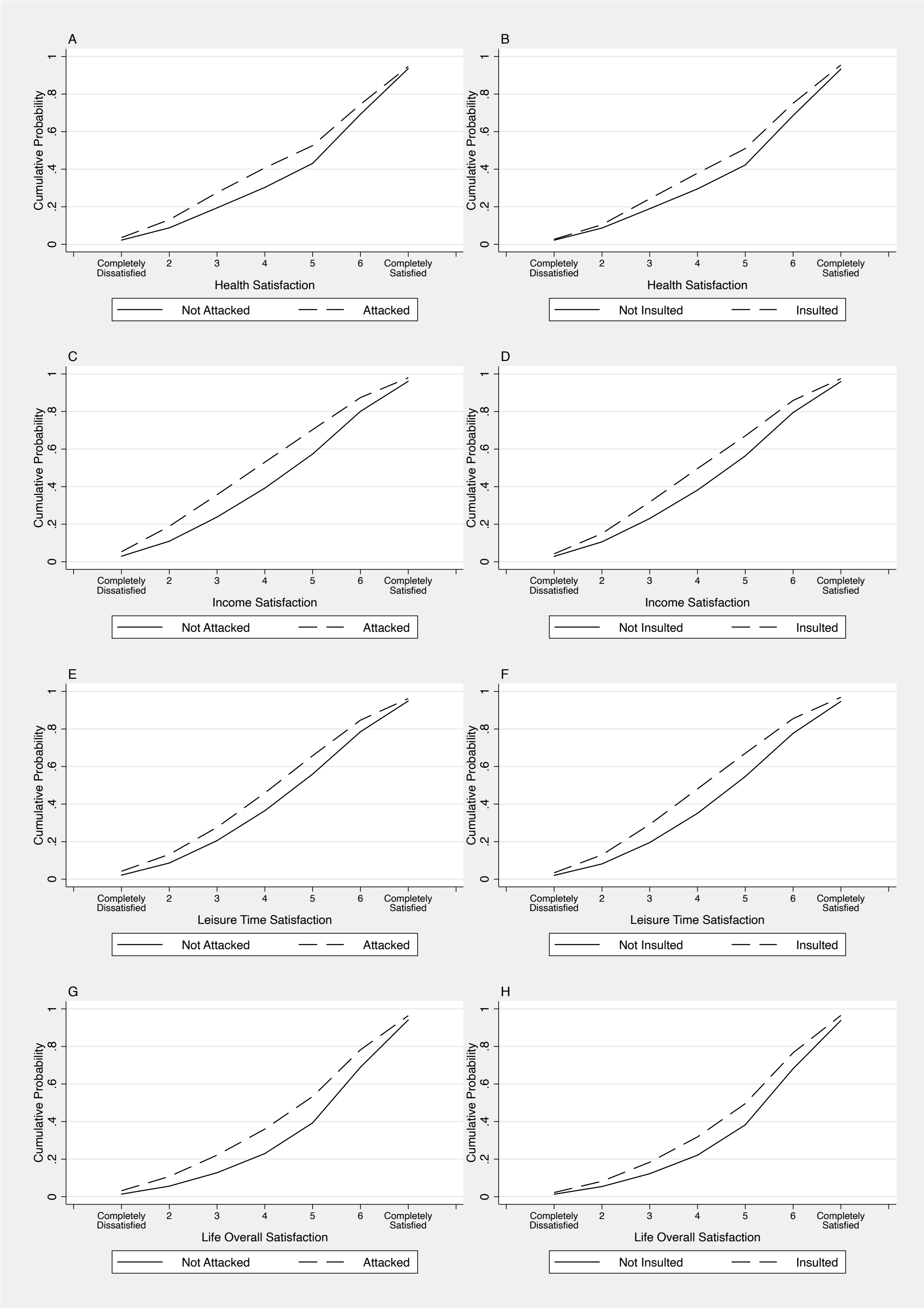


Figure 13: CDF Satisfaction Domains of SWB by Victim Status

A.11 Additional Average Relationship by Gender Estimates (OLS and FE Models

Table 10: Mean Effects of Victimisation on SWB, by Gender (Pooled OLS and FE), Caseness Score

	Pooled OLS (Caseness)				Fixed Effects (Caseness)			
	(1) Full	(2) Male	(3) Female	(4) p-value	(5) Full	(6) Male	(7) Female	(8) p-value
Attacked	1.50***	1.51***	1.49***	.95	.37**	.46**	.27	.85
	(.14)	(.19)	(.21)		(.16)	(.23)	(.24)	
Insulted Only	1.09***	1.00***	1.14***	.27	.31***	.34***	.30***	.77
	(.068)	(.095)	(.095)		(.077)	(.11)	(.10)	
Additional Controls	Yes	Yes	Yes		Yes	Yes	Yes	
$H_0: Attacked = Insulted$ $p\text{-}value$	.007	.013	.125		.714	.624	.930	
No. of Observations	27013	11968	15045		27013	11968	15045	

Notes: All models control for age, age-squared, educational attainment indicators, marital status indicators, employment status indicators, an indicator for children in the household, an urban/rural indicator, log of household income, region of residence indicators, and survey wave indicators. The pooled OLS models include gender and race indicators. The fixed effects models include individual fixed effects. Standard errors clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01.

Table 11: Mean Effects of Victimisation on SWB, by Gender (Pooled OLS and FE), MCS Score

	Pooled OLS (MCS Score)				Fixed Effects (MCS Score)			
	(1) Full	(2) Male	(3) Female	(4) p-value	(5) Full	(6) Male	(7) Female	(8) p-value
Attacked	.46***	.43***	.50***	.48	.21***	.28***	.16**	.32
	(.045)	(.064)	(.063)		(.050)	(.074)	(.069)	
Insulted Only	.37***	.39***	.35***	.32	.12***	.16***	.091***	.21
	(.021)	(.032)	(.028)		(.023)	(.036)	(.031)	
Additional Controls	Yes	Yes	Yes		Yes	Yes	Yes	
$H_0: Attacked = Insulted$ $p\text{-}value$	.053	.509	.023		.096	.136	.372	
No. of Observations	27013	11968	15045		27013	11968	15045	

Notes: All models control for age, age-squared, educational attainment indicators, marital status indicators, employment status indicators, an indicator for children in the household, an urban/rural indicator, log of household income, region of residence indicators, and survey wave indicators. The pooled OLS models include gender and race indicators. The fixed effects models include individual fixed effects. Standard errors clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01.

Table 12: Mean Effects of Victimisation on SWB, by Gender (Pooled OLS and FE), Satisfaction Domains

	Pooled OLS				Fixed Effects			
	Full	Male	Female	p-value	Full	Male	Female	p-value
	Health Satisfaction							
Attacked	-.52***	-.47***	-.58***	.41	-.24***	-.25**	-.23*	.93
	(.070)	(.092)	(.11)		(.080)	(.10)	(.12)	
Insulted Only	-.43***	-.39***	-.45***	.42	-.096**	-.044	-.14***	.22
	(.033)	(.049)	(.045)		(.040)	(.059)	(.054)	
$H_0: Attacked = Insulted$, *p-value*	.206	.443	.222		.082	.058	.467	
	Pooled OLS				**Fixed Effects**			
	Full	Male	Female	p-value	Full	Male	Female	p-value
	Income Satisfaction							
Attacked	-.50***	-.47***	-.53***	.68	-.13*	.0082	-.27**	.07
	(.065)	(.092)	(.090)		(.078)	(.11)	(.11)	
Insulted Only	-.41***	-.47***	-.36***	.10	-.10***	-.091	-.12**	.75
	(.032)	(.047)	(.043)		(.038)	(.057)	(.051)	
$H_0: Attacked = Insulted$, *p-value*	.210	.939	.0802		.727	.366	.184	
	Pooled OLS				**Fixed Effects**			
	Full	Male	Female	p-value	Full	Male	Female	p-value
	Leisure Time Satisfaction							
Attacked	-.36***	-.35***	-.38***	.79	-.0027	.16	-.18	.04
	(.065)	(.089)	(.096)		(.081)	(.10)	(.12)	
Insulted Only	-.43***	-.44***	-.42***	.75	-.14***	-.096*	-.18***	.32
	(.031)	(.046)	(.042)		(.039)	(.058)	(.052)	
$H_0: Attacked = Insulted$, *p-value*	.348	.341	.719		.101	.018	.991	
	Pooled OLS				**Fixed Effects**			
	Full	Male	Female	p-value	Full	Male	Female	p-value
	Life Overall Satisfaction							
Attacked	-.54***	-.50***	-.59***	.48	-.22***	-.20**	-.25**	.73
	(.065)	(.089)	(.093)		(.073)	(.097)	(.11)	
Insulted Only	-.42***	-.44***	-.40***	.47	-.15***	-.13***	-.16***	.70
	(.031)	(.045)	(.041)		(.036)	(.052)	(.050)	
$H_0: Attacked = Insulted$, *p-value*	.068	.508	.045		.376	.546	.466	
Additional Controls	Yes	Yes	Yes		Yes	Yes	Yes	
N (Health)	26861	11902	14959		26861	11902	14959	
N (Income)	26815	11875	14940		26815	11875	14940	
N (Leisure Time)	26830	11885	14945		26830	11885	14945	
N (Life Overall)	26835	11886	14949		26835	11886	14949	

Notes: All models control for age, age-squared, educational attainment indicators, marital status indicators, employment status indicators, an indicator for children in the household, an urban/rural indicator, log of household income, region of residence indicators, and survey wave indicators. The pooled OLS models include gender and race indicators. The fixed effects models include individual fixed effects. Standard errors clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01.

A.12 Dynamic Effects of Victimisation on SWB - Tables

Table 13: Anticipation and Duration Effects of Victimisation on SWB – (Likert Score)

	Original Estimates	Anticipation Effects		Adaptation Effects	
	(1) No Leads/Lags	(2) 1 Lead	(3) 2 Leads	(4) 1 Lag	(5) 2 Lags
Attacked$_{t-4yrs}$			-.203		
			(.889)		
Attacked$_{t-2yrs}$		.181	-.459		
		(.503)	(.899)		
Attacked$_{t}$	.810***	1.247***	1.753***	.981*	.216
	(.305)	(.419)	(.664)	(.504)	(.867)
Attacked$_{t+2yrs}$				.342	-.215
				(.399)	(.720)
Attacked$_{t+4yrs}$					-.913
					(.586)
Insulted Only$_{t-4yrs}$			.481		
			(.340)		
Insulted Only$_{t-2yrs}$		.142	.134		
		(.205)	(.331)		
Insulted Only$_{t}$	.605***	.500**	.950***	.436**	.365
	(.140)	(.209)	(.317)	(.221)	(.337)
Insulted Only$_{t+2yrs}$				-.302	-.262
				(.208)	(.377)
Insulted Only$_{t+4yrs}$					.182
					(.340)
Additional Covariates	Yes	Yes	Yes	Yes	Yes
No. of Observations	26157	12936	5889	12954	5906

Notes: See Table 4 for a list of the additional controls used. Standard errors clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01.

Table 14: Anticipation and Duration Effects of Victimisation on SWB – (MCS Score)

	Original Estimates	Anticipation Effects		Adaptation Effects	
	(1)	(2)	(3)	(4)	(5)
	No Leads/Lags	1 Lead	2 Leads	1 Lag	2 Lags
Attacked_{t-4yrs}			.0247		
			(.137)		
Attacked_{t-2yrs}		.0634	-.0654		
		(.0799)	(.133)		
Attacked_{t}	.208***	.173**	.174	.254***	.107
	(.0512)	(.0741)	(.121)	(.0777)	(.126)
Attacked_{t+2yrs}				-.0153	-.147
				(.0670)	(.129)
Attacked_{t+4yrs}					-.0559
					(.0980)
$\text{Insulted Only}_{t-4yrs}$			.0527		
			(.0630)		
$\text{Insulted Only}_{t-2yrs}$		.0285	-.0137		
		(.0367)	(.0610)		
Insulted Only_{t}	.117***	.0957***	.138**	.0724*	.0589
	(.0237)	(.0356)	(.0550)	(.0374)	(.0566)
$\text{Insulted Only}_{t+2yrs}$				.0141	.0283
				(.0352)	(.0600)
$\text{Insulted Only}_{t+4yrs}$					-.0369
					(.0544)
Additional Covariates	Yes	Yes	Yes	Yes	Yes
No. of Observations	26157	12936	5889	12954	5906

Notes: See Table 4 for a list of the additional controls used. Standard errors clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01.

Table 15: Anticipation and Duration Effects of Victimisation on SWB – Satisfaction with Health

	Original Estimates	Anticipation Effects		Adaptation Effects	
	(1)	(2)	(3)	(4)	(5)
	No Leads/Lags	1 Lead	2 Leads	1 Lag	2 Lags
Attacked$_{t-4yrs}$			.155		
			(.222)		
Attacked$_{t-2yrs}$		.0699	.264		
		(.138)	(.235)		
Attacked$_{t}$	-.222***	-.224*	-.299*	-.305**	.267
	(.0814)	(.119)	(.171)	(.143)	(.186)
Attacked$_{t+2yrs}$				-.218*	-.0883
				(.124)	(.215)
Attacked$_{t+4yrs}$					.303*
					(.155)
Insulted Only$_{t-4yrs}$			.235**		
			(.101)		
Insulted Only$_{t-2yrs}$		-.0179	.111		
		(.0637)	(.108)		
Insulted Only$_{t}$	-.0912**	-.130**	-.146	-.0618	-.0733
	(.0409)	(.0628)	(.0964)	(.0672)	(.102)
Insulted Only$_{t+2yrs}$				-.0142	-.144
				(.0640)	(.107)
Insulted Only$_{t+4yrs}$					-.0328
					(.0935)
Additional Covariates	Yes	Yes	Yes	Yes	Yes
No. of Observations	26005	12862	5837	12947	5903

Notes: See Table 4 for a list of the additional controls used. Standard errors clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01.

Table 16: Anticipation and Duration Effects of Victimisation on SWB – Satisfaction with Income

	Original Estimates	Anticipation Effects		Adaptation Effects	
	(1)	(2)	(3)	(4)	(5)
	No Leads/Lags	1 Lead	2 Leads	1 Lag	2 Lags
Attacked$_{t-4yrs}$			-.201		
			(.216)		
Attacked$_{t-2yrs}$		.00101	.214		
		(.138)	(.208)		
Attacked$_{t}$	-.117	-.0351	-.159	-.198	-.0382
	(.0798)	(.114)	(.159)	(.130)	(.217)
Attacked$_{t+2yrs}$				-.200*	-.200
				(.107)	(.195)
Attacked$_{t+4yrs}$					.171
					(.155)
Insulted Only$_{t-4yrs}$			-.175*		
			(.0955)		
Insulted Only$_{t-2yrs}$		-.0521	-.0220		
		(.0606)	(.0996)		
Insulted Only$_{t}$	-.0997**	-.0710	-.158*	-.0732	-.104
	(.0388)	(.0576)	(.0879)	(.0596)	(.0899)
Insulted Only$_{t+2yrs}$				.00462	-.0366
				(.0584)	(.0956)
Insulted Only$_{t+4yrs}$					-.0174
					(.0891)
Additional Covariates	Yes	Yes	Yes	Yes	Yes
No. of Observations	25959	12845	5827	12941	5900

Notes: See Table 4 for a list of the additional controls used. Standard errors clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01.

Table 17: Anticipation and Duration Effects of Victimisation on SWB – Satisfaction with Leisure Time

	Original Estimates	Anticipation Effects		Adaptation Effects	
	(1)	(2)	(3)	(4)	(5)
	No Leads/Lags	1 Lead	2 Leads	1 Lag	2 Lags
Attacked_{t-4yrs}			.0349		
			(.214)		
Attacked_{t-2yrs}		-.0511	-.0281		
		(.129)	(.188)		
Attacked_{t}	.0320	.0972	.0189	.110	.337
	(.0830)	(.115)	(.172)	(.139)	(.219)
Attacked_{t+2yrs}				.0335	.0473
				(.117)	(.187)
Attacked_{t+4yrs}					.0753
					(.151)
$\text{Insulted Only}_{t-4yrs}$			-.00939		
			(.101)		
$\text{Insulted Only}_{t-2yrs}$		-.0824	-.0191		
		(.0652)	(.107)		
Insulted Only_{t}	-.127***	-.165***	-.185*	-.189***	-.200**
	(.0401)	(.0610)	(.0950)	(.0632)	(.0978)
$\text{Insulted Only}_{t+2yrs}$				-.00446	-.0169
				(.0592)	(.0991)
$\text{Insulted Only}_{t+4yrs}$					-.0193
					(.0902)
Additional Covariates	Yes	Yes	Yes	Yes	Yes
No. of Observations	25974	12848	5830	12944	5901

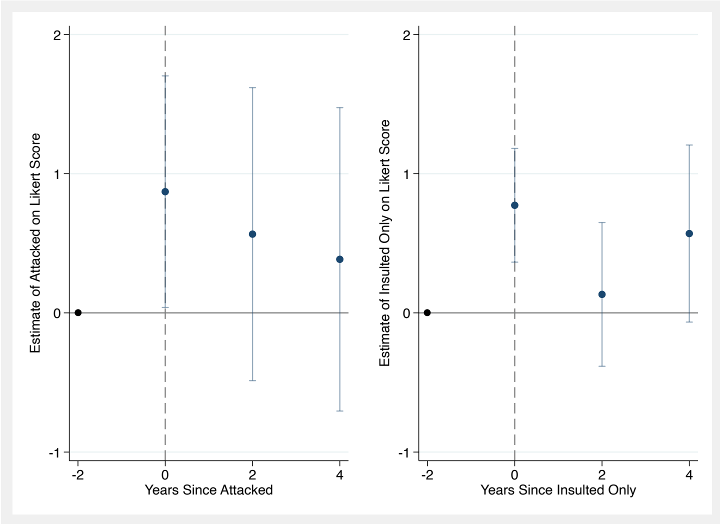
Notes: See Table 4 for a list of the additional controls used. Standard errors clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01.

Table 18: Anticipation and Duration Effects of Victimisation on SWB – Satisfaction with Life Overall

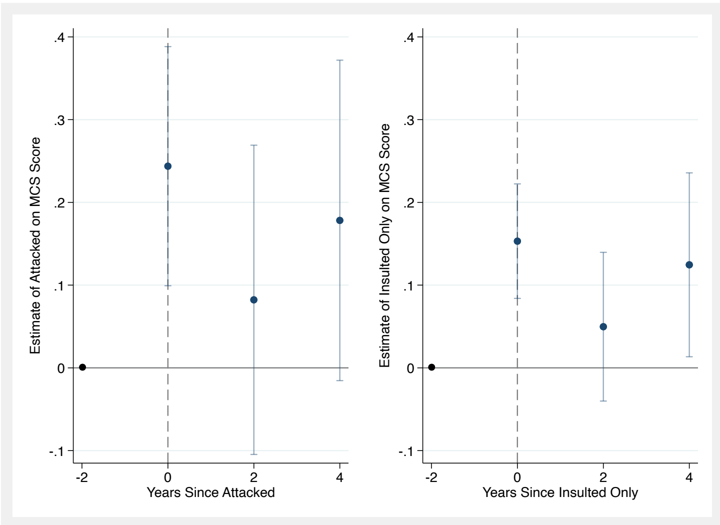
	Original Estimates	Anticipation Effects		Adaptation Effects	
	(1)	(2)	(3)	(4)	(5)
	No Leads/Lags	1 Lead	2 Leads	1 Lag	2 Lags
Attacked$_{t-4yrs}$			.213		
			(.200)		
Attacked$_{t-2yrs}$		.147	.533**		
		(.137)	(.231)		
Attacked$_{t}$	-.207***	-.0528	.0917	-.287**	-.0228
	(.0745)	(.108)	(.166)	(.122)	(.181)
Attacked$_{t+2yrs}$				-.136	-.122
				(.104)	(.169)
Attacked$_{t+4yrs}$					.0465
					(.141)
Insulted Only$_{t-4yrs}$			-.121		
			(.0901)		
Insulted Only$_{t-2yrs}$		-.104*	-.121		
		(.0546)	(.0929)		
Insulted Only$_{t}$	-.161***	-.167***	-.259***	-.153***	-.115
	(.0368)	(.0559)	(.0848)	(.0552)	(.0811)
Insulted Only$_{t+2yrs}$				.0498	.0576
				(.0530)	(.0911)
Insulted Only$_{t+4yrs}$					-.0452
					(.0857)
Additional Covariates	Yes	Yes	Yes	Yes	Yes
No. of Observations	25979	12854	5832	12944	5901

Notes: See Table 4 for a list of the additional controls used. Standard errors clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01.

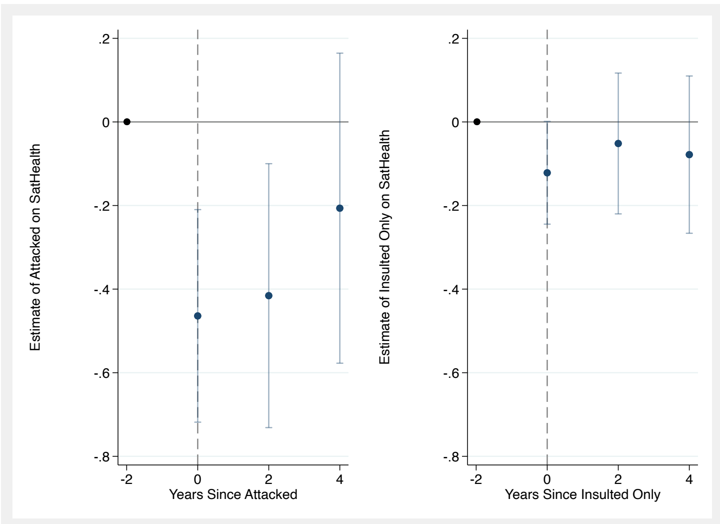
A.13 Dynamic Effects of Victimisation on SWB - Event Study Figures



(a) Likert Score

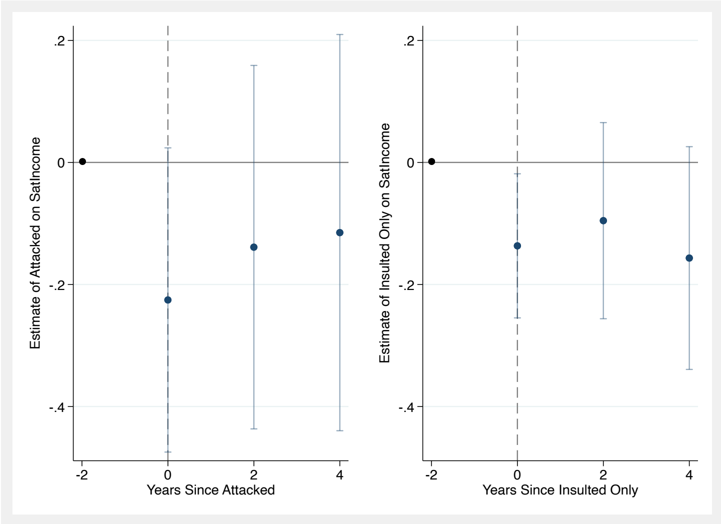


(b) MCS Score

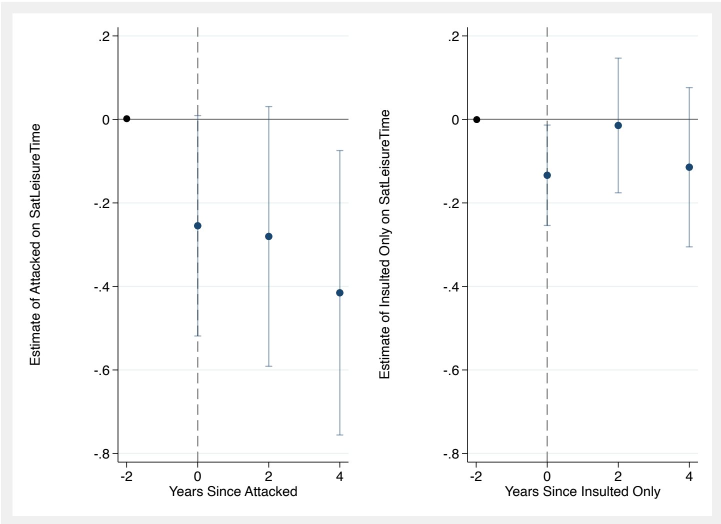


(c) Health Satisfaction

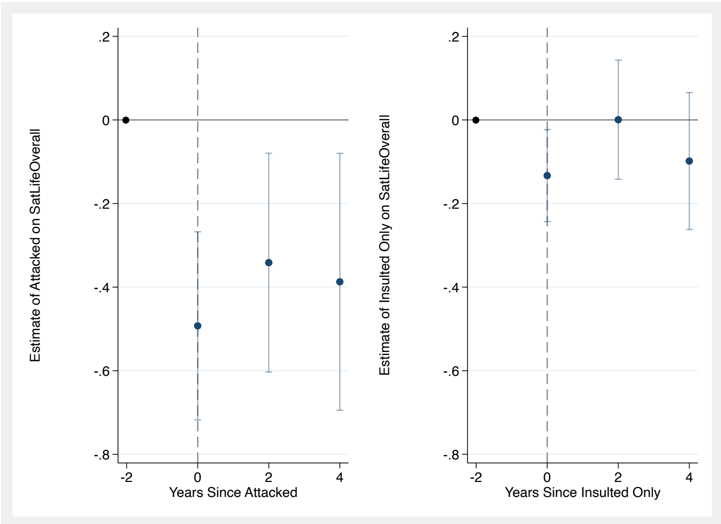
Figure 14: Event Study – 2 Lags (1 of 2)



(a) Income Satisfaction

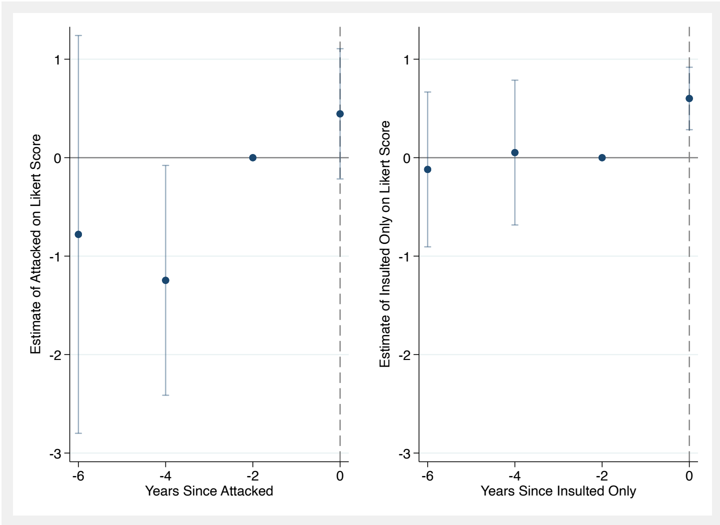


(b) Leisure Time Satisfaction

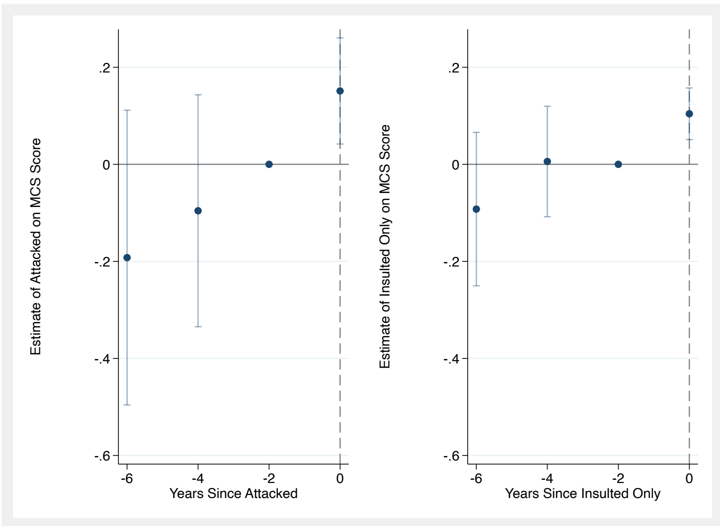


(c) Life Overall Satisfaction

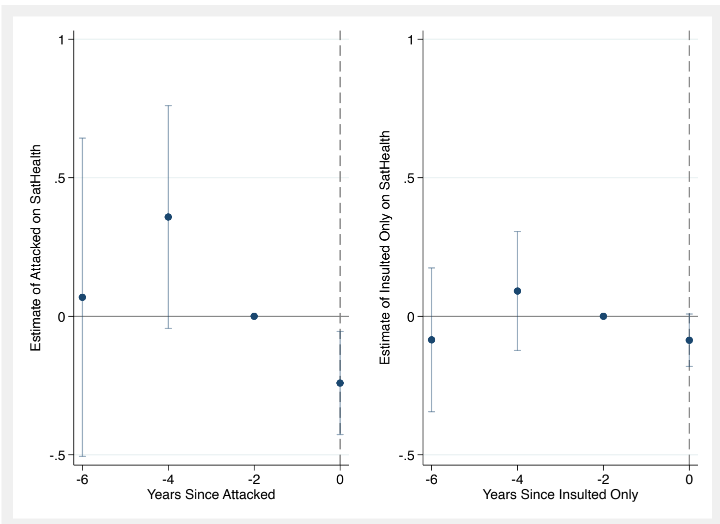
Figure 15: Event Study – 2 Lags (2 of 2)



(a) Likert Score

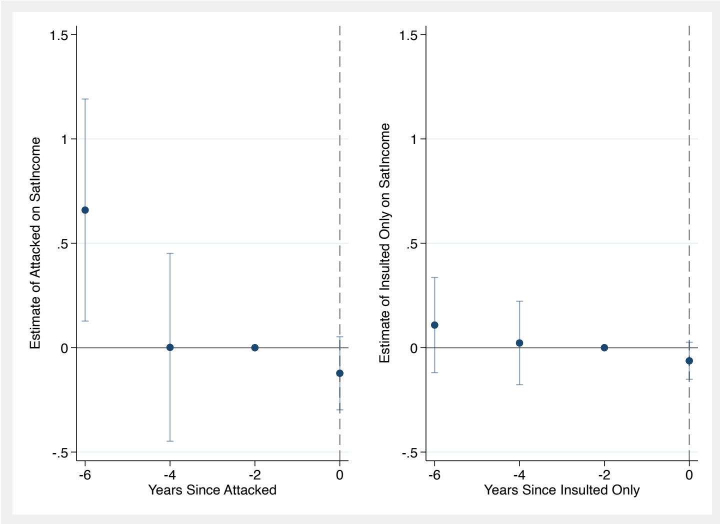


(b) MCS Score

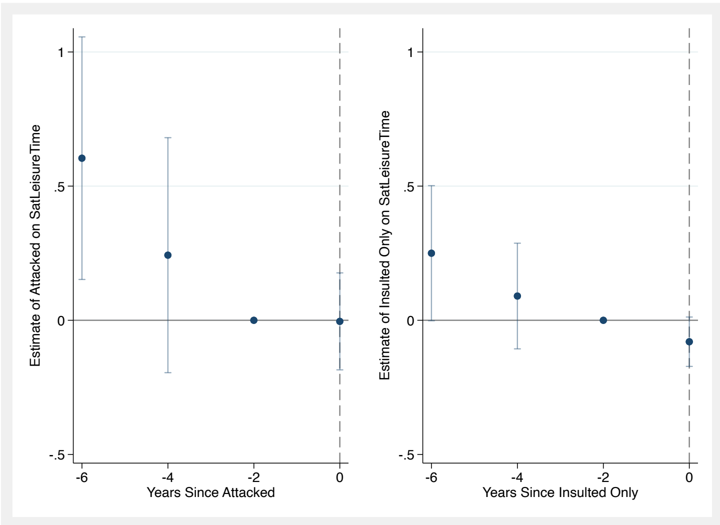


(c) Health Satisfaction

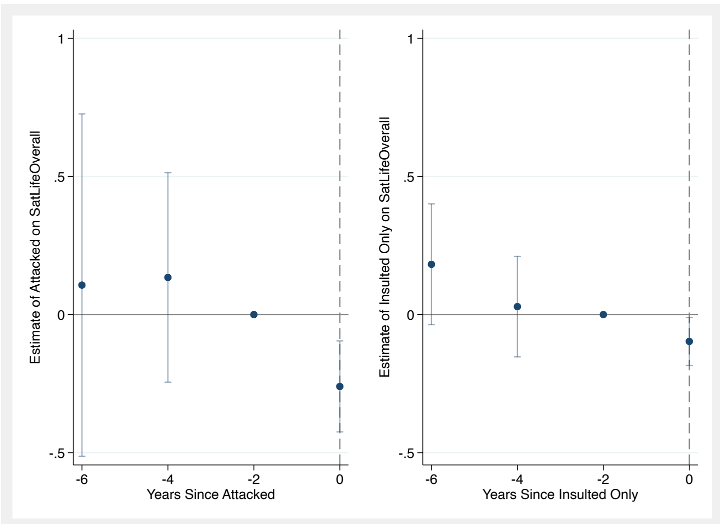
Figure 16: Event Study – 2 Leads (1 of 2)



(a) Income Satisfaction

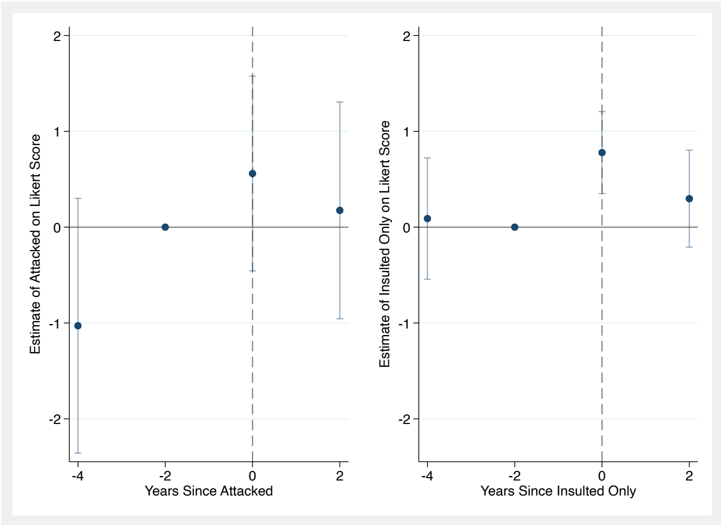


(b) Leisure Time Satisfaction

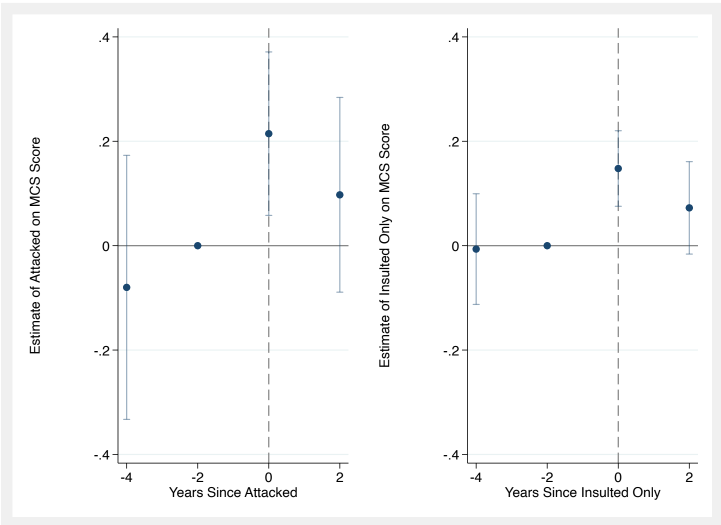


(c) Life Overall Satisfaction

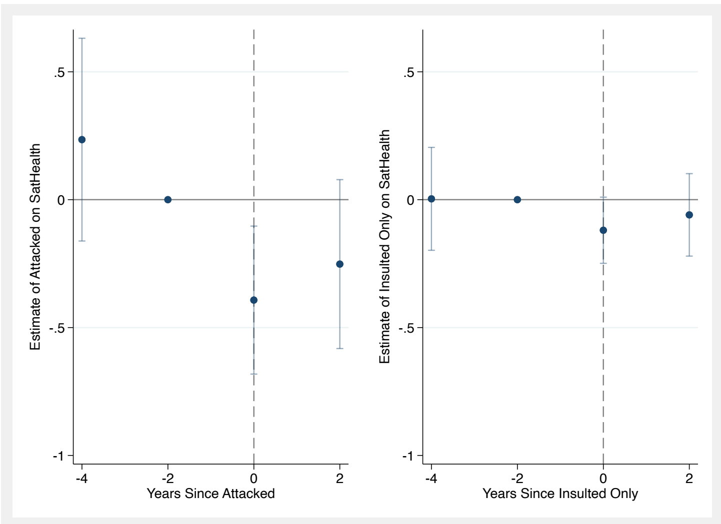
Figure 17: Event Study – 2 Leads (2 of 2)



(a) Likert Score

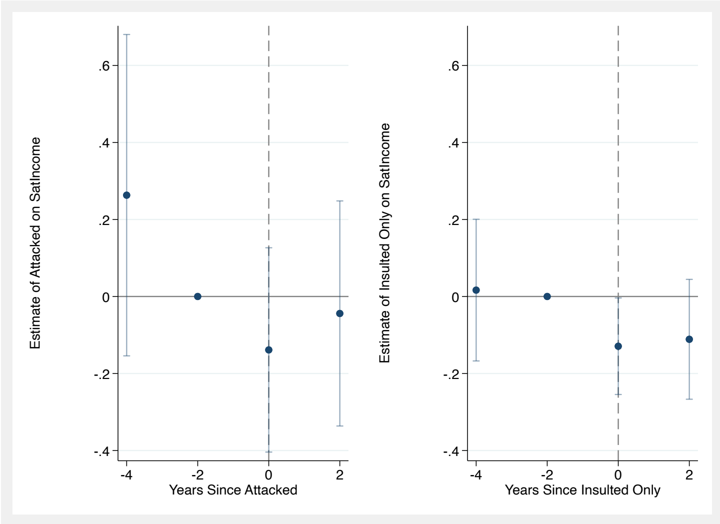


(b) MCS Score

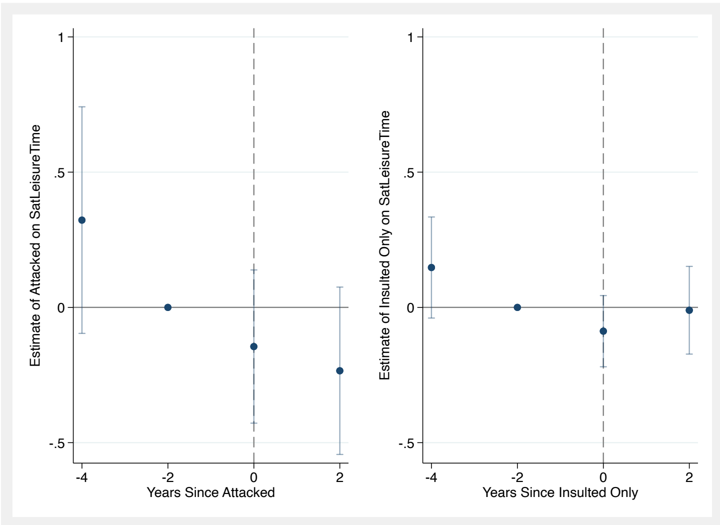


(c) Health Satisfaction

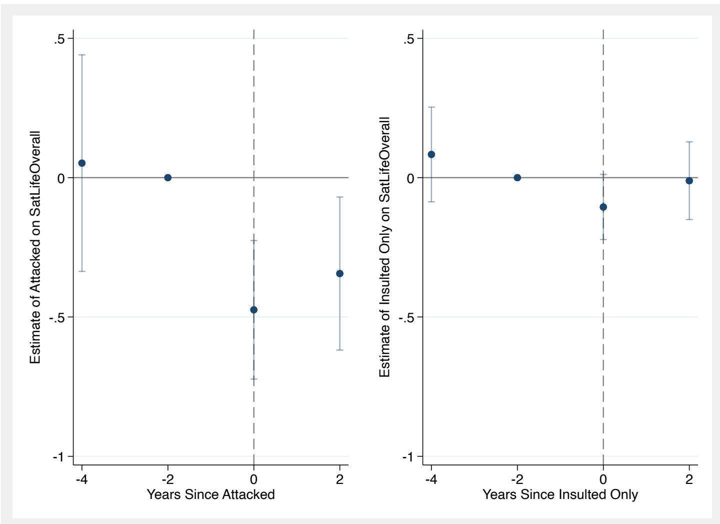
Figure 18: Event Study – 1 Lead, 1 Lag (1 of 2)



(a) Income Satisfaction



(b) Leisure Time Satisfaction



(c) Life Overall Satisfaction

Figure 19: Event Study – 1 Lead, 1 Lag (2 of 2)

A.14 CDFs of SWB by Victim Status

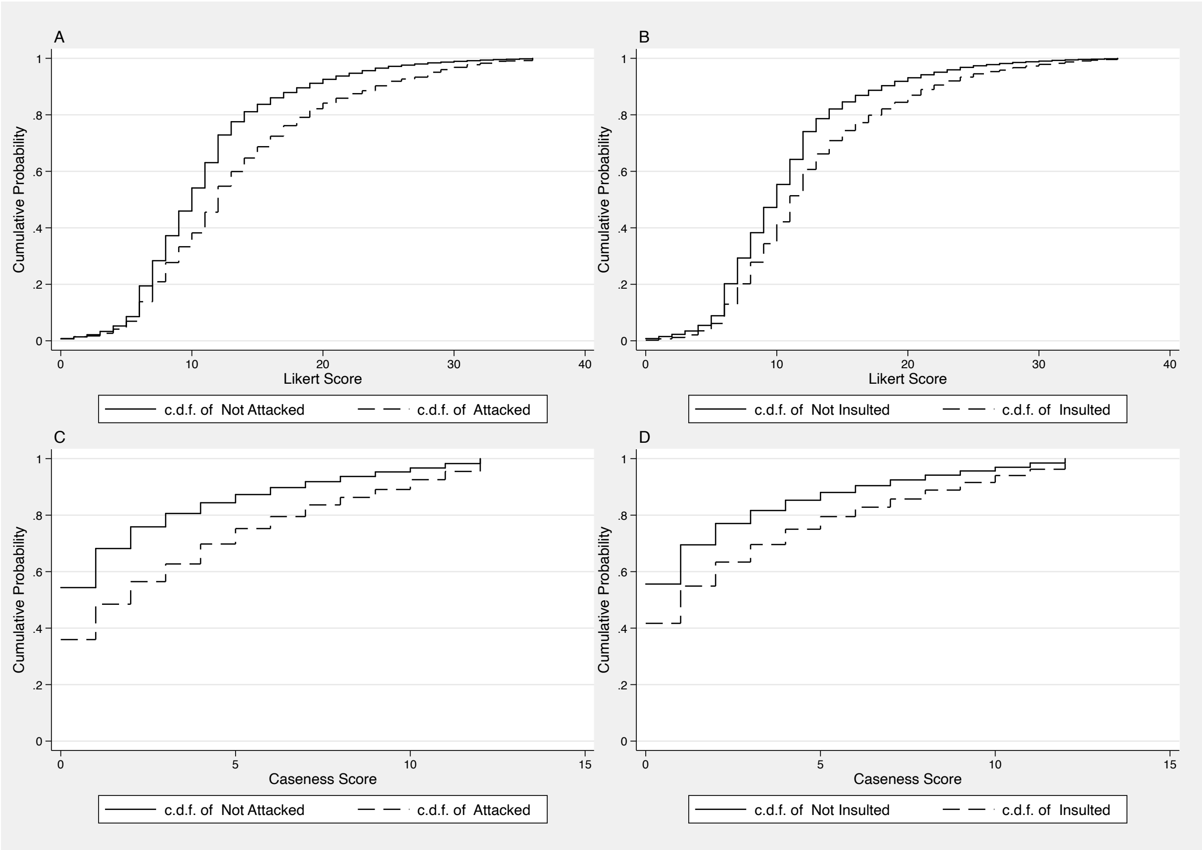


Figure 20: CDFs – SWB (Caseness and Likert Scores), by Victim Status

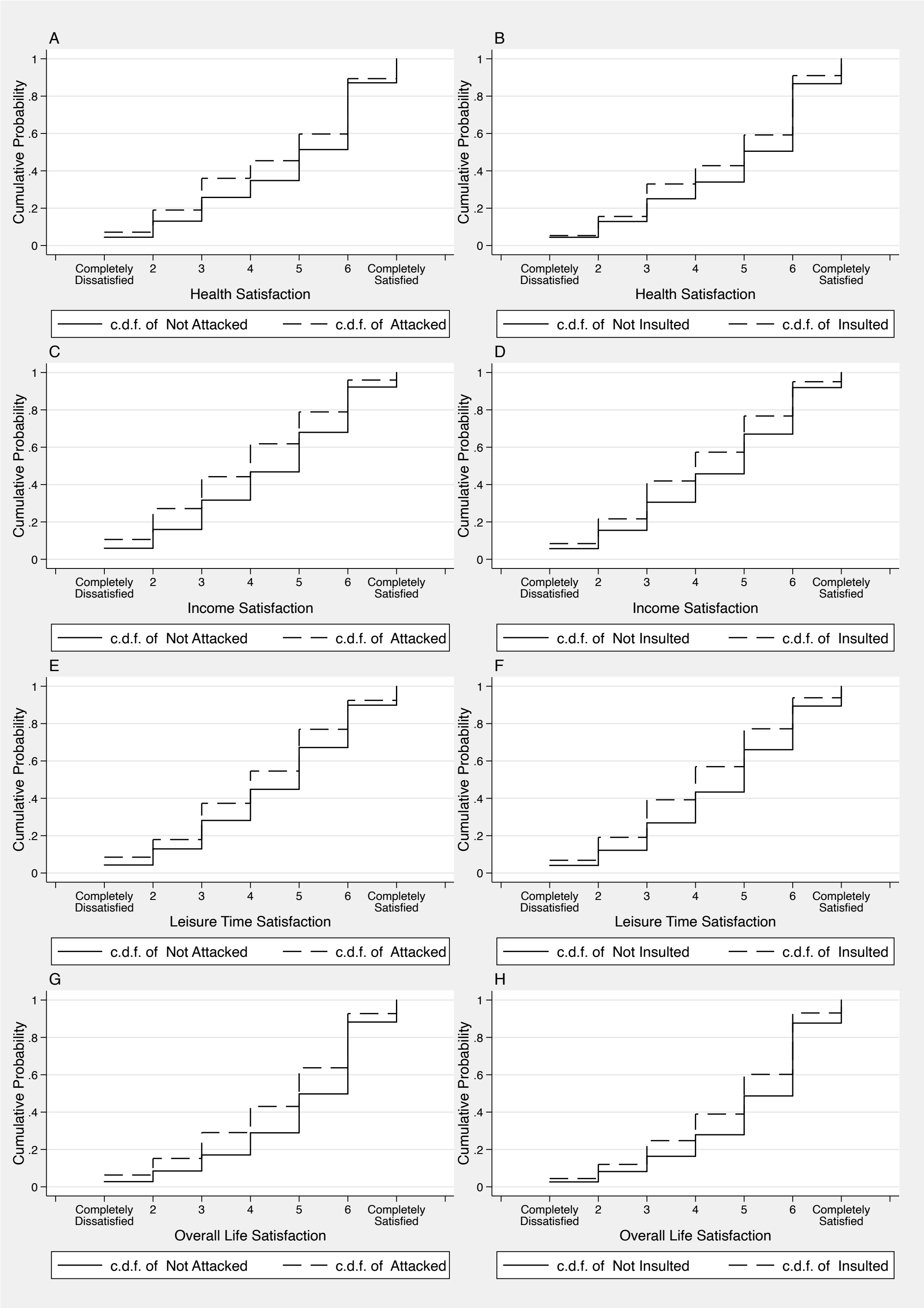


Figure 21: CDFs – SWB (Satisfaction), by Victim Status

A.15 LMA Curves

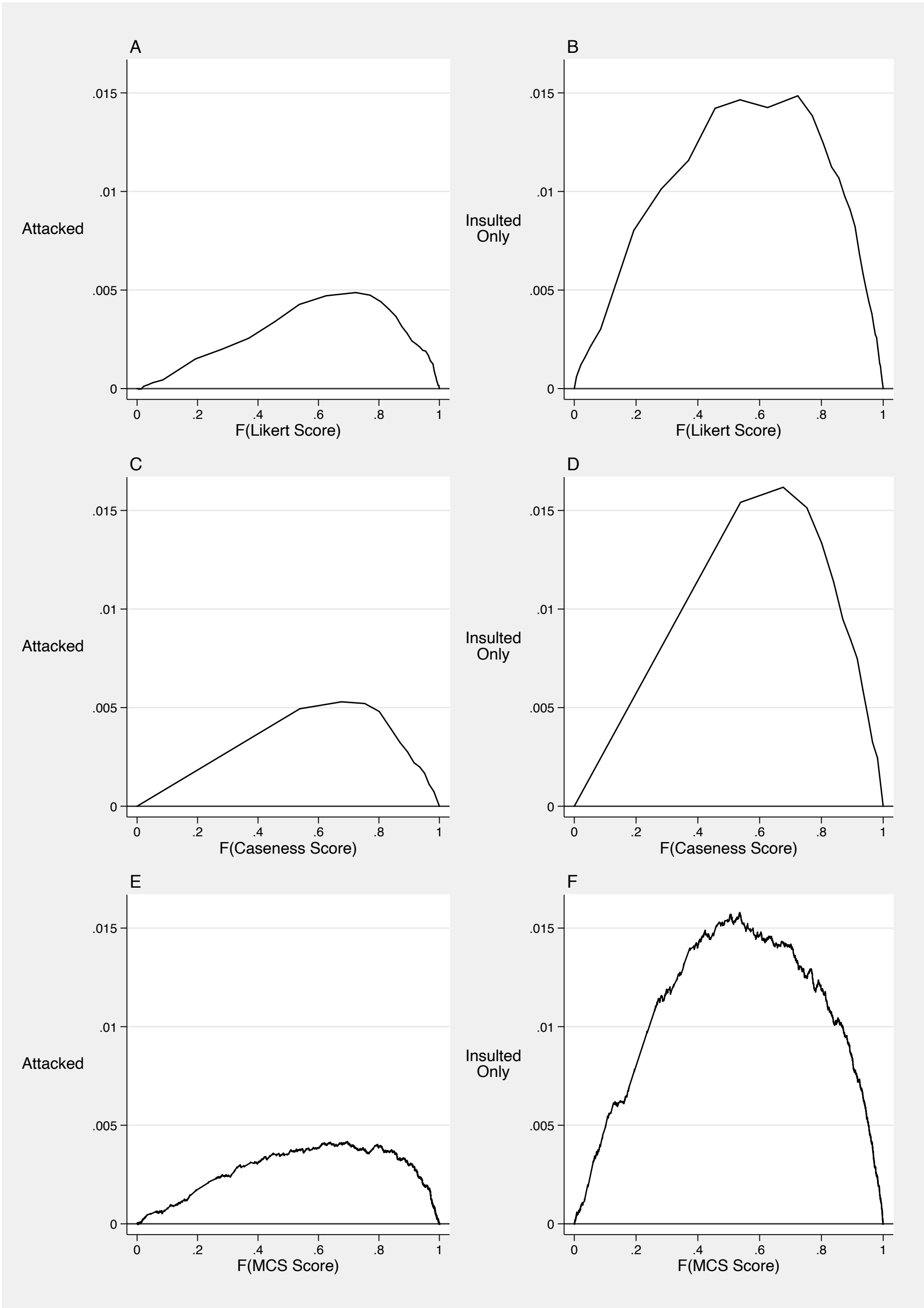


Figure 22: LMA Curves Between SWB (Likert and Caseness) Measures and Victimisation

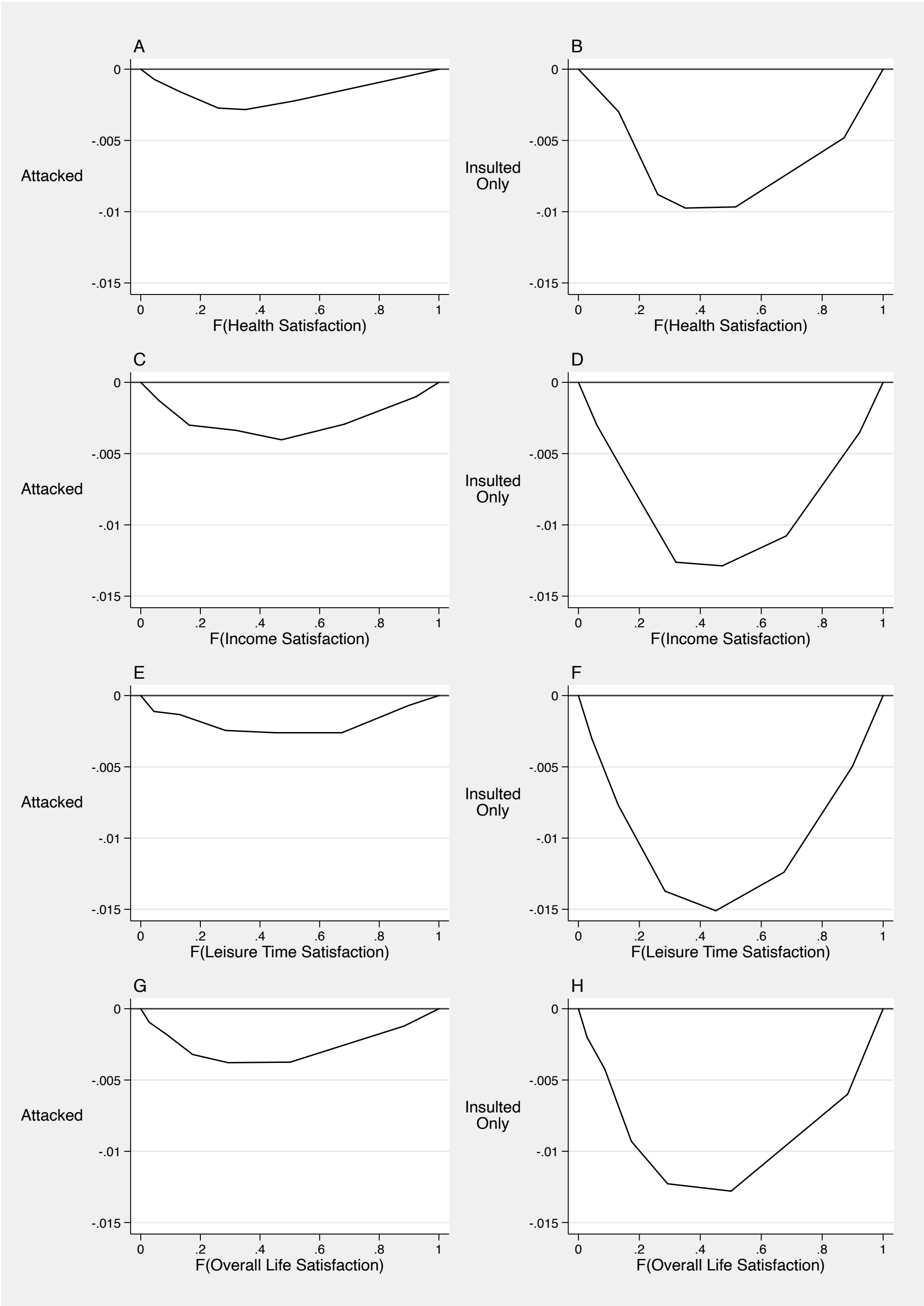


Figure 23: LMA Curves Between SWB (Satisfaction) Measures and Victimisation

A.16 Convex/Concave Transformations

$$T(Y) = Y_{max} \; . \; (\frac{Y}{Y_{max}})^{\sigma} \qquad \forall \;\; \sigma > 0$$
$$T(Caseness) = 12 \; . \; (\frac{Caseness_i}{12})^{\sigma} \qquad \forall \;\; \sigma[0.2, 5]$$
$$T(Likert) = 36 \; . \; (\frac{Likert_i}{36})^{\sigma} \qquad \forall \;\; \sigma[0.2, 5]$$
$$T(Satisfaction) = 6 \; . \; (\frac{Satisfaction_i}{6})^{\sigma} \qquad \forall \;\; \sigma[0.2, 5]$$

A.16.A Convex/Concave Transformations – Caseness Score

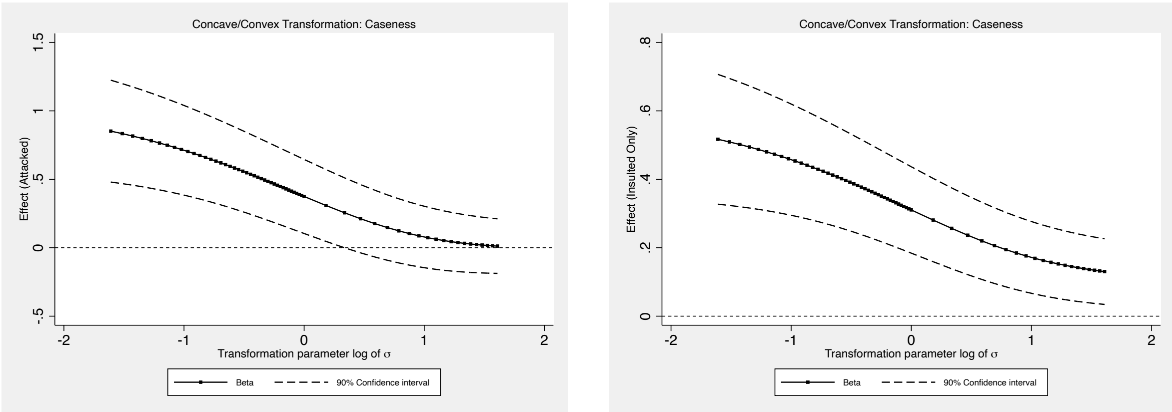


Figure 24: Robustness to Monotonic (Concave/Convex) Transformations of the Caseness Score (log σ)

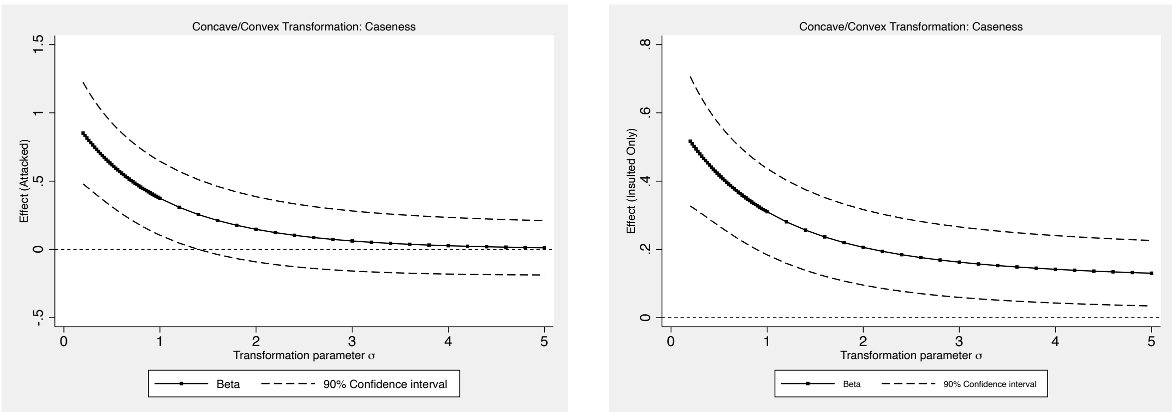


Figure 25: Robustness to Monotonic (Concave/Convex) Transformations of the Caseness Score (σ)

A.16.B Convex/Concave Transformations – Likert Score

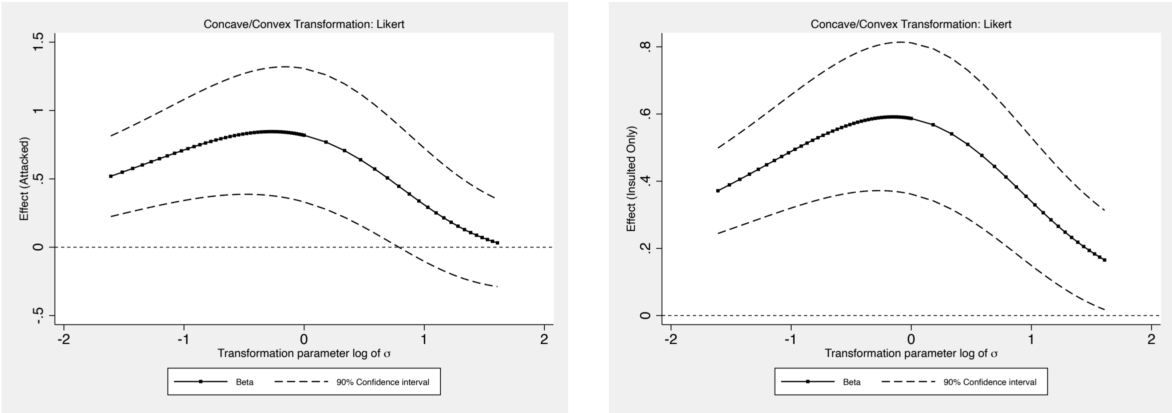


Figure 26: Robustness to Monotonic (Concave/Convex) Transformations of the Likert Score (log σ)

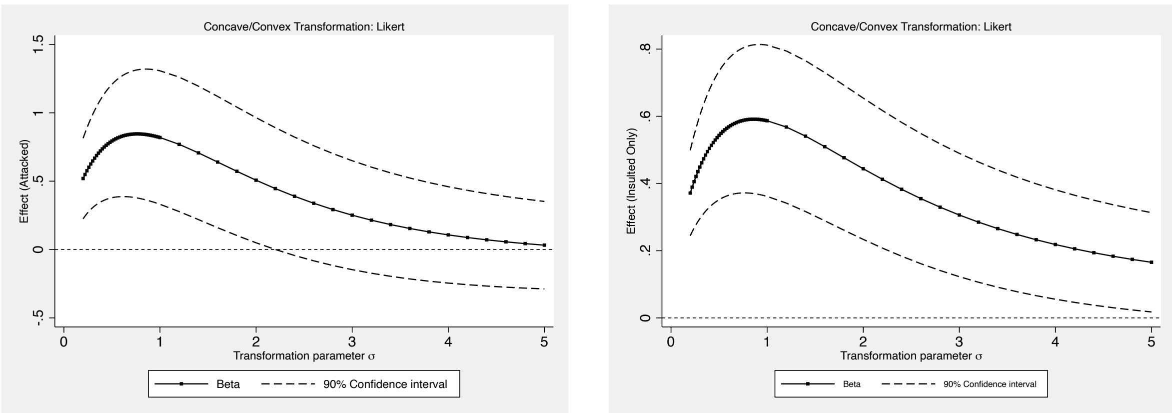
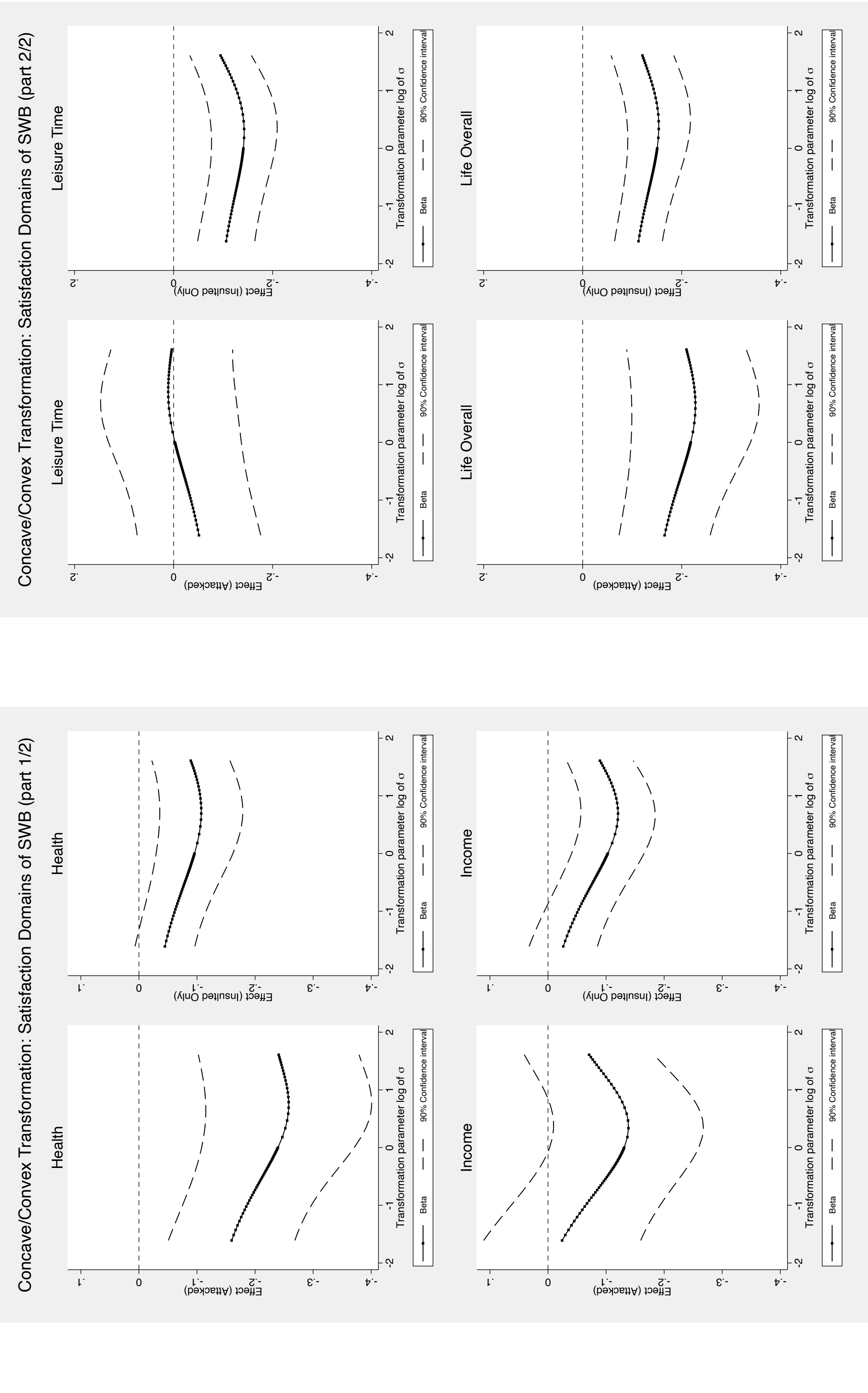


Figure 27: Robustness to Monotonic (Concave/Convex) Transformations of the Likert Score (σ)

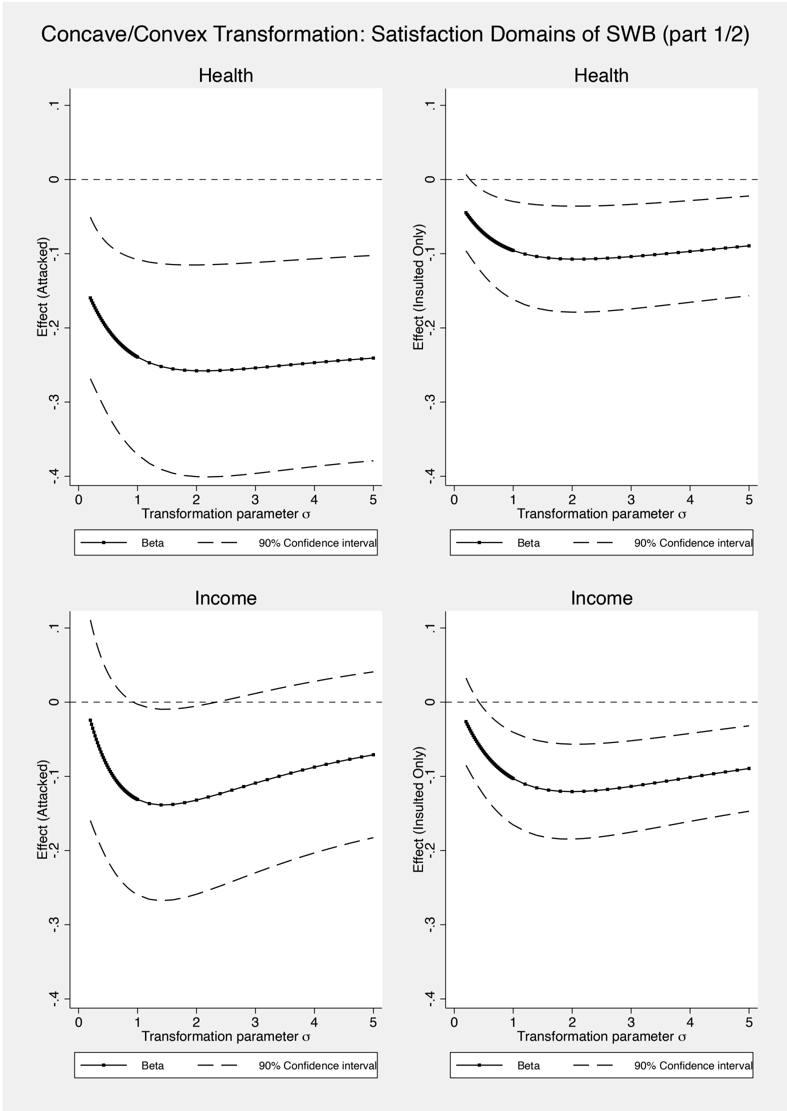
A.16.C Convex/Concave Transformations – Evaluative (Satisfaction) Measures of SWB



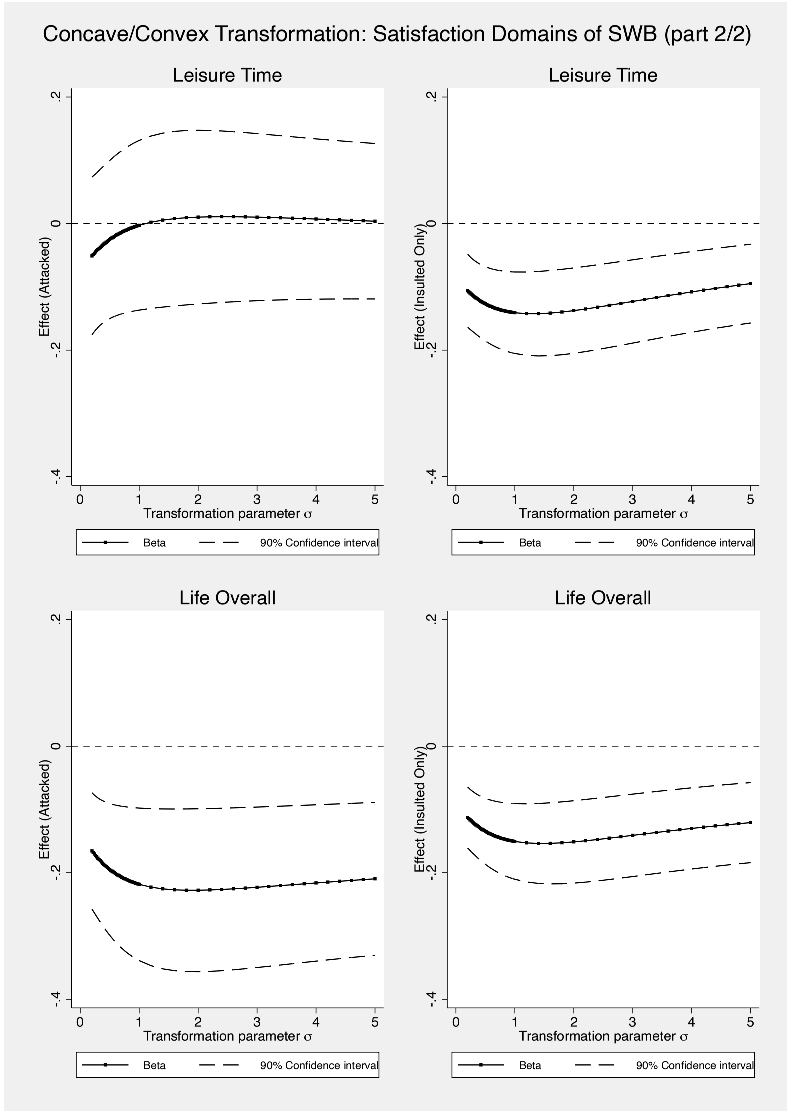
(a) Satisfaction with Health and Income (log σ)

(b) Satisfaction with Leisure Time and Life Overall (log σ)

Figure 28: Robustness to Monotonic (Concave/Convex) Transformations of Satisfaction Domains of SWB (log σ)



(a) Satisfaction with Health and Income (σ)



(b) Satisfaction with Leisure Time and Life Overall (σ)

Figure 29: Robustness to Monotonic (Concave/Convex) Transformations of Satisfaction Domains of SWB (σ)

A.17 Transformations with an Inflection Point

The second type of parameterised function introduced by Bloem (2020) is:

$$T(Y) = Y_{max} \; . \; F(\frac{X - Y_{mid}}{\sigma}) \qquad \forall \;\; 0 < \sigma \leq Y_{mid}$$

Y is a rank order (linear) SWB scale ranging from Y_{min} to Y_{max}, with a middle point, Y_{mid}. $F(.)$ is the cumulative density function with mean, Y_{mid}, and standard deviation, σ. When $\sigma = Y_{mid}$, $T(Y)$ maintains an approximately linear reporting function. As σ approaches zero, $T(Y)$ looks more and more like a step function occurring at Y_{mid}. Between these two extremes of σ, $T(Y)$ is variously convex below, and variously concave above the inflection point at Y_{mid} (see Figure 30 for a graphical representation of these inflection point transformations for each SWB measure).

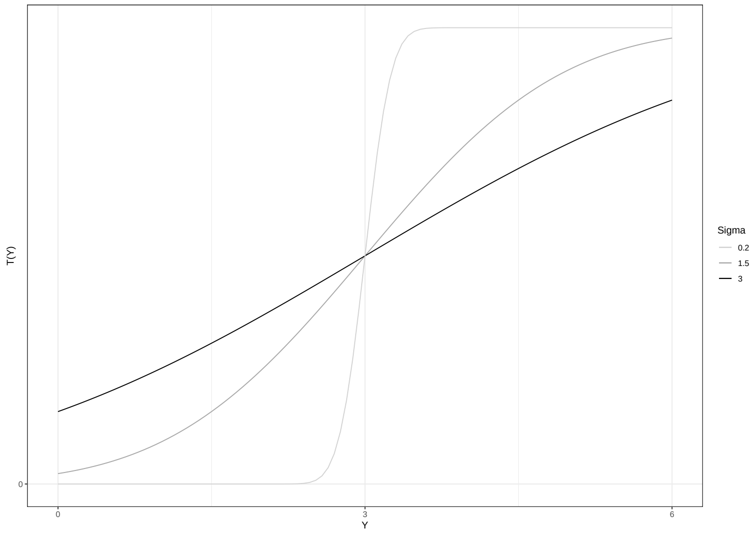


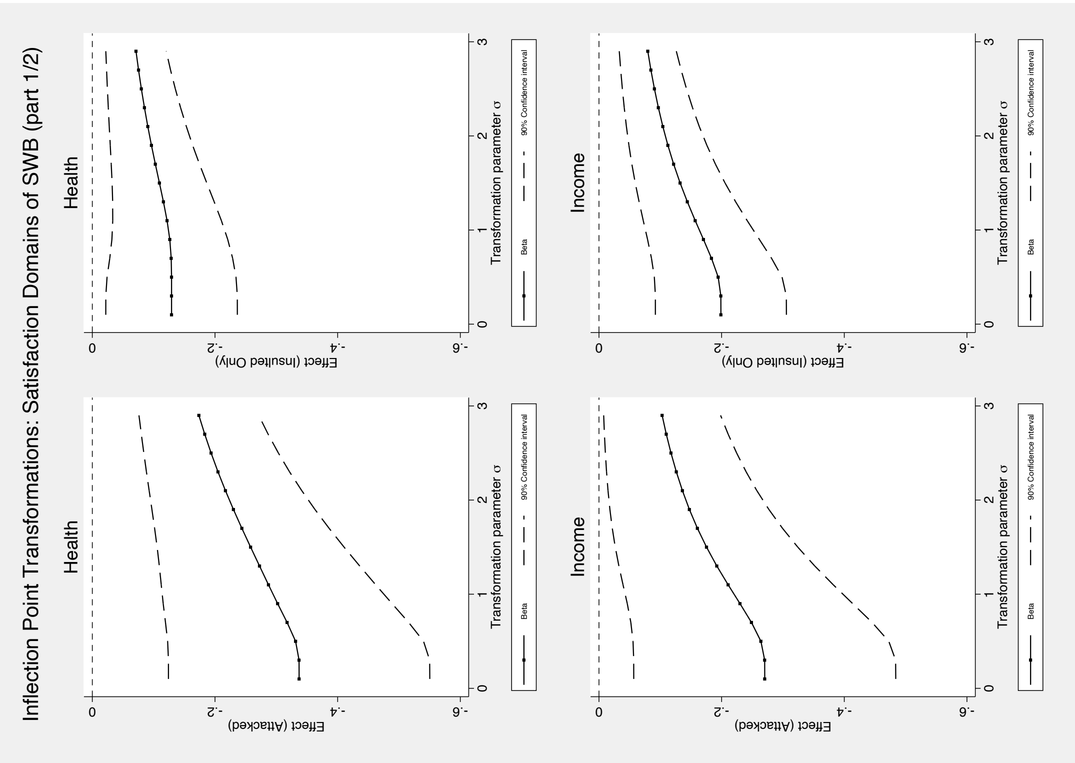
Figure 30: Transformations with an Inflection Point (Satisfaction based Measures of SWB)

Mathematically, we can put the inflection point anywhere along the SWB scale. Ng (2008) and Oswald (2008) both present arguments that individuals may be reluctant to report the extremes of bounded scales. Therefore, I place the inflection point at the midpoint of each of the satisfaction based measures of SWB. The midpoint of these evaluative/satisfaction measures is a neutral 'neither satisfied nor dissatisfied' response. Transforming SWB in this way captures the idea that an increase/decrease in reported SWB requires larger increases/decreases in underlying actual well-being at the extremes of the bounded scale.

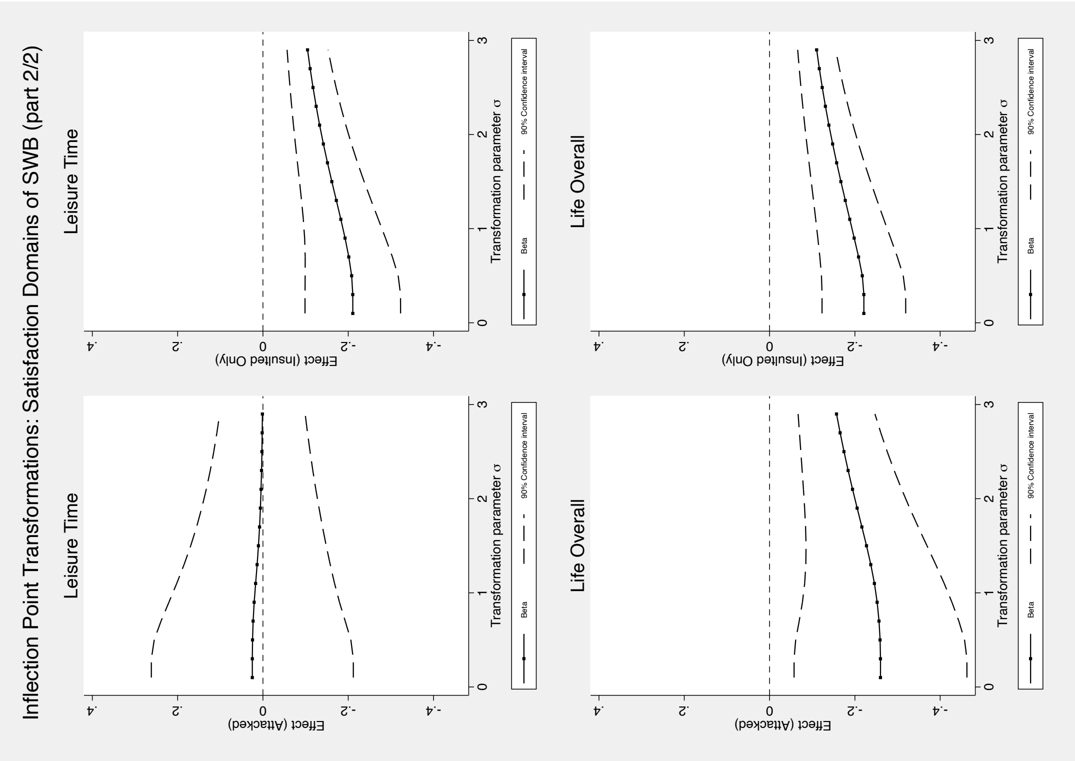
Previously, I found that being Insulted (but not Attacked) reduced satisfaction with Leisure Time, while being Attacked or Insulted were both associated with reduced satisfaction across the other Health, Income, and Life Overall domains. I re-estimate a set of effect estimates for victimisation, across the range of σ, on each of the satisfaction based measures of SWB:

$$T(Satisfaction) = 6 \; . \; F(\frac{X - 3}{\sigma}) \qquad \forall \;\; 0 < \sigma \leq 3$$

I present these results graphically in Figure 31, and find that the results are replicated across the range of σ. Therefore, I conclude that the estimated effect of victimisation on the satisfaction based measures of SWB are robust to this class of transformations with an inflection point.



(a) Satisfaction with Health and Income (σ)



(b) Satisfaction with Leisure Time and Life Overall (σ)

Figure 31: Robustness to Transformations with an Inflection Point, of Satisfaction Domains of SWB (σ)

A.18 Conditional Quantile Regression

A.18.A Conditional Quantile Regressions, Pooled

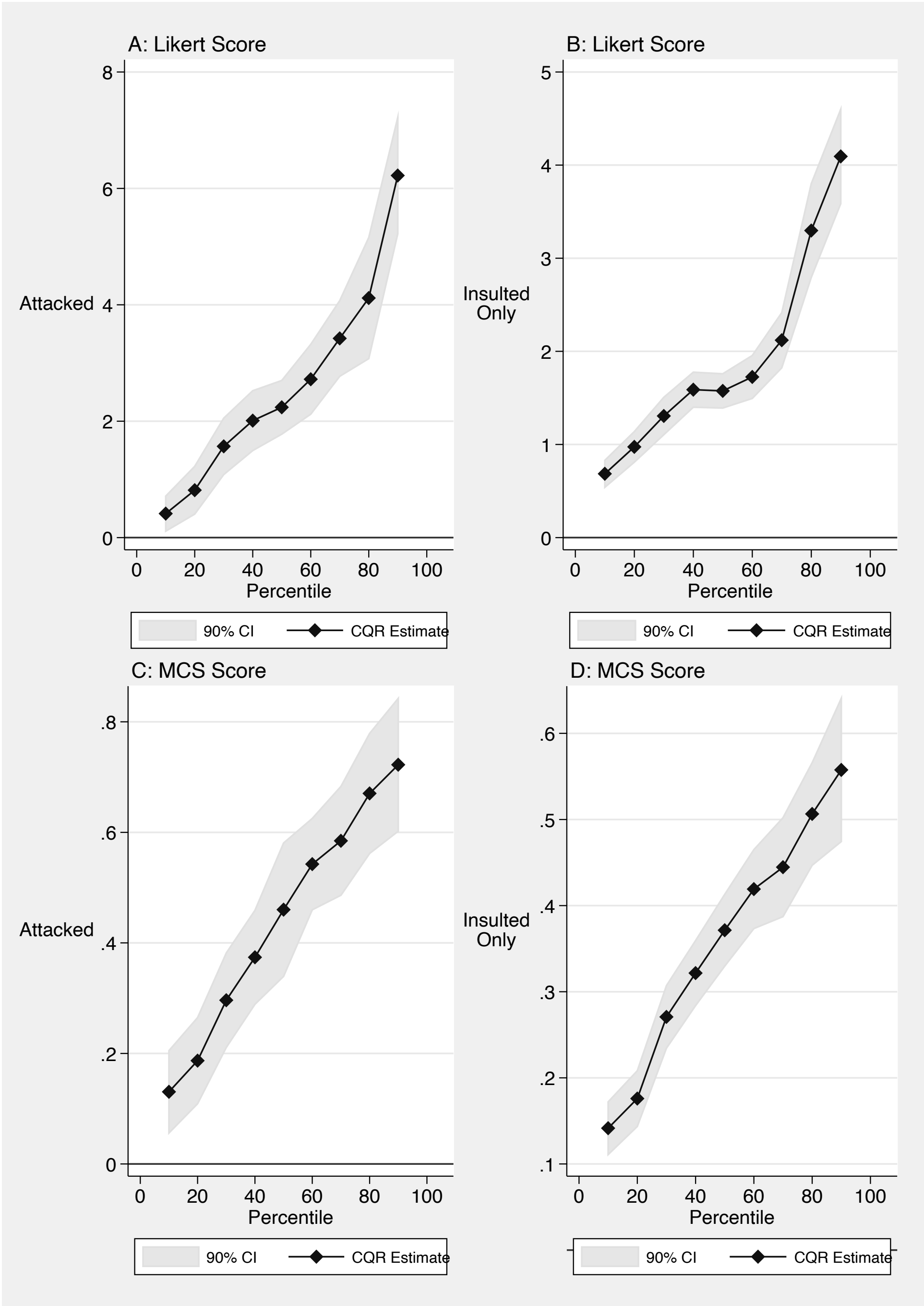


Figure 32: Conditional Quantile Regression Estimates (Pooled Waves)

A.18.B Conditional Quantile Regressions, Cross-Sectional (by Wave)

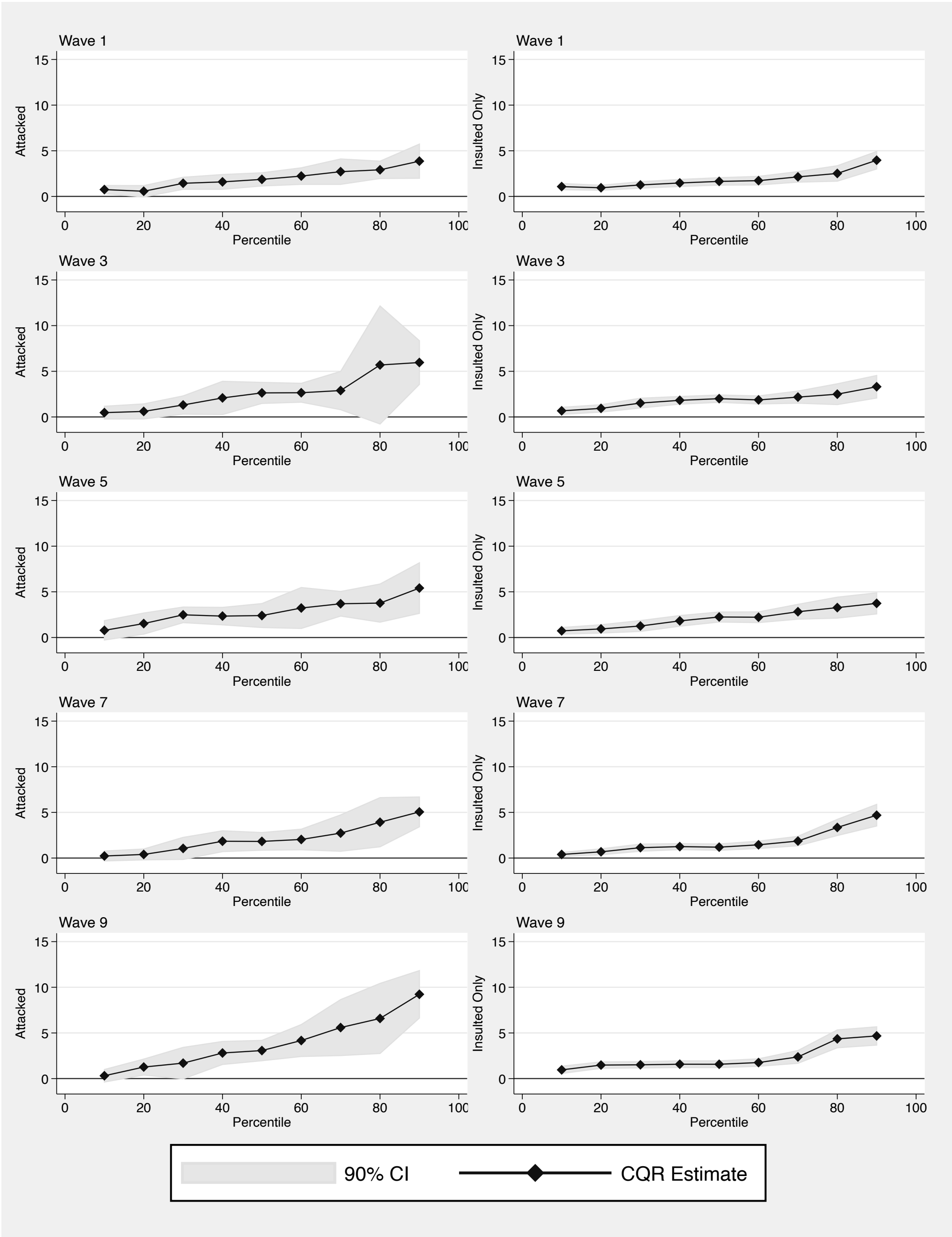


Figure 33: Conditional Quantile Regression Estimates (Cross-Sectional) – Likert Score

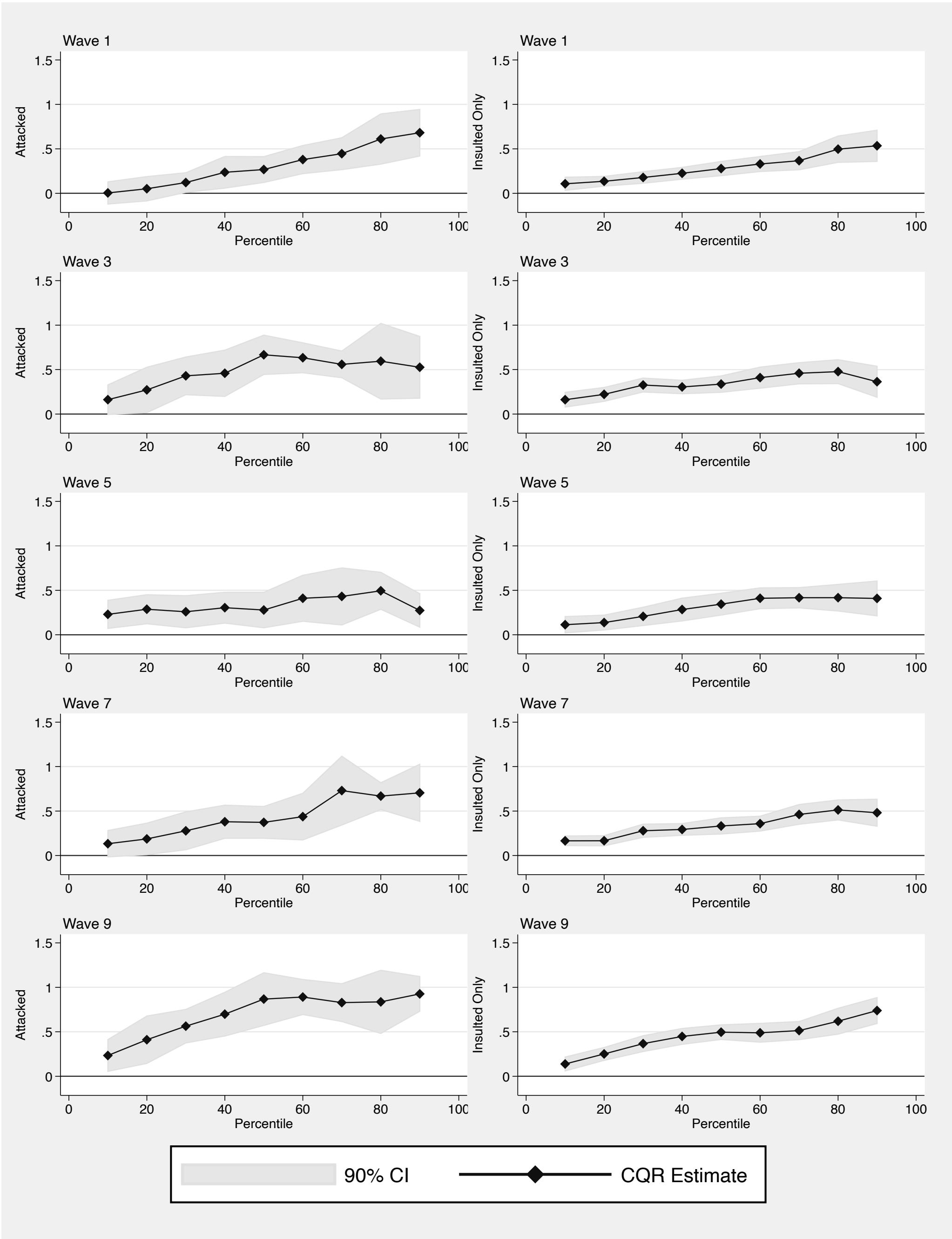


Figure 34: Conditional Quantile Regression Estimates (Cross-Sectional) – MCS Score

A.19 Ordered Response Models

A.19.A Pooled OLS vs. Ordered Probit vs. Ordered Logit Models

Table 19: Pooled OLS vs. Ordered Probit vs. Ordered Logit Models

Dependent Variable...:	**Health**	**Income**	**Leisure Time**	**Life Overall**	**Caseness**
Pooled OLS:					
Attacked	-.303***	-.295***	-.223***	-.359***	.494***
	(.041)	(.039)	(.040)	(.043)	(.047)
Insulted Only	-.249***	-.244***	-.263***	-.276***	.359***
	(.019)	(.019)	(.019)	(.020)	(.022)
Ordered Probit:					
Attacked	-.291***	-.298***	-.231***	-.348***	.496***
	(.041)	(.038)	(.040)	(.041)	(.040)
Insulted Only	-.252***	-.243***	-.260***	-.280***	.383***
	(.019)	(.019)	(.019)	(.020)	(.021)
Ordered Logit:					
Attacked	-.285***	-.280***	-.215***	-.332***	.471***
	(.040)	(.037)	(.038)	(.039)	(.039)
Insulted Only	-.249***	-.238***	-.253***	-.266***	.356***
	(.019)	(.018)	(.018)	(.019)	(.020)
N (OLS)	27026	26979	26995	27000	27179
N (OProbit)	26861	26815	26830	26835	27013
N (OLogit)	26861	26815	26830	26835	27013

Notes: Standard errors, clustered at the individual level. Ordered probit and ordered logit model coefficients are average marginal effects estimates. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

A.20 Disaggregating SF-12 Domains

The SF-12 general health questionnaire contains eight domains of well-being, of which four primarily load onto the Mental Component Summary (MCS) score: Vitality (VT, 1-item); Social Functioning (SF, 1-item); Role Emotional (RE, 2-items); and Mental Health (MH, 2-items). These domain items are detailed in Table 20. To operationalise the disagregation of the MCS score into these factors, all scales are ordered such that higher points on the scale indicate more negative responses. For ease of comparison, I normalise each of these domains to share the same scale ranging from 1 (best factor well-being) to 5 (worst factor well-being). To explore which MCS domains are impacted more strongly by victimisation, I re-run the linear FE baseline specification from Table 4, using each of these domain scales as the dependent variable. These results are presented in Table 21. I find that victimisation has a limited impact on the VT domain, but the coefficients for each victim indicator are large and similar in magnitude across SF, RE, and ME domains. The coefficient on Attacked is significantly larger than the coefficient on Insulted for the SF and MH domains suggesting that being physically attacked has a more negative impact on these domains than being insulted.

Table 20: SF-12 Domains Loading onto the MCS

Factor	**Item**	**Question** In the last 4 weeks:...
SF - Vitality (VT)	SF-6b	Did you have a lot of energy?
SF - Social Functioning (SF)	SF-7	Physical or mental health interfered with social life?
SF - Role Emotional (RE)	SF-4a	Mental health meant accomplished less?
	SF-4b	Mental health meant worked less carefully?
SF - Mental Health (MH)	SF-6a	Felt calm and peaceful?
	SF-6b	Had a lot of energy?

Table 21: Mean Effects of Victimisation on SWB – SF-12 MCS Domains

	VT	SF	RE	MH
Attacked	0.058	0.16***	0.15***	0.19***
	(1.24)	(2.94)	(3.06)	(4.56)
Insulted Only	0.038*	0.062**	0.073***	0.099***
	(1.68)	(2.53)	(3.25)	(5.18)
Additional Controls	Yes	Yes	Yes	Yes
P-value (victim diff)	0.679	0.0791	0.123	0.0399
No. of Observations	27013	27013	27013	27013

Notes: See Table **??** for a list of additional controls used. Standard errors clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01.

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