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Honours Thesis

Social Capital and Mental Health

An Empirical Study of the Buffering Effect

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Declaration

I declare that this thesis is my own work and that, to the best of my knowledge, it contains no material which has been written by another person or persons, except where acknowledgement has been made. This thesis has not been submitted for the award of any degree or diploma at the University of New South Wales Sydney, or at any other institute of higher education.

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5th November, 2018

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Enjoy!

Contents

Abstract

I examine the protective effect of social capital on self-assessed mental health after exposure to a psychologically stressful life event ('shock'). Using 16 waves Australian individual-level panel data[1] I conduct a fixed-effects estimation including the interaction of a shock indicator and a social capital measure to assess the presence of a buffering effect. I repeat analysis over three groups of shocks and four social capital measures - club participation, trust, community participation and perceived social support. I observe a statistically and clinically significant buffering effect of social capital on mental health with respect to employment-related shocks, but less so for health or family-related shocks. Results are robust over the social capital measures used, as well as for a number of specifications including instrumental variable estimation. Mechanisms underlying results are discussed. I contribute to the literature by confirming effects using a number of measures and shocks to give a full characterization of the buffering effect with respect to significant life events. I also contribute to the literature by using panel data methods to avoid confounding from unobserved heterogeneity and by focusing on threats to causal inference, as opposed to many previous studies.

[1]This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the authors and should not be attributed to either DSS or the Melbourne Institute.

Chapter 1
Introduction

The nature of social networks has been of interest to economists and sociologists because of their frequently observed association with socio-economic outcomes (Woolcock, 2001). To explain this association, the concept of social capital has been developed over the past half-century. Broadly defined, social capital for an individual or a group is the network of social connections and associated norms (i.e. trust and reciprocity) that can be used to facilitate collective action (see Portes (1998) for a brief review). Since the seminal work of Coleman (1988) and Putnam et al. (1993), empirical studies have identified measures of social capital and estimated their relationship with education, income and other outcomes.

Of interest to health economics and epidemiology has been the relationship between social capital and health. Physical health is hypothesized to be influenced through social norms for healthy behaviour, which affect those with higher social capital (Lindström, 2008). From the social support literature, two hypotheses establish the influence of social capital on mental health. First, the main effect hypothesis entails that a dense social network provides a constant and direct benefit to mental health (Kawachi and Berkman, 2001). Second, the buffering hypothesis entails that social connections act as a resource used to mitigate the effect of a psychological stressor (i.e. death of a relative, assault etc.). While the first hypothesis is well studied, empirical research of the second hypothesis has been scant, with social capital research generally being criticized for use of cross-sectional data and little attention paid to methodology.

This thesis investigates whether an individual's stock of social capital helps to mitigate the negative effect of a stressful life event on their mental health. Using high-quality panel data from the Household Income and Labour Dynamics in Australia (HILDA) survey, I conduct a fixed-effects estimation to test the protective effect of social capital on self-assessed mental health across a number social capital measures common to the literature. I find significant buffering effects for a range of social capital measures in response to employment-related shocks, but less so for family or health-related shocks. This result is robust to changes in the measure of social capital used, with the exception of club membership and community participation - common measures of social capital.

The result partly corroborates the existing literature on the buffering effect of social capital on mental health and general health, as well as providing further support for the main effect hypothesis.

I contribute the the literature in several ways. First, I make a contribution by adding to the small number of studies using longitudinal data to determine the buffering effect of social capital on health. Previous literature typically focuses on shocks caused by change to employment status (i.e. Milner et al. (2016); Winkelmann (2009)), or the effect of low socioeconomic status on health (Kawachi et al., 1997). The richness of the HILDA survey allows me to make a novel contribution by investigating the mitigating role of social capital for a variety of psychological stressors, including family, employment and health related shocks. This permits a test of the consistency of the buffering effect across a number of contexts relevant to individual mental health.

Secondly, by conducting my estimation for a number of social capital measures, I am able to conclude with more certainty about the effect this latent variable has on mental health. This follows arguments made by Putnam (2001) and is common practice in many empirical studies of social capital (Woolcock, 2001). Finding both a direct and buffering effect of social capital on mental health with a number of measures lends additional credibility to the link between social capital and health. Moreover, using these measures sets the precedent for future econometric studies of social capital in the Australian context.

A third contribution is made in the specification and estimation of my econometric model. Throughout the study, I attempt to account for methodological issues often ignored by researchers in the area of social capital and health. Similar to Milner et al. (2016), I use a fixed effects regression over a number of years of data to remove the effects of individual specific heterogeneity potentially affecting estimates. A novel contribution is the use of a design typical of event studies in which I account for the dynamic effect of a psychological shock by including leads and lags of the event. This allows the study of the mitigating role of social capital on anticipation and after effects. In the course of the present study, however, I find little evidence of a buffering effect in the before and after period of a psychological shock.

The results of this thesis have relevant policy implications. According to the present findings, those who are socially isolated may fare worse after a psychologically stressful event than those who are better connected. Provision of social support for the socially isolated through community mental health services is therefore encouraged. This may lead to better outcomes in the face of common, stressful life events.

Chapter 2
Literature Review

2.1 Defining social capital

A key challenge of the social capital literature across all fields has been constructing a clear definition of the concept. In its modern form, the concept of social capital developed through the work of three primary thinkers in sociology. Each thinker's ideas have since been adapted and modified for different contexts. In the following, I present the key definition from each thinker, summarize further developments in the definition of social capital, and present my own stance in relation to the definition.

The idea that social norms influence economic behaviour has been in existence since the enlightenment (Woolcock, 1998). Further development of this idea had primarily taken place in the classical sociology of Durkheim, Weber and Marx (Portes and Sensenbrenner, 1993; Woolcock, 1998). The concept of social norms and networks as a form of capital stems from this grounding in sociology and was developed in its modern form under the term 'social capital' by sociologist Pierre Bourdieu.

Bourdieu's work primarily considered the nature of power and hierarchy in social structures (Field, 2003). Bourdieu posited that the position of a social agent in a hierarchy depends upon their possession of two types of 'capital', cultural and social. Cultural capital consists of one's tastes and ownership of forms of culture (music, art etc.) (Bourdieu, 1986; Field, 2003). Social capital on the other hand "is the aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance and recognition..." (Bourdieu, 1986, p.250). Bourdieu believed social capital is something possessed by the individual, where quantity is determined by the size of the network of connections they maintained (Bourdieu, 1986). Social structures (and hence hierarchies) are maintained by the profits each member of a group accrues from their social capital (Bourdieu, 1986; Portes, 1998). In this way, Bourdieu maintained that social and cultural capital were mainly the resource of privileged members of a society, used to maintain their privilege (Field, 2003).

Building on the work of Bourdieu and economist Glenn Loury, American sociologist James Coleman made contributions of the theory and definition of social capital. Social capital, Coleman claims, is the feature of social structures which helps to facilitate collective action (Coleman, 1988). As such, social capital can take many forms specific to certain contexts. Examples Coleman provides are norms of reciprocity and trust, sanctions against non-complying members, and information channels between members (Coleman, 1990). In contrast with Bourdieu's individualistic view of social capital, Coleman posited that "social capital inheres in the structure of relations between actors and among actors" (Coleman, 1988, p.S98), and is not something possessed by each actor individually. However, individuals may use it, or invest in it. It is not necessarily number of connections one has, as with Bordieu, which constitutes social capital, but rather social capital is a more abstract feature of a society with a function of leveraging collective action.

In recent years, the most notable work on the concept of social capital has been of sociologist Robert Putnam. Putnam built heavily on the concept as defined by Coleman. In his seminal 1993 text on civic traditions in Italy, Putnam provides a definition of social capital very similar to Coleman's, stating that "social capital [...] refers to features of social organizations, such as trust, norms and networks, that can improve the efficiency of society by facilitating coordinated actions" (Putnam et al., 1993, p.167). Differing from Coleman, however, Putnam places even less emphasis on the individual and thinks about social capital as an attribute of whole groups or communities (Portes, 1998). Putnam also breaks social capital down into two types: bonding and bridging. Bonding social capital relates to ties with family, friends and close relatives, while bridging social capital refers to ties with groups outside of close friends and relatives (Woolcock, 2001).

Since the contributions of Bourdieu, Coleman and Putnam, the debate that has ensued over the definition of the term has not been settled. At the turn of the millennium, during the height of research into social capital, prominent social scientists Alejandro Portes and Michael Woolcock claimed that there was consensus in the literature as to the definition of social capital:

> "There is an emerging consensus on the definition of social capital [...] and it is as follows: social capital refers to the norms and networks that facilitate collective action." (Woolcock, 2001, p.8)

> "Despite [definitional] differences, the consensus is growing in the literature that social capital stands for the ability of actors to secure

> benefits by virtue of membership in social networks or other social structures." (Portes, 1998, p.6)

The apparent difference in these definitions, however, appears to reflect the lack of consensus that has carried on into the 2000s.

Since the late 90s, social capital's defintion has been developed and adapted even further by the literatures of various fields. Social scientists in development have been preoccupied with levels of social capital at the 'macro', 'meso' and 'micro' levels, as well as the concept of 'linking' social capital building on Putnam's defintion (Woolcock, 2001). Studies in epidemiology on the other hand follow Uphoff (1999) in dividing social capital into 'structural' and 'cognitive' components (Berry and Welsh, 2010). The structural component is defined by an individual's active participation and role in a network, while the cognitive component is the perception of the relationship with a group.

Given the various definitions, adaptations and refinements of social capital, I present my stance in relation to the debate as the following: In like with Portes (1998), I agree more with Coleman and Bourdieu's definitions of social capital than Putnam's. It is a resource embodied in a social structure - but one that an individual has access to and may invest in. I take this stance in part because of its frequency in the epidemiological and economic literature (i.e. Rocco et al. (2014), Glaeser et al. (2002)) around which the present thesis centers. These literatures tend to take this view because of the availability of micro-data containing information about social capital and outcomes of interest (education, health and well-being, etc.).

2.2 Measuring social capital

Given social capital's contested definition, debate has also surrounded the issue of how to measure social capital. Empirical work attempting to measure social capital and its effect on outcomes has centered around two typical measures, which I attempt to use in the present thesis. Here, I outline the idea behind these measures and identify other approaches to measuring social capital.

The first typical measure of social capital popularized by Putnam (2000) is individual membership in civic and professional organizations, or 'clubs'. The idea behind using this type of measure is that membership in a number of social organizations, such as sporting clubs or leisure groups, acts as a "barometer of community involvement" (Putnam, 2000, p.49), indicating connection to a network or broader social group. Since Putnam (2000), other notable studies such as Glaeser et al. (2002) have used club participation items to study social capital.

The second typical measure of social capital is survey items measuring norms of trust. This measure was popularized after Knack and Keefer (1997) who studied the relationship between macroeconomic outcomes and aggregate responses to a survey item from the World Values Survey. The item asks "Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people?" (Knack and Keefer, 1997, p.1256). The idea behind this measure is that norms of trust are central to social capital as they act as a mechanism by which one leverages action from others. Attempting to measure general attitudes of trusting towards others aims to identify the strength of these norms. This measure has been used widely to assess the impact of social capital on macroeconomic (Knack and Keefer, 1997; Zak and Knack, 2001), developmental (Narayan and Pritchett, 1999) and health outcomes (d'Hombres et al., 2010; Kawachi et al., 1999; Rocco et al., 2014). A notable study by Glaeser et al. (2000) has questioned the used of the measure, finding that survey items on attitudes toward trust or trustworthiness do not predict trusting behaviour in an experimental setting. Moreover, Putnam (2001) and Woolcock (2001) argue that trust is more the consequence of social capital rather than social capital itself. Despite this, measures of trusting attitudes are still commonly used in the empirical literature on social capital.

Given the debate surrounding the definition of social capital, some researchers have developed other methods for measuring social capital. Often these measurement methods build upon the key concepts presented above - that social capital is manifested in norms, as well as active participation in a network (Stone, 2001; Woolcock, 2001). Hence, in addition to trusting and club participation, some measures use survey items assessing civic and community participation (Berry and Welsh, 2010; Fiorillo et al., 2017; Putnam et al., 1993) as well as attitudes of 'reciprocity' (Ziersch et al., 2005) to measure social capital. A well-cited Australian example is Onyx and Bullen (2000) who develop a 63-item measure of civic participation, trusting and other social norms. This heterogeneity in measurement methods has often been a point of criticism for the social capital literature (Durlauf and Fafchamps, 2005; Fischer, 2005).

Nonetheless, while most studies have continued to use the two typical measures of social capital, a common approach given the heterogeneity of measurement methods is to conduct analysis using multiple measures of social capital. For example, d'Hombres et al. (2010) use survey items measuring trust, social isolation and community organization membership to identify the relationship between health and social capital in transitioning economies. In the present thesis, I attempt to take a similar approach by using a number of social capital measures. Finding similar effects among different measures should strengthen the argument that an underlying social capital affects mental health. I elaborate on the idea behind this approach in chapter 4.

2.3 Social capital and mental health

The relationship between social networks and general health has been a point of focus in epidemiology since the late 1980s (Berkman and Glass, 2000). Following empirical work by Putnam et al. (1993) on macro-level trends in social capital, research in epidemiology began to study the impact of social networks on health within the conceptual framework of social capital. As an example of a macro-level study, Kawachi et al. (1997) identify a correlation between mortality and membership in clubs, as well as a measure of trusting attitudes in the United States. Kawachi et al. (1999) find a similar positive association for self-rated health using the same measures. Studies investigating the relationship at the individual level also support the general result that higher social capital is associated with better physical (Daniel Kim and Kawachi, 2008) and mental health (Almedom and Glandon, 2008; van der Gaag and Webber, 2008).

As most early studies merely identified the association between social capital and health, research has since focused on understanding the mechanism underlying their connection. For physical health, a proposed mechanism is that more social interactions allow easier access to health-relevant information, such as healthy behaviours, medications and access to services (Berkman and Glass, 2000). Norms of trust and reciprocity - a key component of social capital - aid in this diffusion of information (Lindström, 2008). The link between social capital and physical health has been well-established empirically, with many studies observing network effects on habits such as exercise and drug use (see Lindström (2008) for review of network effects on health behaviour up to 2008.)

For mental health, however, the connection with social capital is less well established. To identify a mechanism, Kawachi and Berkman (2001) link the concept of social capital to the existing psychological literature on the concept of 'social support'. From the social support literature, there are two proposed hypotheses linking social networks to mental health. First, the 'main effect' hypothesis states that connection to a social network provides constant psychological benefits to an individual regardless of stressful circumstances (Kawachi and Berkman, 2001). This is due in part to positive affective states, such as a sense of belonging and security, which develop from social connections (Cohen and Wills, 1985). Empirical evidence tends to support the main effect hypothesis, finding that more social capital is associated with better mental health for a range of measures and across contexts (Bassett and Moore, 2013; Berry and Welsh, 2010; Ding et al., 2015; Fiorillo et al., 2017; Giordano and Lindström, 2011; Helliwell and Putnam, 2004).

Second, the 'buffering' hypothesis of social support states that social resources aid mental health after the occurrence of a psychologically stressful event (Cohen and Wills, 1985; Kawachi and Berkman, 2001). In this case, social resources act to make the individual's appraisal of a stressful situation more benign. When a stressful event occurs, the presence of assistance from others may reduce the perceived potential for harm and may increase the individual's perceived ability to cope with the situation (Cohen and Wills, 1985). The result of these changes in the appraisal of an event is improved psychological resilience to the effects of the event. The buffering effect is difficult to assess empirically, however. This is because it concerns the effect of social capital on changes in mental health (Winkelmann, 2009). Consequently, the optimal method for research is to use longitudinal data.

Because of the necessity of longitudinal data, the buffering hypothesis in the context of social capital has not been well studied. Most studies have tended to focus on economic stressors. For example, using German Socio-economic Panel, Winkelmann (2009) finds that social capital is predictive of greater subjective well-being (main effect) but exhibits no mediating role on the mental health impact of becoming unemployed. On the other hand, from the social support literature, Milner et al. (2016) uses a fixed-effects model on Australian panel data, finding a significant buffering effect of a social support measure in response to an unemployment shock. Other notable longitudinal studies investigate the mediating effect of social capital on health after macroeconomic shocks (Lindström and Giordano, 2016), natural disasters (Hikichi et al., 2017) and armed conflict (Hall et al., 2014).

There are gaps that remain in the literature, however. Not much attention has been paid to the mitigating role of social capital for common life events (i.e. the passing of friends and relatives, injury or illness). Investigating the role of buffering for such life events is important from a clinical perspective, as distress from such events can be detrimental to longer term health, especially for those who are already less well psychologically (Schneiderman et al., 2005). Estimating the buffering effect for common life events has been a point of focus in the social support literature (i.e. Hewitt et al. (2012)). However, these studies tend not to acknowledge common threats to causal inference. Another gap in the literature, therefore, is that very few of the studies mentioned above attempt to address threats to inference such as reverse causality, endogeneity in the social capital process, or the effect of unobserved individual-specific heterogeneity. Those that have focused on such issues (i.e. Ding et al. (2015); Rocco et al. (2014)), however, do not investigate the buffering role of social capital.

Therefore, there are a few potential contributions to be made. First, I may contribute by investigating the mitigating role of social capital for several common life events. Second, I may contribute by investigating this mitigating role within an econometric framework, paying special attention to threats to inference, avoiding some confounding through panel data methods. I may also contribute by investigating the mitigating effect of social capital using a range of social capital measures, thereby strengthening the argument for the existence of a buffering role for social capital. Lastly, I may contribute by adding to the small, but growing literature on the role of social capital in the Australian context.

Chapter 3
Data

3.1 The Household, Income and Labour Dynamics in Australia (HILDA) survey

To look at the effect of social capital on mental health, I use data from waves 2-16 of the Household, Income and Labour Dynamics in Australia (HILDA) survey. HILDA is household-based longitudinal survey which began collection in 2001 with a sample of 13,969 persons from 7,682 households (Summerfield et al., 2017). The survey aims to be nationally representative with the exception of overseas residents and residents in very remote areas of Australia. In each wave of HILDA, interviews are conducted within households by a field worker using a number of questionnaires. In addition to face-to-face interviews, HILDA participants are given a self-completion questionnaire (SCQ) containing questions on more sensitive topics (i.e. about health, attitudes). The SCQ is then collected by the interviewer at a later date after the interview. For the present thesis, items from the SCQ are of primary interest, as they contain survey items on mental health and significant life events. This chapter will provide details on these survey items, which I use as the dependent and independent variables in my analysis.

As with many longitudinal surveys, participants have left the HILDA sample, some re-joining after failing to respond for a number of waves. As of the 16th wave (2016), 64.6 percent of the original wave 1 sample are still participants in HILDA. In response to this attrition, a top-up sample of 4,009 persons was added in the 11th wave of the survey. Therefore, in the provision of HILDA, a balanced panel with respondents present in all 16 waves is given along with an unbalanced panel containing the responses of individuals who have left or entered part-way through the survey. In addition to leaving the sample, some participants may fail to complete their SCQ in a given wave, meaning observations for key variables such as mental health may be missing even in the balanced panel. I may therefore run my analyses over three sets of data: First, the unbalanced panel containing responses from approximately 13,000 persons per wave. Second, the balanced panel containing responses from 6,179 individuals per wave but missing some SCQ observations. Third, the fully balanced panel containing responses from 3,179 individuals per wave and their SCQ responses in every wave with no missing observations.

For my main analysis I use the balanced panel containing 6,179 individuals per wave. As a robustness check, I repeat analyses for the other data sets in section 5 to assess attrition bias. For the remainder of the present chapter, I use the balanced 6,179 person data set to produce summary statistics and variable descriptions.

3.2 Measure of mental wellbeing (MHI-5)

As the dependent variable, I use a five-item version of the Mental Health Inventory (MHI-5). The MHI-5 is a mental health measure constructed from a subset of 5 mental health-related questions from the 36-item short-form (SF-36) health survey taken in every wave of HILDA as part of the self-completion questionnaire. The SF-36 is widely used and validated self-completion survey of general health (Ware and Gandek, 1998). The mental health sub-scale has been shown to be useful in detecting a range of affective disorders, such as Major Depressive Disorder (MDD) and a number of anxiety disorders (Berwick et al., 1991; Rumpf et al., 2001). In the Australian context, the MHI-5 items of the HILDA survey have been shown to have a high internal consistency (Butterworth and Crosier, 2004), and have been used in previous econometric studies of mental health in Australia (Frijters et al., 2014; Roy and Schurer, 2013).

To construct the measure, the survey asks the participant how much time in the past four weeks they have experienced the following:

1. Been a nervous person
2. Felt so down in the dumps that nothing could cheer you up
3. Felt calm and peaceful
4. Felt downhearted and blue
5. Been a happy person.

For each item the respondent chooses a response from 1 (all of the time) to 6 (none of the time). Using the method recommended by Ware et al. (1993), the scores are then adjusted for reverse coding (questions 3 and 5), summed, and transformed using the following formula:

$$MH_i = \left[\frac{x_i - 6}{30}\right] \times 100$$

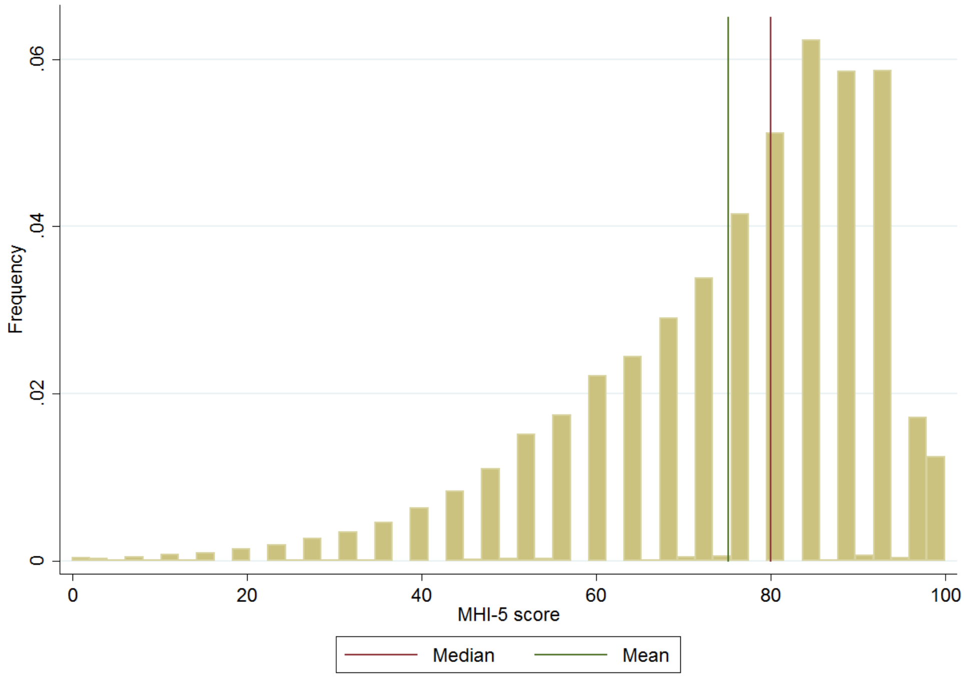

Figure 3.1: Histogram of the MHI-5 measure for the balanced HILDA panel with mean and median highlighted, $N = 93,467$ **person-year observations.**

where x_i is the sum of the scores from the items adjusted for reverse coding. The resulting measure (MH_i) ranges from 0 to 100, where 100 represents very good mental health and 0 represents very poor mental health.

The distribution of the transformed MHI-5 measure in HILDA is given in figure 3.1. The distribution of mental health scores is evidently skewed, with the majority of HILDA respondents showing a transformed MHI-5 score of 80 and above. To give an idea of the clinical relevance of the scale, Rumpf et al. (2001) and Kelly et al. (2008) find that a score below the cut-off point of approximately 60-65 points on the transformed MHI-5 scale is predictive of a mood or anxiety disorder. The 25th percentile of the distribution is 64 points. This roughly corresponds with an estimate from the Australian Institute of Health and Welfare (2017) that approximately 20% of Australians between 16 and 85 years of age will experience a common mental disorder in a given year.

The average of the mental health score in the balanced panel is approximately 75 points and is relatively constant throughout the survey. However, there is a considerable amount of variation within individuals over time. To produce an estimate of the typical variation within individuals across the 16 waves of HILDA, for each person-year observation I calculate the individual's deviation from their respective time mean. Formally, this is

$$MH_{it} - \bar{MH_i} \tag{3.1}$$

where $\bar{MH_i}$ is the mean MHI-5 score across all observations of individual i. The mean of the resulting deviation from (3.1) is zero. However its standard deviation is informative in describing the typical deviation of an individual from their respective long-run mean in any given year of HILDA. This is a typical measure of within variation in panel data[1].

Using the above method, I find that the standard deviation of the MHI-5 score within individuals from their respective long-run mean is 10.49 points. This indicates that although the variation in the aggregate MHI-5 score over time is minimal there is a substantial amount of variation within individuals over time to be explained by a fixed-effects estimation. To give an idea of the clinical significance of this variation in the MHI-5 score, Ware et al. (1993) note that a change of approximately 20 points corresponds roughly to a 15 percentage point change in the probability of a clinical diagnosis of depression and a 10 percentage point change in the likelihood of being a mental health inpatient in the previous 12 months. Ware et al. (1993) also note that the relationship between the MHI-5 scale and mental health outcomes is approximately linear such that changes toward the top and bottom ends of the distribution are comparable in terms of clinical outcomes.

3.3 Social capital measures

I conduct my analysis using four measures of social capital collected as part of the self-completion questionnaire of the HILDA survey.

3.3.1 Index of community participation

In waves 6, 10 and 14 of the HILDA survey, participants were asked 12 questions on how often they have interacted with their community. These questions are provided in appdenix B in table B.1. Participants were asked to respond to each item on a Likert scale from 1 (Never) to 6 (Very often).

Using these responses, I construct an index of community participation using principal components analysis (PCA) on the 12 survey items. I do so because another approach such as averaging the items would be uninformative due to the

[1] Note that this is also how Stata calculates its estimate of the within standard deviation as part of the command `xtsum` for panel data.

varied nature of the questions. Instead, principal components analysis determines the underlying components of the data which explain the greatest proportion of the variance. My method for conducting the PCA is detailed in appendix A. In sum, I predict values for the first two principal components given their eigenvalues. The first principal component appears to be most strongly related to questions regarding interactions with persons outside of one's immediate family. Hence I identify this component as a measure of 'bridging' or 'exclusive' dimension of social capital as defined by Putnam (2000). The second principal component is positively related to items regarding interactions with one's family, and negatively related to items regarding participation in broader community events. I identify the second principal component as the family-centric 'bonding' or 'inclusive' dimension social capital as defined by Putnam (2000).

Because the scale of the principal components lacks interpretable meaning, I subtract the global mean of the components calculated using the entire balanced panel and divide by the global standard deviation. Therefore, a 1 unit change in the principal components is interpretable as a one standard deviation change. The average value of the variables is constant across the three waves, deviating less than 1% of a standard deviation from the global mean. Using the same method as detailed for the MHI-5 score, the within standard deviation for the first principal component is 0.85, or 85 percent of the global standard deviation. For the second component the within standard deviation is lower at 0.65, or 65 percent of the global standard deviation. This indicates that there is within variation with which to conduct a fixed effects estimation, however the extent of the variation is smaller for the second principal component than the first.

3.3.2 Social support

To create a measure of perceived social support, I use a set of ten survey items detailed in appendix B in table B.2, following previous Australian research in doing so (Crosier et al., 2007; Hewitt et al., 2012; Milner et al., 2016). In every wave of the HILDA survey, participants are asked how much they agree with each statement in table B.2 on a Likert scale from 1 (Strongly disagree) to 7 (Strongly agree). Before creating a measure from these items, I first attempt to identify whether they are measuring the same underlying construct. Firstly, similar to Crosier et al. (2007) and Milner et al. (2016), I find that the survey items have high internal consistency with a Cronbach's alpha of 0.83. Moreover, principal components analysis provides two components with eigenvalues greater than one. The first component explains 41% of the variance and weights the items relatively evenly such that the correlation coefficient between the simple

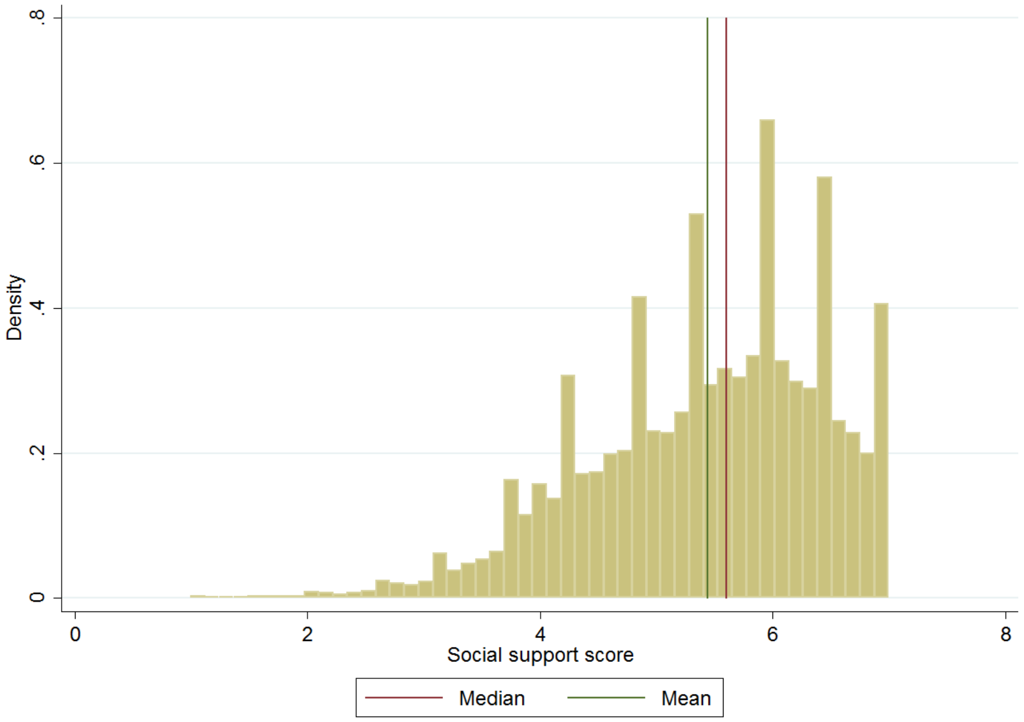

Figure 3.2: Histogram of the untransformed social support measure for the balanced HILDA panel with mean and median highlighted, $N = 93,467$ person-year observations.

average of the items and the component is 0.997. The second principal component on the other hand simply generates factor loadings which distinguish between negative and positively worded items and explains 14% of the variance. I conclude therefore, in line with previous studies, that the simple average of the ten items sufficiently reflects the degree of an individual's perceived social support. The resulting measure has a scale extending from 1 to 7 points, where lower scores indicate less perceived social support and higher scores indicate more. As with my other measures of social capital, I centre the final measure around the global mean and divide it by its global standard deviation, such that a one unit change is interpretable as a one standard deviation change.

To give an idea of the distribution of perceived social support, figure 3.2 (a) plots the histogram of the untransformed measure. As with the MHI-5 scores, the measure is negatively skewed, with a mean of 5.4 points and a standard deviation of 1 point. The majority of participants therefore show a high degree of perceived social support. The sample mean of the measure is also very stable across waves. However, as with the other measures of social capital used in this thesis, there is substantial variation within individuals over time. The within standard deviation for the transformed measure of social support is 59.4% of a global standard deviation, leaving variation over time with which to explain changes in the MHI-5 score.

3.3.3 Trust

To create a measure of trusting attitudes, I use a set of five survey questions asked in 5 of the 16 waves of the HILDA survey. As part of the SCQ, participants are asked the extent to which they agree to the following statements and are able to respond to each on a Likert scale from 1 (Strongly disagree) to 7 (Strongly agree):

1. Generally speaking, most people can be trusted
2. Most people you meet keep their word
3. Most people you meet make agreements honestly
4. Most people you meet succeed by stepping on other people
5. Most people would try to take advantage of you if they got a chance

To make a measure of trust, I simply take the average of the responses to each of these questions for each individual, adjusting for reverse coding in items 4 and 5 such that lower score indicate less trust and higher scores indicate more. Previous studies in the broader literature have tended to use one survey item to measure trust (Glaeser et al., 2000). Most notably Knack and Keefer (1997) only use one survey question, similar to item 1 above, to assess trusting norms at the aggregate level.

As opposed to previous studies, I use the average of the items as a measure of trust instead of only item 1 for two reasons. First, preliminary testing provides evidence that the items measure the same underlying construct. Principal components analysis generates only one principal component with an eigenvalue above one, which explains approximately 60% of the variance in the items. This principal component weights the items very evenly such that the correlation coefficient between the component and the simple average of the items is 0.995. In addition, the Cronbach's alpha for the items is strong at 0.813, indicating high internal consistency between items. Second, given that item 1 is an ordinal variable taking discrete values 1 through 7, variation over time for each individual is not very granular. This is especially the case for those with higher responses (6 and 7). Consequently, in a fixed effects estimation there is little variation left to explain changes in the MHI-5 measure. Averaging the items on the other hand allows for more granular variation within the trust measure.

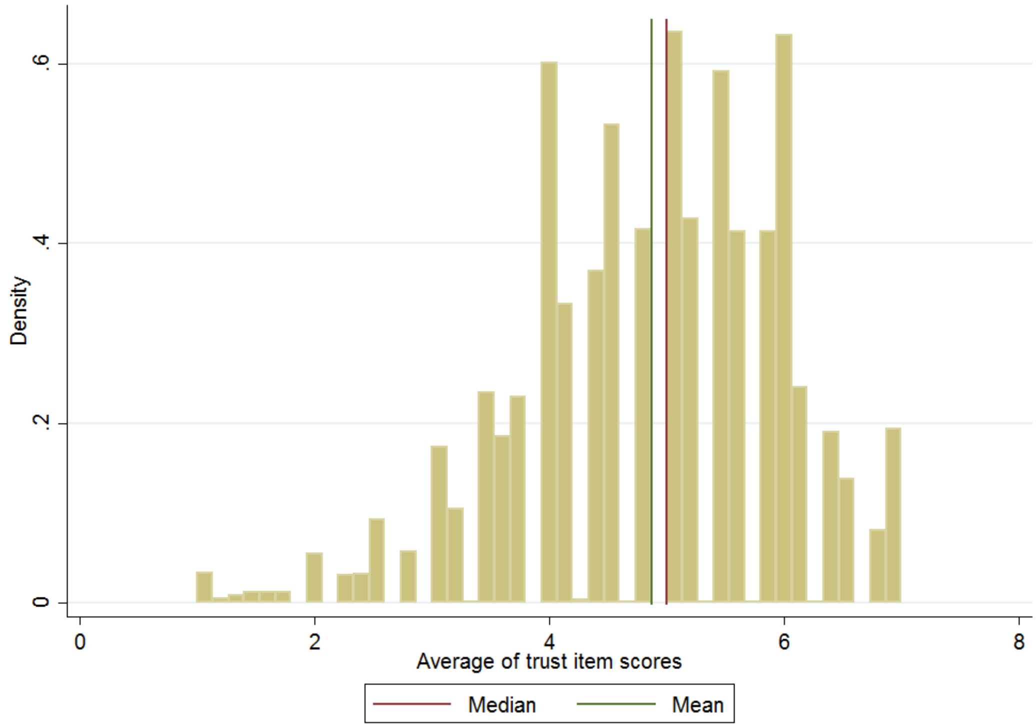

Figure 3.3: Histogram of the untransformed trust measure for the balanced HILDA panel with mean and median highlighted, $N = 34,860$ person-year observations.

To give an idea of the distribution and stability of the trust measure, figure 3.3 plots the histogram of measure for the entire balanced panel. It is evident that responses tend to be skewed negatively with a mean of approximately 5 points on a scale of 1 to 7, with a standard deviation of 1.12 points. This implies that people tend to agree with items 1, 2 and 3 and to disagree with items 4 and 5. The aggregate level of the measure does not tend to fluctuate over time, indicating stability. However, as with the other measures of social capital, there is substantial variation within individuals. The within standard deviation is 0.67 of a point. This corresponds roughly to a decrease (or increase) of four points in one of the items, or shared across items. As with the social support and community participation measures, I centre the trust measure around the global mean and divide it by the global standard deviation. The within standard deviation then corresponds to 60% of one global standard deviation.

3.3.4 Participation in clubs

As noted in section 2.2, a typical measure of social capital has been survey items identifying participation in clubs or associations. In every wave of the HILDA survey as part of the self-completion questionnaire, participants are asked the following question:

> Are you currently an active member of a sporting, hobby or community-based club or association?

Participants select either yes (1) or no (0). I use their response as an indicator variable for club participation. Approximately 40% of the pooled sample within the balanced panel participates in a club or association. This proportion is relatively stable over waves. Within individuals, however, there is considerable variation. Conditional on not being a member of a club or association (0) in one wave, there is an approximate 15% chance of an individual transitioning into being a club member (1) in the next wave. On the other hand, conditional on being a member of a club (1) in one wave, there is an approximate 22% chance of the individual not being a member (0) in the next wave. Moreover, conditional on having ever participated in a club or association, an individual is also a member of a club or association for approximately 50% of their observations. This creates variation in club membership with which to explain variation in the MHI-5 score over time.

3.4 Covariates and summary statistics

Crucial to my study of the buffering effect is individuals' experiences of psychologically stressful events. As part of the SCQ, the HILDA survey asks participants if they have experienced a number of significant life events in the past 12 months. Table B.3 in appendix B lists the variables names and the original questions asked, while table B.4 lists the frequencies of these items in each wave. For ease of analysis, and to improve the number of observations per event, I group these life events ('shocks') together as family-related, employment-related and health-related. I create an indicator variable for each group, equal to one if the individual has experienced at least one of the shocks within the grouping in a given year. These groupings follow previous econometric work by Cobb-Clark and Schurer (2012) who assess the impact of these significant life events on measures of personality in HILDA. Issues surrounding the co-occurrence of shocks and their aggregation into these groups are addressed in sections 5.2.3 and 5.2.4 as robustness checks.

In table B.5 in appendix B I provide a covariate balance analyzing the difference in the mean of covariates between individuals who have and who have not experienced a psychologically stressful event. I repeat the balance of covariates for the three groups of shocks. It is evident that those who experience family-related, employment-related and health-related shocks tend to be older, less educated and have lower incomes. This may indicate some selection into treatment through

Variable	Non participator	Participator	t-stat
Age	48.85	52.28	-33.47***
Female	0.57	0.52	13.64***
MHI-5 score	73.32	77.92	-42.60***
Foreign born	0.24	0.18	20.96***
Highest level of education:			
High school	0.13	0.12	6.68***
Primary	0.33	0.29	12.65***
Tertiary certificate	0.32	0.31	1.32
University	0.22	0.28	-19.79***
Couple	0.7	0.72	-4.99***
Has children	0.38	0.34	12.34***
Unemployed	0.02	0.02	6.38***
Out of labour force	0.31	0.37	-17.31***
Household income (000s)	77.15	81.45	-9.03***
Family shock	0.24	0.27	-9.56***
Emp. shock	0.08	0.07	6.34***
Health shock	0.1	0.09	2.48*
'Bridging'	-0.27	0.4	-44.19***
'Bonding'	0.11	-0.15	17.17***
Social support	-0.1	0.15	-38.91***
Trust	-0.12	0.17	-27.29***
N	55,030	37,982	93,012

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.05$

Table 3.1: Balance of covariates for club participators versus non-club participators. Produced using the pooled balanced panel. N is person-year observations. t-stat in column 3 is for a test of the significance of the difference in means between groups.

these observables. Hence during estimation I control for a number of factors including income, having children, being part of a couple, levels of education, whether the person is out of the labour force or unemployed, age and age squared. As I am using a within estimator, the effect of time-constant observable factors such as sex and migrant status is removed.

I also conduct a balance of covariates analysis for each of the social capital variables described in section 3.3. For the club participation measure, I compare those individuals who do participate in clubs against those who do not. This comparison is given in table 3.1, and is representative of the balance of covariates for the other social capital measures. For the social support, trust and community participation variables, I compare the characteristics of observations one standard deviation below the mean with the characteristics of those observations at the mean. I similarly compare observations one standard deviation above the mean with mean-level observations. As above, I find that those with higher social capital tend to be more educated, wealthier and older, however most differences are small. When conducting the balance of covariates conditional on having had a shock, results are similar. Therefore, controlling for aspects listed above should counter potential bias from selection on observables.

Chapter 4
Method

4.1 Econometric model

To investigate the buffering and main effect hypotheses, I use the following econometric model. Let $MH_{it} \in [0, 100]$ be individual i's SF-36 mental health score in wave t, for $i = 1, ..., n$ and $t = 1, .., T$ where n is the number of individuals in the sample and T is the terminal wave of the sample. I assume the mental health score is determined as a linear function of a number of variables, including social capital and a psychologically stressful event. Let social capital (SC_{it}) be a continuous variable, and let $x_{it} \in \{0, 1\}$ be a binary variable equal to one if individual i has experienced a psychologically stressful event in wave t. I also assume the individual's mental health score is affected by some observed (control) factors collected in column vector Z_{it}, as well as some unobserved time-constant factors (α_i) such as personality (Cobb-Clark and Schurer, 2012; DeNeve and Cooper, 1998), unobserved time-varying factors (μ_{it}), and a wave-specific fixed effect (λ_t). Given this specification of mental health, the population regression equation of interest is:

$$MH_{it} = \alpha_i + \lambda_t + \beta SC_{it} + \sum_{k=-l}^{l} \gamma_k x_{i,t+k} + \sum_{k=-l}^{l} \delta_k (x_{i,t+k} \times SC_{it}) + Z'_{it}\theta + \mu_{it} \quad (4.1)$$

In this specification, the direct effect of social capital on mental health is determined by the parameter β. As the main effect hypothesis proposes, I expect β to have a positive sign, as an increase in the social capital variable is proposed to increase mental health. If the individual experiences a psychologically stressful event their mental health is expected to decline in wave t by $(\gamma_0 + \delta_0 SC_{it})$. The parameter δ_0 will therefore be the difference in the effect of the event for different levels of social capital. As I expect γ_0 to have a negative sign, if a buffering effect exists, I expect δ_0 to be positive such that for higher levels of SC_{it} the negative effect of the event is reduced.

As part of equation (4.1) I include up to l leads and lags of the shock variable to allow analysis of the anticipation and after-effects of the event. In estimation, I find that the number of lags and leads beyond $l = 2$ are uninformative. Moreover, adding lags beyond $l = 2$ restricts the data available for estimation to 9 waves or fewer, which discards a large amount of information with which to conduct my analysis. Therefore I let the number of leads and lags for estimation be $l = 2$. As the event may have lasting psychological effects, I expect γ_1 and γ_2 to have a negative sign. The interaction of the lags of the psychological stressor with the social capital then allows me to test if there is a buffering effect on the after effects of the events. If so, parameters δ_1 and δ_2 will have a positive sign. Parameters γ_{-2} and γ_{-1} as well as interaction coefficients δ_1 and δ_2 are expected to be zero if shocks are unexpected.

The consistent estimation of the parameters will depend on a number of assumptions. Most important is the assumption of exogeneity - that the included covariates must not be related to the unobserved random error. If α_i is unobserved, this assumption is easily violated. To see this, let $v_{it} = \alpha_i + \mu_{it}$ such that equation (4.1) may be stated as

$$MH_{it} = \beta SC_{it} + \sum_{k=-l}^{l} \gamma_k x_{i,t+k} + \sum_{k=l}^{l} \delta_k (x_{i,t+k} \times SC_{it}) + Z_{it}'\theta + v_{it}.$$

It is likely that time-constant unobserved individual-specific factors such as personality or hardiness may be associated not only with mental health but also with one's level of social capital, or with the likelihood of their being exposed to a shock. In this case $\mathbb{E}[v_{it}|SC_{it}, x_{it}, Z_{it}] \neq 0$, implying that the estimated parameters for these variables are not consistent.

Therefore, to avoid this potential biasing effect of the individual specific fixed-effect, I use a within estimator. For any variable X_{it}, let $\bar{X}_i$ be the average of the variable across all waves for individual i. Then, let $\ddot{X}_{it}$ be the per-wave deviation from that mean for individual i. That is, $\ddot{X}_{it} = X_{it} - \bar{X}_i$. The within transformed model may then be stated as

$$\ddot{MH}_{it} = \beta \ddot{SC}_{it} + \sum_{k=-l}^{l} \gamma_k \ddot{x}_{i,t+k} + \sum_{k=-l}^{l} \delta_k (\ddot{x}_{i,t+k} \times \ddot{SC}_{it}) + \ddot{Z}_{it}'\theta + \ddot{\mu}_{it}. \tag{4.2}$$

The transformation used to form equation (4.2) therefore removes the potential bias from time-constant unobserved effect α_i. The equation is estimated in the following sections using pooled OLS to determine the effect of social capital on mental health. The downside of using such a transformation, however, is the removal of time-constant factors that may be of interest for analysis, and not just confounding factors. The only information with which the estimation is conducted is from time-varying factors.

For the pooled OLS estimation of equation (4.2) to provide consistent estimations of the parameters of interest, the key assumption required is that the explanatory variables $(\ddot{SC}_{it}, \ddot{x}_{it}, \ddot{Z}_{it})$ are exogenous. Formally stated, exogeneity implies that

$$\mathbb{E}[\ddot{\mu}_{it}|\ddot{SC}_{it}, \ddot{x}_{it}, \ddot{Z}_{it}] = 0. \tag{4.3}$$

There are a few cases where this condition may not be fulfilled. Firstly, the process determining social capital may be endogenous. Following the economic model proposed by Glaeser et al. (2002), we may think of social capital partly as the result of an investment decision on behalf of an individual. Consider a simple model where a person's level of social capital is determined as a function of time-varying components (a_{it}) such as changes in types of employment, moving neighbourhoods or unobserved changes in one's social circle, as well as a time-constant factor (b_i), which may reflect the person's inclination to be social (an element of personality) or the level of culture or community-based social capital. We may state the social capital process as

$$SC_{it} = f(a_{it}, b_i).$$

An issue may arise with regard to assumption (4.3) if the time-varying component a_{it} covaries with the error variable $\ddot{\mu}_{it}$ in equation (4.2). This may be expected if factors such as changes in the sociability of one's employment or moving neighbourhoods also affect an individual's mental health.

A second case where (4.3) may not be fulfilled is where mental health and social capital are simultaneously determined. In this case, we might consider social capital to be a function of mental health:

$$SC_{it} = f(a_{it}, b_i, MH_{it}).$$

The estimated parameters of equation (4.2) from pooled OLS may then be inconsistent due to simultaneity bias. This concern has motivated previous work investigating the reciprocal relationship between social capital and health (Rocco et al., 2014).

I try to address the issue of endogeneity in social capital by using an instrumental variable. Instrumental variable studies of social capital and health are rare, and the endogeneity of social capital is often a point of criticism, especially for studies attempting to analyse community-level social capital (see Durlauf (2002) for a review of these criticisms). I outline my approach to instrumenting in section 5.2.2. A limitation of this study, however, as with other studies of social capital and health, is that the problems of reverse causality and endogeneity in the social capital process are not fully accounted for.

A further concern regarding the assumption (4.3) is that the shocks (x_{it}) may not be exogenous. The result of the balance of covariates in section 3.4 demonstrate that shocks may occur non-randomly. For this reason I control for the time-varying factors which may be associated with selection bias with regard to psychologically stressful events. To further address endogeneity in the shock variables, in section 5.2.4 I disaggregate the shocks from their respective groups to analyse the buffering effect for those events which are arguably more exogenous. This may reveal the extent of any potential biasing from endogeneity in the aggregated shock terms. Disaggregating the shocks should also reveal more specifically which life events are driving observed effects.

Given the presence of attrition from the sample over the span of the HILDA survey, there is also the possibility of non-random attrition biasing estimation results. As a robustness check in section 5.2.3, I re-estimate model (4.2) using the different data sets provided, as outlined in section 3.1. Similarity in the estimates from respective data sets should provide an idea of the extent to which attrition has affected estimation.

4.2 Estimation strategy

My estimation strategy follows an argument made by Putnam (2000) in relation to his own empirical work investigating social capital. Because social capital is a latent variable which lacks a direct measure, it is best to repeat analysis using a number of variables that are presumed to measure some aspect of social capital. If several measures return similar results, then this corroboration strengthens the argument that there is an underlying factor these measures represent that is driving the effect. As stated in section 2.2, different measures of social capital may represent the different dimensions or types of social capital. Therefore repeating the analysis for the different measures of social capital available in HILDA may also reveal the effect of different dimensions of social capital on mental health.

I therefore re-estimate the model using the four measures of social capital available in HILDA, as outlined in section 3.2. For each measure of social capital, I also repeat estimation for each group of psychologically stressful events - family-related shocks, employment-related shocks and health-related shocks. The idea of doing so is to obtain a broad picture of the buffering effect, by assessing whether it appears for different types of life events. This will also provide an idea of the potential mechanisms underlying a buffering effect. Following baseline regression results, I repeat analyses for a number of modifications to address issues of potential bias in the estimates. as noted in section 4.1 and earlier sections. Note that in all regressions standard errors are cluster-robust, making them robust to both heteroskedasticity and clustering at the individual level. [1]

Note as well that in equation (4.1) the coefficients of the shock variable $(\delta_{-2}, ..., \delta_2)$ are not interpretable unless the social capital variable SC_{it} has meaning at the value zero. For the purpose of correct interpretation, I center the social support, trust and community participation measures around their global means and divide them by their global standard deviations. I choose to center the variables around their respective global means because of the stability of the global mean across all waves. Therefore the interpretation of the de-meaned variable remains the same across waves - the coefficient β in model (4.1) will be the change in the mental health score for a one standard deviation increase in the social support, trust, or community participation measures, holding other factors constant. If these social capital variables are centered at the mean, then the coefficients of shock variable (x_{it}) have an interpretation of being the effect of the shock on the mental health score when the social capital measure is at the level of the global mean, holding other factors constant. Club membership, on the other hand, has meaning at the value zero, and so it is not de-meaned in the same way. The coefficient on the shock term in the case of the clubs measure is the effect of the shock when the individual is a member of no clubs or associations.

[1] A concern is that I should be clustering at the household level. Correcting for household-level clustering is not possible given the way HILDA is distributed for general release. While the survey provides cross-wave IDs of individuals, it does not do the same for households. Instead, the household ID is randomized in every wave. This remains a minor limitation of my analysis.

Chapter 5
Estimation

5.1 Baseline regression results

I begin estimation using club participation as the measure of social capital in the main regression equation (4.1). Table 5.1 provides estimation results for the club participation variable. Each column of table 5.1 corresponds to one of the three shock indicators (x_{it} in equation (4.1)) described in section 3.4.

As noted in the previous section, the estimated coefficient of the club participation variable corresponds to the estimated direct effect of social capital on mental health as described by the main effect hypothesis. For all three columns, answering 'Yes' to the question "Are you currently an active member of a sporting, hobby or community-based club or association?" is associated with an approximate 0.7 point increase in the mental health score over those who answer 'No' to the same question. This effect is clinically small according to Ware et al. (1993) who identify that a 4 point change is moderately clinically relevant, as described in section 3.2. I find a similar result in section 5.1 when attempting to give more clinically interpretable estimates.

The observed coefficients of the shock variables in table 5.1 are the estimated effects of the shock for those people who do not participate in clubs. The family-related shock variable has the weakest effect on the mental health score of approximately 1 point. This will be a common result throughout the remaining estimations. The employment shock on the other hand has a larger effect at approximately 3 points, while the health-related shock has the largest effect at approximately 5 points. The decrease of 3 points for an employment related shock is very similar to the finding summarized by Ware et al. (1993) that a 3 point difference in the MHI-5 score is "roughly equivalent to the psychological distress caused by being fired or laid off from one's job" (Ware et al., 1993, 9:14).

The leads and lags of the employment shock are also significant, with individuals experiencing an anticipatory decrease of 1.4 points in the mental health score one year before the shock, as well as an approximate 1 point decline after. Changes in the mental health score two years prior and two years after the occurrence of the shock are also significant but the effect is minor in magnitude. The health

Variable:	(1) Family	(2) Employment	(3) Health
Participator	0.708***	0.748***	0.610***
	(0.192)	(0.156)	(0.155)
Shock (T_0)	-1.204***	-2.890***	-4.551***
	(0.168)	(0.317)	(0.296)
Shock (T_0)*Participator	0.425*	0.835*	1.604***
	(0.225)	(0.443)	(0.417)
Shock (T_{-1})	-0.459***	-1.394***	-1.470***
	(0.162)	(0.294)	(0.279)
Shock (T_{-2})	-0.075	-0.727***	-0.319
	(0.157)	(0.277)	(0.270)
Shock (T_{+1})	-0.234	-1.003***	-0.646**
	(0.163)	(0.275)	(0.279)
Shock (T_{+2})	-0.283*	-0.737***	-0.941***
	(0.157)	(0.261)	(0.295)
Shock (T_{-1})*Participator	-0.128	0.321	0.661*
	(0.222)	(0.423)	(0.387)
Shock (T_{-2})*Participator	0.370*	0.383	0.390
	(0.217)	(0.394)	(0.358)
Shock (T_{+1})*Participator	-0.120	0.278	-0.399
	(0.226)	(0.391)	(0.380)
Shock (T_{+2})*Participator	0.170	-0.002	0.189
	(0.220)	(0.379)	(0.395)
Highest level of education:			
Tertiary (certificate)	-0.204	-0.173	-0.139
	(0.600)	(0.601)	(0.584)
Tertiary (university)	0.392	0.523	0.461
	(0.847)	(0.835)	(0.846)
Couple	2.002***	1.928***	1.949***
	(0.346)	(0.346)	(0.341)
Has children	-0.960***	-0.999***	-1.025***
	(0.254)	(0.255)	(0.253)
Unemployed	-2.324***	-1.570***	-2.382***
	(0.501)	(0.492)	(0.504)
Out of labour force	-1.002***	-0.628**	-0.844***
	(0.243)	(0.247)	(0.240)
Household Income (000s)	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)
Constant	74.999***	74.860***	75.243***
	(0.421)	(0.406)	(0.409)
N	55,517	55,446	54,803
n	5,923	5,919	5,921

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.1: Baseline estimation results where club participation is the social capital measure. Results are produced using the balanced panel, $n = 6,179$. N is person-year observations, n is the number of individuals included to produce estimation results. Standard errors are clustered at the individual level.

shock also display a significant anticipation effect 1 year prior to onset and in the two years after onset. A family-related shock on the other hand shows little evidence of any anticipation or after effects, with the exception of the year prior to the shock.

The buffering hypothesis is tested by observing the magnitude and significance of the interaction between the shock variable and the social capital variable. For the club participation measure, in table 5.1 I find that the interaction term has the expected sign for all three types of shock, and is significant at least at the 10% level, with 1% significance for the health shock. To provide an intuitive idea of the magnitude of the buffering effect, I take the ratio of the coefficients of the interaction term and the shock term. From table 5.1, the magnitude of the family related shock is reduced by 34% for club participators over non-participators, and is similarly reduced by 29% and 35% for employment and health-related shocks over non-participators. With respect to the anticipation and after effects of the shocks, I find that all but two of the interacted coefficients are not significantly different from zero, indicating little evidence of buffering in the before and after periods of a psychologically stressful life event. Testing for the joint significance of the pre and post-shock interaction coefficients finds no evidence that they are jointly different from zero.

As part of table 5.1, I also include the estimated coefficients of the control variables included in the regressions. Each of the control variables has the expected sign, with the exception of the binary variable indicating whether or not the individual has children. The negative and significant coefficient may occur because individuals have less time and resources immediately after having children. In this case it is important to note that the within estimator only detects changes in the variables - otherwise having children might feasibly produce a positive effect. Omitted from the table are the wave-specific fixed effects, none of which are significant at the 10% level. Estimated coefficients for the control variables are similar for each of the three columns. I find throughout almost all of the specifications that follow that the estimated coefficients for the controls are similar in magnitude and significance to those presented in table 5.1 - the estimated coefficients of the controls appear to be very robust. Hence, throughout estimation, I omit the estimated coefficients of the control variables for brevity.

Because I use the balanced panel without all SCQ responses to generate these results, the number of person-year observations across the three columns of table 5.1 varies by a few hundred observations. This may occur because participants forget or fail to respond to items in the questionnaire. Across the three columns, the average number of periods in which an individual is present is 9.4 of 11 periods. To asses the possible effect of any attrition caused by failure to respond to the SCQ, in section 5.2.3 I re-estimate the model using a fully balanced data set. Note that through tables 5.1 to 5.4 this difference in person-year observations is also present. It appears to be consistently the case that a small number of respondents fail to respond to questions pertaining to health-related shocks. However, the difference in the number of person-year observations between columns only corresponds to approximately 60-70 persons, a small number relative to size of the sample.

In table 5.2 I present the results of estimation using the trust measure described in section 3.3.3. The direct effect of the trust variable in this case may be interpreted as the effect on the mental health score of a one standard deviation increase in trust measure relative to the mean. The estimated direct effect is approximately 1.5 points on the MHI-5 scale for each specification in table 5.2 and is significant at the 1% level. The estimated coefficients on the shock variables are significant at the 1% as with the clubs measure. At the mean level of trusting, a family related shock is associated with a 1 point decline in the MHI-5 score, while an employment related shock is associated with 2.4 point decline, and a health related shock with 3.8 point decline.

I note that the estimated coefficients on the shock terms are smaller than those from table 5.1 for the club participation measure. The reason for this discrepancy may be that the estimated coefficients of the shock variables in table 5.2 are determined for the mean level of the trust variable, whereas in table 5.1 they are determined for the case where the individual is not a member of a club or association. Within the balanced panel, those who do not participate in clubs on average score below the mean in the trust measure, the community participation variables, and the social support measure. Therefore the estimated coefficients of the shock variables in table 5.1 may be larger due to the lack of a buffering effect from non-participating individuals' lower social capital.

For the buffering effect, the interactions between the trust measure and the family and health-related shocks are not statistically different from zero. However, the estimated coefficient of the interaction term between the trust measure and the employment shock is large relative to the size of the shock and is significant at the 1% significance level. From table 5.2 we may conclude that an increase in the trust measure by one standard deviation is estimated to reduce the impact of an employment shock by 40% compared to the mean. Conversely, we may also conclude given the linear nature of the model that a one standard deviation

Variable:	(1) Family	(2) Employment	(3) Health
Trust	1.724***	1.491***	1.546***
	(0.159)	(0.127)	(0.132)
Shock (T_0)	-0.958***	-2.399***	-3.851***
	(0.167)	(0.315)	(0.296)
Shock (T_0)*Trust	-0.071	0.966***	0.165
	(0.178)	(0.322)	(0.316)
Shock (T_{-1})	-0.616***	-1.114***	-1.270***
	(0.165)	(0.296)	(0.279)
Shock (T_{-2})	-0.110	-0.695**	-0.362
	(0.167)	(0.282)	(0.270)
Shock (T_{+1})	-0.470***	-0.892***	-0.671**
	(0.171)	(0.280)	(0.282)
Shock (T_{+2})	-0.252	-0.595**	-0.708**
	(0.163)	(0.272)	(0.278)
Shock (T_{-1})*Trust	-0.110	0.126	0.180
	(0.184)	(0.305)	(0.275)
Shock (T_{-2})*Trust	-0.051	-0.193	0.081
	(0.179)	(0.290)	(0.281)
Shock (T_{+1})*Trust	0.011	0.776***	0.465
	(0.189)	(0.293)	(0.291)
Shock (T_{+2})*Trust	0.013	-0.082	0.214
	(0.174)	(0.284)	(0.292)
Constant	97.142***	95.801***	97.456***
	(9.606)	(9.629)	(9.568)
N	30,386	30,351	29,986
n	5,854	5,859	5,859
Overall R^2	0.01	0.01	0.002
Wave Fixed Effects	Yes	Yes	Yes
Covariates	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.2: Baseline estimation results where trust is the social capital measure. Results are produced using the balanced panel, $n = 6,179$. N is person-year observations, n is the number of individuals included to produce estimation results. Standard errors are clustered at the individual level.

decrease in the trust measure worsens the impact of an employment-related shock by 40% compared to those at the mean.

With respect to the anticipation and after effects of the shocks, similar to the clubs measure I find significant anticipation and after effects one year prior to and after the shock occurs. However, the interactions between the lagged shock variables are not significantly different from zero, with the exception of the one year lead of the employment-related shock. Here, a one standard deviation increase in the trust measure decreases the impact of the shock one year after onset by 87%. However, the estimated coefficients of the interactions with the lags and leads of the shocks are not jointly significant.

Table 5.3 presents estimation results using the two principal components generated from the set of community participation items described in section 3.3. As with the other social capital measures, I observe a statistically and economically significant direct effect from the principal components. For a 1 standard deviation increase in the first principal component representing 'bridging' social capital, the MHI-5 score increases by approximately 2.5 points compared to the mean, holding other factors constant. The increase in mental health for the second principal component representing 'bonding' social capital is smaller at approximately 1.5 points.

The estimated impacts of the shocks are approximately the same size as those presented in table 5.2. The observed coefficient of the family-related shock using the second 'bonding' principal component appears to be smaller than other estimations. However, the 95% confidence interval extends from -1.36 to -0.002, which contains the other estimates of the impact. Estimated coefficients of the before and after effects of each shock are similar to those presented for other social capital variables.

In table 5.3 I find a significant buffering effect for the first principal component. For bridging social capital, the estimated coefficient of the buffer is approximately 66% the size of the family shock and 34% the size of the employment shock for a 1 standard deviation increase over the mean level. The buffering effect for the health shock on the other hand is negligibly small. Interestingly, for the second principal component I find negative estimated coefficients for the interactions with both the employment and health shocks. However, note that the standard errors of both coefficients are very large relative to the size of the coefficient implying that even a low confidence interval will contain zero. As with other social capital variables, I fail to find a significant buffering effect when interacting the social capital variable with the leads and lags of the shock term.

Lastly, table 5.4 presents estimation results when using perceived social support as the measure of social capital. As with other measures, I find a statistically and economically significant direct effect of a one standard deviation increase in the social support measure on the mental health score. As opposed to the other social capital measures presented, the direct effect of the social support measure is very large at almost twice the size of the direct effect of the remaining measures, with an effect of approximately 4.4 points on the MHI-5 scale. This estimated direct

	PC 1: 'Bridging'			PC 2: 'Bonding'		
	(1)	(2)	(3)	(4)	(5)	(6)
Variable:	Family	Employment	Health	Family	Employment	Health
PC	2.647***	2.552***	2.573***	1.580***	1.630***	1.547***
	(0.276)	(0.243)	(0.235)	(0.242)	(0.205)	(0.202)
Shock (T_0)	-0.764***	-2.481***	-3.843***	-0.680**	-2.696***	-3.994***
	(0.273)	(0.520)	(0.458)	(0.271)	(0.524)	(0.462)
Shock (T_0)*PC	0.503*	0.835*	0.068	0.060	-0.240	-0.126
	(0.284)	(0.503)	(0.468)	(0.272)	(0.495)	(0.484)
Shock (T_{-1})	-0.421	-1.491***	-1.315***	-0.414	-1.604***	-1.109**
	(0.268)	(0.488)	(0.466)	(0.266)	(0.492)	(0.464)
Shock (T_{-2})	-0.489*	-0.837*	-0.716	-0.475*	-0.939*	-0.731
	(0.273)	(0.487)	(0.457)	(0.272)	(0.483)	(0.454)
Shock (T_{+1})	-0.821***	-1.105**	-0.419	-0.816***	-1.166**	-0.456
	(0.286)	(0.444)	(0.448)	(0.284)	(0.455)	(0.452)
Shock (T_{+2})	-0.725**	-0.623	-0.822*	-0.791***	-0.603	-0.778
	(0.287)	(0.492)	(0.489)	(0.285)	(0.496)	(0.494)
Shock (T_{-1})*PC	-0.314	0.239	0.841*	-0.221	0.147	0.412
	(0.270)	(0.486)	(0.433)	(0.282)	(0.496)	(0.483)
Shock (T_{-2})*PC	0.047	-0.309	-0.164	0.170	0.017	0.075
	(0.271)	(0.466)	(0.414)	(0.260)	(0.499)	(0.423)
Shock (T_{+1})*PC	0.343	0.363	0.643	0.312	0.472	0.989**
	(0.292)	(0.436)	(0.463)	(0.296)	(0.458)	(0.481)
Shock (T_{+2})*PC	-0.340	0.530	-0.205	-0.018	0.386	-0.201
	(0.274)	(0.471)	(0.477)	(0.281)	(0.505)	(0.448)
Constant	80.665***	80.651***	79.960***	79.813***	79.683***	79.207***
	(3.944)	(3.950)	(3.924)	(3.955)	(3.959)	(3.930)
N	15,013	14,980	14,797	15,013	14980	14797
n	5,763	5,761	5,754	5,763	5,761	5,754
Overall R^2	0.12	0.1	0.1	0.06	0.07	0.1
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.3: Baseline estimation results where two indexes of community participation are the social capital measure used. Results are produced using the balanced panel, $n = 6,179$. N is person-year observations, n is the number of individuals included to produce estimation results. Standard errors are clustered at the individual level.

effect is nonetheless smaller than the direct effect estimated by (Milner et al., 2016) using a similar model.

The estimated impact of the shocks in table 5.4 is also similar to those found in tables 5.1 through 5.3, with the health-related shock producing the largest estimated impact. The observed impact of the leads and lags of the shock are also similar to those estimated for other measures of social capital.

Variable:	(1) Family	(2) Employment	(3) Health
Social Support	4.599***	4.337***	4.367***
	(0.141)	(0.119)	(0.123)
Shock (T_0)	-1.007***	-2.124***	-3.705***
	(0.118)	(0.220)	(0.216)
Shock (T_0)*Social Support	0.338***	1.224***	0.066
	(0.130)	(0.215)	(0.213)
Shock (T_{-1})	-0.444***	-1.091***	-1.008***
	(0.115)	(0.205)	(0.193)
Shock (T_{-2})	0.064	-0.564***	-0.093
	(0.114)	(0.192)	(0.182)
Shock (T_{+1})	-0.261**	-0.656***	-0.674***
	(0.115)	(0.195)	(0.195)
Shock (T_{+2})	-0.214*	-0.483***	-0.748***
	(0.113)	(0.186)	(0.200)
Shock (T_{-1})*Social Support	-0.314**	0.289	0.560***
	(0.123)	(0.204)	(0.194)
Shock (T_{-2})*Social Support	-0.233*	0.074	0.150
	(0.121)	(0.204)	(0.178)
Shock (T_{+1})*Social Support	-0.006	0.577***	0.328*
	(0.124)	(0.194)	(0.193)
Shock (T_{+2})*Social Support	0.179	0.396**	0.446**
	(0.119)	(0.192)	(0.202)
Constant	82.202***	82.462***	82.063***
	(8.832)	(8.828)	(8.799)
N	55778	55702	55065
n	5,924	5,921	5,922
Overall R^2	0.21	0.2	0.24
Wave Fixed Effects	Yes	Yes	Yes
Covariates	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.4: Baseline estimation results where social support is the social capital measure used. Results are produced using the balanced panel, $n = 6,179$. N is person-year observations, n is the number of individuals included to produce estimation results. Standard errors are clustered at the individual level.

Estimated coefficients on the interaction between the social support measure and the shock variables are statistically and economically significant for family and employment-related shocks. All else equal, a one standard deviation increase in the social support measure reduces the impact of a family-related shock by approximately 34%. Similarly, a one standard deviation increase in the social support measure decreases the impact of an employment related shock by 58%. In the year of onset, the buffering effect for a health-related shock is not statistically distinguishable from zero.

In table 5.4, I also identify a statistically and economically significant buffer effect for the one year lead of the employment shock. Here, a one standard deviation increase in the social support measure decreases the one year after-effect by approximately 88%. Moreover, I find a statistically significant buffering effect for the one year lag of the health shock which is approximately 56% the size of the estimated impact of the year prior to onset. I also observe significant coefficients for the leads of the family shock, however with negative coefficients. In all three specifications, the interaction coefficients with leads and lags are jointly significant at the 5% level.

Overall so far, I observe significant buffering effects primarily for the employment-related shock across most of the social capital variables used. To some extent, I also observed a slight buffering effect against a family-related shock - albeit the effect tends to be small, and nearly non-significant with the exception of the social support measure. The regression results described in the above tables will serve as the basis for the robustness checks and alternative specifications which follow.

5.2 Alternative specifications and sensitivity analyses

5.2.1 Transformations of the dependent variable

In the foregoing section, I provided estimated results using the untransformed MHI-5 score. Such an approach to estimation is recommended by Ware et al. (1993) in order to standardize measurement of effect sizes in psychology and epidemiology. Milner et al. (2016), who address a similar question to the present thesis, take the same approach reporting effect sizes in terms of MHI-5 points. However, given the potential difficulty with interpreting changes in the MHI-5 score with respect to clinical outcomes, in the following subsection I estimate my specification using two transformations of the dependent variable. These estimations will provide a more intuitive interpretation of the estimated effects observed in the previous section.

Firstly, I re-estimate my specification using the natural logarithm of the MHI-5 score. Consequently, the estimated coefficients of the social capital and shock variables may be interpreted in terms of percentage changes in the mental health score. Secondly, I estimate a linear probability model (LPM) using a binary dependent variable indicating whether individual i in wave t has an MHI-5 score under 60 points. As noted in section 3.2, an MHI-5 score below 60 is highly predictive of a common mental disorder (CMD). Coefficient estimates in the case of the binary dependent variable may then be interpreted as the change in the percentage likelihood of an individual being below the threshold score. The resulting estimates should therefore have a more clear clinical interpretation.

Tables 5.5 and 5.6 present the estimation results, where the MHI-5 mental health score has been transformed using the natural logarithm. Using this transformation, the estimated impact of a family related shock corresponds approximately to a 1-2% decline in the mental health score. An employment shock corresponds approximately to a 4-5% decline and a health shock to a 7-8% decline. These estimates appear to be consistent across the trust, social support, and community participation variables. For the reasons specified in the previous section, the estimated magnitudes of the shocks for club non-participators are slightly higher.

The estimated direct effect of being a participator in a club or association is an approximate 1.3% increase in the mental health score over those who do not participate, holding other factors constant. For the trust measure, the estimated impact of a one standard deviation change is an approximate 2.4% increase in the mental health score. For the social support measure, the same change is associated with a 7% increase, while for the first and second principal components the estimated increase is approximately 4.4% and 2.5% respectively.

As with the untransformed measure of mental health, I find economically and statistically significant estimates on the interaction between the shock variables and the social capital measures. As before, for the club participation measure, being a member of a club or association lessens the impact of a health shock from an 8% drop in the mental health score for non-participators to 5% drop. This change corresponds approximately to a 38% decrease in the impact of a health shock over non-participators. Similarly, for club participators, the estimated impact of an employment-related shock is reduced by 35%, while the impact of the family-related shock is reduced by 42%.

For the trust measure, as before, the only significant buffering effect is for the employment-related shock. A one standard deviation increase in the trust measure reduces the impact of the shock from -4.4% for those at the mean to -1.9%. For the social support measure, the interaction term is significantly different from zero for all three shocks. A one standard deviation change in the social support measure reduces the impact of the family-related and employment related shocks to a very small -0.6% and -0.7% in the mental health score respectively. Interestingly, for the log transformation of the mental health measure as opposed to the untransformed measure, a one standard deviation change in the social support variable decreases the impact of a health shock by approximately 20%.

SC measure:	Club participation			Trust measure			Social support measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable:	Family	Employment	Health	Family	Employment	Health	Family	Employment	Health
SC	0.014***	0.013***	0.010***	0.029***	0.024***	0.024***	0.076***	0.071***	0.069***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Shock (T_0)	-0.019***	-0.055***	-0.082***	-0.013***	-0.044***	-0.067***	-0.015***	-0.038***	-0.064***
	(0.003)	(0.007)	(0.006)	(0.003)	(0.006)	(0.006)	(0.002)	(0.004)	(0.004)
Shock (T_0)*SC	0.008*	0.019**	0.031***	0.002	0.025***	0.009	0.009***	0.031***	0.013**
	(0.004)	(0.009)	(0.008)	(0.004)	(0.008)	(0.007)	(0.003)	(0.005)	(0.005)
Shock (T_{-1})	-0.006**	-0.027***	-0.028***	-0.008***	-0.020***	-0.021***	-0.006***	-0.020***	-0.017***
	(0.003)	(0.006)	(0.006)	(0.003)	(0.006)	(0.005)	(0.002)	(0.004)	(0.004)
Shock (T_{-2})	0.001	-0.012**	-0.003	-0.001	-0.012**	-0.007	0.003	-0.009**	0.000
	(0.003)	(0.006)	(0.006)	(0.003)	(0.005)	(0.005)	(0.002)	(0.004)	(0.004)
Shock (T_{+1})	-0.003	-0.021***	-0.016***	-0.005*	-0.014***	-0.013**	-0.004*	-0.014***	-0.012***
	(0.003)	(0.005)	(0.006)	(0.003)	(0.005)	(0.006)	(0.002)	(0.004)	(0.004)
Shock (T_{+2})	-0.003	-0.014***	-0.019***	-0.001	-0.011**	-0.014**	-0.002	-0.007**	-0.013***
	(0.003)	(0.005)	(0.006)	(0.003)	(0.005)	(0.005)	(0.002)	(0.003)	(0.004)
Shock (T_{-1})*SC	-0.003	0.009	0.015*	-0.001	0.008	0.007	-0.004	0.009*	0.017***
	(0.004)	(0.008)	(0.008)	(0.004)	(0.007)	(0.006)	(0.003)	(0.005)	(0.005)
Shock (T_{-2})*SC	0.004	0.008	0.003	0.001	-0.005	0.004	-0.004	0.001	0.006
	(0.004)	(0.007)	(0.007)	(0.004)	(0.007)	(0.006)	(0.003)	(0.005)	(0.004)
Shock (T_{+1})*SC	-0.004	0.006	-0.001	-0.001	0.015**	0.009	0.001	0.012***	0.013***
	(0.004)	(0.007)	(0.007)	(0.004)	(0.006)	(0.007)	(0.003)	(0.004)	(0.005)
Shock (T_{+2})*SC	0.001	0.006	0.007	-0.002	0.002	0.009	0.002	0.011**	0.014***
	(0.004)	(0.007)	(0.008)	(0.003)	(0.006)	(0.007)	(0.003)	(0.005)	(0.005)
Constant	5.350***	5.383***	5.352***	5.807***	5.769***	5.825***	5.368***	5.390***	5.369***
	(0.160)	(0.159)	(0.157)	(0.173)	(0.173)	(0.172)	(0.156)	(0.155)	(0.154)
N	55,478	55,408	54,766	30,364	30,330	29,965	55,738	55,662	55,026
n	5,923	5,919	5,921	5,859	5,859	5,854	5,924	5,921	5,922
Overall R^2	0.05	0.04	0.09	0.00	0.00	0.00	0.23	0.21	0.25
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.5: Estimation results of the baseline specification across three measures of social capital where the dependent variable is $\ln(MH_{it})$. N is person-year observations, n is the number of individuals included to produce estimation results. Standard errors are clustered at the individual level.

	PC 1: Bridging			PC 2: Bonding		
	(1)	(2)	(3)	(4)	(5)	(6)
Variable:	Family	Employment	Health	Family	Employment	Health
SC	0.047***	0.044***	0.043***	0.025***	0.025***	0.024***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Shock (T_0)	-0.010*	-0.044***	-0.067***	-0.009*	-0.048***	-0.070***
	(0.005)	(0.010)	(0.009)	(0.005)	(0.010)	(0.009)
Shock (T_0)*SC	0.009	0.025**	0.007	0.003	0.002	0.002
	(0.006)	(0.010)	(0.010)	(0.006)	(0.010)	(0.011)
Shock (T_{-1})	-0.007	-0.029***	-0.022**	-0.007	-0.032***	-0.018**
	(0.005)	(0.010)	(0.009)	(0.005)	(0.010)	(0.009)
Shock (T_{-2})	-0.006	-0.015	-0.011	-0.006	-0.017*	-0.011
	(0.005)	(0.009)	(0.009)	(0.005)	(0.009)	(0.009)
Shock (T_{+1})	-0.014***	-0.016**	-0.009	-0.014***	-0.016**	-0.010
	(0.005)	(0.008)	(0.009)	(0.005)	(0.008)	(0.010)
Shock (T_{+2})	-0.009*	-0.010	-0.018*	-0.010**	-0.010	-0.016*
	(0.005)	(0.009)	(0.010)	(0.005)	(0.009)	(0.010)
Shock (T_{-1})*SC	-0.006	0.011	0.016*	-0.005	0.005	0.007
	(0.005)	(0.010)	(0.009)	(0.005)	(0.010)	(0.011)
Shock (T_{-2})*SC	-0.001	-0.003	0.003	0.003	0.003	0.001
	(0.005)	(0.010)	(0.009)	(0.005)	(0.010)	(0.010)
Shock (T_{+1})*SC	0.009	0.006	0.017	0.005	0.011	0.025**
	(0.006)	(0.009)	(0.010)	(0.006)	(0.009)	(0.012)
Shock (T_{+2})*SC	-0.005	0.009	0.002	-0.001	0.013	0.002
	(0.005)	(0.010)	(0.010)	(0.006)	(0.010)	(0.009)
Constant	5.457***	5.451***	5.448***	5.443***	5.435***	5.437***
	(0.071)	(0.071)	(0.071)	(0.072)	(0.071)	(0.071)
N	15,004	14,971	14,788	15,004	14,971	14,788
n	5,763	5,761	5,754	5,763	5,761	5,754
Overall R^2	0.8	0.09	0.11	0.04	0.05	0.08
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.6: Estimation results of the baseline specification across two measures of social capital where the dependent variable is $\ln(MH_{it})$. N is person-year observations, n is the number of individuals included to produce estimation results. Standard errors are clustered at the individual level.

For the community participation principal components, the only significant interaction effect is for the first principal component with respect to the employment-related shock. A one standard deviation increase in bonding social capital reduces the impact of an employment related shock by approximately 57%.

Tables 5.7 and 5.8 present estimation results where the dependent variable is a binary indicator equal to one if the MHI-5 mental health score is below the cut-off of 60 points. In this specification, a family-related shock increases the chance of falling below the cut off by approximately 1.5%, however the shock does not appear to be significantly different from zero across all estimations. The estimated effect of an employment-related shock on the other hand is an approximate 5% increase in the likelihood of being below the cut-off holding other factors constant. This effect is consistent and significant across the estimations. Similarly, a health-related shock is estimated to increase the likelihood of being below the threshold by approximately 7%.

In the binary dependent variable specification, the direct effect of the social capital measures is to decrease the likelihood of being below the cut-off value. All else equal, becoming a member of a club or association is estimated to decrease the likelihood of being below the cut-off value by 1.2-1.7% over those who are not participants. A one standard deviation increase in the trust measure is estimated to decrease the likelihood of being below the threshold by approximately 3%. For a similar change, the social support measure, the estimated decrease in likelihood is approximately 9%. For the first and second principal components of community participation, the decrease in likelihood is estimated to be approximately 4.5% and 3.8% respectively. The direct effects are significant at the 1% level for all measures, with the exception of the clubs measure where it is significant in one of the estimations at the 5% level.

The buffering effect for the specification with a binary dependent variable may be interpreted as the reduction in the impact of the shock on the likelihood of being below the cut-off for different levels of social capital. For example, in table 5.5, I observe that the increase in likelihood of being below the threshold after a health shock decreases from 9.3% to 5.1% for club participators over non-participators in the year of onset. I also observe that being a club participator reduces the impact of a family-related shock from a 2.5% increase in likelihood to a 0.7% increase.

The estimated coefficients in tables 5.5 and 5.6 are otherwise similar to the estimation results produced using the untransformed measure. Compared to the mean, a one standard deviation increase in the trust measure reduces the impact of an employment-related shock from a 5% increase in likelihood to a 3.3% increase, but is not significantly difference from zero for the other types of shocks. A one standard deviation increase in the social support measure also reduces the impact of an employment shock to approximately 2.6% compared to the mean, and roughly halves the impact of a family-related shock. For the community participation variables on the other hand, I find no significant buffering effects and estimated coefficients have very small magnitudes.

As in the case of the baseline specification, I do not observe much buffering in the

SC measure:	Club participation			Trust measure			Social support measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable:	Family	Employment	Health	Family	Employment	Health	Family	Employment	Health
SC	-0.012**	-0.019***	-0.017***	-0.033***	-0.030***	-0.030***	-0.092***	-0.087***	-0.088***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
Shock (T_0)	0.025***	0.059***	0.093***	0.012**	0.050***	0.070***	0.016***	0.045***	0.070***
	(0.005)	(0.008)	(0.008)	(0.005)	(0.009)	(0.008)	(0.003)	(0.006)	(0.006)
Shock (T_0)*SC	-0.018***	-0.019	-0.042***	0.007	-0.017**	-0.010	-0.009**	-0.019***	-0.005
	(0.006)	(0.012)	(0.012)	(0.005)	(0.008)	(0.008)	(0.004)	(0.005)	(0.005)
Shock (T_{-1})	0.007	0.032***	0.023***	0.005	0.026***	0.026***	0.006	0.031***	0.020***
	(0.005)	(0.008)	(0.008)	(0.005)	(0.008)	(0.008)	(0.003)	(0.006)	(0.005)
Shock (T_{-2})	0.003	0.016**	0.010	0.003	0.012	0.011	0.000	0.011**	0.005
	(0.004)	(0.007)	(0.008)	(0.005)	(0.008)	(0.008)	(0.003)	(0.005)	(0.005)
Shock (T_{+1})	0.005	0.019**	0.009	0.011**	0.017**	0.013	0.007**	0.012**	0.013**
	(0.005)	(0.008)	(0.008)	(0.005)	(0.008)	(0.008)	(0.003)	(0.005)	(0.006)
Shock (T_{+2})	0.011**	0.005	0.017**	0.008*	0.011	0.014*	0.004	0.007	0.017***
	(0.005)	(0.007)	(0.008)	(0.005)	(0.008)	(0.008)	(0.003)	(0.005)	(0.006)
Shock (T_{-1})*SC	0.001	0.007	0.000	0.004	-0.001	-0.005	0.008**	-0.008	-0.006
	(0.006)	(0.012)	(0.011)	(0.005)	(0.008)	(0.007)	(0.003)	(0.005)	(0.005)
Shock (T_{-2})*SC	-0.007	-0.012	-0.007	-0.004	0.004	0.006	0.007*	0.000	0.002
	(0.006)	(0.011)	(0.010)	(0.005)	(0.008)	(0.007)	(0.003)	(0.006)	(0.005)
Shock (T_{+1})*SC	0.006	-0.003	0.016	-0.005	-0.016*	-0.009	0.002	-0.010**	-0.003
	(0.006)	(0.011)	(0.011)	(0.005)	(0.008)	(0.008)	(0.003)	(0.005)	(0.005)
Shock (T_{+2})*SC	-0.014**	0.017	0.006	0.003	0.012	0.006	-0.005	-0.008	-0.008
	(0.006)	(0.011)	(0.011)	(0.005)	(0.008)	(0.008)	(0.003)	(0.005)	(0.005)
Constant	-0.002	0.036	0.021	-0.264	-0.314	-0.343	0.037	0.072	0.059
	(0.272)	(0.273)	(0.272)	(0.286)	(0.286)	(0.285)	(0.269)	(0.270)	(0.269)
N	55,654	55,579	54,931	30,491	30,451	30,087	55,978	55,899	55,256
n	5,924	5,920	5,921	5,859	5,859	5,854	5,925	5,922	5,920
Overall R^2	0.00	0.01	0.01	0.00	0.00	0.01	0.12	0.13	0.15
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.7: Estimation results for the baseline specification where the dependent variable is a binary indicator variable equal to 1 if the individual scores below 60 points. N is person year observations, n is the number of individuals within the data. Standard errors are clustered at the individual level.

	PC 1: Bridging			PC 2: Bonding		
	(1)	(2)	(3)	(4)	(5)	(6)
Variable:	Family	Employment	Health	Family	Employment	Health
PC	-0.043***	-0.045***	-0.045***	-0.039***	-0.038***	-0.037***
	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)	(0.005)
Shock (T_0)	0.009	0.046***	0.072***	0.007	0.050***	0.075***
	(0.008)	(0.015)	(0.013)	(0.008)	(0.015)	(0.013)
Shock (T_0)*PC	-0.011	-0.013	-0.008	-0.005	0.009	-0.002
	(0.008)	(0.014)	(0.013)	(0.007)	(0.015)	(0.013)
Shock (T_{-1})	-0.001	0.041***	0.028**	-0.002	0.041***	0.024*
	(0.008)	(0.014)	(0.013)	(0.008)	(0.014)	(0.013)
Shock (T_{-2})	0.012	0.021	0.021	0.011	0.021	0.020
	(0.008)	(0.014)	(0.013)	(0.008)	(0.014)	(0.013)
Shock (T_{+1})	0.018**	0.035***	-0.003	0.018**	0.036***	-0.003
	(0.008)	(0.013)	(0.012)	(0.008)	(0.013)	(0.012)
Shock (T_{+2})	0.016*	0.021	0.018	0.016**	0.020	0.017
	(0.008)	(0.014)	(0.014)	(0.008)	(0.014)	(0.014)
Shock (T_{-1})*PC	0.010	0.010	-0.005	0.004	-0.014	-0.011
	(0.008)	(0.015)	(0.012)	(0.008)	(0.013)	(0.012)
Shock (T_{-2})*PC	-0.007	0.004	0.005	-0.003	-0.020	-0.010
	(0.008)	(0.013)	(0.012)	(0.007)	(0.013)	(0.011)
Shock (T_{+1})*PC	-0.006	-0.010	-0.006	-0.012	0.001	0.000
	(0.008)	(0.013)	(0.013)	(0.008)	(0.013)	(0.012)
Shock (T_{+2})*PC	0.001	-0.020	0.000	0.009	-0.008	-0.001
	(0.008)	(0.013)	(0.013)	(0.007)	(0.013)	(0.012)
Constant	0.147	0.122	0.135	0.169	0.154	0.154
	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)
N	15,043	15,009	14,827	15,043	15,009	14,827
n	5,764	5,762	5,756	5,764	5,762	5,756
Overall R^2	0.06	0.07	0.08	0.04	0.04	0.06
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.8: Estimation results for the baseline specification where the dependent variable is a binary indicator variable equal to 1 if the individual scores below 60 points. N is person year observations, n is the number of individuals within the data. Standard errors are clustered at the individual level.

anticipation or after effects of the shocks, with the exception of the social support variable exhibiting a significant buffering effect for the year after an employment-related shock. As well, the club participation measure demonstrates a buffering effect for the second year after a family-related shock.

For a binary dependent variable, there are two primary concerns when using a linear probability model instead of a non-linear model such as a probit or a logit. Firstly, the linear probability model does not ensure that that predicted probabilities of being under the cutoff stay between zero and one. To address this concern, I calculate the predicted probabilities for each of the estimations in tables 5.5 and 5.6 and find the proportion of the predicted probabilities below zero. For the club participation and community participation variables, less than 1% of the predicted probabilities for each estimation fall below zero. For the social support variable approximately 1-2% fall below zero, whereas for the trust measure, approximately 7-10% fall below zero. Therefore for most of my estimations, an LPM is not inappropriate based on predicted probabilities. The second concern is that by construction linear probability models are heteroskedastic. To address this, as noted in section 4.2 standard errors in all estimations are cluster-robust, implying they are robust both to clustering and to heteroskedasticity.

5.2.2 Instrumental variables estimation

As noted in section 4.1, a primary concern when estimating the current specification is that the social capital measures used may not satisfy the condition of exogeneity. That is, in model 4.2, the time-varying component of social capital ($\ddot{SC}_{it}$) may be associated with error term ($\ddot{\mu}_{it}$) such that $Cov(\ddot{SC}_{it}, \ddot{\mu}_{it}) \neq 0$, leading to inconsistent estimation of the direct and buffering effects of social capital. A violation of exogeneity may either be due to omitted unobservables associated with the social capital process, such as one's friends or associates moving neighbourhoods, or through simultaneity bias due to reverse causality from mental health. One approach to generating consistent estimates of the effect of social capital is to use instrumental variables and then estimate using two-stage least-squares (2SLS). This approach however requires identifying a time-varying instrument ($\ddot{I}_{it}$) that satisfies conditions of relevancy ($Cov(\ddot{SC}_{it}, \ddot{I}_{it}) \neq 0$) and exogeneity ($Cov(\ddot{\mu}_{it}, \ddot{I}_{it}) = 0$).

In the context of social capital and health, particularly in epidemiological studies, the use of instrumental variables to overcome endogeneity in social capital is not common. However, a parcel of recent studies from the health economics literature have attempted the use of instruments to identify the effect of social captial on general health (d'Hombres et al., 2010; Rocco et al., 2014; Ronconi et al., 2012). Ronconi et al. (2012) and Rocco et al. (2014) use items related to public transport and health care density as instruments for social capital. Such data are unavailable as part of HILDA, nor are these factors which vary much over time, which makes them unsatisfactory in the context of fixed effects estimation. However, d'Hombres et al. (2010) proposes using the aggregate level of social capital within a community as an instrument for individual-level social capital. The argument for using such an instrument is based on previous studies' findings that community-level social capital only affects health through influencing individual level social capital. A simultaneous equations study by (Rocco et al., 2014) confirms this relationship by finding little direct effect of community level trust on health.

While the aggregate of the social capital variables is an available instrument in the HILDA survey, there are a number of factors which make its use unappealing. Firstly, the average of the social capital variables at any geographic level does not tend to vary much over time, as noted in section 3.3, which leaves little information with which to conduct a fixed effects regression. Moreover, estimating the effect of aggregate social capital on individual outcomes poses identification problems related to the Manski (1993) reflection problem as elaborated by Durlauf (2002).

Therefore instead of an aggregate measure, I propose to conduct a 2SLS estimation using a lag of the social capital variable as an instrument. This instrument is likely to be associated with the contemporary level of social capital as social bonds once developed may take more than a year to break. Moreover, the lag cannot be determined by the contemporary level of the mental health score and should only affect contemporary mental health through its association with contemporary social capital. This variable therefore plausibly satisfies the conditions of relevance and exogeneity. The downside of using this instrument is that it is only available for the social capital measures available in every wave of HILDA - club participation and social support. Despite this, instrumental variable estimation using these two variables should provide an idea of the extent of reverse causality or endogeneity in the social capital process.

For the two stage least squares estimation, I simplify the main regression equation (4.1) by excluding the interactions with the leads and lags of the shock variable. This simplification may be fair given that the interactions do not tend to be significant for most specifications. After this simplification, the structural equation may be stated as

$$MH_{it} = \alpha_i + \lambda_t + \beta SC_{it} + \sum_{k=-l}^{l} \gamma_k x_{i,t+k} + \delta(x_{it} \times SC_{it}) + Z'_{it}\theta + \mu_{it}. \tag{5.1}$$

Under the assumption that both the shock variable x_{it} and the instrument I_{it} are exogenous, a suitable instrument for the interaction term $x_{it} \times SC_{it}$ is the interaction between the exogenous instrument and the shock ($x_{it} \times I_{it}$). The two first stage regression equations are then

$$SC_{it} = \pi_{01} + \pi_{11} \sum_{k=-l}^{l} x_{i,t+k} + Z'_{it}\pi_{21} + \pi_{31} I_{it} + \pi_{41}(x_{it} \times I_{it}) + v_{it,1}$$

and

$$(SC_{it} \times x_{it}) = \pi_{02} + \pi_{12} \sum_{k=-l}^{l} x_{i,t+k} + Z'_{it}\pi_{22} + \pi_{32} I_{it} + \pi_{42}(x_{it} \times I_{it}) + v_{it,2}.$$

The linear projections of each endogenous variable are then used to conduct the second stage estimation in a fixed effects regression. Note that in the second stage I do not substitute the predicted values of social capital variable SC_{it} into the interaction term in equation (5.1). This is to avoid a 'forbidden regression' (Wooldridge, 2001, p.236).

The first and second stage regression results for 2SLS using the lagged social capital instrument are provided in table 5.9. From the first stage regression results we may assess the relevancy of the two instruments. In panel 1 of table 5.9, for both the social support and club participation measures the estimated coefficient of the lagged measure is statistically significant at the 1% level. This indicates that the lagged social capital instrument most likely satisfies the condition of relevancy. However, the second instrument is not statistically significant across estimations in panel 1, with the exception of the clubs measure with respect to an employment-related shock. This is to some extent expected if the shocks are assumed not to co-determine social capital. The F statistics of the excluded instruments in panel 1 exceed the rule-of-thumb value of 11, suggesting that jointly they are not weak instruments.

In the second first-stage regression in panel 2 of table 5.9, I again observe that the estimated coefficients of the instruments are statistically significant at the 1% level. This result suggests again that the interaction instrument satisfies the relevancy condition with respect to the interaction between the shock and contemporary social capital. Like panel 1, the F-statistic of the excluded instruments is above 11, suggesting the instruments are not weak. However, on inspecting the first-stage partial-R^2 of the instruments, I find that the lagged social capital variables appear to explain very little of the variation in the endogenous variables once other factors have been partialled out. This suggests that the lagged social capital instrument may be weak. Consequently, we may expect any inconsistency in the 2SLS estimator to be amplified.

In panel 3 of 5.9, I provide the second stage estimation results. Interestingly, I see an unexpected contrast between the club participation measure and the social

Variable:	Club participation: Family	Employment	Health	Social support measure: Family	Employment	Health
	Panel 1: First stage, dependent variable is SC_{it}					
$SC_{i,t-1}$	0.135***	0.138***	0.135***	0.069***	0.071***	0.068***
	(0.007)	(0.007)	(-0.012)	(0.006)	(0.006)	(0.006)
$SC_{i,t-1}$*Shock (T_0)	0.004	-0.027**	-0.012	-0.001	-0.012	-0.006
	(0.008)	(0.013)	(0.012)	(0.007)	(0.012)	(0.011)
F-stat of excluded instruments	194***	197***	188***	63***	65***	60***
	Panel 2: First stage, dependent variable is SC_{it}* Shock (T_0)					
$SC_{i,t-1}$	-0.117***	-0.034***	-0.042***	-0.160***	-0.055***	-0.066***
	(0.003)	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)
$SC_{i,t-1}$*Shock (T_0)	0.599***	0.561***	0.574***	0.674	0.656***	0.661***
	(0.008)	(0.015)	(0.014)	(0.008)	(0.014)	(0.012)
F-stat of excluded instruments	4140***	1558***	1949***	4383***	1677***	2098***
Partial R^2 of $SC_{i,t-1}$	0.019	0.019	0.018	0.005	0.005	0.005
Partial R^2 of $SC_{i,t-1}$*Shock (T_0)	0.311	0.302	0.317	0.397	0.412	0.415
	Panel 3: Second stage, dependent variable is MHI-5 score					
SC_{it}	-0.675	-0.472	-0.435	14.962***	14.871***	15.127***
	(1.053)	(1.04)	(1.063)	(1.523)	(1.501)	(1.566)
Shock	-1.081***	-2.872***	-5.031***	-0.996***	-1.590***	-3.283***
	(0.220)	(0.423)	(0.398)	(0.136)	(0.271)	(0.251)
SC_{it}*Shock	0.1	0.817	2.627***	0.355*	1.505***	-0.385
	(0.380)	(0.807)	(0.740)	(0.215)	(0.396)	(0.373)
Kleibergen-Paap Wald F statistic	194.22	195.02	187.27	62.49	63.85	59.36
Stock and Yogo 10% critical value	7.03	7.03	7.03	7.03	7.03	7.03
N	54,972	54,911	54,270	55,546	55,472	54,840
n	5,813	5,813	5,810	5,818	5,819	5,816

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.9: Estimation results from first stage and second stage of a 2SLS procedure. Dependent variable is the untransformed MHI-5 the mental health score. N is person-year observations, n is the number of individuals within the data. Standard errors are cluster-robust at the individual level.

support measure regarding the estimated direct effect. I fail to find a statistically or economically significant estimate of the direct effect for the club participation measure. This stands in contrast to the results of the baseline specification.

On the other hand, the estimated direct effect of the social support measure is statistically significant and much larger than the baseline regression estimates. Given that the partial-R^2 of the lagged social capital instrument is very low, I expect the 2SLS estimate of the direct effect of social support to be inflated due to a weak instrument.

However, while the estimated main effect is very different from the baseline specification, the estimated buffering effect is similar. For the club participation measure, I do not observe a buffering effect with respect to family or employment-related shocks, however I do observe an economically and statistically significant estimate with respect to the health shock. Likewise, for the social support measure, I fail to find a buffering effect for a health shock, but as in the baseline specification, I find a significant buffering effect with respect to the employment and family-related shocks. I note, however, that the magnitude of the estimated buffering effect for social support on an employment shock appears to be very large relative to the shock. This again may be due to a weak instrument amplifying any inconsistency.

As part of table 5.9, I provide the test statistic and critical value for a Stock and Yogo (2005) test of weak identification. For each of the estimations in table 5.9, there appears to be sufficient evidence to reject the null hypothesis that the instruments are weak. However, this result may be due to the strength of the instrument for the interaction term and not the lag of social capital.

Aside from a weak instrument, there are other limitations to the present estimation. Firstly, in interacting the instrument with the shock term, I have made the assumption that the shocks are exogenous. Given the results of the balance of covariates in section 3.4, I have attempted to control for a number of observable factors which may be associated with selection into treatment. However, if there is selection on unobservables, assuming the exogeneity of the shocks may still be problematic. Secondly, inference is threatened if the lagged social capital variable does not satisfy the condition of exogenity. This may be the case if individuals change their level of social capital in anticipation of the shock occurring. Such an intertemporal relationship between social capital and mental health would require the use of a more complex dynamic model and would be an interesting avenue for future study.

Overall, however, in finding a significant buffering effect using a presumably exogenous instrument, I believe there is evidence to suggest that the effects observed in the baseline and other specifications are not entirely driven by reverse causality. Due to the potential weakness of the instruments, interpreting magnitudes in this 2SLS specification may not be very informative. However, at a minimum the results in table 5.9 suggest the presence of some buffering effect of social capital on mental health.

5.2.3 Balanced versus unbalanced data sets

The HILDA survey, like many longitudinal surveys, faces the threat of attrition over time. As noted in section 3, only 65% of the original wave one sample of HILDA have been present in every wave up until the most recent. Attrition may be a concern if observations in the unbalanced panel are not missing completely at random (MCAR) (Rubin, 1976). Otherwise, if the process by which an individual's observations become missing (denoted r_{it}) is associated with the random error term ($\ddot{\mu}_{it}$ from equation (4.2)), there may be selectivity bias present in the fixed effects coefficient estimators. Formally, from Verbeek and Nijman (1992), the required assumption for consistent estimation in the presence of selection is that

$$\mathbb{E}[\ddot{\mu}_{it}|r_i] = 0.$$

In describing a more formal test for selectivity bias, Verbeek and Nijman (1992) note that a within estimator may be robust to selectivity bias if it's the case that the selection process is associated with the unobserved individual-specific heterogeneity (α_i in model (4.1)). This is a potential argument in favour of using a fixed effects estimator.

The assumption of selection's independence of the transformed error term is difficult to assess. As a less formal assessment, I provide a balance of covariates between those individuals in the 'balanced' panel against those who at some point leave the data set. I also compare the individuals in the fully balanced panel, including no missing responses, against those who have some missing responses in the balanced panel. In table 5.10, I observe that there is a statistically significant difference between those who leave the sample and those in the balanced panel for most covariates. Important to note, however, is that few of these differences are economically significant - the statistical significance of the difference is most likely driven by the large number of person-year observations. Of the economically significant differences, those who leave the sample tend to have a slightly lower mental health score with an approximate 2 point difference, are younger, more likely to be foreign born, slightly less likely to part of a couple or have children, and also have slightly higher income. Those who leave are also less likely to participate in clubs compared to the balanced panel, will have slightly less bonding social capital, and less trust. However, again the differences are economically small.

With respect to the fully balanced panel in table 5.11, those who have incomplete responses also have slightly lower mental health score with a 2 point difference between groups, are less educated, less likely to be part of a couple, are less

Variable:	Left sample	Balanced sample	t-stat
Age	44.99	50.09	-64.20***
Female	0.53	0.55	-8.91***
MHI-5 score	73.28	75.18	-22.83***
Foreign born	0.25	0.22	17.95***
Highest level of education:			
High school	0.14	0.13	7.62***
Primary	0.32	0.32	0.58
Tertiary certificate	0.31	0.31	-3.34***
University	0.24	0.24	-3.09**
Couple	0.64	0.7	-29.64***
Has children	0.33	0.36	-15.67***
Unemployed	0.04	0.02	24.29***
Out of labour force	0.34	0.34	4.27***
Household income (000s)	79.69	78.65	3.26**
Family shock	0.25	0.25	0.48
Emp. shock	0.09	0.08	5.80***
Health shock	0.11	0.1	10.96***
Bridging	-0.06	0.11	-14.84***
Bonding	0	-0.04	3.84***
Social support	-0.05	0.02	-14.90***
Trust	-0.05	0.08	-15.70***
Club participator	0.34	0.41	-27.72***
N	92,079	98,864	190,943

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.10: Balance of covariates comparing those individuals who left the HILDA sample against those who are present in the balanced sample without full SCQ responses. N is person-year observations. t-stat in column 3 is for a test of the significance of the difference in means between groups.

wealthy, and slightly more prone to shocks. Overall from the balance of covariates, we might conclude that the persons who leave the sample are systematically different from those who stay.

However, as a second informal assessment of the extent of any bias from selection, I estimate the baseline specification using the unbalanced panel, as well as the fully balanced panel. The results are provided in the appendix in tables B.6 and B.7 for the unbalanced panel, and tables B.8 and B.9 for the fully balanced panel. Despite statistically significant differences in the balance of covariates, estimating the model using either the fully balanced or unbalanced panels produces remarkably similar coefficient estimates to the baseline specification. The magnitudes of the estimates between panels are rarely more than 0.3 of an MHI-5 point away from one another. This is particularly the case for the direct and buffering effects of social capital. The only major difference between the

Variable:	Part response	Full response	t-stat
Age	49.72	50.76	-10.52***
Female	0.55	0.54	2.60**
MHI-5 score	74.26	76.71	-21.97***
Foreign born	0.22	0.21	5.27***
Highest level of education:			
High school	0.13	0.12	5.42***
Primary	0.34	0.28	17.67***
Tertiary certificate	0.31	0.32	-2.15*
University	0.22	0.28	-20.27***
Couple	0.68	0.75	-24.15***
Has children	0.36	0.37	-3.80***
Unemployed	0.02	0.02	8.57***
Out of labour force	0.35	0.31	11.35***
Household income (000s)	74.91	85.49	-22.52***
Family shock	0.26	0.24	7.19***
Emp. shock	0.09	0.07	10.08***
Health shock	0.11	0.09	10.01***
'Bridging'	-0.03	0.03	-3.86***
'Bonding'	-0.05	0.04	-6.24***
Social support	-0.04	0.07	-16.08***
Trust	-0.07	0.06	-12.44***
Club participator	0.4	0.43	-8.66***
N	63,895	34,969	98,864

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.11: Balance of covariates comparing those individuals who gave responses to the SCQ in every wave of HILDA against those who failed to do so. N is person-year observations. t-stat in column 3 is for a test of the significance of the difference in means between groups.

estimations in this informal eyeball test is the change in significance for some of the buffering effects when using the unbalanced panel. This is expected in part simply because of the larger N in the unbalanced panel. The absence of major differences in the estimated coefficients across panels may therefore suggest robustness from selection, possibly through the mechanism suggested above by Verbeek and Nijman (1992).

To assess the consistency of coefficient estimates in the presence of selection bias, Verbeek and Nijman (1992) also suggest a more formal Hausman-type test between the estimated coefficients of the balanced data set and the estimated coefficients of the unbalanced data set. To attempt implementing this test, I save the estimates from the balanced and unbalanced regressions, and then conduct Hausman test where the balanced estimates are assumed to be consistent under the null hypothesis. If there is sufficient evidence to reject the null hypothesis, this may suggest the presence of possible selectivity bias in the estimates. The p-values for these tests provided in tables B.6 and B.7 assume the balanced panel under the null is the data set without all SCQ responses. In tables B.8 and B.9 the fully balanced panel is assumed to have consistent estimates. I find using this test that I tend to reject the null hypothesis, suggesting selectivity bias. However, the test statistic appears to be very sensitive to the covariates included within the model. For example, excluding wave-specific fixed effects in some cases leads to a failure to reject the null hypothesis.

Despite this more formal test, I remain confident that the extent of potential biasing from selectivity remains small within the model. This is evidenced by the minor differences between panel groups, and in the very minor differences between estimated coefficients for the varying types of panels. Overall, none of these differences would lead me to different qualitative conclusions from the baseline specification.

5.2.4 Disaggregating shocks

For the baseline specification, I have aggregated the life event indicators into three broad groups to simplify analysis and to improve sample size with respect to the shock indicators. The downside of doing so is the loss of more granular information about the impact of significant life events and extent to which their effects are buffered by social resources. Therefore, repeating estimations for each of the life events individually should provide an idea of the life events which drive the effects I observed during baseline estimation. Moreover, as noted in section 3.4 when conducting the balance of covariates, there exist some significant differences in observables between treated and non-treated groups when using the aggregated shock indicators. Disaggregating the shocks should reveal the extent of a buffering effect for the life events which are arguably more exogenous. Therefore, for each of the social capital measures, I re-estimate the baseline specification for all 9 significant life events, including their leads and lags. For each of these estimations, it is important to note the per-wave frequency of the events given in table B.4, as low event frequency may lead to imprecise estimation. The results of estimation are provided in appendix B, tables B.10 through B.14.

With respect to the family-related shocks, the death of a spouse or child has an expectedly large estimated impact of approximately 5.5 points on the MHI-5 scale throughout estimations. If estimation results from the level and log mental health scores are comparable, this may correspond to an approximate 5-10% decrease in the mental health score. I fail to observe a statistically significant buffering effect for this type of shock using any of the social capital measures, with the exception of the first community participation principal component. Here, a one standard deviation increase in the community participation measure decreases the impact of the shock by approximately 58%.

The death of a close friend, on the other hand, does not appear to have as strong an effect on the mental health score. This shock is only statistically significant when estimated using the social support and club participation measures where there is the largest number of observations available. The economic significance of the effect is also small at less than one point on the MHI-5 scale. There does not appear to be a statistically significant buffering effect for this shock for any measure of social capital, except the first principal component at the 10% significance level. Interestingly, the coefficient of the interaction term is greater than the shock in magnitude, however the 95% confidence interval is wide, and contains the absolute value of the shock coefficient.

Similarly, being the victim of a property crime does not have a large estimated effect on the mental health. Estimated coefficients are between 0.4 and 0.7 of a point. Moreover, there does not appear to be a significant buffering effect, except for social support where the size of the buffer is nearly the same magnitude as the estimated impact of the shock.

Lastly, the event 'death of a close relative or family member' has an estimated impact of approximately 1 point on the MHI-5 scale across estimations. This is reflective of the estimated impact of the aggregated family-related shock indicator observed during baseline estimation. If the death of a close friend does not produce a statistically or economically significant impact, and the death of a spouse or child is infrequent, then the death of a family member may be primarily driving the effects observed in the baseline estimation. This may be plausible as well given the high frequency of the shock as seen in table B.4. Despite the impact of the shock, only the interaction with the social support variable produces a statistically significant buffering effect at approximately 30% the size of the shock.

For the employment-related shocks, having a major worsening of finances is estimated to cause a large 6-7 point decline in the mental health score, while the impact of being fired is estimated to be between 1.5 to 2 points on the MHI-5 scale. For a major worsening in finances, I observe a buffering effect for the social support and club participation measures, while for the effect of being fired I only observe a significant effect for the social support measure. Retirement on the other hand does not seem to produce a statistically significant effect on the mental health score. Consequently, there is no estimated buffering effect with respect to retirement. Therefore it appears to be that a major worsening in finances and being fired are the primary drivers of the effect observed for the employment-related shock.

With respect to the health related shocks, both a serious injury or illness and being the victim of a violent crime produce a large and significant effect on the mental health score. The estimated impact of injury or illness is approximately 3-4 points on the MHI-5 scale, while the estimated impact of crime victimization is larger at approximately 5-7 points. As in the baseline specification, I fail to observe a statistically significant buffering effect for any measures with respect to the shocks, with the exception of club participation. Participation in a club or association is estimated to reduce the impact of an injury or illness by approximately 36% over non-participators. Similarly, the estimated reduction in impact for a violent crime is 38%. However this effect is only significant at the 10% level.

As in the baseline specification, throughout estimations, I find little evidence of any buffering effect for the leads and lags of the shocks for most social capital measures. Again the exception is the social support measure, where I observe similar buffer effects for employment-related shocks in the two years after onset. Moreover, I also observe the same negative interaction coefficient for the one year lead for the death of a friend.

5.2.5 Using the working age subsample

In conducting my estimation, I am concerned that heterogeneous treatment effects within the sample may strongly influence the average effect estimate I have produced when reporting my baseline regression results. In particular, approximately 25% of the sample in the balanced panel is over the age of 60. As Glaeser et al. (2002) note in their economic model of social capital, age is significantly related to the rate of investment into social capital. Moreover, different mechanisms may underlie the interaction between mental health and social capital for the young and the old due to effects from schooling and retirement (Almedom and Glandon, 2008). Differences in mechanisms may therefore affect the average estimates of the direct and buffering effects if a large proportion of the population is at retirement age or still in school. For this reason, it is of interest to re-estimate the model using the sub-sample of working age persons between the ages of 25 and 60.

Tables 5.12 and 5.13 present estimation results for the baseline specification

SC measure:	Club participation			Trust measure			Social support measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable:	Family	Employment	Health	Family	Employment	Health	Family	Employment	Health
SC	0.804***	0.719***	0.770***	2.081***	1.878***	1.878***	5.279***	5.008***	5.076***
	(0.237)	(0.194)	(0.194)	(0.202)	(0.167)	(0.172)	(0.176)	(0.154)	(0.158)
Shock (T_0)	-1.290***	-3.496***	-4.736***	-0.930***	-2.821***	-4.093***	-1.131***	-2.533***	-3.893***
	(0.215)	(0.415)	(0.375)	(0.221)	(0.450)	(0.414)	(0.155)	(0.306)	(0.288)
Shock (T_0)*SC	0.369	0.810	1.667***	0.073	1.091**	0.175	0.381**	1.397***	0.035
	(0.304)	(0.622)	(0.572)	(0.235)	(0.441)	(0.420)	(0.171)	(0.284)	(0.287)
Shock (T_{-1})	-0.485**	-1.934***	-1.732***	-0.451**	-1.360***	-1.729***	-0.430***	-1.402***	-1.262***
	(0.201)	(0.391)	(0.360)	(0.205)	(0.423)	(0.378)	(0.146)	(0.286)	(0.256)
Shock (T_{-2})	-0.125	-0.705**	-0.510	0.048	-0.788**	-0.575	-0.010	-0.572**	-0.177
	(0.196)	(0.345)	(0.348)	(0.214)	(0.377)	(0.376)	(0.145)	(0.252)	(0.249)
Shock (T_{+1})	-0.322	-1.147***	-0.693*	-0.456**	-0.606	-0.863**	-0.333**	-0.591**	-0.733***
	(0.208)	(0.369)	(0.354)	(0.221)	(0.395)	(0.386)	(0.151)	(0.271)	(0.271)
Shock (T_{+2})	-0.194	-0.973***	-0.844**	-0.052	-0.860**	-0.531	-0.168	-0.498*	-0.582**
	(0.199)	(0.342)	(0.378)	(0.213)	(0.379)	(0.369)	(0.145)	(0.255)	(0.269)
Shock (T_{-1})*SC	-0.025	0.720	0.434	0.051	-0.100	0.397	-0.238	0.464*	0.681***
	(0.295)	(0.592)	(0.531)	(0.239)	(0.411)	(0.377)	(0.161)	(0.261)	(0.261)
Shock (T_{-2})*SC	0.271	0.460	0.331	0.111	-0.111	0.314	-0.114	0.150	0.341
	(0.286)	(0.538)	(0.498)	(0.226)	(0.382)	(0.389)	(0.156)	(0.264)	(0.240)
Shock (T_{+1})*SC	-0.097	0.397	-0.908*	-0.183	1.101***	0.236	-0.044	0.821***	0.310
	(0.301)	(0.552)	(0.531)	(0.256)	(0.388)	(0.387)	(0.166)	(0.255)	(0.256)
Shock (T_{+2})*SC	0.095	0.562	0.091	0.080	-0.206	0.545	0.210	0.419*	0.450*
	(0.298)	(0.523)	(0.528)	(0.236)	(0.388)	(0.378)	(0.155)	(0.250)	(0.265)
Constant	86.547***	87.692***	85.921***	103.521***	102.493***	102.179***	81.560***	82.231***	80.534***
	(9.974)	(9.961)	(9.919)	(10.631)	(10.643)	(10.583)	(9.691)	(9.687)	(9.652)
N	37,493	37,426	37,141	20,510	20,470	20,304	37,637	37,567	37,280
n	4,713	4,717	4,708	4,551	4,554	4,537	4,715	4,719	4,710
Overall R^2	0.02	0.03	0.05	0.04	0.05	0.06	0.25	0.26	0.28
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.12: Estimation results from the baseline specification for three SC variables where the estimation sample has been reduced to those persons of working age (25-60 years). Produced using the balanced panel. N is person-year observations, n is the number of individuals within the sample.

SC measure:	PC 1: 'Bridging'			PC 2: 'Bonding'		
	(1)	(2)	(3)	(4)	(5)	(6)
Variable:	Family	Employment	Health	Family	Employment	Health
SC	2.760***	2.648***	2.644***	1.912***	1.952***	1.895***
	(0.347)	(0.307)	(0.300)	(0.308)	(0.265)	(0.262)
Shock (T_0)	-0.423	-3.049***	-4.145***	-0.437	-3.487***	-4.291***
	(0.375)	(0.785)	(0.667)	(0.382)	(0.789)	(0.669)
Shock (T_0)*SC	0.571	0.842	0.374	0.073	-0.527	0.009
	(0.406)	(0.701)	(0.711)	(0.403)	(0.730)	(0.704)
Shock (T_{-1})	-0.543	-1.571**	-1.296**	-0.444	-1.796**	-1.279*
	(0.360)	(0.704)	(0.651)	(0.361)	(0.727)	(0.667)
Shock (T_{-2})	0.019	-1.359*	-1.211*	-0.058	-1.318*	-1.023
	(0.375)	(0.703)	(0.687)	(0.379)	(0.698)	(0.684)
Shock (T_{+1})	-0.893**	-1.086*	-0.606	-0.829**	-1.130*	-0.649
	(0.384)	(0.648)	(0.637)	(0.389)	(0.680)	(0.642)
Shock (T_{+2})	-0.278	-1.185	-0.987	-0.440	-1.027	-0.887
	(0.391)	(0.743)	(0.665)	(0.391)	(0.753)	(0.676)
Shock (T_{-1})*SC	-0.778**	0.385	0.195	-0.437	0.682	0.403
	(0.376)	(0.653)	(0.607)	(0.381)	(0.712)	(0.691)
Shock (T_{-2})*SC	0.338	-0.402	-0.123	0.103	-0.242	-0.048
	(0.379)	(0.645)	(0.654)	(0.375)	(0.698)	(0.607)
Shock (T_{+1})*SC	0.263	0.270	0.226	0.230	0.797	1.261*
	(0.404)	(0.640)	(0.664)	(0.428)	(0.712)	(0.648)
Shock (T_{+2})*SC	-0.517	-0.275	0.201	0.473	0.172	-0.352
	(0.388)	(0.695)	(0.675)	(0.382)	(0.704)	(0.626)
Constant	83.785***	85.506***	83.383***	80.029***	81.523***	79.601***
	(5.789)	(5.825)	(5.770)	(5.830)	(5.857)	(5.813)
N	9,955	9,932	9,852	9,955	9,932	9,852
n	4,347	4,347	4,324	4,347	4,347	4,324
Overall R^2	0.09	0.1	0.12	0.07	0.09	0.11
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.13: Estimation results from the baseline specification for community participation principal components where the estimation sample has been reduced to those persons of working age (25-60 years). Produced using the balanced panel. N is person-year observations, n is the number of individuals within the sample.

where the sample has been restricted to those persons between the ages of 25 and 60 years. Comparing the estimation results for the restricted sample to the original baseline regression results, I observe that the working-age subsample exhibits a slightly stronger direct effect of social capital on mental health. For the club participation measure, the direct effect is 0.1 points higher than the baseline case, while for the trust and social support measures, the direct effect is 0.4 to 0.7 points larger. Similarly, the estimated direct effect of the first principal component is 0.1 points larger across specifications, while the second principal component is approximately 0.4 points larger. These differences are clinically small.

I also observe a difference compared to the baseline estimation with respect to the estimated impact of the shocks on the mental health score. This is especially the case for the employment and health-related shocks, where I estimate a slightly stronger impact on the working age subsample in comparison to the general population. For the employment shock, the estimated effect is approximately 0.5 of a point on the MHI-5 scale higher for the subsample as opposed to the full sample. Similarly, the estimated impact of a health-related shock is approximately 0.4 points higher than for the subsample as opposed to the full sample. The estimated effects of the leads and lags of these shocks also demonstrate an increase in strength compared to the baseline sample. These results are intuitive as working age people depend on employment for income and hence shocks to this income flow from either an employment-related or health-related shock will be more distressing than for the young or old who may depend primarily on pension funds or support from parents and guardians. On the other hand, the family-related shock appears to have a similar estimated effect on the working-age subsample of approximately 1 point on the MHI-5 scale for the club, trust and social support measures. However, for the community participation principal components, I do not observe an effect with respect to the family-related shock that is statistically distinguishable from zero. This contrasts with the baseline regression results presented in table 5.3 where I observe an economically and statistically significant effect with the respect to the family-related shock. One reason this may occur is due to the reduced sample size in comparison with the other estimations in table 5.12.

Interestingly, despite the slightly larger effect of the employment and health-related shocks, the magnitude and significance of the buffering effect for the working-age subsample is very similar to the full sample for each of the social capital measures. The only major difference is for the principal components, where there is no longer any significant buffering effect for any type of shock. This may suggest that for the working age subsample, community participation is less important for mental health than the general population. This result is also intuitive, as those who are of working age will generally have less time to devote toward community participation due to engagement in the workforce. With respect to the leads and lags of the shock terms, as in the baseline specification, for most estimations the social capital measures do not demonstrate a significant buffering effect. However, for the social support measure, the buffering effect on the lag of the employment shock and the lead of the health shock appear to be slightly larger than the baseline specification.

Although the estimated direct and buffering effects for the working age subsample appear similar to the full sample, it may be the case that there is further heterogeneity in treatment effects. For example, individuals who have recently entered into employment may be more affected by an employment-related shock. If the individual had gained employment through social resources, then the effectiveness of social resources as a buffer to psychological stress may not be the same as in the case of those employed for a longer term. In the baseline specification, I have simply identified the average of such treatment effects. A deeper exploration of heterogeneity in the buffering effect may be an interesting avenue for future study.

5.2.6 Controlling for co-occurring shocks

When producing the balance of covariates in section 3.4, I note that those individuals who experience shocks within any one of the three groupings are more likely to experience shocks from the other two groups within the same year. This may suggest that experiencing a shock within any of the three groups increases the likelihood of experiencing other types of shocks. An example may be that a serious injury or illness prompts a major worsening of finances if the person is uninsured, or may lead to retirement. Omitting shocks which are positively related with one another may therefore downward bias coefficient estimates for the shock variables. The relative size of the buffering effect may also therefore be biased as the omitted shocks will be associated with the interaction term. Hence it is of interest to control for the co-occurrence of the shocks within the year of onset.

In the following section, I therefore estimate a specification where I include all three types of shock, their leads and lags, and their interactions in the year of onset. For parsimony, I omit interactions between the leads and lags of the shocks and the social capital variables, and only allow interactions in the year of onset. Estimating such a model controls for the possibility of shocks co-occurring, while also allowing analysis of the potential impact of having multiple shocks within the year of onset. Interacting the social capital measure with the interacted shock terms should then also allow an estimation of any buffering effect on the interaction between shocks.

In table 5.14, I present estimation results from the specification controlling for all types of shocks for each of the five social capital measures. For brevity, I omit the leads and lags of the shocks from the table, noting that their estimated impact does not vary much from the baseline specification, and that as before I do not observe a significant buffering effect in the leads or lags of an event.

Variable	(1) Clubs	(2) Trust	(3) Social Support	(4) 'Bridging'	(5) 'Bonding'
SC	0.416**	1.463***	4.296***	2.383***	1.553***
	(0.204)	(0.164)	(0.147)	(0.291)	(0.251)
Family shock (T_0)	-1.031***	-0.746***	-0.808***	-0.546*	-0.464
	(0.174)	(0.176)	(0.123)	(0.290)	(0.287)
Family shock (T_0)*SC	0.505**	-0.087	0.074	0.565*	-0.126
	(0.232)	(0.188)	(0.139)	(0.301)	(0.286)
Emp. shock (T_0)	-2.019***	-1.971***	-1.526***	-1.783***	-1.919***
	(0.372)	(0.370)	(0.262)	(0.616)	(0.634)
Emp. shock (T_0)*SC	0.514	1.454***	1.091***	0.195	-0.086
	(0.550)	(0.405)	(0.268)	(0.604)	(0.570)
Health shock (T_0)	-3.844***	-3.265***	-3.196***	-3.067***	-3.227***
	(0.361)	(0.376)	(0.260)	(0.570)	(0.576)
Health shock (T_0)*SC	1.291**	0.269	1.088**	0.036	-0.471
	(0.508)	(0.400)	(0.503)	(0.604)	(0.644)
Family shock (T_0)*Emp. shock (T_0)	-0.179	-0.323	-0.112	-0.796	-0.856
	(0.714)	(0.725)	(0.461)	(1.249)	(1.271)
Family shock (T_0)	-0.437	-0.971	-0.134	1.296	-0.145
*Emp. shock (T_0)*SC	(1.035)	(0.753)	(0.252)	(1.297)	(1.177)
Health shock (T_0)*Family shock (T_0)	-0.603	-0.874	-0.355	-0.476	-0.575
	(0.674)	(0.672)	(0.452)	(1.090)	(1.073)
Health shock (T_0)*	0.087	0.159	0.661	-1.285	1.386
Family shock (T_0)*SC	(0.950)	(0.657)	(0.442)	(1.099)	(1.194)
Health shock (T_0)*Emp. shock (T_0)	-2.715***	-1.039	-1.816**	-0.539	-1.052
	(0.981)	(1.194)	(0.834)	(2.001)	(1.972)
Health shock (T_0)	3.180*	-1.907	-0.919	0.788	-0.982
*Emp. shock (T_0)*SC	(1.663)	(1.216)	(0.698)	(1.742)	(1.953)
Health shock (T_0)*Family shock (T_0)	0.318	-0.253	-0.886	-2.459	-2.060
*Emp. shock (T_0)	(1.845)	(1.836)	(1.398)	(3.080)	(3.002)
Health shock (T_0)*Family shock (T_0)	-3.210	0.800	-1.348	0.387	-0.746
*Emp. shock (T_0)*SC	(2.753)	(1.753)	(1.210)	(2.919)	(3.303)
Constant	82.817***	99.031***	82.322***	82.692***	82.027***
	(9.125)	(9.672)	(8.861)	(3.975)	(3.974)
N	53,834	29,455	54,081	14,535	14,535

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5.14: Estimation results for the specification including interactions between the three shocks and the social capital term in the year of onset. Produced using the balanced panel. N is person-year observations.

I observe in table 5.14 that the direct effects of the social capital variables are approximately the same as those found in the baseline estimation. However, the clubs measure has a slightly smaller direct effect. Most interestingly, the estimated coefficients of the shock variables are slightly different than in the baseline specification. While the estimated coefficient for the family-related shock is similar to those estimated in the baseline case, the estimated effect of an employment related shock in table 5.14 is generally smaller than the baseline specification. The estimated effect is reduced by approximately one point on the MHI-5 scale. The health-related shock also produces a lower estimated impact, however the decrease in the coefficient's magnitude is small. One reason for the decrease in the estimated magnitudes is that the interaction between the health and employment shocks has a large and statistically significant estimated coefficient for the clubs and social support measure - those with the greatest number of observations. This variable may be accounting for some of the impact each shock had when included in the regression equation on its own.

As in the baseline case, I still find a significant buffering effects for the interaction between individual shocks and social capital variables. As before, I find a significant buffering effect for the trust and social support measures in response to an employment shock. Similarly, club participation produces a significant buffering effect in response to a health shock in the year of onset. There is a contrast with the baseline specification in that the club participation measure has an economically and statistically significant buffer to a family-related shock, while the social support measure has a significant buffer with respect to the health-related shock. However the 95% confidence intervals for these two effects are wide, and contain the baseline estimates, evident in the size of the standard error relative to the estimated coefficient.

Despite the buffering effects found for individual shock variables, I do not find a significant buffering effect for the interactions between them. This may occur because experiencing multiple shocks within the same year is not very frequent. For example, the number of individuals who experience both an employment and a health shock is between 77 and 102 per wave. This relatively low frequency may imply a small number of observations with which an effect is estimated. Overall, therefore, it may be important to control for the co-occurence of shocks, as part of the effects estimated for the shocks in the baseline estimation may be explained by interactions between them. However, this does not appear to confound the conclusion that there exists a significant buffering effect.

5.2.7 Quantile regression

Section 5.2.5 partly addressed the issue of heterogeneous treatment effects at different levels of the independent variables such as age. However, an additional question is whether there is heterogeneity of treatment effects within the distribution of the dependent variable. For example, those individuals at the lower end of the MHI-5 distribution may respond more severely to a psychological stressor than those at the mean level if they are already psychologically unwell and close to the threshold score of 60. To explore this possibility, I estimate the baseline specification using a fixed-effects quantile regression. That is, instead of the predicting the effect of social capital on the conditional mean of the mental health score ($\mathbb{E}[MH_{it}|SC_{it}, x_{it}, Z_{it}]$), we may predict the effect at the conditional percentile (Q) of the mental health score ($MH_{Q|SC_{it},x_{it},Z_{it}}$). This estimation method will allow the analysis of the impact of a shock, and of social capital, at different parts of the mental health distribution.

Because a full analysis of the combinations of shocks and social capital measures at different quantiles would require presenting and analyzing a laborious amount of output, I have chosen to present the results of the quantile regression for two of the social capital measures, regressing each with one of the psychological shocks. I conduct the analysis using the social support measure with the employment shock and the club participation measure with the health shock as there has been a consistent buffering effect estimated for these pairs. For each variable, I plot the estimated coefficients of the direct effect across predicted percentiles of the mental health distribution, as well as the estimated impact of the shock.

In figure 5.1 (a) and (b), I present a plot of the estimated coefficient of the social capital variables when the quantile regression is run at each tenth percentile, increasing in tenths from the 10th to 90th percentile of the MHI-5 distribution. Evident in figure 5.1 is that as the predicted quantile increases toward the higher end of the mental health distribution (1 on the X-axis), the estimated direct effect of both social capital variables declines in strength. This may indicate that social capital plays a more important role in the determination of mental health for those who are already psychologically unwell. Note that the 20th percentile of the distribution is approximately 60 points, the cut-off score below which the MHI-5 measure is predictive of a common mental disorder. For those around the 20th percentile, improving social capital may be a way to significantly better mental health.

What is not noted on figure 5.1 is the statistical significance of the direct effect for each measure. For the social support measure, the direct effect is significant at the 1% level across the entire distribution of the mental health score. On the other hand, the clubs measure is only statistically significant from the 10th to 70th percentiles, while at the 80th and 90th percentiles it is not significant at any

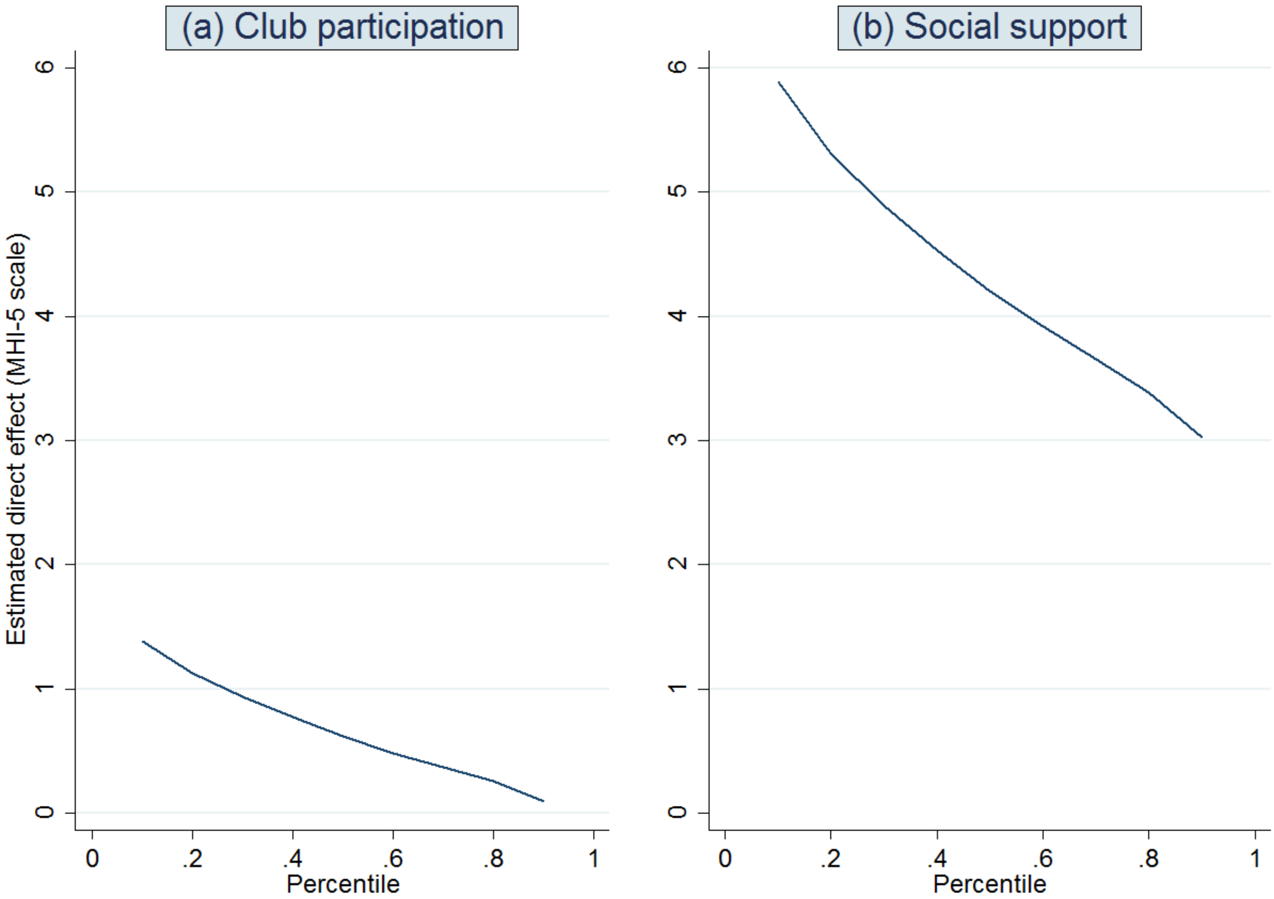

Figure 5.1: (a) Plot of the estimated direct effect of club participation from a fixed-effects quantile regression predicting each 10th percentile of the MHI-5 distribution. Produced using the balanced panel with 54,803 person-year observations (N). (b) Likewise plot of the estimated direct effect for the social support measure. $N = 55,702$.

relevant significance level. Interestingly, this may indicate that club participation is not important in determining mental health for those already in very good psychological health.

In figure 5.2 (a) and (b), I present the estimated impact of each psychological shock across the percentiles of the MHI-5 distribution. For each coefficient, I also present the impact of the shock for different levels of the social capital measures, by adding (or subtracting) the coefficient of the interaction term at each percentile. I observe in both figures (a) and (b) that the impact of the shock, regardless of the level of social capital, tends to become larger toward the bottom of the mental health distribution. This indicates that it is indeed the case that those who are already psychologically unwell will be more affected by the occurrence of a psychologically stressful event. For the club participation measure, despite not finding a significant direct effect, I do observe a statistically

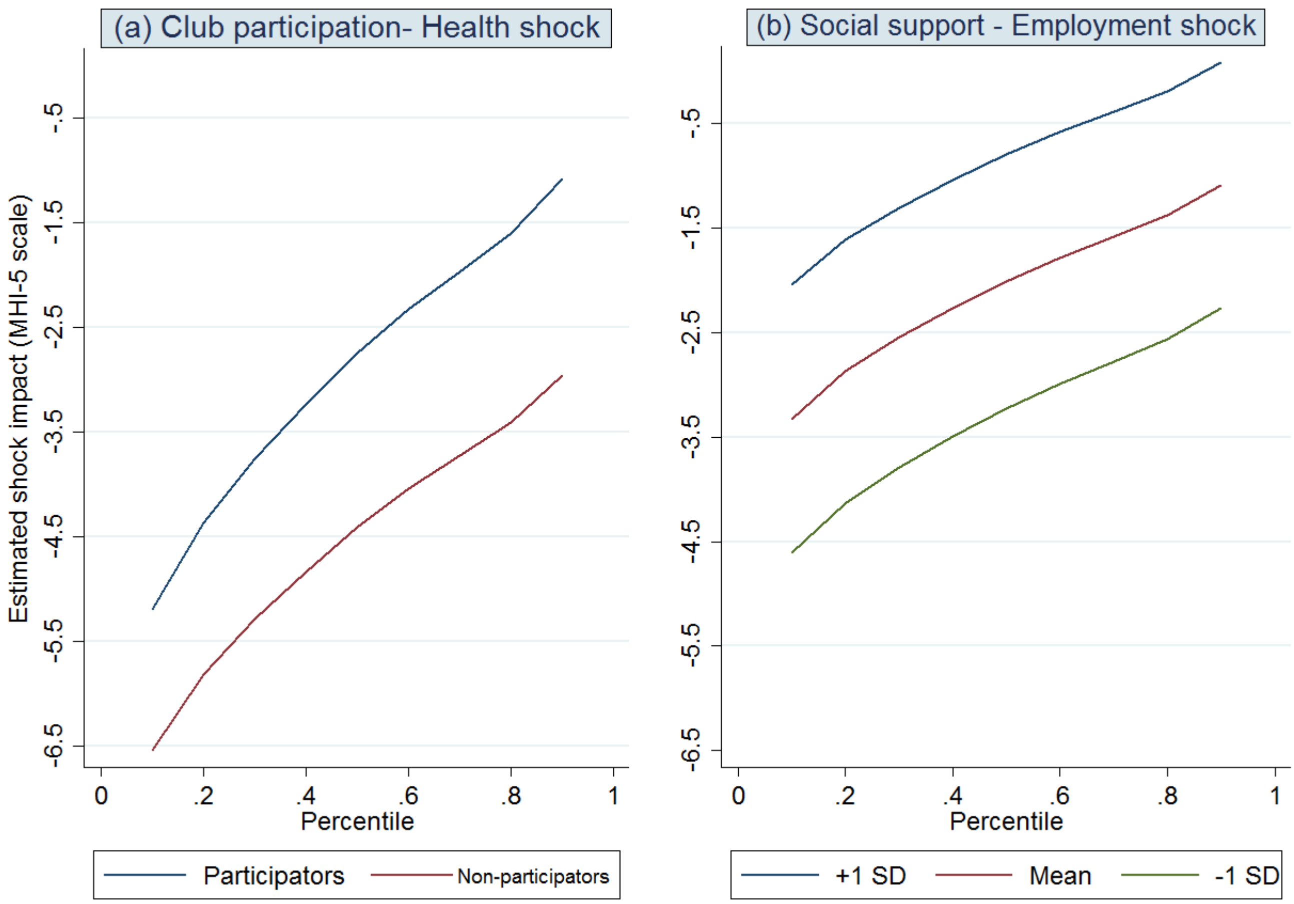

Figure 5.2: (a) Plot of the estimated effect of a health-related shock for club participators vs. non-participators predicted at every 10th percentile using a fixed-effects quantile regression. $N = 54,803$ person-year observations. (b) Plot of the estimated effect of an employment-related shock at different levels of the social participation measure, predicted at every 10th percentile using a fixed-effects quantile regression. $N = 54,803$ person-year observations. '+1 SD' here implies being one standard deviation above the mean level of the measure while '-1 SD' implies being one standard deviation below the mean.

significant interaction effect at the 1% level for every percentile of the distribution. This is evident in the smaller estimated impact of the shock for club participators over non-participators for each percentile of the distribution. Interestingly, however, the estimated magnitude of the buffering effect tends to decline from the 10th percentile to the 90th, such that those who are in the higher end of the distribution experience a stronger buffer effect than others. The change in the size of the buffer is clear in figure 5.2 (a) as the lines are not parallel toward the top end of the distribution and the difference between participators and non-participators is wider than at the bottom end.

On the other hand, for the social support measure I estimate a buffering effect that is consistently sized throughout the distribution. In figure 5.2, this is evident in the approximately parallel lines formed by the estimated impact of the shock for those one standard deviation above (+1 SD) and below (-1 SD) the global mean. Overall, this may indicate that there is little heterogeneity in the buffering effect for social support on an employment-related shock, despite there being clear heterogeneity in the impact size of the shock.

To the best of my knowledge, there are no other studies which analyse the impact of life events or social capital on mental health using the quantile regression in a panel data setting. This is likely due to the fact that such procedures are non-standard and software to implement the procedure has only recently become widely available (Machado and Silva, 2018). The results of this analysis appear promising as an avenue for future study of mental health trends using panel data. This is especially because it may give an idea of the heterogeneity of treatment effects for specific parts of the mental health distribution, perhaps allowing more targeted treatment strategies.

Chapter 6
Discussion of Results

6.1 Mechanisms

In the following section, I discuss the mechanisms which may underlie the results presented in the previous section. To summarize briefly, I identify a significant buffering effect using nearly all my proposed measures of social capital. The observed buffering effect appears to be primarily in relation to employment-related shocks. Health and family-related shocks on the other hand do not exhibit a consistent buffering effect across measures. These results appear to be stable across a number of specifications, within a working-age subsample and between balanced and unbalanced data sets.

The observed buffering effects with respect to an employment shock relate to previous research linking social ties to employment outcomes. Most notably, sociologist Mark Granovetter (1973) modelled the relationship between informal ties and employment. The research proposed that a greater number of informal ties allows more access to information about potential employment opportunities at a low cost. Through a number of surveys in the United States, Granovetter (1974) found that approximately 60-90% of workers in non-white collar work found their employment through informal mechanisms such as contacts with friends and relatives.

If more social ties are related to better employment outcomes, then the presence of a buffering effect against an employment shock is intuitive. When a person is fired or otherwise becomes unemployed, they will be more resilient to the psychological stress if their social resources are able to provide them information about new employment. When disaggregating the shocks, I find a significant buffering effect with respect to a major worsening of finances in particular. It may be then that social ties provide financial support, or information on welfare programs (Bertrand et al., 2000). Through these channels therefore, I expect social capital to provide a buffering effect from psychological stress relating to employment.

For a family-related shock on the other hand, the reason why I observe only a weak buffering effect may be that the shock is not strong enough to warrant appealing to social resources. Throughout estimation, for the family-related shock indicator I observe a decline in mental health of approximately 1 point on the MHI-5 scale, which corresponds to a 1-1.5% decline in the mental health score. This is very small compared to the 5-10% decline I observe with respect to health and employment related shocks. One explanation for this small effect may be that individuals recover very quickly from the event. The MHI-5 score only measures mental health in the previous four weeks. Therefore, if the event occurred far outside of this window and recovery time is quick, then the observed effect of the shock will be small. However, where I do observe a significant buffering effect, particularly with respect to the social support measure, this may be in part explained by the psychological comfort that social contacts provide, as proposed by Kawachi and Berkman (2001).

A health-related shock on the other hand exhibits a strong impact on mental health, but little evidence for a buffer from social resources. One reason this may be occurring is that as part of the treatment for an injury or illness, the individual is offered more formal psychological care in the form of counselling or other health care services, and is choosing this avenue over appealing to social resources.

To develop this connection between social resources and more formal mental health care, I present a basic economic framework following similar economic modelling by Folland (2008) and Becker and Murphy (2009). Consider a hypothetical case where an individual is exposed to a psychological shock and must then choose to appeal either to health care (H) or social resources (S). The utility obtained from either choice ($i = H, S$) will be a function both of the effectiveness of the treatment (e_i) and the cost (c_i). It is reasonable to assume that utility ($u_i(c_i, e_i)$) will be increasing in effectiveness and decreasing in cost. Presumably, formal health care is more effective ($e_H > e_S$), but will be more expensive ($c_H > c_S$) due to payments required, search costs and possible stigma associated with accessing mental health care, few of which will be present when appealing to social resources.

Within this framework, we would expect individuals to choose social resources when formal care is not as effective for treatment. Perhaps in the case of an employment shock, social resources may even be more effective for treatment given their relationship with employment outcomes, hence the observed buffering effect. For a health-related shock on the other hand, the reason I do not observe a buffer may be that formal psychiatric care is more effective against health-related stress. Moreover, it may be the case that formal care is provided with a lower search cost when an individual is within the institutional framework of the health care system. An example of this may be counselling services often provided to cancer patients during the course of cancer treatment.

This theory is difficult to assess within HILDA however, as I have limited information about access to formal health care. It may also be the case that health care and social resources are compliments and not substitutes - although in this case I would have presumably observed a buffering effect with respect to a health shock more frequently.

Interestingly, the only social capital measure where I do observe a consistently significant buffer of the health shock is club participation. There may be two reasons for this buffering effect. The first is that being part of a club or association may require physical presence at a club-specific location. If a health shock occurs, the other members of an association or club will be more aware of the individual's physical absence, and hence may be more inclined to provide social support. This explanation may seem contradictory - a health shock prevents one from being physically present at clubs or associations, presumably lowering mental health through the direct effect. However, it is unlikely that these social ties will be completely severed. If associates of the individual then provide psychological comfort after noting the absence of the individual, there may be a positive net effect on mental health from the buffering effect this comfort provides.

The second explanation is that the survey item asks specifically for sporting associations. The positive buffering effect for club participation may therefore be driven by the fact that persons in sporting clubs will be more exposed to serious injuries, but will also have better mental health by virtue of being physically active and most likely younger. Unfortunately, I am unable to discriminate between what types of associations individuals participate in. However, investigating the connection between different types of clubs and health may be an interesting direction for future studies.

Lastly, in using different measures of social capital to conduct my analysis I have argued following Putnam (2000) that if I find a common effect between measures, this may be considered evidence for an underlying construct which is driving the effect. I consider this to be the case for the employment shock, where I find an economically and statistically significant buffering effect for four of five measures at least at the 10% significance level. However, for the family and health-related shocks, not all measures provide significant buffering effects, and they are sensitive to the specification and social capital measure used. The social support measure appears to consistently generate a significant buffering effect with respect to the family-related shock. Interestingly, it is also the one variable where I observe a buffering effect in the leads and lags of the shock. Social support may be thought of as a reflection of 'cognitive' social capital - the perceived amount of social resources one has and their quality. It may therefore be that the perceived amount of social resources is more important for providing comfort after a family-related shock than how many associates one actually has. However, as I note when presenting the baseline estimates, the social capital variable also appears to worsen mental health one period before a shock. This raises the possibility that being well connected to a social group increases distress when a group member is unwell. However, to study the connection between perceived social support and mental health in more detail would require a setting that is less prone to reverse causality.

6.2 Limitations

One limitation of the present study is that I have not been able to account for all sources of endogeneity within the model. Namely, while some of the psychological shocks used are arguably more exogenous (i.e. a family related shock, or being the victim of a violent or property crime), it may be that there are time-varying unobservable factors underlying the occurrence of the life events which I have failed to control for. For example, one of the employment related shocks is being fired, an event which may depend on unobservable factors such the circumstances of the firm or past individual performance which may impact individual mental health. There is therefore still potential for bias from omitted variables, especially with regard to the life event indicators. Circumventing this potential bias would require the use of further instruments, which may be a direction for future research on the concept of social support.

With respect to endogeneity in social capital, I have attempted to use an instrumental variable to avoid possible simultaneity bias due to reverse causality from mental health. I am still able to identify buffering and direct effects, which is an indication that these effects are not entirely driven by reverse causality from mental health. However, as noted when conducting the instrumental variable analysis, the instruments I have used may be weak, and hence interpreting the magnitudes of the estimates may not be very informative for policy. Moreover, if there are intertemporal relations between the shocks and social capital, the exogeneity of the instrument may be weakened. Given the limited use of time-varying instruments in previous research, and the limits of HILDA, I believe however that I have taken a suitable approach to attempting an instrumental variables analysis in this context.

Another concern given the imperfect measures of social capital I have used is the presence of attenuation bias from measurement error. If individual outcomes are systematically related to the error in each social capital variable's measurement of underlying latent social capital, then OLS estimates of the direct and buffering effects may be attenuated. Estimates may therefore fail to reflect the true extent of any buffering effect.

Furthermore, the general criticisms of the social capital literature apply to this thesis as well. Social capital is not a clearly defined variable. Because of the similarity of effects between measures, I am to some extent confident that they are measuring the effect of the same underlying concept. However, there remains the possibility that each of these items is measuring something different. This is particularly the case if one thinks of these social capital variables as the reflection of unobserved norms, in which case the question is raised of whether social capital is something an individual can possess. Such concerns relate back to the definitional arguments elaborated in section 2.1. Given my economic and econometric approach to the problem, an individual-based framework is favourable. It is also favourable when studying mental health, whose issues are most often studied and addressed at the individual and not societal level. However, criticisms concerning imprecise definitions still apply.

Lastly, a criticism may apply to how I have chosen the covariates to include in my analysis. I have followed previous literature and the investment model proposed by Glaeser et al. (2002) in determining the control variables to include in analysis. It may be the case, however, that I have excluded some factors which may be important to determining both mental health and social capital. An example may be general health, however one may argue that this would constitute a 'bad control' after previous research (Rocco et al., 2014). Given the richness and size of HILDA, a future approach may be able to select covariates based on a more formal model selection procedure (i.e. through machine learning).

Chapter 7
Conclusion

This thesis attempts to answer the question of whether having greater social capital buffers an individual's mental health from common, stressful life events. I contribute to the literature by assessing the mitigating role of a number of social capital measures on a range of common life events, thereby giving a broad picture of the buffering effect of social capital. Previous literature examining the buffering role of social capital often fails to account for potential confounding factors such as unobserved individual-specific heterogeneity, reverse causality and endogeneity in social capital. As another contribution to the literature, I examine this question using panel data methods with 16 waves of Australian panel data, which allows inference without confounding from time-constant unobservables, while paying special attention to issues of confounding and bias, unlike many previous studies.

A further novel contribution to the literature is the specification of the model used in analysis, which allows study of the dynamics effects of the shock. In estimating my model, using a number of social capital measures I find that having greater social capital buffers mental health against an employment-related shock in the year of onset. I find less evidence of buffering with respect to family-related and health-related shocks. Furthermore, I find little evidence of any buffering effect in the before and after periods of a shock. The results appear to be robust to a number of specifications. These include transformations of the dependent variable, instrumental variable estimation and variation of the study sample. Some limitations remain, however, with respect to endogeneity in the social capital measures and life event indicators, leaving opportunities for future studies.

The findings of this thesis therefore support the existing literature on the benefit to mental health of having greater social capital. It also contributes to the small but growing literature investigating the impact of social capital on health outcomes in the Australian context. The results also have minor policy implications. I find that the negative effect of psychologically stressful life events are particularly strong for those toward the lower end of the distribution of mental health score. Provision of social support through community health care services or encouraging community participation for those with poorer mental health may therefore assist in reducing the severity of a common, distressing life event.

Appendix A
Principal Components Analysis

To construct a measure of community participation, I perform a principal components analysis (PCA) using the survey items listed in table B.1. Generally, the purpose of a PCA is to reduce the dimensionality of a data set with many interrelated variables (Jackson, 2005). This is accomplished by generating new variables ('principal components') which are linear combinations of the original variables, whose weights are chosen to maximize the variance among the original variables that is explained by the linear combination. For k variables included in the analysis, k principal components are generated by the procedure, each explaining some proportion of the variance. The components are ordered by the amount of variance explained and the size of a corresponding eigenvalue. The 'first principal component' has the largest eigenvalue and explains the greatest proportion of the variance. The second principal component explains the second greatest amount of variance, and so forth. All the components are orthogonal to one another by construction. Given the k components, the main challenge is then to select the number of components to use in analysis and interpret their meaning.

Component selection follows a rule of thumb that the components with eigenvalues with magnitude greater than one should be selected (Jackson, 2005). In figure A.1, I provide a scree plot of the principal components output for the 12 community participation items in the HILDA data set. The graph plots the eigenvalues on the Y-axis and the order of principal components on the X-axis. I observe that the first two principal components have eigenvalues above one. The third principal component has a corresponding eigenvalue of 0.99. In table A.1, I provide the weights of the first three principal components, the amount of variance they explain, and their corresponding eigenvalues. The first two principal components explain 31% and 14% of the variance among the community participation variables, while the third component explains only 8% of the variance. Given that the third component explains very little of the variance in comparison with the first two components, and has an eigenvalue less than one, I decide not to use it for analysis. I therefore select only the first two principal components.

Because the components are constructed by the procedure to explain the most

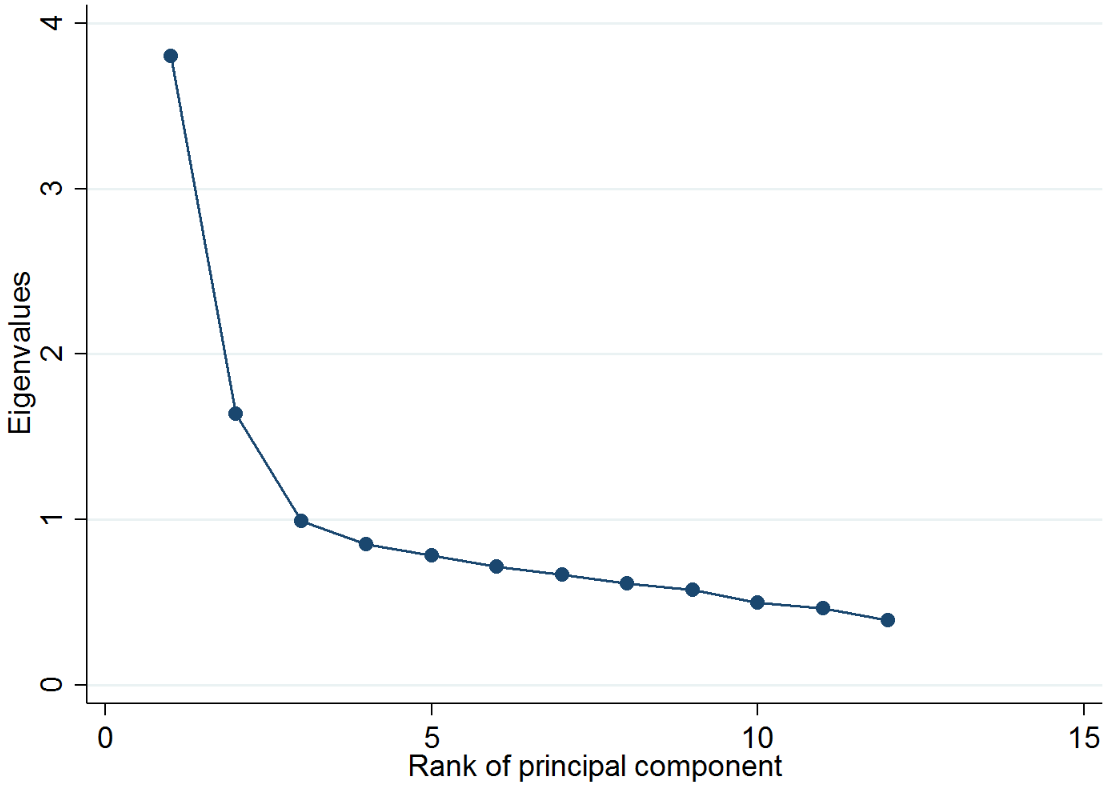

Figure A.1: Scree plot of principal components' eigenvalues. $N = 17,217$ **person-year observations. Note that 'rank' here means 1st, 2nd, 3rd etc.**

variance, their weightings must be interpreted to identify the underlying feature the components may represent. To understand what the components might measure, I look at the magnitude and sign of the weight each item is given in table A.1. I observe that the first principal component is positively related to all of the items, however it gives the greatest weight to the items which relate to civic participation (i.e. attending community events, volunteering, involvement in community groups). I propose that this item measures a form of 'bridging' social capital. That is, the extent to which an individual has contact with persons outside of their family who are not similar to themselves. The second principal component appears to give positive weighting to items concerning contact with friends and relatives, and negative weighting to items concerning civic participation. I associate this component with the 'bonding' dimension of social capital, which relates to one's relationship with family and friends similar to oneself.

However, as I must assess the meaning of these items myself, I allow for the fact that I may not be correct in my interpretation. Providing the generated weights for each principle component should also allow the reader to reach their own conclusions regarding the meaning of these components.

Variable:	First component	Second component	Third component
attend_events	0.348	0.036	-0.132
chat_neigh	0.264	0.215	-0.256
contact	0.265	0.435	-0.099
extended_fam	0.254	0.347	0.168
involved	0.355	-0.34	0.076
keep_touch	0.310	0.388	-0.008
charity	0.246	0.0536	0.420
poli_issues	0.278	-0.334	-0.270
union_party	0.278	-0.358	-0.356
worship	0.217	-0.202	0.698
curr_affairs	0.303	0.125	-0.085
volunteer	0.314	-0.274	0.055
Eigenvalue	3.80	1.64	0.99
Proportion of variance explained	0.317	0.137	0.083

Table A.1: Weights of the first through third principal components of the community participation variables. $N = 17,217$ **person-year observations. Variable descriptions are given in table B.1.**

Given that the community participation items were only observed in three of the waves of HILDA, a question may be whether the underlying factor the principal components measure is stable between waves. If not, using the pooled data set to calculate them may result in misleading inferences concerning the underlying factor. To answer this question, for each wave I generate the principal components using the data available in that wave, and then merge the resulting scores together to form one variable where scores in each wave are from the wave-specific components.

In figure A.2 (a), I provide the scatter plot between the first principal component generated using the pooled data and the first principal component generated using wave-specific data. Figure A.2 (b) provides the same but for the second principal component. I find that the pooled and wave-by-wave components are almost exactly identical and very highly correlated. Moreover, inspection of the weightings given to the original variables reveals little change. I consider this evidence that the underlying structure the components are measuring is stable over time.

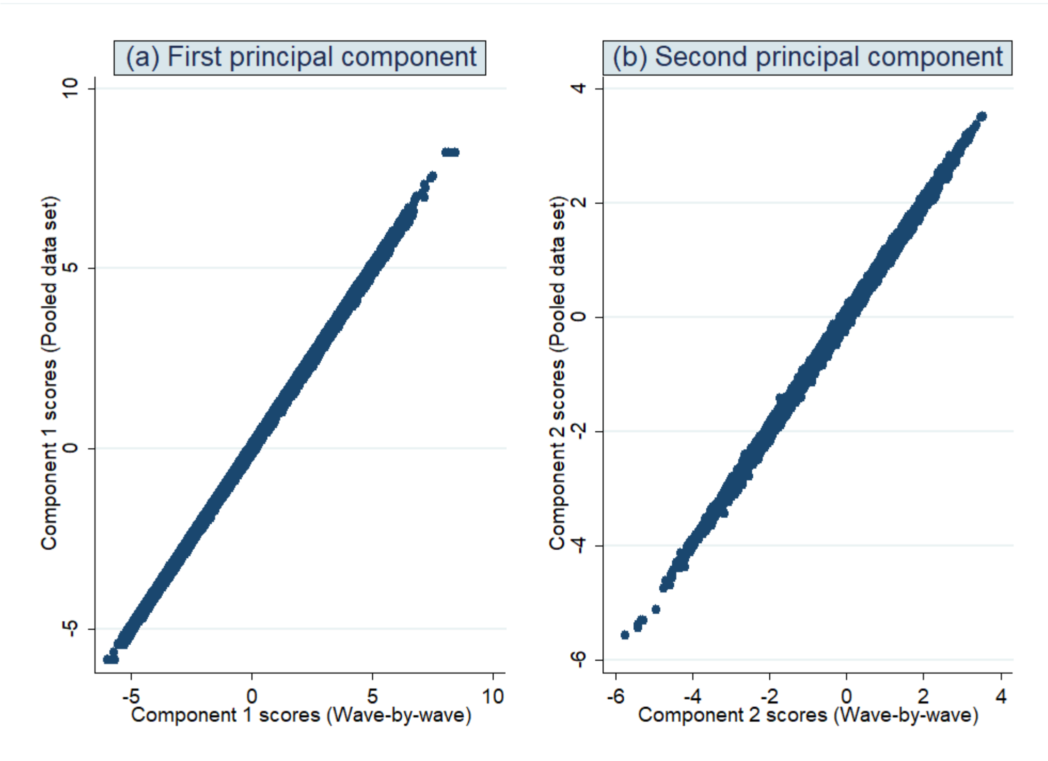

Figure A.2: (a) Scatter plot of the first principal component generated using the pooled balanced panel against the principal component generated wave-by-wave. (b) Scatter plot of the second principal component generated using the pooled balanced panel against the principal component generated wave-by-wave. $N = 17,217$ **person-year observations.**

Appendix B
Additional tables

Variable name	Description
attend_events	Attend events that bring people together such as fetes, shows, festivals or other community events
chat_neigh	Chat with your neighbours
contact	Have telephone, email or mail contact with friends or relatives not living with you
extended_fam	See members of my extended family (or relatives not living with me) in person
involved	Encourage others to get involved with a group thats trying to make a difference in the community
keep_touch	Make time to keep in touch with friends
charity	Give money to charity if asked
poli_issues	Get in touch with a local politician or councillor about issues that concern me
union_party	Get involved in activities for a union, political party, or group that is for or against something
worship	Make time to attend services at a place of worship
curr_affairs	Talk about current affairs with friends, family or neighbours
volunteer	Volunteer your spare time to work on boards or organising committees of clubs, community groups or other non-profit organisations

Table B.1: Community participation items as provided in the self-completion questionnaire in waves 6, 10 and 14 of HILDA. Participants respond on a Likert scale from 1 (Never) to 6 (Very often).

Variable name	Item description
confide	I don't have anyone that I can confide in
cheer_up	There is someone who can always cheer me up when I'm down
lots_friends	I seem to have a lot of friends
lean_trouble	I have no one to lean on in times of trouble
dont_visit	People don't come to visit me as often as I would like
talk_people	When something's on my mind, just talking with the people I know can make me feel better
lonely	I often feel very lonely
no_help	I often need help from other people but can't get it
enjoy_people	I enjoy the time I spend with the people who are important to me
finds_help	When I need someone to help me out, I can usually find someone

Table B.2: Percieved social support items as provided in the self-completion questionnaire in all waves of HILDA. Participants respond on a Likert scale from 1 (Strongly disagree) to 7 (Strongly agree).

Variable name	Item
Family	Death of close relative/family member
Friend	Death of a close friend
Spouse	Death of spouse or child
Property	Victim of a property crime
Finances	Major worsening in finances
Fired	Fired or made redundant
Injury	Serious personal injury/illness
Violence	Victim of physical violence
Retire	Retired from workforce

Table B.3: Major life event variables and item definitions. Respondents are asked to indicate if they have experienced any of the items in the past 12 months.

Group:	Family-related shocks				Employment shocks			Health shocks	
Variable:	Spouse	Friend	Family	Property	Finances	Fired	Retire	Injury	Violence
Wave 1	-	-	-	-	-	-	-	-	-
Wave 2	60	643	658	389	203	216	158	451	97
Wave 3	44	652	635	368	207	182	151	463	95
Wave 4	48	638	645	325	175	161	146	464	79
Wave 5	46	614	635	237	159	146	112	477	64
Wave 6	43	652	644	246	147	144	150	457	73
Wave 7	41	630	581	179	137	143	158	441	60
Wave 8	43	644	633	209	203	128	165	417	71
Wave 9	44	666	649	189	243	202	155	484	56
Wave 10	36	769	677	196	198	155	160	514	52
Wave 11	45	746	686	168	201	161	196	553	51
Wave 12	89	886	755	177	159	142	195	583	56
Wave 13	46	710	691	173	162	170	192	550	50
Wave 14	50	867	717	161	140	155	198	597	40
Wave 15	53	802	672	147	142	149	244	620	39
Wave 16	66	916	752	168	139	159	206	679	43

Table B.4: Frequency of life events across waves of the balanced panel.

Group:	Family-related			Employment-related			Health-related		
Variable:	No shock	Shock	t-stat	No shock	Shock	t-stat	No shock	Shock	t-stat
Age (years)	49.79	53.51	-30.78***	50.6	52	-7.64***	50.36	53.76	-18.97***
Female	0.55	0.56	-3.61***	0.55	0.51	6.37***	0.55	0.54	1.97*
MHI-5 score	75.66	74.05	11.90***	75.79	69.05	26.67***	76.18	66.8	40.46***
Foreign Born	0.22	0.21	3.57***	0.21	0.23	-2.73**	0.22	0.21	1.32
Highest level of education:									
High School	0.13	0.12	5.12***	0.13	0.12	1.94	0.13	0.11	3.48***
Primary	0.29	0.35	-14.67***	0.31	0.33	-3.79***	0.31	0.33	-4.73***
Tertiary certificate	0.31	0.33	-3.78***	0.32	0.33	-2.92**	0.32	0.34	-4.72***
University	0.26	0.21	16.97***	0.25	0.22	6.08***	0.25	0.21	8.10***
Couple	0.72	0.69	8.40***	0.72	0.64	13.61***	0.72	0.63	15.84***
Kids	0.38	0.31	19.59***	0.37	0.28	14.76***	0.37	0.27	19.02***
Unemployed	0.02	0.02	-1.44	0.01	0.09	-22.10***	0.02	0.03	-3.83***
Out of labour force	0.32	0.41	-24.33***	0.33	0.47	-23.18***	0.32	0.47	-24.77***
Household income (000s)	82.02	77.31	8.07***	81.33	75.06	6.50***	81.94	71.09	13.87***
Family shock	-	-	-	0.24	0.32	-12.53***	0.24	0.33	-17.85***
Emp. shock	0.07	0.1	-12.44***	-	-	-	0.07	0.15	-20.67***
Health shock	0.09	0.13	-17.65***	0.09	0.19	-20.79***	-	-	-
'Bridging'	-0.04	0.13	-10.01***	0.01	-0.15	5.49***	0	-0.03	1.2
'Bonding'	0	0.01	-0.84	0.01	-0.13	4.84***	0.01	-0.04	1.81
Social support	0	0.01	-0.26	0.03	-0.28	22.87***	0.03	-0.24	21.88***
Trust	0	0	0.14	0.02	-0.26	12.55***	0.02	-0.19	10.64***
Participator	0.4	0.44	-9.57***	0.41	0.37	6.35***	0.41	0.4	2.48*
N	65,286	21,814	87,100	80,175	6,869	87,044	78,391	8,433	86,824

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.5: Balance of covariates between those who are exposed to a shock and those who are not for the three groups of life events. Produced using the balanced panel. N is person-year observations. t-statistics provided are for a test of the significance of the difference in means between groups.

SC measure:	Club participation			Trust measure			Social support measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable:	Family	Employment	Health	Family	Employment	Health	Family	Employment	Health
SC	0.640***	0.697***	0.616***	1.702***	1.519***	1.629***	4.741***	4.470***	4.600***
	(0.165)	(0.134)	(0.135)	(0.138)	(0.112)	(0.116)	(0.122)	(0.102)	(0.104)
Shock (T_0)	-1.350***	-2.901***	-4.425***	-1.095***	-2.605***	-3.882***	-1.100***	-2.093***	-3.650***
	(0.144)	(0.274)	(0.254)	(0.151)	(0.283)	(0.262)	(0.103)	(0.192)	(0.184)
Shock (T_0)*SC	0.547***	0.999***	1.376***	0.014	0.801***	0.210	0.267**	1.108***	0.053
	(0.194)	(0.386)	(0.352)	(0.156)	(0.286)	(0.271)	(0.113)	(0.183)	(0.179)
Shock (T_{-1})	-0.501***	-1.416***	-1.421***	-0.652***	-1.138***	-1.204***	-0.430***	-1.177***	-1.023***
	(0.141)	(0.253)	(0.235)	(0.152)	(0.262)	(0.246)	(0.102)	(0.179)	(0.166)
Shock (T_{-2})	-0.190	-0.692***	-0.269	-0.138	-0.567**	-0.399*	-0.041	-0.510***	-0.093
	(0.136)	(0.243)	(0.233)	(0.150)	(0.255)	(0.243)	(0.099)	(0.170)	(0.159)
Shock (T_{+1})	-0.040	-0.986***	-0.646***	-0.217	-0.893***	-0.711***	-0.149	-0.748***	-0.621***
	(0.139)	(0.245)	(0.239)	(0.153)	(0.253)	(0.246)	(0.101)	(0.174)	(0.167)
Shock (T_{+2})	-0.459***	-0.747***	-0.787***	-0.396***	-0.579**	-0.497**	-0.317***	-0.464***	-0.579***
	(0.137)	(0.230)	(0.249)	(0.150)	(0.243)	(0.248)	(0.099)	(0.166)	(0.172)
Shock (T_{-1})*SC	-0.011	0.159	0.554*	-0.101	0.218	-0.131	-0.307***	0.566***	0.363**
	(0.194)	(0.366)	(0.329)	(0.161)	(0.271)	(0.238)	(0.108)	(0.184)	(0.165)
Shock (T_{-2})*SC	0.316*	0.471	0.193	-0.024	-0.252	0.064	-0.126	0.008	-0.015
	(0.189)	(0.345)	(0.308)	(0.153)	(0.258)	(0.240)	(0.107)	(0.179)	(0.154)
Shock (T_{+1})*SC	-0.365*	0.033	-0.366	-0.051	0.530**	0.301	-0.089	0.579***	0.157
	(0.195)	(0.350)	(0.324)	(0.164)	(0.254)	(0.255)	(0.109)	(0.173)	(0.168)
Shock (T_{+2})*SC	0.358*	0.158	0.215	0.020	0.078	-0.090	0.152	0.233	0.292*
	(0.193)	(0.334)	(0.337)	(0.157)	(0.249)	(0.250)	(0.106)	(0.170)	(0.175)
Constant	72.965***	73.964***	72.752***	106.942***	106.090***	109.017***	73.597***	74.241***	73.317***
	(7.715)	(7.705)	(7.673)	(8.109)	(8.122)	(8.107)	(7.472)	(7.462)	(7.443)
N	79,558	79,347	78,557	43,425	43,309	42,874	79,968	79,751	78,967
n	12,407	12,365	12,342	11,815	11,779	11,756	12,412	12,377	12,350
Hausman p-value	0.006	0.251	0.091	0.014	0.093	0.001	0.010	0.010	0.000
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.6: Estimation results of the baseline specification for three measures of social capital where the estimating sample is the unbalanced panel. N is person-year observations.

SC variable:	PC 1: 'Bridging'			PC 2: 'Bonding'		
	1	2	3	4	5	6
Variable:	Family	Employment	Health	Family	Employment	Health
SC	2.568***	2.542***	2.480***	1.845***	1.898***	1.846***
	(0.249)	(0.219)	(0.214)	(0.225)	(0.192)	(0.191)
Shock (T_0)	-0.923***	-2.910***	-3.973***	-0.780***	-3.057***	-4.155***
	(0.259)	(0.476)	(0.431)	(0.248)	(0.477)	(0.424)
Shock (T_0)*SC	0.579**	0.925**	-0.053	0.122	-0.472	-0.160
	(0.259)	(0.441)	(0.428)	(0.255)	(0.450)	(0.445)
Shock (T_{-1})	-0.491*	-1.166***	-1.217***	-0.504**	-1.188***	-0.929**
	(0.256)	(0.441)	(0.428)	(0.246)	(0.441)	(0.417)
Shock (T_{-2})	-0.418	-0.599	-0.615	-0.391	-0.745*	-0.617
	(0.257)	(0.446)	(0.425)	(0.249)	(0.439)	(0.415)
Shock (T_{+1})	-0.500*	-1.378***	-0.550	-0.515**	-1.419***	-0.462
	(0.266)	(0.416)	(0.411)	(0.254)	(0.420)	(0.401)
Shock (T_{+2})	-0.793***	-0.430	-0.559	-0.876***	-0.371	-0.526
	(0.266)	(0.459)	(0.453)	(0.259)	(0.454)	(0.447)
Shock (T_{-1})*SC	-0.127	0.109	0.644	-0.230	0.471	0.526
	(0.250)	(0.429)	(0.392)	(0.267)	(0.443)	(0.451)
Shock (T_{-2})*SC	-0.070	-0.615	0.007	0.250	-0.052	0.047
	(0.253)	(0.435)	(0.379)	(0.250)	(0.472)	(0.403)
Shock (T_{+1})*SC	0.074	0.318	0.397	0.034	0.629	0.816*
	(0.266)	(0.410)	(0.409)	(0.275)	(0.448)	(0.435)
Shock (T_{+2})*SC	-0.255	0.144	0.177	0.009	0.131	-0.423
	(0.247)	(0.424)	(0.428)	(0.262)	(0.452)	(0.427)
Constant	78.788***	78.434***	78.983***	77.178***	76.740***	77.622***
	(3.375)	(3.372)	(3.371)	(3.365)	(3.366)	(3.356)
N	22,498	22,431	22,196	22,498	22,431	22,196
n	11,190	11,169	11,131	11,190	11,169	11,131
Hausman p-value	0.03	0.022	0.081	0.022	0.014	0.162
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.7: Estimation results of the baseline specification for the two community participation principal components where the estimating sample is the unbalanced panel. N is person-year observations.

SC measure:	Club Participation			Trust measure			Social support measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable:	Family	Employment	Health	Family	Employment	Health	Family	Employment	Health
SC	0.531**	0.623***	0.515***	1.715***	1.541***	1.619***	4.755***	4.483***	4.592***
	(0.235)	(0.194)	(0.193)	(0.197)	(0.161)	(0.163)	(0.177)	(0.151)	(0.158)
Shock (T_0)	-1.281***	-2.867***	-4.679***	-0.904***	-2.360***	-3.796***	-1.075***	-2.185***	-3.631***
	(0.212)	(0.410)	(0.380)	(0.208)	(0.397)	(0.382)	(0.147)	(0.278)	(0.278)
Shock (T_0)*SC	0.418	0.756	1.869***	-0.041	1.050**	0.173	0.385**	1.467***	0.339
	(0.280)	(0.566)	(0.530)	(0.229)	(0.429)	(0.431)	(0.169)	(0.282)	(0.279)
Shock (T_{-1})	-0.655***	-1.974***	-1.754***	-0.696***	-1.584***	-1.448***	-0.570***	-1.362***	-1.206***
	(0.205)	(0.376)	(0.362)	(0.209)	(0.381)	(0.354)	(0.145)	(0.255)	(0.246)
Shock (T_{-2})	-0.203	-0.615*	-0.325	-0.213	-0.476	-0.051	0.022	-0.453*	-0.034
	(0.197)	(0.359)	(0.353)	(0.206)	(0.351)	(0.340)	(0.143)	(0.240)	(0.230)
Shock (T_{+1})	-0.551***	-0.839**	-0.868**	-0.597***	-0.739**	-0.642*	-0.447***	-0.595**	-0.835***
	(0.202)	(0.355)	(0.366)	(0.210)	(0.355)	(0.364)	(0.144)	(0.249)	(0.254)
Shock (T_{+2})	-0.146	-0.989***	-1.022***	-0.017	-0.641*	-1.155***	-0.022	-0.778***	-1.016***
	(0.199)	(0.331)	(0.373)	(0.204)	(0.346)	(0.351)	(0.143)	(0.239)	(0.257)
Shock (T_{-1})*SC	-0.006	1.050*	0.990**	0.165	0.246	0.285	-0.113	0.478*	0.836***
	(0.278)	(0.543)	(0.498)	(0.238)	(0.371)	(0.355)	(0.162)	(0.269)	(0.258)
Shock (T_{-2})*SC	0.382	0.451	0.443	0.063	0.180	0.346	-0.262*	0.081	-0.092
	(0.274)	(0.508)	(0.459)	(0.215)	(0.377)	(0.371)	(0.156)	(0.273)	(0.223)
Shock (T_{+1})*SC	0.163	0.291	-0.073	0.205	0.987***	0.905**	-0.117	0.690***	0.285
	(0.281)	(0.501)	(0.488)	(0.245)	(0.372)	(0.382)	(0.163)	(0.257)	(0.254)
Shock (T_{+2})*SC	0.320	0.044	-0.147	-0.084	0.072	0.088	0.207	0.510**	0.063
	(0.277)	(0.488)	(0.500)	(0.224)	(0.380)	(0.381)	(0.155)	(0.256)	(0.266)
Constant	79.240***	78.757***	79.494***	95.010***	91.897***	95.405***	82.256***	81.691***	81.913***
	(11.042)	(11.025)	(10.985)	(11.971)	(11.985)	(11.875)	(10.653)	(10.636)	(10.623)
N	34,969	34,969	34,969	19,074	19,074	19,074	34,969	34,969	34,969
n	3,179	3,179	3,179	3,179	3,179	3,179	3,179	3,179	3,179
Hausman p-value	0.000	0.000	0.002	0.001	0.002	0.001	0.000	0.000	0.000
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.8: Estimation results of the baseline specification for three of the social capital measures when the estimation sample is the fully balanced panel with no missing SCQ observations. $n = 3,179$ **individuals within the sample.**

SC variable:	PC 1: 'Bridging'			PC 2: 'Bonding'		
	(1)	(2)	(3	(4)	(5)	(6)
Variable:	Family	Employment	Health	Family	Employment	Health
SC	2.450***	2.346***	2.394***	1.706***	1.762***	1.721***
	(0.332)	(0.295)	(0.280)	(0.285)	(0.246)	(0.234)
Shock (T_0)	-1.037***	-2.638***	-3.626***	-0.934***	-2.879***	-3.752***
	(0.329)	(0.632)	(0.553)	(0.326)	(0.633)	(0.554)
Shock (T_0)*SC	0.814**	0.905	-0.297	0.107	-0.148	-0.413
	(0.337)	(0.623)	(0.592)	(0.317)	(0.639)	(0.620)
Shock (T_{-1})	-0.466	-2.092***	-1.546***	-0.480	-2.166***	-1.379**
	(0.323)	(0.585)	(0.557)	(0.318)	(0.588)	(0.553)
Shock (T_{-2})	-0.629*	-0.335	-0.108	-0.610*	-0.439	-0.027
	(0.327)	(0.576)	(0.539)	(0.324)	(0.571)	(0.533)
Shock (T_{+1})	-1.038***	-1.091**	-0.459	-1.011***	-1.247**	-0.619
	(0.342)	(0.545)	(0.549)	(0.340)	(0.554)	(0.553)
Shock (T_{+2})	-0.471	-0.505	-1.129*	-0.549	-0.441	-1.019*
	(0.345)	(0.609)	(0.600)	(0.341)	(0.613)	(0.601)
Shock (T_{-1})*SC	-0.273	-0.355	0.943*	-0.030	0.374	0.002
	(0.336)	(0.566)	(0.513)	(0.336)	(0.617)	(0.607)
Shock (T_{-2})*SC	-0.000	-0.225	-0.018	0.267	-0.008	-0.033
	(0.331)	(0.587)	(0.493)	(0.323)	(0.602)	(0.514)
Shock (T_{+1})*SC	0.428	0.676	1.110*	0.144	0.135	1.430**
	(0.364)	(0.558)	(0.568)	(0.368)	(0.620)	(0.598)
Shock (T_{+2})*SC	-0.520	0.390	-0.651	0.083	0.955	0.227
	(0.331)	(0.586)	(0.602)	(0.341)	(0.642)	(0.562)
Constant	77.309***	76.291***	76.397***	76.325***	74.905***	75.210***
	(4.644)	(4.658)	(4.611)	(4.654)	(4.665)	(4.627)
N	9,537	9,537	9,537	9,537	9,537	9,537
n	3,179	3,179	3,179	3,179	3,179	3,179
Hausman p-value	0.001	0.001	0.001	0.020	0.028	0.001
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.9: Estimation results of the baseline specification for the two community participation principal components when the estimation sample is the fully balanced panel with no missing SCQ observations. $n = 3,179$ individuals within the sample.

Variable:	(1) Spouse	(2) Friend	(3) Family	(4) Property	(5) Finances	(6) Fired	(7) Retire	(8) Injury	(9) Violence
Participator	0.868***	0.822***	0.774***	0.887***	0.820***	0.885***	0.854***	0.648***	0.843***
	(0.146)	(0.165)	(0.167)	(0.152)	(0.148)	(0.148)	(0.151)	(0.154)	(0.147)
Shock (T_0)	-5.727***	-0.702***	-1.277***	-0.819**	-7.037***	-1.094**	-0.290	-4.405***	-6.767***
	(0.929)	(0.228)	(0.224)	(0.392)	(0.536)	(0.503)	(0.422)	(0.306)	(1.008)
Shock (T_0)*Participator	0.298	0.294	0.219	0.090	2.322***	-0.963	0.264	1.599***	2.570*
	(1.461)	(0.296)	(0.301)	(0.559)	(0.788)	(0.761)	(0.601)	(0.431)	(1.494)
Shock (T_{-1})	-1.745*	-0.180	-0.505**	-0.222	-2.427***	-0.498	-1.244***	-1.374***	-3.365***
	(0.908)	(0.213)	(0.208)	(0.406)	(0.520)	(0.468)	(0.419)	(0.284)	(0.967)
Shock (T_{-2})	0.075	0.065	-0.178	-0.424	-1.231**	0.179	-0.985**	-0.282	-0.160
	(0.774)	(0.216)	(0.205)	(0.410)	(0.479)	(0.435)	(0.405)	(0.270)	(0.998)
Shock (T_{+1})	-0.207	-0.210	-0.418*	0.027	-2.328***	-0.750*	0.118	-0.614**	-2.139**
	(0.877)	(0.225)	(0.224)	(0.355)	(0.483)	(0.426)	(0.407)	(0.291)	(0.886)
Shock (T_{+2})	-1.484*	-0.437*	-0.245	-0.023	-1.383***	-0.529	-0.467	-0.817***	-1.448*
	(0.773)	(0.228)	(0.208)	(0.343)	(0.446)	(0.395)	(0.444)	(0.308)	(0.867)
Shock (T_{-1})*Participator	-2.262*	-0.252	-0.040	-0.247	-0.034	-0.297	0.372	0.604	1.660
	(1.264)	(0.283)	(0.295)	(0.585)	(0.733)	(0.751)	(0.578)	(0.394)	(1.440)
Shock (T_{-2})*Participator	0.418	0.150	0.453	0.434	1.156	-0.635	-0.150	0.359	-0.315
	(1.168)	(0.287)	(0.286)	(0.602)	(0.707)	(0.667)	(0.559)	(0.361)	(1.355)
Shock (T_{+1})*Participator	-0.480	-0.260	0.510*	0.165	-0.083	1.003	0.234	-0.234	-1.711
	(1.303)	(0.299)	(0.308)	(0.508)	(0.701)	(0.684)	(0.552)	(0.396)	(1.322)
Shock (T_{+2})*Participator	-0.045	0.458	-0.129	-0.507	-0.425	0.325	0.313	0.020	0.792
	(1.180)	(0.303)	(0.299)	(0.489)	(0.673)	(0.648)	(0.575)	(0.413)	(1.126)
Constant	82.013***	82.893***	82.030***	83.125***	82.876***	81.096***	82.597***	83.417***	81.861***
	(9.065)	(9.082)	(9.060)	(9.049)	(9.043)	(9.059)	(9.066)	(9.033)	(9.038)
N	55,398	55,497	55,561	55,808	55,727	55,612	55,669	55,335	55,244
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.10: Estimations results of the baseline specification for the club participation measure conducted for each major life event individually. N is person-year observations in the balanced panel. Variable definitions are given in table B.3.

	(1) Spouse	(2) Friend	(3) Family	(4) Property	(5) Finances	(6) Fired	(7) Retire	(8) Injury	(9) Violence
Trust	1.731***	1.673***	1.716***	1.667***	1.570***	1.636***	1.654***	1.563***	1.630***
	(0.123)	(0.140)	(0.139)	(0.127)	(0.124)	(0.125)	(0.126)	(0.132)	(0.123)
Shock (T_0)	-5.743***	-0.362	-1.330***	-0.446	-5.716***	-1.919***	-0.191	-3.753***	-5.100***
	(1.110)	(0.221)	(0.221)	(0.389)	(0.585)	(0.532)	(0.467)	(0.307)	(1.126)
Shock (T_0)*Trust	-0.694	-0.066	0.135	-0.005	0.647	-0.173	0.447	0.091	0.475
	(1.076)	(0.235)	(0.235)	(0.428)	(0.539)	(0.541)	(0.512)	(0.330)	(0.987)
Shock (T_{-1})	-2.714***	-0.410*	-0.527**	0.102	-1.719***	-0.607	-1.288***	-1.309***	-0.293
	(0.973)	(0.222)	(0.216)	(0.415)	(0.546)	(0.483)	(0.454)	(0.284)	(1.133)
Shock (T_{-2})	-0.270	0.198	-0.267	-0.527	-1.197**	0.022	-1.048***	-0.342	-0.051
	(0.872)	(0.223)	(0.219)	(0.415)	(0.516)	(0.472)	(0.402)	(0.277)	(1.142)
Shock (T_{+1})	-0.926	-0.534**	-0.386*	0.323	-1.717***	-0.193	-0.006	-0.573**	-3.444***
	(0.935)	(0.232)	(0.226)	(0.362)	(0.508)	(0.461)	(0.438)	(0.289)	(1.113)
Shock (T_{+2})	-1.869**	-0.177	-0.430*	0.010	-1.716***	0.023	0.273	-0.687**	-0.646
	(0.906)	(0.225)	(0.224)	(0.335)	(0.487)	(0.449)	(0.422)	(0.294)	(0.833)
Shock (T_{-1})*Trust	-0.892	-0.340	-0.308	0.850*	0.109	0.353	0.312	0.135	2.085**
	(1.094)	(0.246)	(0.240)	(0.442)	(0.502)	(0.512)	(0.507)	(0.288)	(0.886)
Shock (T_{-2})*Trust	0.515	0.137	-0.009	-0.038	-0.431	0.321	0.148	-0.030	0.295
	(1.113)	(0.224)	(0.249)	(0.427)	(0.511)	(0.535)	(0.381)	(0.290)	(1.025)
Shock (T_{+1})*Trust	0.123	0.208	-0.067	-0.601	0.880*	1.000**	0.050	0.521*	-0.399
	(1.113)	(0.260)	(0.258)	(0.398)	(0.501)	(0.456)	(0.489)	(0.298)	(0.918)
Shock (T_{+2})*Trust	-1.226	0.071	-0.128	0.225	0.078	-0.051	-0.750	0.332	-0.137
	(0.914)	(0.237)	(0.246)	(0.347)	(0.443)	(0.471)	(0.462)	(0.309)	(0.741)
Constant	95.594***	95.336***	94.571***	93.873***	94.597***	95.732***	95.216***	96.185***	94.419***
	(9.587)	(9.593)	(9.548)	(9.579)	(9.563)	(9.550)	(9.607)	(9.541)	(9.596)
N	30,318	30,381	30,413	30,549	30,504	30,438	30,473	30,289	30,228
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.11: Estimations results of the baseline specification for the trust measure conducted for each major life event individually. N **is person-year observations in the balanced panel. Variable definitions are given in table B.3.**

	(1) Spouse	(2) Friend	(3) Family	(4) Property	(5) Finances	(6) Fired	(7) Retire	(8) Injury	(9) Violence
Social Support	4.577***	4.726***	4.569***	4.575***	4.412***	4.493***	4.590***	4.433***	4.518***
	(0.117)	(0.132)	(0.124)	(0.119)	(0.115)	(0.118)	(0.119)	(0.122)	(0.117)
Shock (T_0)	-5.119***	-0.560***	-1.058***	-0.761***	-4.974***	-1.333***	-0.132	-3.577***	-4.814***
	(0.721)	(0.157)	(0.157)	(0.272)	(0.409)	(0.359)	(0.306)	(0.221)	(0.804)
Shock (T_0)*Social Support	0.360	-0.209	0.303*	0.843***	1.158***	1.033***	0.385	-0.008	0.704
	(0.603)	(0.169)	(0.178)	(0.295)	(0.351)	(0.372)	(0.315)	(0.214)	(0.595)
Shock (T_{-1})	-2.216***	-0.253	-0.456***	-0.273	-1.883***	-0.562	-1.031***	-0.951***	-1.976**
	(0.652)	(0.156)	(0.150)	(0.292)	(0.392)	(0.363)	(0.291)	(0.198)	(0.771)
Shock (T_{-2})	0.297	0.129	0.050	-0.320	-0.644*	-0.004	-0.991***	-0.033	-0.006
	(0.577)	(0.156)	(0.148)	(0.291)	(0.338)	(0.324)	(0.284)	(0.183)	(0.710)
Shock (T_{+1})	-0.241	-0.295*	-0.172	-0.018	-1.812***	0.085	0.245	-0.585***	-2.072***
	(0.636)	(0.163)	(0.156)	(0.256)	(0.361)	(0.313)	(0.291)	(0.203)	(0.694)
Shock (T_{+2})	-1.199*	-0.247	-0.267*	-0.264	-1.217***	-0.157	-0.103	-0.725***	-0.433
	(0.615)	(0.162)	(0.150)	(0.245)	(0.345)	(0.303)	(0.291)	(0.209)	(0.599)
Shock (T_{-1})*Social Support	-0.135	-0.681***	-0.106	-0.198	0.336	0.245	0.292	0.474**	0.873
	(0.640)	(0.167)	(0.165)	(0.329)	(0.338)	(0.345)	(0.310)	(0.199)	(0.591)
Shock (T_{-2})*Social Support	-0.922*	-0.274*	-0.264	0.101	0.484	0.277	-0.179	0.108	0.541
	(0.538)	(0.164)	(0.165)	(0.316)	(0.343)	(0.345)	(0.281)	(0.183)	(0.662)
Shock (T_{+1})*Social Support	-0.099	0.005	0.083	-0.362	0.788**	1.010***	-0.323	0.236	0.535
	(0.605)	(0.177)	(0.173)	(0.272)	(0.313)	(0.334)	(0.295)	(0.200)	(0.540)
Shock (T_{+2})*Social Support	-0.357	0.131	0.202	0.198	0.197	1.079***	0.203	0.423**	0.959*
	(0.578)	(0.168)	(0.164)	(0.263)	(0.303)	(0.310)	(0.291)	(0.209)	(0.511)
Constant	82.335***	83.646***	82.336***	84.050***	83.376***	81.474***	82.964***	83.820***	82.070***
	(8.809)	(8.828)	(8.814)	(8.792)	(8.792)	(8.802)	(8.815)	(8.794)	(8.783)
N	55,654	55,756	55,815	56,070	55,987	55,873	55,929	55,597	55,509
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.12: Estimations results of the baseline specification for the social support measure conducted for each major life event individually. N is person-year observations in the balanced panel. Variable definitions are given in table B.3.

	(1) Spouse	(2) Friend	(3) Family	(4) Property	(5) Finances	(6) Fired	(7) Retire	(8) Injury	(9) Violence
'Bridging'	2.680***	2.726***	2.764***	2.698***	2.588***	2.683***	2.685***	2.663***	2.629***
	(0.230)	(0.255)	(0.252)	(0.234)	(0.229)	(0.236)	(0.237)	(0.233)	(0.230)
Shock (T_0)	-6.449***	-0.340	-1.032***	0.209	-6.420***	-1.777**	-0.286	-3.736***	-6.033***
	(1.628)	(0.384)	(0.350)	(0.681)	(0.977)	(0.890)	(0.713)	(0.470)	(1.728)
Shock (T_0)*'Bridging'	3.733**	0.748*	-0.032	0.204	1.134	0.769	1.071	0.100	-0.919
	(1.846)	(0.385)	(0.383)	(0.726)	(0.885)	(0.860)	(0.820)	(0.477)	(1.428)
Shock (T_{-1})	-2.240	-0.463	-0.444	0.906	-2.404***	-0.837	-2.107***	-1.211**	-1.220
	(1.581)	(0.377)	(0.354)	(0.754)	(0.887)	(0.883)	(0.674)	(0.475)	(1.950)
Shock (T_{-2})	-1.137	-0.045	-0.586	-1.444**	-2.292***	-0.421	-0.364	-0.711	-1.166
	(1.239)	(0.379)	(0.369)	(0.715)	(0.878)	(0.775)	(0.686)	(0.474)	(1.913)
Shock (T_{+1})	-1.820	-0.873**	-0.614	0.091	-1.426*	-1.081	-0.045	-0.401	-2.975*
	(1.418)	(0.412)	(0.376)	(0.600)	(0.777)	(0.680)	(0.696)	(0.453)	(1.599)
Shock (T_{+2})	-3.632**	-0.384	-0.921**	-0.601	-2.039**	0.052	0.644	-0.773	0.334
	(1.569)	(0.379)	(0.390)	(0.587)	(0.880)	(0.806)	(0.741)	(0.506)	(1.617)
Shock (T_{-1})*'Bridging'	-0.186	-0.291	0.199	-0.658	-0.418	0.552	0.725	0.771*	2.479
	(1.914)	(0.347)	(0.347)	(0.690)	(0.902)	(0.824)	(0.653)	(0.437)	(1.940)
Shock (T_{-2})*'Bridging'	-0.101	-0.133	0.166	0.174	-0.266	-0.527	0.023	-0.338	-0.084
	(1.104)	(0.365)	(0.348)	(0.818)	(0.870)	(0.776)	(0.639)	(0.428)	(1.652)
Shock (T_{+1})*'Bridging'	0.977	-0.329	0.272	1.976***	0.645	0.375	0.016	0.844*	1.997
	(1.265)	(0.409)	(0.408)	(0.639)	(0.714)	(0.700)	(0.679)	(0.469)	(1.985)
Shock (T_{+2})*'Bridging'	1.108	0.024	-0.484	-0.395	0.402	0.298	0.178	-0.697	2.658**
	(1.386)	(0.367)	(0.371)	(0.637)	(0.856)	(0.724)	(0.636)	(0.486)	(1.337)
Constant	78.589***	79.390***	79.693***	79.154***	80.525***	79.762***	78.891***	79.874***	79.346***
	(3.948)	(3.965)	(3.955)	(3.931)	(3.919)	(3.940)	(3.943)	(3.922)	(3.930)
N	14,976	14,999	15,018	15,090	15,065	15,019	15,040	14,942	14,929
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.13: Estimations results of the baseline specification for the first community participation principal component conducted for each major life event individually. N **is person-year observations in the balanced panel. Variable definitions are given in table B.3.**

	(1) Spouse	(2) Friend	(3) Family	(4) Property	(5) Finances	(6) Fired	(7) Retire	(8) Injury	(9) Violence
‘Bonding’	1.677***	1.657***	1.747***	1.582***	1.635***	1.648***	1.665***	1.605***	1.577***
	(0.199)	(0.218)	(0.218)	(0.201)	(0.194)	(0.200)	(0.200)	(0.202)	(0.195)
Shock (T_0)	-5.459***	-0.099	-1.080***	0.138	-6.953***	-2.131**	-0.446	-3.894***	-6.608***
	(1.653)	(0.359)	(0.355)	(0.679)	(0.983)	(0.915)	(0.687)	(0.471)	(1.720)
Shock (T_0)*‘Bonding’	1.018	0.057	0.015	0.792	-0.706	-0.539	1.083	-0.026	-2.060
	(1.571)	(0.350)	(0.345)	(0.658)	(1.016)	(0.791)	(0.664)	(0.496)	(1.352)
Shock (T_{-1})	-3.122*	-0.533	-0.433	1.118	-2.498***	-1.266	-2.067***	-1.040**	-0.872
	(1.597)	(0.356)	(0.353)	(0.767)	(0.895)	(0.877)	(0.656)	(0.469)	(1.954)
Shock (T_{-2})	-1.173	0.051	-0.641*	-1.293*	-2.523***	-0.262	-0.506	-0.747	-0.977
	(1.229)	(0.361)	(0.373)	(0.719)	(0.869)	(0.788)	(0.671)	(0.470)	(1.912)
Shock (T_{+1})	-1.292	-0.919**	-0.544	0.067	-1.590*	-1.078	-0.116	-0.420	-3.063*
	(1.436)	(0.388)	(0.375)	(0.606)	(0.835)	(0.690)	(0.680)	(0.458)	(1.649)
Shock (T_{+2})	-3.758**	-0.363	-0.974**	-0.772	-2.022**	0.271	0.568	-0.796	-0.855
	(1.553)	(0.370)	(0.390)	(0.609)	(0.896)	(0.835)	(0.721)	(0.506)	(1.605)
Shock (T_{-1})*‘Bonding’	-0.874	-0.233	-0.433	-0.240	-0.377	-0.159	0.458	0.125	4.384**
	(1.764)	(0.359)	(0.388)	(0.779)	(0.950)	(0.873)	(0.689)	(0.481)	(2.022)
Shock (T_{-2})*‘Bonding’	1.159	0.145	-0.308	1.090	0.353	0.297	-0.158	0.292	-2.233
	(0.938)	(0.337)	(0.376)	(0.798)	(1.010)	(0.716)	(0.756)	(0.453)	(1.590)
Shock (T_{+1})*‘Bonding’	-1.440	-0.017	0.472	-0.207	-0.058	0.129	0.022	0.757	3.556**
	(1.494)	(0.366)	(0.419)	(0.756)	(0.852)	(0.717)	(0.710)	(0.471)	(1.632)
Shock (T_{+2})*‘Bonding’	-2.864*	-0.113	-0.283	0.550	1.099	1.195	-0.500	-0.206	0.030
	(1.610)	(0.386)	(0.377)	(0.655)	(0.888)	(0.859)	(0.683)	(0.465)	(1.504)
Constant	77.445***	78.384***	78.597***	78.068***	79.774***	78.590***	78.101***	79.097***	78.626***
	(3.964)	(3.981)	(3.963)	(3.946)	(3.935)	(3.949)	(3.951)	(3.933)	(3.935)
N	14,976	14,999	15,018	15,090	15,065	15,019	15,040	14,942	14,929
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.14: Estimations results of the baseline specification for the second community participation principal component conducted for each major life event individually. N is person-year observations in the balanced panel. Variable definitions are given in table B.3.

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