THE SHORT-TERM IMPACT OF A PARTNER'S NEGATIVE PHYSICAL HEALTH SHOCK ON ONE'S OWN MENTAL HEALTH

MSc Health Economics, Policy & Law Research Report

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Abstract

Objectives

To determine the impact of a partner's physical health shock on one's own mental health. To ensure a homogenous study population and consistent results, the scope of this thesis was limited to the short term (one year) impact of first-time health shocks in partners on one's own mental health.

Research question

How are negative physical health shocks of a cohabiting partner related to one's own mental health in the year of the shock?

Method

Fixed-effect analyses were conducted using 154,554 observations stemming from 32,161 unique individuals (aged 16-99) that had a cohabiting partner. Data was derived from waves 1 to 10 (2009-2019) of the United Kingdom Household Survey (otherwise known as 'Understanding Society').

Results

An individual's partner experiencing a negative physical health shock of -10 or deeper in the SF-12 physical component score (PCS) was associated with a mean decrease of -0.398 in own mental health, measured through the SF-12 mental component score (MCS). This association remained significant when 'controlled' for the impacts of caregiving, which confirms the notion of the family effect (mental health impact due to caring *about* someone). Results showed a substantial additional mental health impact in people who did assume a caregiving role, which confirms the notion of a caregiver effect (mental health impact due to caring *for* someone). Results did not differ significantly by sex. The mental health effects were greatest in seniors (65+) and nonsignificant in young adults (16-35).

Discussion

The modest short-term mental health impacts of a partner's physical health shock are a result of both the family (caring about) and caregiver effect (caring for). Policy makers should be aware that a patient's physical health decline can have negative spillover effects on their significant others. Future research should focus on the long-term effects.

Contents

Introduction

In the Netherlands, a staggering 18.7% of the adult population has had a depressive disorder in their lifetime (RIVM, 2017). It is a widespread sentiment that mental health is a critical subject that should get more attention from policy makers and society as a whole. Often, people consider the multitude of health services in place for physical conditions and argue that the health services and the research concerning mental health lag behind (Russel et al., 2018). To a certain extent, this places physical and mental health in separate boxes, as is often the case when we discuss our health care systems. However, this view on health disregards the interconnectedness of physical and mental health that has been found in the past decades. This translates into the fact that someone's physical health declining can lead to an increased risk of developing mental health problems. Similarly, having mental health issues can ultimately negatively impact one's physical health (Ohrnberger et al., 2017). This thesis concerns the possibility of the level of interaction going one step further: moving on from interactions within the individual and focusing instead on interpersonal effects. Specifically, it explores whether the existence of a relationship between physical and mental health could be present at the *couple* level.

When a patient is ill, modern medicine tends to treat them as an individual case, separated from their environment. However, when you are in an intimate relationship with another person, it is plausible that a partner's well-being will affect you in one way or another. Thus, Bobinac et al. (2010) offer that we should abandon the isolated manner in which we think of a patient. They theorize that a partner's worsening physical health can have an impact on one's own mental health through two separate mechanisms. Namely, caring *for* and caring *about* your loved one. These result in the so-called caregiver effect and family effect, respectively. In the tendency to treat patients as isolated individuals, modern day health care is disregarding these so-called spillover health effects of their illnesses on significant others.

Of course, when one's partner experiences a decline in *mental* health, this could have a potential impact on one's own mental health as well. Findings in this research area include (but are far from limited to) a 2011 study by Rosenquist et al. (2011). They find that changes in depression over time are strongly correlated within friends, spouses, siblings, and neighbors. However, Golberstein et al. (2011) suggest that the size of the estimates that originated from the study by Rosenquist et al. are biased, stating that people choose where they live and work, and with whom they interact, and they may share characteristics with others in their social network that lead to similar outcomes. In their own study concerning college roommates they find less evidence of contagion, but still find modest evidence for anxiety and depression contagion. In conclusion, the interpretation of the impact of a patient's mental health on other individuals is complicated, just like that of a patient's physical health. As their respective interpretations would take place mostly separated, a choice was made to focus on one of the two.

Robust evidence on the effects of a partner's negative physical health shock on one's own mental health is still scarce. Bobinac et al. (2010) found that the well-being of Dutch informal caregivers is associated with the health of the patient (family effect) and the number of caregiving tasks (caregiving effect). While this study strengthens the theory of these effects, its main limitation was that the found association could be evidence of the baseline similarities in partners' mental and physical wellbeing, not evidence of their influence on one another. Min et al. (2020) conducted a longitudinal study into this subject, performing fixed-effect analyses in 3,055 Korean couples. Their results contribute to the investigation of the spillover effects, suggesting variations across health condition types and gender.

Investigating the existence and magnitude of a relationship between the physical health of a partner and one's own mental health is relevant in two ways. Firstly, finding out the magnitude of the impact of a partner's decrease in physical health (or: physical health shock) on one's own mental health could help the mobilization of care towards people in need of it. If spouses can be identified as 'at risk' concerning the stability of their mental health, they can be more readily offered a conversation with a health care professional to give them the opportunity to discuss their feelings and be heard. It has been found that early intervention can have a significant positive impact on a person's prognosis (Williams et al., 2008). It is also imaginable that it could be comforting for partners to know that it is 'normal' for them to be mentally affected by their partner's illness, as well, and that they should not overlook taking care of themselves.

Secondly, it is important in the context of economic evaluations. Economic evaluations in healthcare aim to measure the cost-effectiveness of medical interventions. The accuracy of an economic evaluation depends on the capacity to accurately capture all costs and effects. If we focus solely on the patient's individual well-being, but a patient's physical health shock also has an impact on the mental health of the patient's partner, we are not considering all negative health effects of the patient's illness. Vice versa, a medical intervention increasing the patient's physical well-being could have additional positive health effects on the partner. If so, these could be taken into account to determine the cost-effectiveness of the medical intervention. Basu & Meltzer (2005) state that economic theory does recognize that individual utility may be affected by the well-being of others, but that actual economic models have paid little attention to this fact in practice. In cases where the family effect is indeed present but not in the context of informal care, the family effect often goes unnoticed. Sometimes spillover effects on significant others are in fact addressed, but this is almost always limited to effects on informal caregivers, effectively disregarding the family effect in significant others that do not have caregiving tasks (Bobinac et al., 2009).

The importance of the distinction between the family effect and the caregiver effect stems from the fact that both effects require fundamentally different responses from policymakers. If, for example, the vast majority of the impact of a partner's negative health shock does stem from the caregiver effect, policy changes could be directed at relieving the caregiving burden through respite care or reprofessionalizing health care. In contrast, if the disregard for the family effect would be unjustified, relief of the caregiver burden will not be sufficient to deal with the full mental health consequences of having a partner who falls ill (Brouwer et al., 2006).

The aim of this thesis is to determine the impact of a partner's physical health shock on one's own mental health. It will make use of 10 years of panel data from the Understanding Society dataset (USoc; University of Essex 2020). To ensure a homogenous study population and consistent results, the scope of this thesis will be limited to the **short term** (one year) impact of **first time**[1] health shocks in partners on one's own mental health. The thesis research question that this thesis will answer reads: *How are negative physical health shocks of a cohabiting partner related to one's own mental health in the year of the shock?*

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[1] Concerns the first health shock that could be observed in the data. This will be discussed in more detail in the *Method* section.

Reader’s guide

The theory and empirical research behind the impact of a partner’s health shock on one’s own mental health will be discussed in more detail in the *Background* section. This will be followed by a *Methods* section, consisting of a description of the general dataset, sample selection and the fixed effects regression model that was constructed for the analysis of the relationship between negative physical health shocks of a cohabiting spouse and one’s own mental health. Subsequently, this section will include the justification and description of all included variables in the model. The findings of the performed analysis will be presented in the *Results* section. Key findings and their implications, accompanied by the strengths and weaknesses applicable to this thesis will be discussed in the final *Discussion* section.

Background

Theoretical framework

Interpersonal effects

The notion that a patient should not be regarded as an isolated individual, but rather that they impact and are impacted by their social environment, stems from the social ecological model. The social ecological model describes the interrelations among diverse personal and environmental factors in human health and illness (Stokols 1995). According to this model, a patient's health changes can have potential spillover effects to a wide range of other individuals, even those beyond immediate family members of a patient. However, the life of partners that cohabit will become increasingly interconnected over time, which intensifies their influence on one another's lives in several domains and increases the likelihood of a measurable (mental) health impact of a partner's health decline.

The family and caregiver effect

As previously mentioned, the impact of a partner's health shock on own mental well-being can be explained through the family and the caregiver effect, i.e. caring *about* and caring *for* a loved one. The family effect was first described by Brouwer et al. (2006), stating quite simply that individuals care about other people and their health to such an extent that it can impact their own well-being. They state that the family effect describes a direct effect, concerning the health of a patient directly influencing the well-being of a significant other.

The effects of performing caregiving tasks for someone who is ill fall under the caregiving effect. When an individual acts as an informal caregiver to their partner, an additional impact on their mental health is expected. After all, they will now experience the effects of caring about as well as the effects of caring for a loved one. The additional impact of caring for a significant other is explained by Bobinac et al. (2010) to stem from the fact that informal care entails sacrifice of time, unpleasant activities, physical and emotional strain and social isolation. Important to take away from the description of these two effects is that a partner who does not perform any caregiving tasks would still, in theory, be impacted by a partner's negative health shock through the family effect.

Sex differences

Multiple studies found sex differences concerning the relationship between a partner's physical health and own mental health (Min et al., 2020). Specific findings will be discussed in the empirical evidence section, but overall, stronger relationships between a partner's physical health and own mental health were found when the latter was female. This is not fully explained nor understood by recent literature. Importantly, it is a consistent finding that women show higher levels of depressive symptoms compared to men in general (Zunzunegui et al., 1998). It could be hypothesized that biological differences underly these consistent gendered mental health differences. However, Sonnenberg et al. (2000) find that sex differences in depressive symptoms can be attributed to a greater exposure of females to risk factors, like low education and an unmarried or widowed status, rather than biological differences.

In a consistent nature with the described sex differences in the over-all relationship between partner's health conditions and own mental health, it is frequently reported that female caregivers perceive more psychological distress than male caregivers, i.e. experience a greater caregiver effect (Burton et al., 2003). The fact that women experience greater caregiver burden can be explained in two ways: their absolute burden in terms of hours and caregiving tasks on the one hand and their coping style on the other. According to Pearlin et al. (1990) an unequal distribution of opportunities and responsibilities (for example in the working field) between men and women makes women assume the caregiver role more often, increasing the absolute caregiving burden. A 2002 study by Hagedoorn et al. sheds light on the coping differences between the genders. Among female partners, self-efficacy and personal accomplishment regarding caregiving is linked to distress. These associations were not significant in male partners. When female partners did feel efficacious with respect to providing appropriate support and care, they scored as low on distress as male partners. In other words, they find that the gender difference lies in the impact of experienced efficacy in their caregiving tasks. A lack of feeling efficacious does not impact the mental health of men in the way it does women. This increases the subjective caregiver burden for female caregivers.

Empirical evidence

The mental health impact of a partner falling ill

There is growing empirical evidence on the impact of a partner's physical health decline on one's own mental health. As for evidence on the general relationship, i.e. the full effect of a partner's health decline on one's own mental health, Ayotte et al. (2010) examined associations among chronic health conditions, sociodemographic factors, and depressive symptomatology in 2,184 US older married couples in a cross-sectional study. For wives, a relationship between husbands' stroke or a husband's high blood pressure and increased depressive symptomatology was found in post hoc analyses (statistical analyses that were specified after the data were seen). Thomeer (2016) analyzed multiple waves of the Health and Retirement study, to investigate whether there was a relationship between spousal multimorbidity and an increase of depressive symptoms. She found the husband's number of chronic conditions to be positively related to wife's depressive symptoms when both spouses are chronically ill. Once more, the association between wife's chronic conditions and husband's depressive symptoms was revealed to be weaker. Min et al. (2020) also conducted a longitudinal study into the subject, performing fixed-effect analyses in 3,055 Korean couples aged 45 and older. They primarily aimed to create a predictive model that would estimate the total risk of depressive symptoms in spouses of chronic patients. Still, they found a significant relationship between spousal stroke and higher depressive symptoms. The onset of cancer in a spouse was related to an increase in depressive symptoms for wives, only. It can be concluded from the described evidence that significant relationships were only found for specific types of physical conditions in partners and were sometimes even limited to a specific sex. This could be due to diseases differing in their severity, but it could also potentially be explained by the sample size: a total of 6,110 participants were surveyed for up to four waves; less than 50 per cent of those individuals experienced any spousal illness. This resulted in less than 3000 'treatment' observations. Splitting this study sample into different subpopulations to explore the impacts of different diseases might not have resulted in enough power to detect all relevant effects.

Division between family and caregiver effect

As previously described, the general mental health impact of experiencing a partner's physical health decline can be ascribed to two mechanisms or effects: the family and the caregiver effect. It is difficult to disentangle these two effects, as they often occur simultaneously (Bom et al., 2018). Here, empirical evidence on the distinct caregiver and family effect is explored.

When focusing in on the empirical evidence on the caregiver effect, studies find that partners who assume a caregiving role because of their partner's negative health shock experience an (additional) mental impact (Del-Pino-Cascade et al., 2019). Del-Pino-Casado et al. (2019) conducted a meta-analysis on the association between subjective caregiver burden and depressive symptoms, including 55 studies with a total of 9,847 caregivers originating from 20 different countries. They found a substantial positive association between subjective caregiver burden and depressive symptoms. The pooled effect was equivalent to an absolute risk reduction of 0.14. This means that if subjective burden could be prevented or eliminated, risk of depressive symptoms would decrease by 14 percentage points. One of the studies that was included in this meta-analysis was conducted by Lacey et al. (2018) and used data from the UK household survey Understanding Society, the same set of data that will be used in the conduction of this thesis research. Women in the UKHLS (UK Household Longitudinal survey) who were long-term or intermittent caregivers reported a modest increase of symptoms of psychological distress at the wave in which caregiving was first reported and did not see a process of adaptation over time. Stöckel & Bom (2020) also used data from the UK household survey to conduct a longitudinal study into the mental impact of informal caregiving, this time in a causal framework (unlike Lacey et al., 2018). They found that caregivers who provide more than 20 weekly hours of care experience substantial negative mental health effects. These effects were concentrated among high-intensity caregivers. Furthermore, findings from this 2020 study show a persistent mental impact for caregivers that provide caregiving for multiple sequential years. Other studies that researched the relationship between caregiving and own mental health in the context of a causal framework were Schmitz & Westphal (2015) and De Zwart et al. (2017). These studies present conflicting evidence on the persistence of mental health decline in caregivers. Some of them see a wear and tear effect, where mental health decline persists as years of caregiving go by, while others find evidence of adaptation, where the impact on the caregiver's mental health decreases over the years of caregiving. In any case, there are consistent findings of a negative mental health impact in the first year after start of care provision. The previously described recent longitudinal study by Min et al. (2020) found evidence for the caregiver effect, as well. Their findings show that wives caring for spouses with cancer reported more depressive symptoms than those not providing care. Additionally, husbands caring for spouses with lung disease reported more depressive symptoms than those not providing care. Again, it should be noted that only specific subpopulations of their study reached statistical significance in their relation to the outcome measure (depressive symptoms). This could mean that the impact of caregiving is only existent/relevant in the context of specific diseases and genders. However, as mentioned before, the sample size of this study could also be the reason for effects in other subpopulations not reaching statistical significance.

The family effect was studied by Basu & Meltzer (2005) when they showed that alternative treatments for prostate cancer patients can produce different direct and indirect welfare effects to all family members. They revealed that when incorporating these welfare effects - which they refer to as family effects - into the economic evaluation, this will result in lowering of the incremental cost-effectiveness ratio. However, there were no corrections for caregiving status. Hence, the effect described here is actually the full effect, theoretically consisting of both the family and caregiver effect. Even so, Bobinac et al. (2010) largely draws on this study to argue the existence of the family effect. Bobinac et al. (2010) do explore the family effect in their own study, as well, using a sample of Dutch informal caregivers. In this group, they find that both effects exist and may be comparable in size, but admit that their evidence is explorative. Importantly, since Bobinac et al. specifically studied caregiving, this study did not offer evidence on the family effect in partners who do not assume an informal caregiving role. Multiple studies investigating the health impacts of caregiving acknowledge the need to correct for the family effect, like Stöckel & Bom (2020). They purified their results so that the impact would come as close as possible to solely represent the caregiver effect and not include the impact of the family effect. The manner in which they controlled for the family effect did not allow them to find the relative magnitude of the caregiver effect compared to the family effect.

In summary, previous studies find evidence for 1) a general mental health impact of the occurrence of a physical health shock and 2) a distinct caregiver and family effect contributing to this general impact. Some studies only find significant results for specific diseases, but this could be due to limited study population sizes. Furthermore, it has proven difficult to disentangle the caregiver and family effect. The caregiver effect has been studied more extensively, while the family effect is less often clearly defined in its magnitude.

Methods & Data

Fixed effects linear regression model

Simplified model

The relationship between the occurrence of a negative physical health shock in one's partner and their own mental health will be estimated by making use of a fixed effects linear regression model. Here, the use of this model will be explained and justified. The data that will be analyzed consists of multiple longitudinal observations per individual, i.e. panel data. In panel data, the 'fixed effects' consist of the individual-specific means; the model will estimate one time-invariant intercept for each individual. This fixed effect will disappear from the regression in the end, making sure that all time-invariant variance between the individuals is controlled for. Examples of time-invariant variables are sex, race and genetic make-up.

The simplified equation that estimates a fixed effect for every individual reads as follows:

$$MH_{it} = \beta_1 X_{1it} + \beta_2 X_{2it} + \ldots + \alpha_i + \mu_{it}, \quad i = 1, \ldots, n;\ t = 1, \ldots, T$$

- MH_{it} is the mental health observed for individual i at time t.
- X_{1it} represents one independent time-variant variable
- β_1 estimates the effect of a change in X_{1i} on MH_i
- α_i is the time-invariant or 'fixed' individual effect
    - An individual-specific intercept caused by both observable (e.g. gender) and unobservable variables: all time-invariant variables are included.
- μ_{it} is the error term.

Since α_i partially describes variables that are unobservable, it cannot be directly controlled for. Fortunately, there are multiple options to eliminate α_i through the fixed effects model. In this thesis, the *within* transformation will be applied by demeaning the variables as follows:

$$MH_{it} - \overline{MH}_i = (X_{1it} - \bar{X}_{1i})\beta + (X_{2it} - \bar{X}_{2i})\beta + \ldots + (\alpha_i - \bar{\alpha}_i) + (\mu_{it} - \bar{\mu}_i)$$

$$\Rightarrow \ddot{MH}_{it} = \ddot{X}_{1it}\beta + \ddot{X}_{1it}\beta + \ddot{\mu}_{it}$$

As α_i is constant over time, α_i is equal to its mean, $\bar{\alpha}_i$. Therefore, the fixed effect disappears from the regression. Hence, all time-invariant effects will be controlled for. Finally, the fixed effects estimator is obtained by an ordinary least square (OLS) regression of $\ddot{X}$ over $\ddot{MH}$. In the *Variables* section, the dependent variable MH as well as the independent variables that will be substituted for X_1, X_2 ,... will be discussed and subsequently placed in the simplified fixed effects model above under *Final model*.

Validity and reliability

Using observational data to create a regression model introduces a risk of bias. Groups were not randomly assigned to, in this case, having a partner experiencing a health shock. This raises the risk of the group of individuals who have a partner that experiences a health shock being inherently different from the group who do not. This would make the health shock variable (which will be defined in the *Variables* section) endogenous, meaning that it would be correlated with the error term and would lead to biased estimates of a causal effect. This endogeneity can be caused by omitted variables, reverse causation and measurement error. This thesis aims to minimize these factors, and as such, to minimize bias in the estimates that will follow from analysis.

For one, performing analysis with a **fixed effects** model as described above allows partial controlling for omitted variable bias. It is not always possible to simply include all relevant control variables, seeing as not all variables can be observed. If the study population in question shows heterogeneity in the unobservable variables that are relevant to the outcome and this is not corrected for, the impact or effect of the omitted variable on the dependent variable will then be wrongfully attributed to the independent variables that were indeed included. A fixed effects model can control for all unobserved heterogeneity in unobservable variables that are constant over time. An example of a relevant fixed effect is the education level of an individual. This might influence factors relevant to health, such as health behaviors (Margolis, 2014). Partners were found to strongly influence each other's health behavior (Jackson et al., 2015). Thus, an individual's education level could impact the likelihood of one's partner experiencing a health shock. Education also has its own t link to mental health (Lorant et al., 2003). However, education level does not change (or barely) after a certain age. Hence, its potentially confounding influence on the relationship between a partner's physical and one's own mental health will be eliminated when the individual fixed effects are eliminated. Granted, this still leaves time-variant variables unaccounted for. The time-invariant variables that are common causes of exposure and outcome will lead to a confounding effect i.e. omitted variable bias and thus will be controlled for. The justification of the inclusion of the control variables can be found in the *Variables* section.

Secondly, the use of a health shock as the independent variable, rather than the use of the continuous physical health level of a partner, decreases the chances of reverse causality bias. Reverse causality could occur in the form of the mental health of an individual actually affecting the physical health of their partner, instead of vice versa. Under the assumption that health shocks are unexpected shocks, analyzing the effects of a shock will increase the odds of the relationship you find to flow one way: from the physical health shock of the partner to the mental health of the individual. It should be acknowledged that this approach minimizes but does not eliminate the risk of reverse causality.

The following **assumptions** were tested for the used regressions, as they need to hold true in order for OLS to produce valid, unbiased estimates:

1. The error term μ_{it} has conditional mean zero, meaning that the error needs to be uncorrelated with all observations of the independent variables $X_1, X_{2,\dots}$ for one individual i over time $t.$ If it is, this introduces biases to the fixed effect estimator.
2. Independent variables $X_1, X_{2,\dots}$ are i.i.d. (independent and identically distributed) across individuals $i = 1, \dots, n.$ This should not be confused with the correlation of the independent variables $X_1, X_{2,\dots}$within an individual. Independent variables are allowed to be autocorrelated (i.e. serially correlated) within individuals over time; this is actually a common property of panel data.
3. Large outliers are unlikely. This is measured through a fourth moment, which described the heaviness of the tail of distribution.
4. There is no perfect multicollinearity. This means there are no two (or more) independent variables included that are perfectly correlated, i.e. one regressor/variable can be written as a linear combination of the other (or multiple others)

Data

Understanding society

This thesis will make use of panel data from the Understanding Society dataset (USoc; University of Essex 2020). This dataset is also known under the name of the United Kingdom Household Longitudinal Study (UKHLS). USoc is conducted by the Institute for Social and Economic Research (ISER) at the University of Essex and two survey research organizations: Kantar Public and NatCen. Its predecessor is the British Household Panel survey (BHPS), a survey the USoc builds on. The USoc surveys 40 000 self-completing adult (16+) respondents from 30 000 unique households across the UK. An overlapping panel design is used: individuals are re-interviewed approximately 12 months apart and each wave is collected over a 24-month period. Its participants are surveyed on a great variety of subjects. The main purpose of USoc is to understand short- and long-term effects of social and economic change in the UK, both at the household and the individual level. Because all household members are surveyed, USoc also lends itself for the studying of interpersonal relationships like the relationship that is studied in this paper. Here, the most recently released dataset will be used, spanning ten waves originating from the period 2009 to 2019. The data that will be used stems from four sample components; a general population sample, a boost sample of ethnic minority group members; an immigrant and ethnic minority boost sample (from wave 6) and lastly participants from the BHPS that were asked to join the USoc after the BHPS closed.

Sample selection

The complete USoc dataset contained 441 310 observations from 86 856 unique individuals. All observations in respondents that did not have a cohabiting partner were excluded. Subsequently, all first-time health shocks were identified. This thesis aims to compare all observations in individuals that have partners who experience a health shock for the first time to observations in people who do not and have not had a partner experiencing a health shock. Hence, all of an individual’s observations that follow a first-time health shock in a partner were excluded from analysis. Exclusion based on the aforementioned criteria left 238 330 observations in 53 087 unique individuals.

Unfortunately, observational datasets will always deal with missing data, especially those relying on surveys. Missing data can be due to a variety of causes: participants quitting the study, respondents leaving their questionnaires incomplete or equipment failure. To obtain a dataset with observations that contained complete data on all included variables, observations with missing data on any of the included dependent or independent variables in the main regression models were dropped (31.0%). Most observations were dropped due to missing data in either one’s own mental health outcomes or one’s partner physical health outcomes. The latter is partly due to the fact that the datasets include individuals of whom the partner did not participate in the survey. From the remaining observations, all single wave observations were excluded (as fixed effects regressions can only analyze changes over time). The final study sample consisted of total of 154,554 observation stemming from 32,161 individuals, as depicted in **Figure 1**.

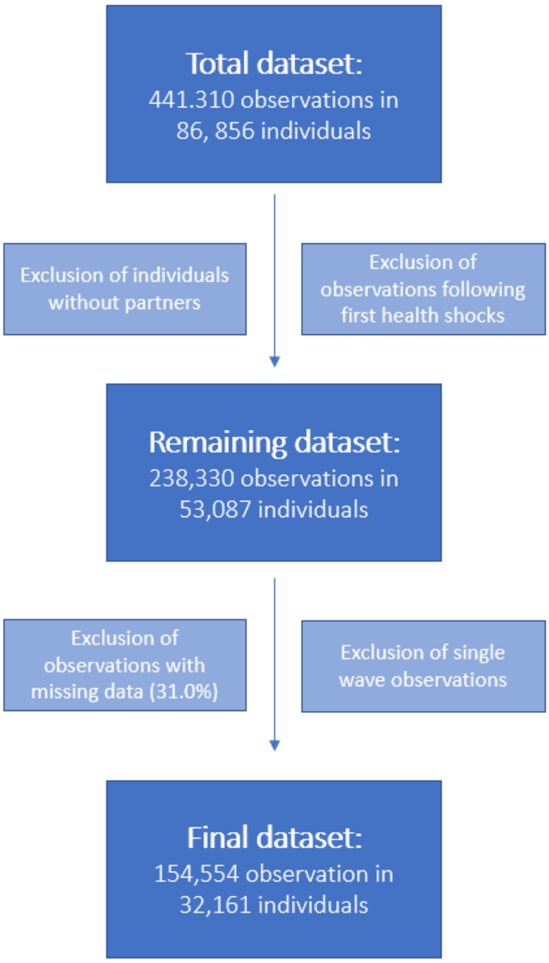


Figure 1. Sample selection.

Measurement error

In the context of large survey datasets like USoc, measurement errors are almost inevitable. In case of the USoc, all data is self-reported, which creates its own source of measurement error. Self-reports are subject to and depend on respondents being honest and having introspective ability. They also need to be able to interpret the questions correctly, which is as much dependent on the respondent as it is on the quality of the survey. Additional kinds of biases are the response bias (previous responses influencing your next response) and sampling bias (people who complete the questionnaire are the sort people who will complete a questionnaire). The latter is not an extensive problem in this thesis, since the USoc makes sure that a representative sample from the UK society fills in the surveys yearly, as was mentioned previously. It is difficult to assess or control for the endogeneity that measurement error will bring to the estimates, one can only minimize it in the design of the survey.

Data analysis

Statistical analysis was performed using Stata MP, version 16. Graphs were constructed using Microsoft Excel.

Variables

Dependent variable

Mental health

The outcome variable of this thesis is the mental health of an individual with a cohabiting partner that experiences a negative physical health shock. The variable that was used to identify potential changes in one's mental health is the mental component summary (MCS) scale from the SF-12. The SF-12 or Short Form Health Survey consists out of 12 questions in which individuals self-report on various aspects of their own health. This summary measure is constructed using a subscale related to mental health. The MCS is validated for the UK context and ranges from 0 to 100, with a higher score representing a better health status. The MCS is transformed to have a mean of 50 and standard deviation of 10 (Ware et al., 1998). The potential change in MCS will be measured only in the first year of a health shock, which means analysis will not yield any long-term results.
The USoc dataset also supplies information on mental well-being in the form of the 12-item General Health Questionnaire (GHQ). This thesis uses the MCS as it outperformed the 12-item General Health Questionnaire in a screening utility study by Gill et al. (2007).

Independent variables

Explanatory variables

A partner's negative physical health shock

The primary explanatory variable included in the model will be the negative physical health shock of a partner. Health shocks are defined as unpredictable illnesses that diminish health status (WHO, 2016) or more practically defined, sudden drops in self-reported measures of health satisfactions (Riphahn, 1999). Health shocks were previously used in research to assess their effects on labor market exits (Jones et al, 2010) and their definition is widely used to study coping strategies with health shocks in developing countries (WHO, 2016). This thesis will make no distinction between permanent and temporary health shocks, a choice that is accompanied by the decision to only assess the MCS outcome variable in the first year of a health shock. The information provided by the physical component summary (PCS) scale from the SF-12 was used to create a binary indicator for experiencing a health shock between two subsequent waves. Like the MCS, the PCS scale ranges from 0-100, in which a physical negative health shock will be defined as a drop of at least 10 points by the example of Stöckel & Bom (2020). This is equivalent to one standard deviation.

There are advantages and limitations in choosing to assess the impact of a health shock rather than take the level of health as an independent variable. The advantages and hence the argumentation to opt for a health shock are the following. Firstly, measuring the occurrence of health shocks disregards the absolute health level of an individual. Because of that, identifying health shocks offers a way to eliminate a potential source of endogeneity bias caused by the correlation between individual-specific unobservable characteristics and level of health (Jones et al, 2010). Unobservable characteristics could be personality traits and social networks. Importantly, due to the use of the fixed effects model, only the time-varying unobservable characteristics could still be relevant sources of bias that can be reduced through the use of the health shock.

Secondly, the use of a health shock decreases the chances of reverse causality bias. As previously described, reverse causality could occur in the form of the mental health of partner two actually affecting the physical health of partner one, instead of vice versa. Under the assumption that health shocks are unexpected, analyzing the effects of a shock will increase the odds of the relationship you find to flow one way: from the physical health shock of partner one to the mental health of partner. Interestingly, in their research into the reliability of self-reported health, Vaillant & Wolff (2012) found that at the individual level, self-reported health is much more sensitive to shocks than to more transitory illness or injury. Under the assumption that this would be true at the couple-level as well, this finding is yet another argument to make use of health-shocks. The limitation to using health shocks is the fact that the data obtained will only describe the impact of health shocks and is thereby disregarding the impact of gradual health deterioration.

Previously discussed studies by Min et al. (2020) and Ayotte et al. (2010) found significant impacts for the onset of only specific diseases in partners, and did not find significant relationships for the onset of other diseases. A possible pitfall in considering changes in diagnoses such as diabetes type II and hypertension health shocks is that the moment of diagnosis does not necessarily represent a sudden fall in physical health status. One should consider diagnostic delay, but even when this is not the case, the conditions that need to be 'met' to get e.g. a diabetes type II diagnosis are reached by gradual worsening of the physiological systems responsible, sometimes even over the years (Hameed et al., 2015). Creating a binary indicator for a drop in the PCS scale as opposed to using one that indicates the onset of specific diseases will ensure the presence of an actual health shock and maximize the generalizability of the results.

Only first-time health shocks are included in analysis. This was done in order to separate the first health shock from consecutive years of health deterioration (which might have a different effect). Within individuals who experience one or more health shocks, all will experience a first health shock, but not all will experience a second or third. In order to be able to accurately quantify the effects of a first health shock, all health shocks that occur thereafter were excluded from analysis. It cannot be ruled out that some of the participants did have a previous health shock before they entered the study, which is a limitation that should be taken into account.

Partner caregiver status

Assuming a caregiving role brings on an additional theoretical and empirically proven impact to an individual when their partner experiences a negative health shock. Caregivers were identified through the following question:

> *"Is there anyone living with you who is sick, disabled or elderly whom you look after or give special help to (for example a sick, disabled or elderly relative/husband/wife/friend etc.)?".*

If respondents answered yes to this question and subsequently entered their cohabiting partner's person number when asked whom they took care of, they are indeed their partner's caregiver.

Control variables

Age, employment status

The ages of partners are correlated, and a higher age in a partner will increase the likelihood of the occurrence of a negative physical health shock. Because age has been linked to mental health as well (Lorant et al., 2003), age has a potential confounding effect on the relationship between the explanatory variables and the outcome variable. Hence, the age's individual should be included in the regression as a control variable.

Finally, the employment status of an individual influences the shared income. As income has been linked to health outcomes, changes in one's employment status might influence the chance of a partner's physical health shock occurring (Marmot 2002). As Lorant et al. (2003) also linked employment status to mental health, employment status was the third variable included as a control.

The confounding effect of age and employment status and the relation between all other included variables are depicted in **Figure 2**. Variables of which the values are fixed (or near fixed) within individuals, like sex and education level, do not need to be included as they will be corrected through the omittance of every individual's fixed effect.

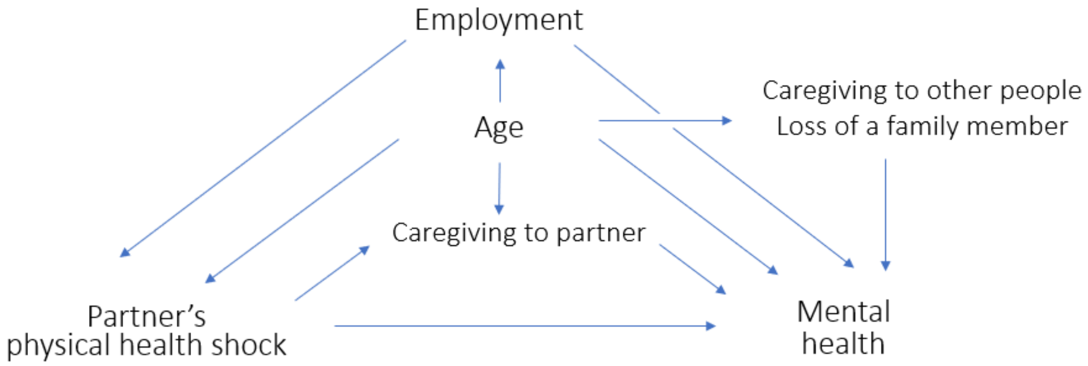


Figure 2. Directed Acyclic Graph. The relationship between the occurrence of physical health shocks in one's partner and the change in own mental health.

Of course, there are other variables that have been linked to mental health besides age, employment and education level. These include but are not limited to providing care to other people than your partner (Stöckel & Bom, 2020) and losing a family member (Parkes, 1998). These variables are also linked to age, as the likelihood of caregiving and losing a family member changes as one gets older. However, as they do not influence the chance to get a health shock, they do not formally need to be included in the models. As none of the mentioned variables lie in the causal path, it also will not hurt the accuracy of the regression estimates. What is more, they serve to test the robustness of the estimates; when included into the regression, one is sure that the effect found cannot be attributed to a potentially inequal distribution of these variables' values among the 'treatment' and control observations.

Final model

The previously described variables have been used to estimate two primary fixed effects regression models using the Xtreg command in StataMP. The fixed effects equations that are displayed here represent each full model. They will all be demeaned (as previously described) to produce a fixed effects OLS regression. Correlations between the dependent and independent variables will be assessed based on their effect size, significance levels and confidence intervals.

The fixed effects equation for the **first model** is specified as follows:

$$MH_{it} = \beta_1 HealthShock_{it} + \beta_n Control_{it} + \ \alpha_i + \mu_{it}$$

Where:

- MH_{it} is the mental health observed for individual i at time t measured by the MCS.
- $HealthShock_{it}$ is the binary indicator of the occurrence of one's partner experiencing of a negative physical health shock for individual i at time t.
- β_1 estimates the effect of a partner's health shock, a change in $HealthShock_{it}$ on MH_i
- $Control_{it}$ represents the values of all relevant control variables for individual i at time t:
    - Age.
    - Education level.
    - Employment status.
    - Caregiving to other resident (besides the partner).
    - Caregiving to nonresident.
    - Loss of a family member.
- β_n estimates the effect of the control variables on MH_i.
- α_i is the time-invariant or 'fixed' individual effect.
    - All fixed effects will be **eliminated** through the within transformation (i.e. demeaning all values) that will produce the fixed effects model.
- μ_{it} is the error term.

The first model estimates the mean impact of a partner's negative physical health shock on one's own mental health. This estimation is made in the full population of individuals whose partners experienced a physical health shock. This means the mean impact follows from the effects measured in individuals who do as well as individuals who do not assume a caregiving role as a result of the partner's physical health shock. Model 1 does not make a distinction in the mechanisms through which this impact is reached. For this reason, it allows for the estimation of the mean mental health burden that impacts the full (and heterogeneous) population of people whose partner experiences a physical health shock.

Possible differences in the health shock effects among subpopulations will be explored. First, to explore potential gender differences, the health shock variable will be interacted with sex. Secondly, the regression will be run separately for three different age groups: young adults (16-35), middle aged adults (36-64) and seniors (65+).

The fixed effects equation for the **second model** reads:

$$MH_{it} = \beta_1 HealthShock_{it} + \beta_2 Care_{it} + \beta_3 Care_{it}\beta_1 HealthShock_{it} + \beta_n Control_{it} + \alpha_i + \mu_{it}$$

Where:

- $Care_{it}$ is the caregiving status i.e. whether individual i performs caregiving tasks for a partner
- β_2 estimates the effect of assuming a caregiving role to a partner on MH_i
- β_3 estimates the interacted effect of the occurrence of a health shock and the assumption of a caregiving role

The second equation facilitates the interpretation of the family and caregiver effect. The full impact is understood to run through two mechanisms, the family and caregiver effect. Importantly, in the second equation β_1 no longer represents the full impact of the health shock because it has been 'controlled' for the caregiver effect; this leaves β_1 to represent the residual effect. It represents the impact that a partner's decline in well-being has on you which cannot be explained by the fact that you are (consider yourself to be) an informal caregiver to this person. The impact of the health shock variable (β_1) can now be fully attributed to the **family effect** mechanism: caring *about*.

The **caregiver effect** is (partly) estimated by coefficient β_2, belonging to the caregiving status variable. The β_2 coefficient describes the estimated impact of commencement of assuming a caregiving role to your partner (for any reason) on an individual's MCS. An example of a different reason than a partner's physical health shock is the gradual decline of a partner's health. Individuals of whom the reason to start caregiving *is* their partner's physical health shock are also impacted by the β_2 coefficient, but that is not the only coefficient that measures the impact of their choice to start caregiving. Namely, these individuals experience an additional impact which is measured through the interaction effect.

The interaction effect β_3 measures the potential additional mental health impact in individuals who start providing care to their partner as a result of their partner's health shock. The interaction effect could run through two 'pathways'. For one, it could show the mediating effect of caregiving on the impact of a partner's health shock. An individual might experience additional concern/worrying about their partner's health shock when they also start caregiving to their partner. This additional concern could be labeled as an additional **family effect** in these caregiving individuals. However, the interaction effect could also show the mediating effect of your partner experiencing a health shock on the impact of caregiving. This would be an additional impact compared to (for example) when people start caregiving due to their partner's gradual health decline. This could be present due to caregiving taking a different toll on an individual when its start feels more sudden. The presence of this pathway would entail an increased **caregiver effect**. As mentioned before, someone who starts caregiving as a result of their partner's health shock will be impacted by both estimates: β_2 and β_3. In contrast, someone who starts caregiving for a different reason will only be impacted by estimate β_2.

As a result of the unknown pathways within the interaction coefficient, this thesis will not be able to fully separate the family and caregiver effect in the population who does assume a caregiving role. It *will* be able to make a distinction between the mean effect in individuals who do not and the individuals who do assume a caregiving role as a result of their partner's health shock. The mean impact in the former is solely described by the coefficient β_1. The mean impact in the latter will consist of the summation of coefficients $\beta_{1,}$ β_2 and β_3. Possible differences in the health shock effects among subpopulations for model 2 will be explored in the same manner as for model 1.

Results

Descriptive statistics

Variable	**Event** **% or mean (SD)** n=10 126 observations from 10 126 unique individuals	**Control** **% or mean (SD)** n=144 428 observations from 32 161 unique individuals	Range
Explanatory variables			
Physical health shock in partner:			
-10 or deeper	100	-	0-100
-15 or deeper	42.18	-	0-100
-20 or deeper	17.10	-	0-100
Caregiver to partner	8.69	4.18	0-100
Positive change in caregiving status is simultaneous to partner's health shock of:		-	0-100
-10 or deeper	5.40		
-15 or deeper	7.78		
-20 or deeper	11.26		
Control variables			
Sex (% female)	47.50	50.89	
Age	52.69 (15.55)	49.85 (14.98)	16-99
Age groups			
Young adults (16 – 35)	15.66	19.57	0-100
Middle aged adults (36-64)	58.26	60.57	0-100
Seniors (65+)	26.08	19.86	0-100
Caregiver to other resident	3.02	2.60	0-100
Caregiver to nonresident	12,87	12.78	0-100
Loss of a family member	0.30	0.18	0-100
Working	58.00	64.34	0-100

Table 1. Descriptive statistics on the main study variables.

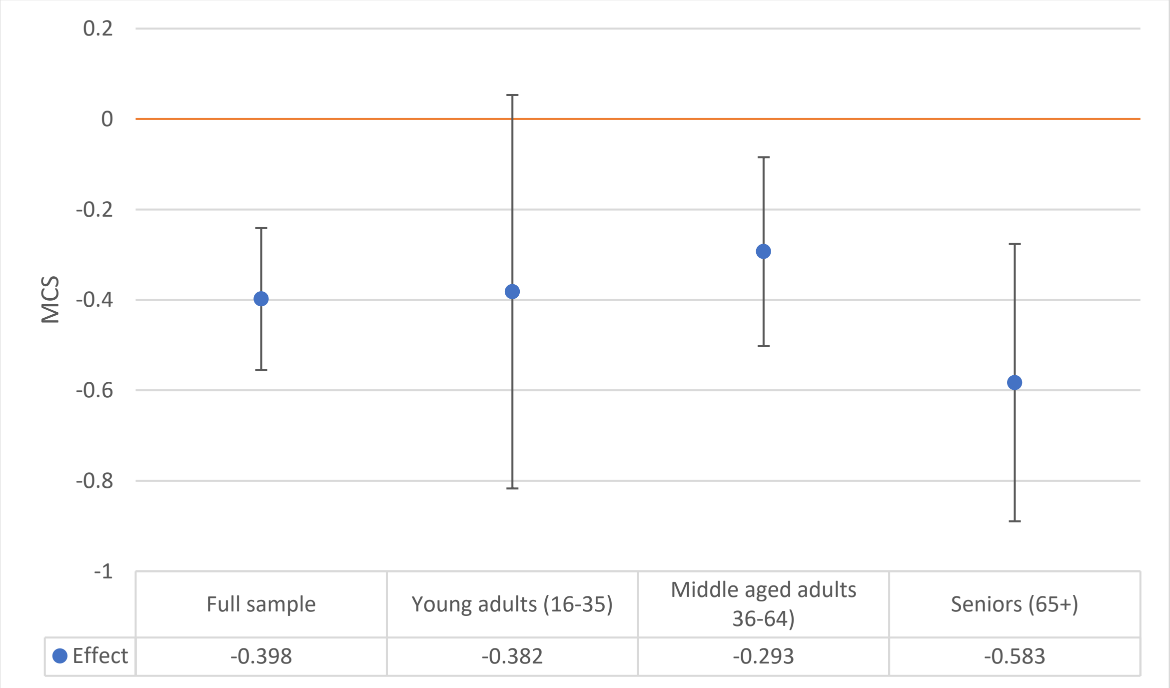
Table 1 provides descriptive statistics for the main study variables. Descriptive statistics were divided into an event and control group. The event group represents all observations in which an individual's partner experienced a health shock of -10 (PCS) or deeper in the year of the observation. The control group represents all observations in individuals whose partners neither experienced a health shock in the year of the observation nor in the observed years that came before. This means that both event and control observations can originate from one and the same individual. A total of 153 554 observation stemming from 32 161 individuals could be analyzed. The event group consists of 10 126 observations in the same number of unique individuals, which logically follows from the fact that only first-time health shocks in partners are included (as is described in the *Method* section). Of all first-time health shocks (and thus, all event observations), 42.18% were -15 or deeper and 17.10% were -20 or deeper. The share of informal caregivers was twice as large in the event group (8.69%) as in the control group (4.18%). Commencement of caregiving did not necessarily coincide with the health shock (-10 or deeper); this was the case in 5.40% of all event observations. When the threshold of a health shock is increased, the likelihood that a partner simultaneously assumes a caregiving role increases. The percentage of females was 47,50% in the event and 50.89% in the control group. This entails that males were more likely to have a partner that experienced a health shock. The mean age originating from the observations in the event group was higher (52.69, SD=15.55) than that of the control group (49.85, SD=14,98). The greatest share of the observations, 58.26% for the event and 60.57% in the control group, were done in the middle-aged population (36-64y). Of the control observations, 64.34% were in people who were employed at the time. For the event observations, this percentage was lower (58.00%). Event observations were slightly more often in people who provided care to other residents (3.02 vs 2.60% in the control group) and non-residents (12.87% vs 12,78% in the control group). Event observations more often coincided with someone losing a family member at the time of the observation (0.30% vs 0.18% in the control group). Differences as small as in the occurrence of family deaths could be due to chance rather than a systematic difference between people whose partner experiences a physical health shock and people whose partner does not.

Results model 1

Table 2 shows unstandardized estimates of the correlation between a physical health shock in a partner and changes in own mental health (measured through the MCS of the SF-12). A partner's health shock of minus 10 or deeper is associated with a significantly lower MCS (β=-0.398; p<0.01). The interaction effect of this health shock with sex is not significant, which means analysis showed no significant difference of the impact of a partner's health shock between female and male individuals. Higher age, caregiving to a different resident than your partner and the loss of a family member were significantly associated with a decrease in MCS. Being employed was significantly associated with a higher MCS. It is important to note that the regression was not created in order to estimate causal effects for any of the control variables. Hence, the coefficients of the control variables should not be interpreted in a causal manner.

Furthermore, model 1 was run separately for three distinct age groups. In young adults, the impact of a health shock was not significant (β=-0.382; p=0.086). In middle aged adults, the association did reach statistical significance (β=-0.293; p<0.01). The measured effect size was greatest in seniors (β=-0.583; p<0.01). The effects in the full population and the three age groups are also visually depicted in **Figure 3.**

Importantly, the three age groups differ in their population sizes and in occurrence of event observations. **Figure A.1**, which can be found in the appendix, explores the variance among the three age groups with respect to occurrence of health shocks, caregiving and the simultaneous occurrence of both. It allows for the observation that the sample size is smallest in the group of young adults and the frequency of the occurrence of relevant events the lowest. This decreases the power of the fixed effect model to reveal significant impacts in the youngest age group.



	Full sample	Young adults (16-35)	Middle aged adults 36-64)	Seniors (65+)
● Effect	-0.398	-0.382	-0.293	-0.583

Figure 3. The association between a partner's health shock of -10 or deeper (PCS) and own mental health (MCS). Depicted are the effect in the full sample and the effect in three separate age groups along with their 95% confidence intervals.

Outcome variable = mental component summary score	**Full sample** *n= 154,554 in 32,161 individuals*	**Full sample (int. with sex)** *n= 154,554 in 32,161 individuals*	**Young adults (16-35 years)** *n=29,853 in 8,684 individuals*	**Middle aged adults (36-64 years)** *n= 93,380 in 21,518 individuals*	**Seniors (65+ years)** *n= 31,321 in 7 661 individuals*
Explanatory variables					
Health shock	-0.398*** (0.080)	-0.332*** (0.109)	-0.382* (0.222)	-0.293*** (0.106)	-0.583*** (0.157)
Health shock · sex	-	-0.130 (0.155)	-	-	-
Control variables					
Age (continuous)	-0.198*** (0.008)	-0.199*** (0.008)	-0.462***(0.025)	-0.144*** (0.010)	-0.248*** (0,019)
Caregiver to other resident	-0.608*** (0,185)	-0.607*** (0.185)	-0.176 (0,460)	-0.629*** (0.225)	-0.974 (0,671)
Caregiver to nonresident	-0.060 (0.072)	-0.060 (0.072)	0,083 (0.243)	-0.143 (0.089)	0.167 (0.155)
Loss of a family member	-1.271** (0.443)	-1.272*** (0.443)	-1.597*(0.923)	-1.064**(0.542)	-2.792 (1.861)
Working	0.435*** (0.077)	0.435*** (0.077)	0.345** (0.171)	0.658*** (0.104)	0.612*** (0.234)
Intercept	60.084*** (0.397)	60.083*** (0.397)	61.977*** (0.739)	56.667*** (0.527)	70.781*** (1.350)

Table 2. Results for model 1. Unstandardized estimates of the linear correlation between physical health shocks in partners and own mental health measured by the MCS (model 1). Standard errors are in parentheses. Significance is depicted at: *10%, **5%, ***1% level

Results model 2

Table 3 shows the coefficients belonging to model 2, which includes the caregiving status in the regression results. In model 2, a health shock of -10 or deeper is still significantly associated with a decrease in MCS (β=-0.281; p<0,01). This association no longer resembles the full effect of a partner's physical health shock on one's own mental health, since the effect of caregiving now runs through different coefficients. In a sense, the health shock has been 'controlled' for the caregiving effect. Therefore, the effect found can be fully attributed to the **family effect** mechanism: caring *about*. The mean impact experienced by people who do not assume a caregiving role as a result of their partner's health shock equals this estimate (β=-0.281) as they are not affected by the other variables (which concern caregiving).

When estimated in the three separate age groups, the effect only reaches (<5% level) significance in seniors (β=-0.401; p<0.01). This is also the age group that shows the highest frequency of event observations, as is shown in **figure A.1** in the appendix. As a result, the power to find significant results in the analysis of distinct effects is greatest in seniors. The effect of the health shock controlled for the effects of caregiving, i.e. the family effect present in all individuals whose partner experienced a health shock is visually depicted for the full sample and separate age groups in **Figure 4.**

As was shown in the descriptive statistics, only 5.4% of physical health shocks in one's partner coincided with the **start** of providing informal care to that partner. This means that in the first year, the effects of providing care only impact a small share of people whose partner has had a health shock. Assuming a caregiving role for any reason is associated with a decrease in MCS (β=-0.738; p<0.01) in the study population.

Analysis also reveals a significant interaction effect between the occurrence of a health shock and the provision of care to your partner. In other words, people who start providing care to their partner experience an additional impact when it coincides with a partner's health shock (β=-1.000; p<0.01). This could be caused by two different pathways. On the one hand, it could mean that any other reason to start providing care, like a gradual decrease of a partner's physical health, causes a lower mean impact to one's own mental well-being. If this is the only true pathway, the interaction effect would be caused by an additional **caregiver effect**. This additional caregiver effect could be due to the fact that a health shock leads to a more sudden need for providing care compared to when one's partner's health has been declining for a while. This suddenness of the commencement of caregiving could be associated with an additional decline in own mental health. Aside from that, caregiving to a partner who has had a health shock (rather than to one whose health has been slowly declining) could be associated with different kinds of caregiving tasks. These different tasks could also result in a different (in this case, greater) mental health impact. In either of these two cases, the interaction effect makes apparent that a health shock being the reason for the commencement of caregiving is associated with an additional decline in own mental health.

A different potential pathway that could have caused the significant interaction effect is the mediating effect of caregiving on the impact of a partner's health shock. An individual might experience additional concern/worrying about their partner's health shock when they also start caregiving to their partner. This additional concern could be labeled as an additional **family effect** in these caregiving individuals.

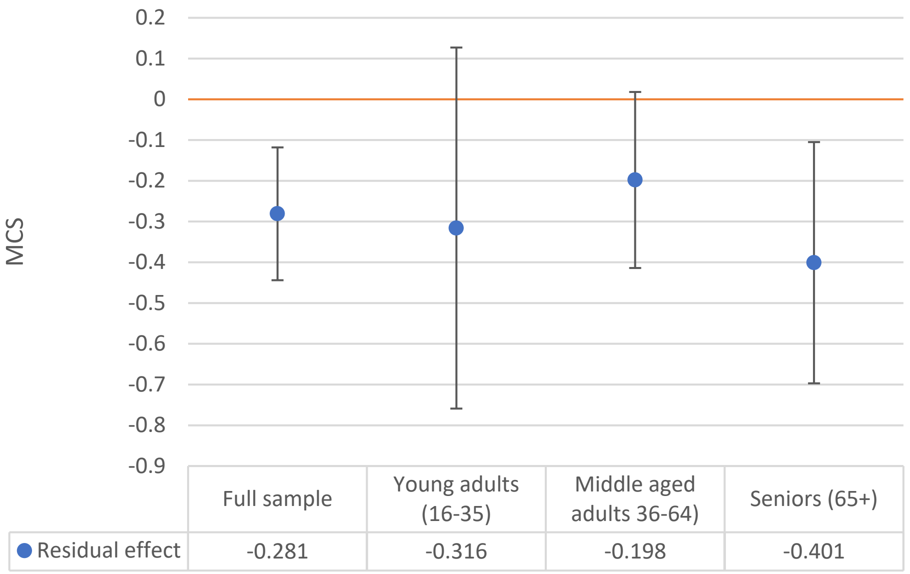
All in all, analysis shows that experiencing a partner's physical health shock and assuming a caregiving role is associated with a mean combined decrease of (β=-0.281 + -0.738 + -1.000 =) -2.019

in one's own MCS. This decrease is caused by both the family and caregiver effect. Said decrease is substantially different than the general impact that was found in model 1, which is due to the fact that 94.6% of individuals do not assume a caregiving role (yet) as a result of a health shock of -10 or deeper. The mean impact in the population who does not assume a caregiving task was estimated at β=-0.281 (p<0,01). As these observations make up 94.6% of the study sample, it makes sense that the mean general impact (β=-0.398; p<0.01) lies closer to the effect present in people who do not assume a caregiving role than it does to the combined effect present in people who experience a partner's physical health shock *and* assume a caregiving role.

The differences in the effects of caregiving between the different age groups do not follow a clear pattern. This could be due to a low variance in the explanatory variables (see **figure A.1** in the Appendix). Lastly, neither the isolated effect of caregiving nor the interacted effect of caregiving and the partner's health shock differed significantly by sex.

Outcome variable = mental component summary score	**Full sample** *n= 154,554 in 32,161 individuals*	**Full sample (int. with sex)** *n= 154,554 in 32,161 individuals*	**Young adults (16-35 years)** *n=29,853 in 8,684 individuals*	**Middle aged adults (36-64 years)** *n= 93,380 in 21,518 individuals*	**Seniors (65+ years)** *n= 31,321 in 7 661 individuals*
Explanatory variables					
Physical health shock in partner	-0.281*** (0.084)	-0.223*** (0.114)	-0.316 (0.226)	-0.198* (0.110)	-0,401*** (0,151)
Caregiving	-0.738*** (0.156)	-0.680*** (0.220)	-0.962 (0,620)	-0.963*** (0.236)	-0.406 (0,222)*
Health shock · caregiving	-1.000*** (0.293)	-1.010*** (0.416)	-1.579 (1.304)	-0.995** (0.446)	-0.936** (0.426)
Health shock · sex		-0.122 (0.163)			
Caregiving · sex		-0.116 (0.312)			
Health shock · caregiving · sex		-0.030 (0.587)			
Control variables					
Age (continuous)	-0.198*** (0.008)	-0.198*** (0.008)	-0.144*** (0.010)	-0.248*** (0,019)	-0,245*** (0,019)
Caregiver to other resident	-0.588*** (0.185)	-0.587*** (0.185)	-0.629*** (0.225)	-0.974 (0,671)	-1,024 (0,673)
Caregiver to nonresident	-0.053 (0.072)	-0,053 (0,072)	-0.143 (0.089)	0.167 (0.155)	0.170 (0.155)
Loss of a family member	-1.273*** (0.443)	-1.275** (0.443)	-1.064**(0.542)	-2.792 (1.861)	-2.744 (1.860)
Working	0.430*** (0.078)	0.430*** (0.078)	0.658*** (0.104)	0.612*** (0.234)	0.614*** (0.234)
Intercept	60.038*** (0.397)	60.038*** (0,397)	61.985*** (0,739)	56.646*** (0.527)	70.583*** (1.352)

Table 3. Unstandardized estimates of the (modulating) effect of caregiving on the linear correlation between physical health shocks in partners and own mental health in MCS (model 2). Standard errors are in parentheses. Significance is depicted at: *10%, **5%, ***1% level.



	Full sample	Young adults (16-35)	Middle aged adults 36-64)	Seniors (65+)
● Residual effect	-0.281	-0.316	-0.198	-0.401

Figure 4. The impact of a health shock controlled for the effects of caregiving. Depicted are the effect in the full sample and the effect in three separate age groups along with their 95% confidence intervals.

Robustness checks

Multiple robustness checks were performed to assess the sensitivity of the estimates to choices in the empirical specification. If the mental health effects found in the assessed individuals are truly associated with the physical health shock experienced by their partner, these estimates should be robust to different specifications of the models. One of the most distinct choices in this thesis is the manner in which a health shock is defined; a drop in the SF-12's physical component summary score of 10 or more between two waves. The effect size of this association increases when the depth of the included health shocks increases to -15 or deeper (β=-0.658; p<0.01) and even further for -20 or deeper (β=-0.735; p<0.01). This positive relation between the depth of the threshold and the effect on own MCS increases the likelihood of the found mental health effect being due to the partner's health shock. **Figure 5** visually depicts the different thresholds for health shocks in a partner and their association with own MCS score, along with the 95% confidence interval (CI). All underlying estimates can be found in Appendix **Table A.2.**

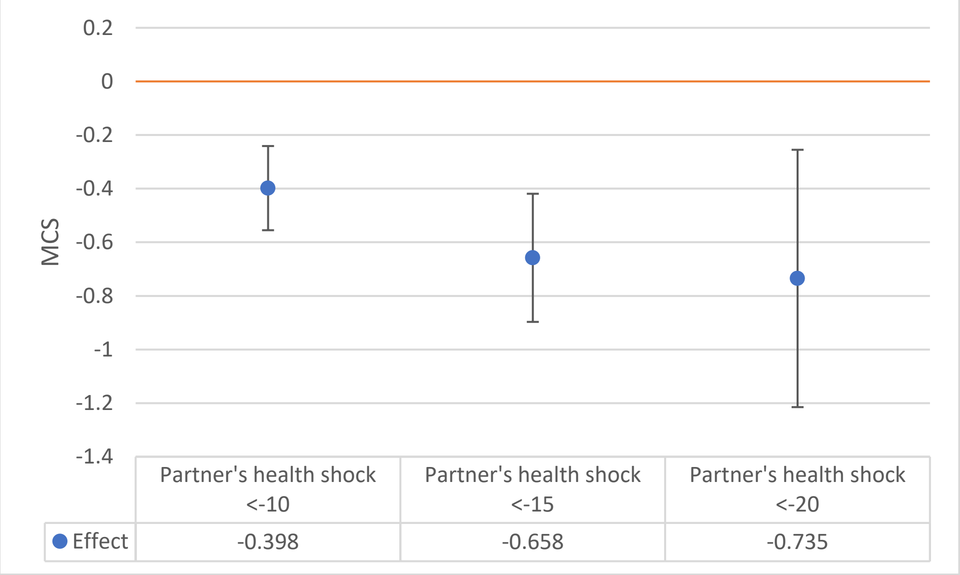


Figure 5. Different thresholds for health shocks in partners and their association with own mental health measured by MCS (model 1).

Another specification choice was made in measuring mental health outcomes through the SF-12's mental health component summary score. As mentioned, this score outperformed the GHQ (Gill et al., 2007). However, if a partner's health shock truly affects own mental health, this should be detectable along different mental health screening scales. All 12 items of the GHQ assess the severity of a distinct mental problem over the past few weeks. The Likert scoring uses a 4-point scale, from 0 to 3. To ensure compatibility between the MCS and GHQ scales, scoring was augmented to range from 0 to -3. Total scores thus range from 0 to -36 and lower scores indicate worse conditions, as is the case for the MCS. Using values from the Likert scoring method provided results that reached statistical significance, as is shown in Appendix **table A.3.** Effect sizes are smaller than for the main model, which is logical when considering the smaller range of the scale (36 in GHQ compared to 100 in the MCS). The GHQ is also responsive to an increasing depth of the health shock threshold, which is visually depicted in **figure 6.** Replacing the MCS with the GHQ allowed for the analysis of n=151,032 observations from 31,881 individuals.

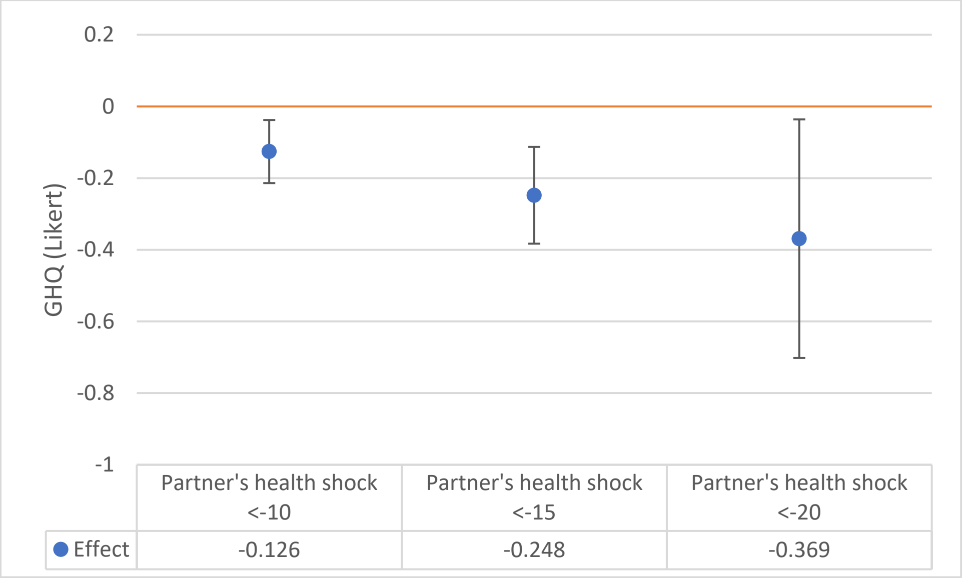


Figure 6. Different thresholds for health shocks in partners and their association with own mental health measured by GHQ.

Furthermore, if the occurrence of an illness in a partner showed the same negative relationship with own MCS as a physical health shock, this would reaffirm the presence of a relationship between a partner's physical state and one's own mental health. Unfortunately, the USoc dataset had a lot of missing values concerning the occurrence of specific diseases in the partners. Changes in the partner's (specific) disease information were not documented well enough to run the fixed effects model on. Instead, a model was conducted using the variable that described whether a partner had a longstanding illness in general. The estimated impact of the presence of a longstanding illness in a partner on one's own mental health was significant and estimated at β=-0.238 (p<0.01). Complete regression results can be found in Appendix **table A.4.**

Finally, there are other events that could be affecting mental health in the wave of the observation in which someone's partner experienced health shock. The found effects should be robust to including such events into the regressions. As external health shocks such as losing a family member were already included in the main model, it can be concluded that they did not cancel out the found effect on own mental health.

Discussion

Main results

Previous literature endorses the theory that a partner's physical health could potentially impact one's own mental health. This impact is understood to run through two mechanisms: the family effect and caregiver effect. Still, present day health care tends to treat patients as isolated individuals, disregarding the so-called spillover health effects of their illnesses on significant others. This thesis uses the USoc panel-survey to quantify the impact of a partner's health shock on one's own mental health in that same year.

Results from the first model indicate that a partner's negative health shock of -10 (PCS) or deeper is significantly associated with a decrease in own mental health in that same year. In the year of the health shock, the MCS of individuals of whom the partner has experienced a physical health shock is -0.398 (*95%CI: -0.555;-0.241*) lower than individuals of whom the partner has not experienced this health shock. The effect size of this association increases when the depth of the included health shocks increases to -15 or deeper (β=-0.658; *95%CI: -0.897;-0-420*) and even further for -20 or deeper (β=-0.735; *95%CI:-1.107;-0.362*). These findings provide confirmation for the theory that partners' physical health can impact own mental wellbeing; in such a way that it brings about a measurable decrease in mental health scores. The primary estimate (β=-0.398) was made in a population of individuals of whom 5.4% did and 94.6% did not assume a caregiving role as a result of their partner's health shock. Model 2 analyzed the differences between these two populations.

The coefficients following from model 2 can be interpreted as follows. The coefficient which belongs to the health shock variable now resembles the first-year mental health impact of caring *about* your significant other (**family effect**), since it has been 'controlled' for the impact of caregiving. This association still proves significant: analysis found a decrease in one's own MCS of -0.281 (*95%CI: -0.445;-0.117*). This strengthens the idea that there is a part of the mental health impact of a partner's health decline that is due to the family effect: the worry and concern for your partner's wellbeing. The coefficient that belongs to the variable indicating the caregiving status was also found to be significantly associated with a decrease in MCS of -0.738 (*95%CI: -0.432;-1.044*). This means that providing care to your partner is significantly associated with a lower MCS, regardless of the reason to start caregiving. Interestingly, analysis also revealed a significant interaction effect between the occurrence of a health shock and the provision of care to your partner. People who start providing care to their partner experience an additional mean decrease in MCS of -1.000 (*95%CI: -1.575;-0.424*) when it coincides with a partner's health shock. This interaction effect could be explained in (at least) two ways, which both argue a different causal mechanism. Firstly, it could mean that a health shock being the reason to start caregiving (rather than a partner's gradual health decline) increases the impact of caregiving. This could be due to a more sudden need for providing care or the need for different kinds of tasks compared to when one's partner's health has been declining for a while. Through this pathway, the interaction effect would be understood to run through the **caregiver effect** mechanism. Secondly, the significant interaction effect could show that an individual might experience additional concern/worrying about their partner's health shock when they also start caregiving to their partner. The rationale for this could be the fact that a partner who takes up a caregiving role is more often confronted with their partner's physical state. This additional concern could be labeled as an additional **family effect** in these caregiving individuals. The potential presence of these two vastly different causes of the interaction effect made it so that the magnitudes of the family and caregiver effect could not be fully disentangled in the population who assumed a caregiving role.

In summation, a partner's physical health shock coinciding with the start of assuming a caregiving role is associated with a mean combined decrease of (β=-0.281 + -0.738 + -1.000 =) -2.019 in one's own MCS. The mean impact in the population who does not assume a caregiving task was estimated at β=-0.281, which equals the health shock variable from model 2 ('controlled' for the effects of caregiving). On the one hand, these findings offer evidence on the theory that people who do not assume a caregiving role still experience a significant decrease in own MCS when their partner falls ill. This finding could potentially offer solace to individuals with partners who have fallen ill who find themselves struggling: it is 'normal' to experience a decline in own mental health. When a partner's physical health declines, one might overlook how this affects themselves. The previously discussed disregard for the family effect in economic evaluations and policy could also be deemed inappropriate based on these findings, as the findings help argue that it does exist. However, the findings also suggest that the mental health impact is substantially greater in people who *do* assume a caregiving role. This explains and could be seen as a defense for literature's and policy's focus on the effects of caregiving.

In the exploration of the differences in effects between the three different age groups, it was found that a partner's health shock was associated with a mean mental health decrease in seniors (65+) of -0.538 (*95%CI:-0.890;-0.276*) in model 1. In middle aged adults, the association did reach statistical significance (β=-0,302)(*95%CI:-0.501;-0.084*) but with a lower estimated decline in mental health. In young adults, the impact of a health shock was not significant (β=-0.382)(*95%CI: 0.054; -0.818*). Model 2 showed that the family effect was also greatest in the eldest age group (β=-0,401; 95%CI), while the coefficients belonging to the caregiver effect did not show a clear pattern among the age groups. The lower frequency of partner's health shocks in the younger population (as can be observed in appendix **table A.2**) decreased the power of finding a significant effect in the younger population. One could argue that this lower frequency of partner's health shocks in the young adults compared to the middle-aged adults and the seniors means that the focus should not be on the younger group, anyway. On the other hand, the fact that it is more common in older aged individuals could mean that it is a more alienating experience for young adults. Furthermore, younger people generally contribute to society more actively, which means that in the context of economic evaluations, their wellbeing could be viewed as more productive (Krol, 2012). The found confidence interval in this study still allows for the true value of the impact in young adults to exceed the true value in seniors. Because of that, I believe a study exploring the mental health effects of a partner's physical health decline in a greater group of young adults that experience a partner's physical health decline could reveal valuable information.

Neither the general impact from model 1, nor the family or caregiver effects from model 2 show significant effects when interacted with sex. Thus, no significant differences in impacts by sex were found.

As for the magnitude of the effect sizes that were found, it is important to note that they are modest: changes of MCS scores have shown to be relevant at a societal level from 1-2 units upward. A 1-point *increase* in MCS is associated with 7% lower total health care expenditure, 4% lower pharmacy expenditures and 15% lower rate of hospital inpatient visits (Kazis et al., 2004). Sensitivity analyses showed that increasing the depth of the health shock threshold increases the effect size, nearing a general 1-point decrease. At an individual level, definitions (and therefore, estimates) of clinical relevancy may vary. In 1996, Ware et al. found that 7,9 units in MCS are required to consider a change clinically relevant (1996). A 2013 study by Janzen et al. cite the same first author to have communicated in writing that a difference in score of 3 points is considered clinically significant (John

E. Ware, Jr, PhD, written communication, March 2011). In any case, the short term-effect of a partner's health shock found in this thesis does not reach this individual relevancy threshold.

Previous literature

When reflecting on previous evidence in general, one finds that previous studies with a similar research design only found significant associations in the onset of specific diseases (Ayotte et al., 2010, Min et al., 2020). Neither of these studies found effect sizes in the first year that would reach clinical relevance, though they did not use the MCS, which makes one on one comparisons of effect sizes difficult.

An important difference between this study's findings and previous literature is the lack of gender specific findings. However, it is important to note that all interaction terms consistently have a negative coefficient, which suggests a greater impact for females in both the general impact as well as the separated family and caregiver effects. The insignificance of the interaction terms could be due to the variance being too small to detect. The results do not provide evidence for a clinically relevant difference in males and females, but do not necessarily contradict previous studies which did find a difference.

A major share of previous literature studied the elderly. Therefore, the findings of a significant impact of a partner's physical health shock in middle aged adults bring new confirmation: it is not just the elderly that experience the family and caregiver effect. In young adults, the impact did not reach statistical significance, which (as discussed previously) could be due to a lower number of event observations in this age group.

Limitations and future directions

The first limitation lies in the fact that estimated from a fixed effect model cannot truly be interpreted in a causal manner. The fixed effects model that was used in thesis does provide valuable information. Namely, it serves to confirm the notion of a mental health impact of a partner's physical health shock, approaches the magnitude of the impact in the first year and offers findings on the relative contributions of the family and caregiver effect to that impact. Yet, while fixed effects models do avoid bias caused by all time-constant heterogeneity, time-variant elements that could bias the regression results could in part be unaccounted for. For example, previous research found that individuals could select into caregiving based on their previous health, which is time-variant. Including pre-treatment health status in an individual FE model is not possible as the lagged dependent variables correlate with the fixed effects in the error term and would give rise to dynamic panel bias (Bom et al., 2018). The risk of reverse causality and omitted variable bias make causal inference difficult to achieve through a regression model. Coefficients should therefore be interpreted with caution. Future research could make use of the Arellano-Bond (1991) (A-B) estimation technique, which allows for the incorporation of previous health of the assessed individuals.

Secondly, this thesis aimed to analyze first-time health shocks, only. However, it cannot be ruled out that the participants did have a previous health shock before they entered the study, which is a limitation that should be taken into account. Second or third time health shocks in a partner might have a greater impact as they could take a repetitive toll on own mental health. In studies researching the isolated caregiver effect, some see a wear and tear effect, where mental health decline persists as years of caregiving go by, while others find evidence of adaptation, where the impact on the caregiver's mental health decreases over the years of caregiving. The same two mechanisms could theoretically be in play for the relationship between a partner’s health shock and one’s own mental health. Hence, it cannot be said with certainty how unrecorded previous health shocks affected this study’s estimates.

Thirdly, this thesis concerns the mental health impact of a partner’s health shock that manifests in the first year, only. It cannot comment on longer term impacts of health shocks. Future research should focus on the manner in which the modest short-term mental health effects of a partner’s health shock develop in the long term. A partner’s illness or physical health shock might also decrease MCS in the following years to come, especially in the context of a partner’s health declining even further. If the first-year effect found in this thesis repeats in the subsequent years, this might very well add up to a clinically relevant decline of own mental health. The long-term impact analysis of caregiving performed by Stöckel & Bom (2020) which performed statistical matching showed persistent and repeating decreases of mental health in caregivers. Analyzing partner’s health shocks in the same causal framework could fill the gap of long-term findings and shed light on the potential yearly accumulation of mental health decline due to a partner’s health shock.

Furthermore, caregiving status was measured as a single item. Previous research found the impact of caregiving to differ significantly for different intensity levels of providing care (Stöckel & Bom, 2020). Future studies could use more complex measurements of caregiving to pinpoint the subpopulations most heavily impacted more accurately by their partner’s physical health shock. A final limitation lies in the choice to perform a complete case analysis with the exclusion of missing values. In performing a complete case analysis, a specific dataset was used that has possibly been biased in its selection of the complete observations.

Policy recommendations

Based on this study’s findings, policy makers who seek to mitigate the negative spillovers from illness should put a greater focus on the partners of patients that experience more severe physical illness. After all, this study found that the impact increases with an increase in depth of the health shock threshold. Furthermore, the individuals who act as an informal caregiver were found to be impacted the most. Therefore, policy directed at minimizing the spillover effect should (at least partly) focus on relieving the burden of caregiver activities.

Importantly, policy makers should not neglect that part of the found mental health impact is not caused by caregiving. As it is less clear how to target the family effect, I would recommend qualitative research into the multitude of mechanisms and interactions that create the family effect: why *does* a partner’s health shock affect your own mental well-being? Findings from such studies can help decide whether it could provide solace to talk about your concerns and worries for the future and give direction to potential support groups.

A final point I would like to touch on is the potential inclusion of these negative spillover effect in the economic evaluation of medical interventions by policymakers. The results from this thesis could mean that individuals with a cohabiting partner may gain more from their treatments than people who are single. However, as offered by Basu & Meltzer (2005), this does not necessarily mean that resource allocation should be altered to favor people who are part of a cohabiting couple. This is because it could entail a maximization of total well-being, but is possibly not a very equitable way to do so. It produces an ethical concern that patients with certain diseases may have lower potential to ‘produce’ these social spillover effect due to lower average family sizes. Granted, this could possibly be addressed using approaches such as equity weights, but equity concerns should always be taken into consideration (Wagstaff, 1991;Williams, 1997; Nord et al., 1999).

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Appendix

	Young adults **(16-35 years)** *n=29,853 in* *8,684 individuals*	**Middle aged adults** **(36-64 years)** *n= 93,380 in* *21,518 individuals*	**Seniors** **(65+ years)** *n= 31,321 in* *7 661 individuals*
A partner's health shock	5.31% of observations (n= 1,586)	6.32% of observations (5,899)	8.43% of observations (n=2641)
Partner caregiving	1.44% of observations (n= 430)	3.57% of observations (n=3,338)	10.08% of observations (n=3,157)
Simultaneous start of caregiving and occurrence of health shock	0.13% of observations (n=34)	0.27% of observations (n=254)	0.84% of observations (n=363)

Table A.1. The variance in explanatory variables across age groups. Table displays frequencies of occurrence (value=1) for explanatory variable.

Outcome variable = mental component summary score *n= 154,554 in 32,161 individuals (full sample)*	**Health shock -10 or deeper**	**Health shock -15 or deeper**	**Health shock -20 or deeper**
Explanatory variables			
Physical health shock in partner	-0.398*** (0,080)	-0.658*** (0.122)	-0.735*** (0.190)
Control variables			
Age (continuous)	-0.198*** (0.008)	-0.202*** (0.008)	-0.206***(0.008)
Caregiver to other resident	-0.608*** (0.185)	-0.609*** (0.185)	-0.608*** (0.185)
Caregiver to nonresident	-0.060 (0.072)	-0.062 (0,072)	-0.061 (0.072)
Loss of a family member	-1.271** (0.443)	-1.263*** (0.443)	-1.275*** (0.443)
Working	0.435*** (0.077)	0.436*** (0,078)	0,436*** (0.077)
Intercept	60.084*** (0.397)	60.224*** (0.391)	60.398*** (0.388)

Table A.2. Unstandardized estimates of the linear correlation between a health shock and own MCS using physical health shocks at different thresholds for model 1. Standard errors are in parentheses. Significance is depicted at: *10%, **5%, ***1% level.

Outcome variable = 12 item general health questionnaire, Likert scoring *n=151,032 observations in 31,881 individuals.*	**Health shock -10 or deeper**	**Health shock -15 or deeper**	**Health shock -20 or deeper**
Explanatory variables			
Physical health shock in partner	-0.126*** (0.045)	-0.248*** (0.069)	0.369*** (0.107)
Control variables			
Age (continuous)	-0.025*** (0.004)	-0.025*** (0.004)	-0.026*** (0.004)
Caregiver to other resident	-0.230** (0.105)	-0.230** (0.105)	-0.230** (0.105)
Caregiver to nonresident	-0.046 (0.041)	-0.046 (0.041)	-0.046 (0.041)
Loss of a family member	-0.891*** (0.250)	-0.887*** (0.250)	-0.891*** (0.250)
Working	0.607*** (0.044)	0.607*** (0.044)	0.607*** (0.044)
Intercept	9.849*** (0.226)	9.822*** (0.222)	9.777*** (0.221)

Table A.3. Unstandardized estimates of the linear correlation between a health shock and own GHQ using physical health shocks at different thresholds for model 1. Standard errors are in parentheses. Significance is depicted at: *10%, **5%, ***1% level.

Outcome variable: MCS *n= 254,469 in 32,160 individuals*	
Explanatory variables	
A partner's long-standing illness (LSI)	-0.238*** (0.058)
Control variables	
Age (continuous)	-0.208*** (0.008)
Caregiver to other resident	-0.606*** (0.185)
Caregiver to nonresident	-0.056 (0.072)
Loss of a family member	-1.291*** (0.444)
Working	0.434*** (0.077)
Intercept	60.593*** (0.387)

Table A.4. Unstandardized estimates of the linear correlation between a partner's long-standing illness and own MCS. Standard errors are in parentheses. Significance is depicted at: *10%, **5%, ***1% level.