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Christian Bünnings
FOM University

Lucas Hafner
University of Erlangen-Nürnberg

Simon Reif
University of Erlangen-Nürnberg

Harald Tauchmann
University of Erlangen-Nürnberg

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Health Shocks and Relationship Breakdown: Empirical Evidence from Germany*

Christian Bünnings
FOM Hochschule
RWI – Leibniz Institut für Wirtschaftsforschung

Lucas Hafner
Universität Erlangen-Nürnberg

Simon Reif
Universität Erlangen-Nürnberg
RWI – Leibniz Institut für Wirtschaftsforschung

Harald Tauchmann
Universität Erlangen-Nürnberg
RWI – Leibniz Institut für Wirtschaftsforschung
CINCH – Health Economics Research Center

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Abstract

From an economic perspective, marriage and long-term partnership can be seen as a risk-pooling device. This informal insurance contract is, however, not fully enforceable. Each partner is free to leave when his or her support is needed in case of an adverse life event. An adverse health shock is a prominent example for such events. Since relationship breakdown itself is an extremely stressful experience, partnership may backfire as informal insurance against health risks, if health shocks increase the likelihood of relationship breakdown. We address this question empirically, using survey data from Germany. Results from various matching estimators indicate that adverse shocks to mental health substantially increase the probability of a couple splitting up over the following two years. In contrast, there is little effect of a sharp decrease in physical health on relationship stability. If at all, physical health shocks that hit both partners simultaneously stabilize a relationship.

JEL codes: I12, J12, D13.
Keywords: separation, partnership dissolution, health shock, MCS, PCS, matching.

*Address for correspondence: Harald Tauchmann, Professur für Gesundheitsökonomie, Findelgasse 7/9, 90402 Nürnberg, Germany. Email: harald.tauchmann@fau.de. Phone: +49 (0)911 5302 635.

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1 Introduction

Many economists think of marriage and long-term relationships as risk-pooling instruments (e.g. Weiss, 1997; Dercon and Krishnan, 2000; Schmidt, 2008). Income uncertainty is the most obvious risk against which long-term partnership may provide informal insurance. Yet, a relationship may also provide informal insurance against non- or just partially monetary adverse life events, such as career and social disappointments, loss of relatives and friends, and in particular negative health shocks. While the income security from marriage can be substituted by the purchase of formal insurance on the market, there is no formal insurance mechanism for emotional support after adverse life events. Marriages and long term-relationships as implicit insurance contracts are – if at all – only partially enforceable. While withdrawing from financial obligations may not be possible in case of divorce, emotional support can be denied at any time. In particular, each partner is free to leave if one does not want to share the (non-monetary) burden of an adverse shock that hits the spouse. Ironically, partnership breakdown itself is a particularly stressful life event (Scully et al., 2000; Dolan et al., 2008). In consequence, if a negative health shock results in partnership breakdown, partnership does not only fail but may even backfire as informal insurance mechanism. In this paper, we show that the informal insurance that marriage provides against the emotional strain of an adverse life effect – here a health shock – works only for selected types of events and fails for others.

The statistical association of health and relationship – in particular marital – status is well established in the empirical literature (e.g. Schoenborn, 2004; Wilson and Oswald, 2005; Wood et al., 2009; Koball et al., 2010). Most relevant to our analysis, Kohn and Averett (2014b) and Lillard and Panis (1996) find that poor health is associated with a higher probability of divorce. In a related analysis that focuses on the interplay of mental health and marital transitions, Wade and Pevalin (2004) not only find divorce to be a predictor of poor mental health but also that divorce rates are higher among those who had poor mental health in the past. Johnson and Wu (2002) conduct an empirical analysis similar to Wade and Pevalin (2004) and disentangle different channels through which psychological distress and marital disruption are linked and find that selection out of marriage due to poor mental health may play a role in the link between psychological health and relationship breakdown. The majority of papers however focuses on marriage – or cohabitation – as a determinant of health. Yet, in several contributions to this literature the reverse direction of causation still comes into play via selection into marriage being identified as affected by health. That is, in a major share of this literature, effects of health on relationship status are primarily regarded as an obstacle to identifying the effect of prime interest that needs to be dealt with (Lillard and Panis, 1996; Brockmann and Klein, 2004; Averett et al., 2013; Kohn and Averett, 2014b,a; van den Berg and Gupta, 2015).[1]

In this paper we contribute to the small literature that directly analyses the effect of

[1] Another strand of the literature exclusively focuses on the role of health for selection into marriage (e.g. Mastekaasa, 1992; Manfredini et al., 2010; Lipowicz, 2014). The latter, for instance, links various health measures measured at pre-marriage age to later marital status. This generates strong indication for good health being a critical success factor at the marriage market. Yet, this is a different question than the one regarding the link between partnership stability and health shocks.

poor health or negative health shocks on partnership stability. An early explicit analysis on the topic comes from Merikangas (1984) who uses a rather small and intentionally selective sample of married individuals who suffer from depression and finds that the probability of later divorce is substantially higher if the spouse also suffers from mental disorders. This telling yet purely descriptive result may however not be informative about the effect of poor health in the general population. Using survey data from the US, Booth and Johnson (1994) find a negative association of self-reported health and self-reported marital quality and marital happiness, which they interpret as adverse effects of deteriorating health. Though they discuss several channels through which these variables might be linked in a non-causal way, the analysis does little to isolate the effect of interest besides controlling for lagged health and lagged outcome variable. In a descriptive study using the National Co-morbidity Survey from the US, Kessler et al. (1998) document a significant association of later divorce with several mental disorders. Based on longitudinal data from the Dutch city of Eindhoven, Joung et al. (1998) examine the association of self-reported health and several marital transitions between the states unmarried, married, divorced, and widowed. Only the transition from 'married' to 'divorced' is significantly correlated with health which can be interpreted as suggestive evidence for an effect of health on partnership stability. Pevalin and Ermisch (2004) use data on cohabiting but unmarried individuals from the British Household Panel and find that the risk of dissolution of a cohabiting union is positively associated with poor mental health in the previous year for men. The corresponding result for women is less clear but points in the same direction.[2] Negrusa and Negrusa (2014), to which in some respects our paper is most closely related, use longitudinal information on deployed US soldiers to establish a strong detrimental effect of post-traumatic stress disorder (PTSD) on marriage stability. Stressing that conditional on deployment developing PTSD is largely a matter of exogenous factors, they interpret this effect as causal. This argument is strengthened by instrumenting PTSD with, for instance, actual involvement in combats, which qualitatively does not change the key result. Interestingly, Negrusa and Negrusa (2014) do not find an effect of general health on the probability of divorce. Referring to earlier work (e.g. Charles and Stephens, 2004) that did not establish negative effects of disability on marriage stability, they hypothesize that shocks to mental and shocks to physical health may exert different effects on the probability of divorce.

Our paper contributes to the existing literature in several dimensions. Similar to Negrusa and Negrusa (2014), we separate the effect of a sharp worsening of health from the role the level of health plays for relationship stability. Yet, unlike Negrusa and Negrusa (2014), our analysis is not restricted to a very specific population. Similar to Pevalin and Ermisch (2004), we base our analysis on a population survey. More precisely, we use data from the German Socioeconomic Panel (SOEP). To our knowledge, the present paper is the first in this mainly US and UK dominated empirical literature to use data from Germany.

[2] Interestingly, the results regarding the effect of poor mental health on the probability to marry are inconclusive. Though the empirical evidence is suggestive, it seems still questionable whether the estimated relative risks reflect a causal effect of mental health on partnership stability. Considering lagged rather than contemporaneous mental health as explanatory variable suggests that the direction of causation is from mental health to partnership stability. However, one still cannot rule out that mental health and relationship quality interactively deteriorate over time, ultimately resulting in a separation.

Moreover, we do not analyze the effects of a specific health shock like developing PTSD or becoming permanently disabled but consider general health shocks. We nevertheless distinguish shocks on mental and on physical health and do not restrict the analysis to one dimension of health. Every other year, the SOEP includes the SF12 questionnaire and aggregates the results to a mental as well as a physical health index (the mental health component scale (MCS) and the physical health component scale (PCS) respectively). Additionally, we do not restrict our analysis to married couples but also consider partners that cohabit without being married and in some variants of our empirical model we also include homosexual couples.

We estimate effects of health shocks on partnership stability that are more relevant to the general population than those estimated for specific sub-populations and specific health events. As we cannot exploit purely exogenous sources of variation in general health, we rely on matching estimators to address the possible endogeneity of changes in mental and physical health. Our results show that mental health shocks increase the probability of relationship breakdown while physical health shocks can stabilize partnerships. The remainder of the paper is organized as follows. In Section 2, we introduce the data and describe how the key variables are constructed. We discuss our empirical approach in Section 3 and present our estimation results in Section 4, followed by a concluding Section 5.

2 Data

2.1 Data Source

We use data from the German Socio-Economic Panel (SOEP), a large annual longitudinal household survey that started in 1984 (Haisken-DeNew and Frick, 2005) and can be regarded as the German counterpart to the British Household Panel (BHPS), which is used in several related studies (Wade and Pevalin, 2004; Pevalin and Ermisch, 2004; Kohn and Averett, 2014b,a). Even though the SOEP comprises rich, retrospective information about the partnership histories of the survey respondents that partly dates back into time long before the start of SOEP, we can only use the panel waves from 2002 on, after health information from the SF12 was included in the survey. Moreover, the SF12 questionnaire is part of the survey only every other year, we therefore use a biennial panel for our analysis.

2.2 Couples and Separations

In our empirical analysis, we consider the 'couple' the unit of observation. A couple is defined as two individuals in the SOEP who mutually identify themselves as partners. This effectively implies living together in one household as the SOEP is a household survey that collects information about all household members but not about individuals living in a different household, even if strong social ties exist.[3] One may regard excluding non-cohabiting couples from the analysis as rather restrictive. Yet, as we look at partnership from a risk pooling perspective, living together can be regarded as a suitable criterion for distinguishing romantic affairs from relationships in which sharing economic resources and life risks play a significant role. Though the vast majority of such defined couples are married couples, the analysis is not confined to the latter group.

Since a couple consists of two partners, distinguishing two 'roles' within a couple is tempting, in particular if one is interested in heterogeneous effects of health shocks within a couple. A traditional way of defining two roles in a couple is to distinguish between the female (♀) and the male (♂) partner. This allows for addressing the question of whether it makes a difference if the male or if the female partner experiences a health shock. We choose this traditional model as reference. One drawback of this model is that it does not allow for considering homosexual couples. Moreover, with respect to partnership as risk-pooling instrument, the sex of the partners might be an ill-suited criterion for differentiating the partners. Hence, we also estimate an alternative model that considers the roles 'main breadwinner' (☉) and 'partner of main breadwinner' (☾). Since the head of the household is usually the prime breadwinner, these roles may better capture economic – and possibly bargaining – power within a couple that may matter for how partners cope with adverse events that hit the couple. Unlike the traditional man-woman model, the alternative model in principal allows for switching roles within an existing couple. Moreover, the main breadwinner-partner model allows for considering homosexual couples. For roughly three in four couple-year observations, the main breadwinner is male.

Our final sample consists of six biennial panel waves (2004–2014) and comprises 8 224 couples and 25 119 couple-year observations. It is possible that different couples are linked by individuals who have relationships with different partners in their lives. This conflicts with the idea that couples are independent observational units. We hence identify couple networks in the data, that is couples that are directly or indirectly linked and use these couple networks for clustering estimated standard errors. In the population some of these couple networks are presumably very large and connect even very distant individuals. The couple networks we identify in our data are however rather small. This is explained by the SOEP being just a small sample from the population and by considering a relatively short period of time in our analysis. The number of couple networks (8 064) is not much smaller than the total number of couples, which implies that we observe most of the individuals in just one couple.

The outcome we consider in the empirical analysis is whether or not an existing relationship breaks down. This binary variable is constructed according to our partnership definition. A couple splits up, if two partners who have mutually identified themselves as partners in the previous period no longer do this. This may or may not involve the formation of new couples. In some sense the outcome is whether or not an observational

[3] Very limited information is available even for some partners who do not live in a 'SOEP household'. Yet this information does not originate from a personal questionnaire and, in consequence, does not comprise the health information that is required in our analysis. One exception is the rare case of one partner leaving the household while not exiting the partnership. In this case, the partner is tracked by the SOEP constituting a 'SOEP couple' that lives in different households.

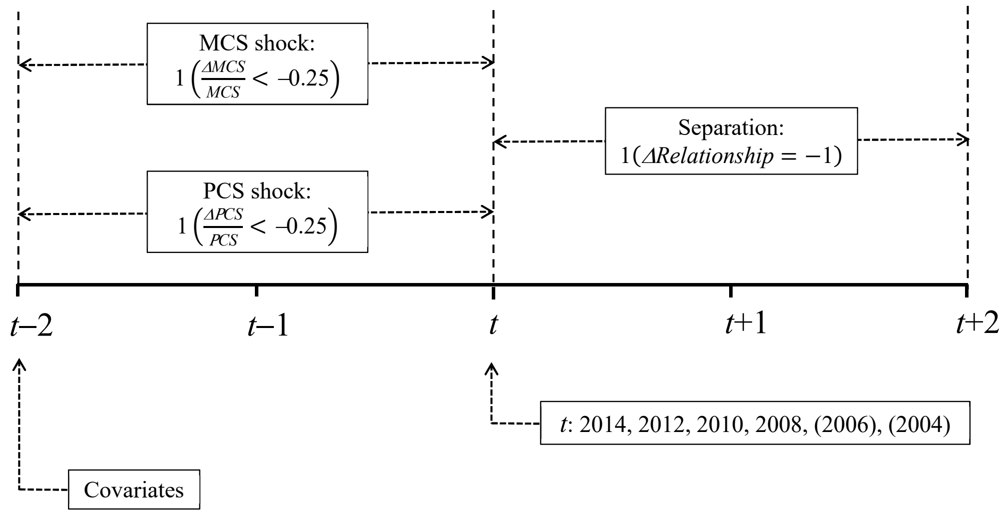

Figure 1: Time Line for Construction of Key Variables

unit disappears from the sample and in consequence is not observed in the subsequent period. One may, for this reason, interpret the analysis as estimating a hazard model in discrete time.[4] Consistent with the availability of health information we stick to the biennial structure of the panel. That is the final panel wave that we use for conditioning on existing partnerships is 2014 while the corresponding outcome 'separation (within the next two years)' is constructed from the 2016 wave of the SOEP (see Figure 1 for an illustration how information from different panel waves is used for constructing the key variables). This definition of the outcome variable is prone to confusing separations with other reasons for a couple disappearing from the data. We hence identify couples in which one partner dies and do not regard this event as separation. Moreover, a separation requires that at least one partner is still observed in the SOEP. This guarantees that panel attrition is not erroneously counted as separation. The biennial panel structure hence ignores temporary separations, if the partners restore their relationship within two years relative to the year of reference.[5] Based on this definition, we observe 652 separations in the estimation sample, which corresponds to an average unconditional separation rate of 0.026, see Table 1. This seems to be a rather small number compared to the divorce rate of 35 percent that is reported for Germany (Destatis and WZB, 2016, p. 50). Due to a relatively short observation period, one should be aware that the number of observed separations over the number of couples is not an appropriate estimate of the probability that a couple ever splits up. Indeed, considering all available panel waves we observe separations for roughly 20 percent of all couples, which is still a conservative estimate due to censoring and panel attrition.

[4] Very few couples are observed to restore their partnership after having split up. The event 'separation' is hence quasi non-repeated.

[5] As a robustness check, we also considered the alternative outcome variable 'separation within the next year'. In terms of the results, this did not make much difference. We still prefer the outcome 'separation within the next two years'. Otherwise we would ignore separations that occur between 12 and 24 months after the point of reference. We only deviate from the biennial framework for couples that are observed to have separated after one year and then drop out from the SOEP. We regard this pattern as separation.

2.3 Health and Health Shocks

The focus of the analysis is on the effect of adverse health shocks. While we want to distinguish between a sharp deterioration in mental and in physical health, we do not focus on a very specific health event to preserve the spirit of general health shocks. By including the SF12v2 questionnaire (Ware et al., 2005) in the survey, the SOEP provides a well suited basis for an empirical analysis of general mental and physical health. The standardized SF12 questionnaire comprises a list of twelve questions concerning physical, mental, and emotional well being.[6] By the means of an explorative factor analysis two factors, the MCS (mental component summary scale) and the PCS (physical component summary scale) are extracted from the information provided through the SF12. This procedure is carried out by the SOEP group and the PCS and MCS are provided as part of the SOEP data. See Andersen et al. (2007) for a detailed description of how PCS and MCS are generated on basis of the SOEP data. Figure A1 in the appendix depicts the distributions of MCS and PCS in the sample. The virtue of this approach to measuring health is that at the one hand it captures self-perceived subjective health rather than a specific diagnosis that may be of different importance to individual well being. On the other hand, it allows for clearly differentiating between mental and physical health. Moreover, MCS and PCS are well established health measures that are advocated as screening tools for quickly identifying health deficits (Salyers et al., 2000; Gill et al., 2007; Huo et al., 2018).

As pointed out, we are less interested in the levels of mental and physical health as determinants of partnership stability but how robust partnerships are to a sudden deterioration of health. In other words, we do not consider PCS and MCS as the key regressors in our analysis but changes in these variables. Figure A1 displays the sample distributions of relative and absolute changes in the MCS and in the PCS, respectively. Obviously, there is no universal answer to the question of how severe a deterioration in health needs to be in order to constitute a negative health shock. In the present analysis we consider a loss in MCS and PCS by more than 25 percent as experiencing a mental and physical health shock respectively. This threshold has been used earlier in the literature (Bünnings, 2017; Li et al., 2019) with respect to MCS and PCS, and also with respect to other health measures such as grip strength (Decker and Schmitz, 2016). Though this definition of a shock is arbitrary to some extent, it still captures the notion of an extraordinary adverse health event as just roughly one in twenty respondents exhibits such severe reductions in MCS or PCS. In Section 4.2 we show results for estimations using alternative definitions of health shocks. They are rather similar to those we get from using the health shock definition of reference. As the SOEP includes MCS and PCS only every other year, health shocks are necessarily defined on basis of a change over two years. Since health shocks may result in future separations but cannot cause relationship breakdown in the past, the two year interval on which a health shock is defined needs to proceed the two year interval in which a separation may happen. Figure 1 illustrates that for this reason several panel waves that span four years are required for constructing the key variables. This explains why the estimation sample is relatively small given an observation period of 14 years.

[6] It is a reduced variant of the SF36 questionnaire.

Table 1: Descriptive Statistics for Estimation Sample - Separations and Health

	Mean	S.D.	Med.	Min.	Max.
separation	0.026	0.159	0	0	1
MCS shock$_{♂}$	0.057	0.233	0	0	1
MCS shock$_{♀}$	0.074	0.262	0	0	1
PCS shock$_{♂}$	0.056	0.230	0	0	1
PCS shock$_{♀}$	0.058	0.234	0	0	1
MCS shock$_{♂♀}$	0.012	0.109	0	0	1
PCS shock$_{♂♀}$	0.006	0.077	0	0	1
$\text{MCS}_{t-2,♂}{}^{b}$	0.521	0.091	0.535	0.088	0.794
$\text{MCS}_{t-2,♀}{}^{b}$	0.501	0.097	0.515	0.019	0.777
$\text{PCS}_{t-2,♂}{}^{b}$	0.492	0.095	0.512	0.092	0.725
$\text{PCS}_{t-2,♀}{}^{b}$	0.491	0.097	0.509	0.101	0.781

Notes: Descriptive statistics based on 25 119 couple-year observations; model that differentiates between male and female partner ignoring homosexual couples; six panel waves (biennially 2004–2014); [b] re-scaled by the factor 0.01; see Table A1 for corresponding statistics for the alternative 'main breadwinner-partner' model.
Source: Own calculations based on SOEP data.

Each partner may suffer from a MCS or from a PCS shock. A couple might hence be hit by four different health shocks. Table 1 provides descriptive statistics for these variables. The corresponding statistics for the model that differentiates between main breadwinner and partner are found in Table A1, upper panel in the Appendix. Health shocks are relatively rare events, each being observed for 5 to 6 percent of couple-year observations. Only shocks to mental health are slightly more frequent among women. Physical health shocks occur at similar rates for women and men. As the empirical analysis considers four 'treatments', there is much room to analyze various treatment interactions. We focus on one particular sort of interactions, joint health shocks. More specifically we are interested in the effect of both partners (♂♀ or ☉☾) being hit by a shock of the same kind. Descriptive statistics for the corresponding interaction variables are presented in Table 1. Although 'joint' health shocks that hit both partners within the same two-years interval are rare, according to the descriptive statistics they occur more frequently than one would expect if health shocks were uncorrelated across both partners. This in particular applies to MCS shocks. This correlation pattern suggests that these shocks might not be purely random. The key objective of our analysis is to identify the effect of health shocks on partnership stability, which should not be intermixed with the effect of the partners' health levels may have. Therefore, we condition on the levels of MCS and PCS of both partners prior to the (possible) occurrence of a health shock. The corresponding descriptives are also displayed in Table 1. Since MCS and PCS are standardized variables[7] these statistics are of limited informational value, apart from women being in somewhat poorer – in particular mental – health as compared to their male partners.

2.4 Covariates

If health shocks were purely random, one could identify their effects on partnership breakdown straightforwardly by just comparing separation rates without considering any further variables. However, as discussed in Section 1, the interrelation of health and

[7] PCS and MCS are both standardized to have a mean of 50 and a variance of 10 in the full sample. In order to align them with the remaining variables, we re-scaled them by the factor 0.01.

relationship stability is complex. In particular confounding variables may exert effects on health as well as relationship stability. In order to isolate the effect of health shocks we condition on several covariates. All time-variant covariates are measured prior to a possible health shock, i.e. two years before the year of reference (see Figure 1). We condition on covariates that are observed on the individual level, i.e. they enter the empirical analysis once for each partner, as well as covariates that are observed on the couple level. The former are age, years of education, an indicator for being employed, and personal gross income [€1 000/month]. The latter is the sum of personal labor and pension income. As expected, male partners are on average older, slightly longer educated, more frequently employed and have a substantially higher personal income. Since the match between the partners is likely to matter for partnership stability and may also be linked to health, we construct variables that capture how different the partners are: the absolute difference in age, the absolute difference in years of education, and share in total labor and pension income that is earned by the male partner.[8] Conditioning variables that are measured at the couple level are indicators for living in the eastern part of Germany, being married, being homeowner, and a dummy indicating that at least one child under 17 lives in the household. The latter three are often regarded as important stabilizers of relationships. For couples with under aged kids we additionally condition on the number of children, the age of the youngest child, and whether the partners are jointly parents to at least one of the children.[9] Finally we condition on the previous duration of the partnership.[10] See Table 2 for descriptive statistics for the estimation sample.[11] We also include a set of year dummies in order to neutralize any spurious correlation between relationship breakdown and health driven by some underlying temporal development.

An important confounder in our analysis is partnership quality. Usually a separation will be preceded by a period of poor relationship quality. At the same time a low-quality marriage or partnership is less likely to generate health benefits (Wu and Hart, 2002) or may even result in declining (mental) health (Wickrama et al., 1997). Unfortunately, partnership quality cannot be observed directly. The closest proxy available in the SOEP is self-reported satisfaction with family life measured on a ten-point scale ranging from low (0) to high (10), a question that has not been included in the survey prior to 2006. In consequence, including this information as covariat reduces the estimation sample from six to only four panel waves.[12] Unlike the remaining variables, the descriptive statistics reported for family-life satisfaction in Table 2, hence, refer to the years 2008 to 2014. Satisfaction with family life does not seem to differ much between men and women and is high on average.

[8]For couples without labor or pension income from either partner, this variable is defined to take the value of 0.5 in order to indicate equal personal income.

[9]The reported value of 65 percent most likely underestimates the true share, since the SOEP does not allow for identifying the relationship of a child to the partner of the mother if he is not the head of the household.

[10]Unfortunately the reported partnership history is incomplete for numerous couples, for long-lasting partnerships in particular. This is the reason for also including a censoring dummy indicating that we could not track the relationship back to its start.

[11]In the model that considers the roles 'main breadwinner' and 'partner' and allows for considering homosexual couples a dummy for 'homosexual' and one for 'male homosexual' are also included. Descriptive statistics for this are found in Table A1 in the Appendix.

[12]In 2013 the SOEP also included a question regarding satisfaction with partnership. Yet this question was not part of the regular version of the questionnaire. This information is hence insufficient for our analysis.

Table 2: Descriptive Statistics for Estimation Sample - Covariates

	Mean	**S.D.**	**Med.**	**Min.**	**Max.**
$\text{age}_{♂}$	54.880	13.900	54	21	98
$\text{age}_{♀}$	52.160	13.730	52	20	92
abs. age difference	3.753	3.589	3	0	37
$\text{education}_{t-2,♂}$	12.650	2.853	11.5	7	18
$\text{education}_{t-2,♀}$	12.170	2.624	11.5	7	18
abs. educ. difference_{t-2}	1.703	1.914	1	0	11
east_{t-2}	0.254	0.435	0	0	1
home owner_{t-2}	0.616	0.486	1	0	1
child in hh_{t-2}	0.334	0.472	0	0	1
common $\text{child}_{t-2}{}^{\sharp}$	0.654	0.476	1	0	1
# of $\text{children}_{t-2}{}^{\sharp}$	1.667	0.776	2	1	8
min. age $\text{child}_{t-2}{}^{\sharp}$	7.899	4.829	8	0	16
married_{t-2}	0.891	0.312	1	0	1
partnership duration_{t-2}	8.910	7.221	7	0	28
censored couple info_{t-2}	0.742	0.438	1	0	1
$\text{employed}_{t-2,♂}$	0.701	0.458	1	0	1
$\text{employed}_{t-2,♀}$	0.609	0.488	1	0	1
$\text{employed}_{t-2,♂♀}$	0.533	0.499	1	0	1
$\text{income}_{t-2,♂}$	2.867	2.624	2.4	0	99.99
$\text{income}_{t-2,♀}$	1.177	1.380	0.81	0	45
income $\text{share}_{t-2,♂}$	0.693	0.258	0.705	0	1
satisfaction fam. $\text{life}_{t-2,♂}{}^{\dagger}$	8.257	1.542	8	0	10
satisfaction fam. $\text{life}_{t-2,♀}{}^{\dagger}$	8.156	1.662	8	0	10
abs. dif. satisf. fam. $\text{life}_{t-2}{}^{\dagger}$	0.970	1.203	1	0	10
$\text{conscientiousness}_{♂}{}^{\ddagger}$	51.29	9.401	52.67	-9.87	72.14
$\text{conscientiousness}_{♀}{}^{\ddagger}$	51.04	9.012	52.49	2.572	71.81
$\text{neuroticism}_{♂}{}^{\ddagger}$	47.85	9.514	47.29	23.04	79.12
$\text{neuroticism}_{♀}{}^{\ddagger}$	52.27	9.925	51.91	26.73	80.55
$\text{extraversion}_{♂}{}^{\ddagger}$	48.88	9.880	48.34	17.62	80.13
$\text{extraversion}_{♀}{}^{\ddagger}$	50.70	9.810	50.12	19.31	79.89
$\text{agreeableness}_{♂}{}^{\ddagger}$	47.62	9.978	48.18	8.988	76.69
$\text{agreeableness}_{♀}{}^{\ddagger}$	52.02	9.293	53.05	12.78	75.34
$\text{openness}_{♂}{}^{\ddagger}$	49.85	9.837	49.96	11.61	79.82
$\text{openness}_{♀}{}^{\ddagger}$	50.05	9.791	50.16	12.49	84.57

Notes: Statistics based on 25 119 couple-year observations; model that differentiates between male and female partner ignoring homosexual couples; six panel waves (biennially 2004–2014); † not available for years earlier than 2008; ‡ not for years earlier than 2008; $^{\sharp}$ conditional on children in household; see Table A1 for corresponding statistics for the alternative 'main breadwinner-partner' model. **Source**: Own calculations based on SOEP data.

Yet, even very conflicting perceptions regarding the quality of a partnership occur in the sample as indicated by the max of the variable 'absolute difference in satisfaction with family life'. Furthermore, we condition our analysis on partner characteristics that are possibly related to partnership quality by considering measures of character traits ('big five', i.e. agreeableness, conscientiousness, neuroticism, extraversion, openness) for each partner as additional covariates. Since this further reduces the sample, we did this only as a robustness check. The corresponding descriptives reported in Table 2 are for this estimation sample.

3 Estimation Procedures

The key challenge for the empirical analysis is to disentangle the effects under scrutiny from the impacts of confounding factors and possible reverse causality. As discussed in Section 1, the latter is a particularly severe concern since the empirical literature provides ample evidence for relationship status and relationship transition affecting health. Yet, we are still confident that our analysis does not generate spurious results due to reverse causality for two reasons: (i) as discussed above, health shocks and separations are chronologically defined such that the former cannot be caused by the latter; (ii) we focus on extraordinary changes in health, while controlling for its past level and – in some specifications – the past level of family-life quality, and hence avoid capturing the effects of an underlying, interactive deterioration of health and relationship quality that ultimately results in relationship dissolution. The considered substantial relative changes in PCS and MCS are, for these reasons, likely to capture some exogenous health events.

For addressing possibly remaining non-randomness of health shocks, we rely on matching and closely related inverse probability weighting (IPW) that is conditioning on observables.[13] Both approaches estimate counterfactual outcomes by weighting the observed data. That is, the mean outcome under no treatment (no health shock) which is not observed for treated observations (couples hit by a health shock) is estimated as a weighted average of the outcomes observed for the control group (couples not hit by a health shock), and vice versa. If the treatment is purely random, no weighting is required since asymptotically the mean outcome under treatment and no treatment is the same for either group. If the treatment is however non-random and the groups differ systematically, the idea is to give more weight to atypical and less weight to typical observations in either group. Intuitively speaking, by selectively 'adding' and 'removing' observations from each group one makes them more similar and in turn, more comparable. One popular class of such estimators is based on the propensity score (PS; Rosenbaum and Rubin, 1983). The PS is the probability of the observed treatment status. IPW (Wooldridge, 2007) uses the propensity score to estimate the counterfactual separation rate of those couples, who have actually experienced a health shock as the weighted average separation rate of those who have not experienced a health shock using the inverse of the estimated probability of not experiencing a health shock as weights. The propensity score IPW estimator is extreme in the sense that every couple from the group without health shock – even those who are very different from any couple that is hit by a shock – enters the estimated counterfactual, though its weight might be very small. PS matching uses a different weighting scheme in which only those couples from the control group receive a weight different from zero, whose propensity score is very similar to the propensity score of at least one couple in the treatment group. For nearest neighbour matching, which can be regarded as the most intuitive approach, only couples who are the most similar to a counterpart in the treatment group receive non-zero weight. In other words, the counterfactual outcome of each couple in the treatment group is estimated as the

[13] Ideally we could use an instrument for health shocks in our analysis. It is however hard to think of any event that strongly affects health but has no direct impact on partnership. Accidents, which are occasionally used as instrument (e.g. Doyle, 2005), may for instance change the partners willingness to take risks in every day live and affect partnership quality through this channel.

observed outcome of its nearest neighbour in the control group.[14] Though asymptotically equivalent, IPW and nearest neighbour matching differ in their small sample properties. By considering many observations for estimating the counterfactual but allowing even very poor matches to enter the weighted mean, IPW reduces sampling error to the expense of accepting a larger finite sample bias. In contrast, nearest neighbor matching is quite picky in what is accepted as a good match. By this it reduces the bias while inflating the variance. All other PS matching estimators can be regarded as approaches that balance variance against bias in a different way.

In this application we only apply inverse probability weighting and nearest neighbour matching, as the two extreme approaches to deal with the trade-off between variance and finite sample bias. Besides basic inverse probability weighting we also use inverse probability weighted regression adjustment (Cattaneo, 2010). That is, instead of comparing weighted averages of observed outcomes, we compare weighted predicted outcomes that are generated in a preceding regression analysis. This approach has the so called double robustness property (e.g. Bang and Robins, 2005). That means for consistent estimation, either the outcome model – i.e. the regression model to generate the predicted outcomes – needs to be correctly specified and in consequence does not suffer from endogeneity bias, or the weighting succeeds in generating quasi randomness of treatment.

In the present analysis we estimate the PS using binary logit models.[15] In doing this, the counterfactual to any health shock, irrespective of whether the female, or the male partner, or both partners are hit, is that no health shock in the considered health domain hits the couple. For all IPW and matching we report the average treatment effect (ATE). Technically, that means the observed and the estimated counterfactual outcomes for all couples, not only those who experience a health shock, enter the comparison of separation rates. Economically, the ATE measures how much a health shock in expectation increases the marginal risk of separation for a couple randomly drawn from the population.

In addition to those covariates discussed in section 2.4 we also match on the respective other type of health shock. That means in comparing couples who are hit by a MCS shock with those who are untroubled by a serious decline in mental health, we condition on the PCS shock status. Interaction terms are not considered in the matching procedures.

4 Results

As a first step, we estimate a simple descriptive regression of separation on health shocks not considering any covariates (see Table 3). We distinguish between two specifications, one without and one with health shock interactions. In both specifications, the separation rate is much higher, if one of the partners has experienced a substantial worsening of mental health in the past, compared to couples that did not experience any health shock. This difference is not only statistically significant but also of relevant magnitude as it is roughly as big as the unconditional sample separation rate. The estimated coefficients do not differ

[14]We use the term 'nearest neighbor matching' in its narrow sense. That is the respective very best matching partner is exclusively used for estimating the counterfactual, but not a weighted average of several good matches.

[15]See Tables A5 and A6 for the estimated coefficients of the binary logit models.

Table 3: Descriptive Linear Regression without Controls

	without interact.		with interact.	
	Est. Coef.	S.E.	Est. Coef.	S.E.
MCS shock$_{♂}$	0.027***	(0.006)	0.029***	(0.007)
MCS shock$_{♀}$	0.025***	(0.005)	0.026***	(0.006)
MCS shock$_{♂♀}$			−0.012	(0.017)
PCS shock$_{♂}$	0.002	(0.005)	0.004	(0.005)
PCS shock$_{♀}$	−0.007*	(0.004)	−0.004	(0.004)
PCS shock$_{♂♀}$			−0.027***	(0.007)
MCS shock$_{♂♀}$‡	0.052***	(0.008)	0.044***	(0.014)
PCS shock$_{♂♀}$‡	−0.005	(0.005)	−0.027***	(0.001)
N	25 119		25 119	
R^2	0.004		0.004	

Notes: *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.1; clustered standard errors; ‡ sum of regression coefficients. **Source**: Own calculations based on SOEP data.

much between shocks hitting the male or the female partner. When we look at physical health shocks, the pattern is quite different. For physical health shocks, the coefficients are very small and statistically insignificant, with the exception of a PCS shock that hits the female partner where we find a weakly significant stabilizing effect in the specification without interactions. The asymmetry between MCS and PCS shocks carries over to the coefficient of the interaction terms (see Table 3, right columns). While interactions do not seem to matter for mental health shocks, we get a negative and highly significant coefficient for the PCS shock interaction. That is, couples which are jointly hit by a physical health shock are less likely to split up, not only compared to couples in which only one partner experiences a deterioration of physical health but also compared to couples who stay healthy. Though these results have much intuitive appeal, they are purely descriptive and may as well capture the effect of confounding factors. As a next step we therefore employ different matching estimators discussed above.

4.1 Matching Analyses

Before we turn to the results from our matching estimations discussed in Section 3, we check how successful these estimators are in balancing the groups of couples hit by a health shock and the group of those who remained untroubled by such shocks. For inverse probability weighting and propensity score nearest neighbor matching Table 4 displays the mean absolute standardized percentage bias (MASPB, Rosenbaum and Rubin, 1985) for the matched and the unmatched estimation sample.[16] Inverse probability weighting does a good job in balancing 'treatment' and 'control' group, irrespective of whether a PCS or a MCS shock is considered. For health shocks that hit either the male or the female partner the MASPB is much smaller than the rule of thumb threshold of 5 percent (Caliendo and Kopeinig, 2008) and is also much smaller than its counterpart for the unmatched sample.[17]

[16] Since regression adjustment does not make a difference with respect to matching as such, we do not distinguish between the variants with and without regression adjustment.

[17] We also tried the Mahalanobis distance to determine matching partners. However, this alternative approach did clearly worse in balancing treatment and control compared the propensity score matching. We hence stick to the latter.

Table 4: Mean Absolute Standardized Percentage Bias (MASPB)

	Unmatched	Matched	
		IPW[♣]	NN Matching[♡]
MCS shock♂	6.592	1.828	3.260
MCS shock♀	6.657	1.211	1.422
MCS shock♂♀	13.193	3.214	6.054
PCS shock♂	11.714	2.028	2.613
PCS shock♀	9.056	1.667	1.968
PCS shock♂♀	24.813	8.661	11.445

Notes: Six panel waves (biennially 2004–2014). ♣ Inverse probability weighting; ♡ Propensity score nearest neighbour matching. **Source**: Own calculations based on SOEP data.

In other words, after inverse probability weighting, both groups are reasonably similar in terms of the observed covariates and by far more alike compared to the unweighted samples. This in essence also applies to nearest-neighbour propensity score matching, although the MASPB is somewhat bigger throughout. Things are different for health shocks that hit both partners. There the matching is clearly less successful in aligning treatment and control group. This in particular applies to joint physical health shocks for which both IPW and nearest neighbor matching fail in reducing the MASPB to a value smaller than five. The small and presumably rather special group of couples who experience a joint physical health shock, even after matching remains rather different from the control group though matching reduces the deviation substantially. Effects estimated for a joint (physical) health shock hence have to be interpreted with some caution.

Effects from the different matching estimators are displayed in Table 5. They are quite similar to the results from our unconditional descriptive analysis. A MCS shock that hits one partner increases the risk of a separation by 2 to 3 percentage points with the effect being somewhat stronger if the male partner is hit. Compared to the expected dissolution rate of 2.3 percent estimated for the control group, this is a rather strong effect. PCS shocks have much smaller and statistically insignificant effects throughout. With respect to the signs of the insignificant coefficients we see the same pattern as for the unconditional analysis. The results for joint health shocks exhibit a pattern similar to the OLS results. That is, if both partners experience a strong deterioration in mental health a separation gets more likely, yet the effects of shocks that hit just one partner seem not to cumulate linearly. Due to the small number of joint health shocks in the data, the effects are however rather noisily estimated and their magnitude has to be interpreted with some caution. For a joint physical health shock we find the same stabilizing effect that we found in the unconditional analysis.

All in all the results yield a coherent picture. A deterioration of mental health strongly increases the risk of separation. It does not seem to make much difference whether the male or the female partner suffers from this health shock. In contrast, negative shocks on physical health seem to be largely immaterial for partnership stability. If at all, a partnership is less likely to be terminated if both partners jointly experience a deterioration of physical health. The different matching estimators and the simple unconditional comparison of means do not differ much in terms of estimated effects. This can be regarded as indication for relationship breakdown not being linked to – at least observed – determinants of health

Table 5: ATE Estimates - Reference Specification

	IPW$^{♣}$		**IPW Reg. Adj.**$^{♠}$		**NN Matching**$^{♡}$	
	Est. Eff.	S.E.	Est. Eff.	S.E.	Est. Eff.	S.E.
MCS shock$_{♂}$	0.031***	(0.007)	0.030***	(0.007)	0.031***	(0.009)
MCS shock$_{♀}$	0.023***	(0.006)	0.023***	(0.006)	0.024***	(0.007)
MCS shock$_{♂♀}$	0.026*	(0.014)	0.029**	(0.014)	0.037**	(0.016)
PCS shock$_{♂}$	0.006	(0.006)	0.008	(0.006)	0.009	(0.007)
PCS shock$_{♀}$	−0.005	(0.004)	−0.004	(0.004)	−0.006	(0.005)
PCS shock$_{♂♀}$	−0.026***	(0.001)	−0.026***	(0.001)	−0.026***	(0.001)

Notes: *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.1; clustered standard errors; $^{♣}$ Propensity score weighting; $^{♠}$ Propensity score weighting with regression adjustment; $^{♡}$ Propensity score nearest neighbour matching; six panel waves (biennially 2004–2014). **Source**: Own calculations based on SOEP data.

shocks.[18]

4.2 Alternative Models and Robustness Checks

In order to get more confidence in the results discussed above, we test the robustness of our estimates by varying the empirical model in three dimensions: (i) we vary the definition of a health shock, (ii) we address possible endogeneity due to unobserved confounders by considering additional covariates, (iii) we vary the selection of the estimation sample and, related to that, consider alternative intra-family roles than the traditional 'male and female partner model'. Due to the superior matching performance, very similar results for the different matching approaches and for the sake of simplicity we solely present the results of the alternative models and robustness checks for the inverse probability weighting without regression adjustment.[19]

4.2.1 Alternative Health Shock Definitions

Firstly we address the issue of our – to some extent – arbitrary health shock definition as a relative decrease in MCS and PCS, respectively, of at least 25 percent. Based on the inverse probability weighting without regression adjustment, we systematically vary the threshold value. Figure 2, depicts the estimated effects on the separation hazard considering different required minimum reductions in MCS (upper panel) and PCS (lower panel), respectively, between 0 and −50 percent. For shocks that hit the mental health of either the male or the female partner we find significant increases in separation probability over the entire range of threshold values. This is different for a joint shock on PCS. Here single shocks for either the male or the female partner do not affect the separation probabilities but we see a significant stabilizing effect for any threshold that exceeds 15.5 percent for joint PCS shocks. For any threshold values that exceed 23.5 percent – except for those close to 50 percent – Figure 2 indicates an almost constant effect of a joint PCS shock with an associated rather narrow confidence band. This is an artifact of quasi complete separation, that is if in absolute terms threshold values ≤ 24 are considered, no separation is observed

[18] Adding further covariates to the descriptive linear regression model (Table 3) does not change the overall pattern of results (see Table A2).

[19] Results for propensity score weighting with regression adjustment and propensity score nearest neighbour matching are similar and available upon request.

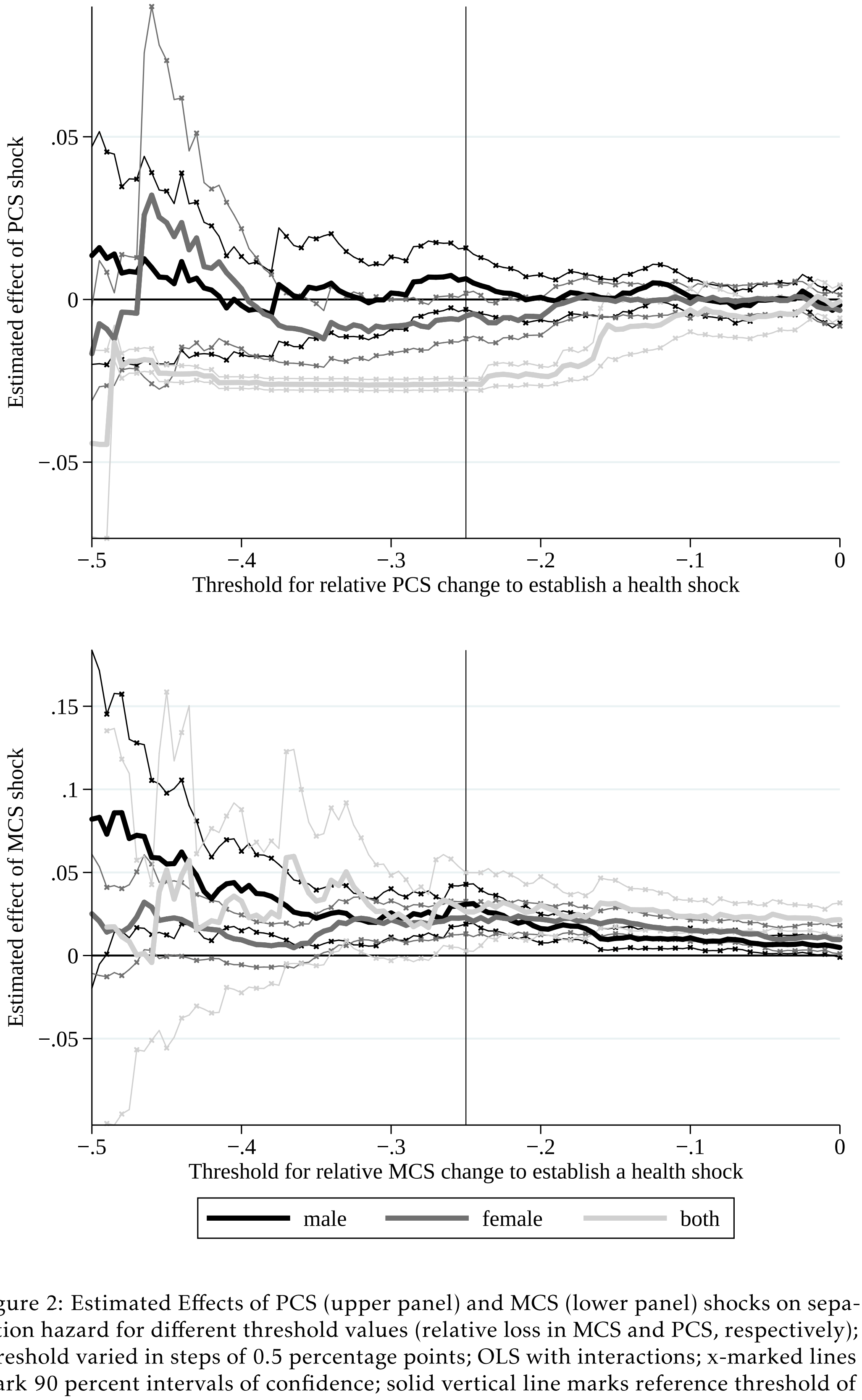

Figure 2: Estimated Effects of PCS (upper panel) and MCS (lower panel) shocks on separation hazard for different threshold values (relative loss in MCS and PCS, respectively); threshold varied in steps of 0.5 percentage points; OLS with interactions; x-marked lines mark 90 percent intervals of confidence; solid vertical line marks reference threshold of −0.25. **Source**: Own calculations based on SOEP data.

Table 6: ATE Estimates - Absolute Health Shock

	Est. Eff.	S.E.
MCS shock$_{♂}$	0.020***	(0.007)
MCS shock$_{♀}$	0.018***	(0.006)
MCS shock$_{♂♀}$	0.029*	(0.015)
PCS shock$_{♂}$	0.001	(0.006)
PCS shock$_{♀}$	−0.008	(0.005)
PCS shock$_{♂♀}$	−0.024***	(0.002)

Notes: *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.1; clustered standard errors in parantheses; six panel waves (biennially 2004–2014); propensity score weighting. **Source**: Own calculations based on SOEP data.

in the group of couples hit by a joined health shock defined this way. In consequence the probability of such shock is estimated to be zero and the estimated effect is just minus one the relative separation frequency in the control group. This explains the rather small standard error. However, a significant effect is also found for threshold values smaller than 24 percent that does not generate quasi complete separation. That is, the stabilizing effect found for joint physical health shock is not an artifact of quasi complete separation.

Turning to shocks to mental health, not surprisingly, the estimated effects get rather small[20] if even very minor deteriorations in health are counted as health shocks. Yet, the estimated effects stay significant a the 10 percent level until a threshold of 0.5 percent is considered. If one regards only very severe relative losses in MCS and PCS as health shocks, the estimates get very noisy as indicated by the rather wide confidence intervals. This is easily explained by health shocks, joint ones in particular, then becoming extremely rare events. However, most importantly, if one considers more reasonable health shock definitions – relative reductions between 15 and 35 percent for instance – the estimates turn out to be very robust and do not strongly deviate from those we got when considering the 25 percent threshold.

Next, we vary the definition of a health shock in another dimension, by considering a minimum absolute change rather than a relative one as criterion. Tables 6 (matching) and A4 (linear regressions, Appendix) display results for a loss of 13 units (original scale) of MCS and PCS, respectively, constituting a health shock. This value was chosen to make health shocks roughly as frequent as in the reference specification.[21] Defining health shocks in terms of absolute changes shifts the occurrence of such shocks from individuals in poor health to individuals in good health. The correlations between the corresponding indicators are high (0.839, 0.837, 0.833, and 0.801) but clearly smaller than one. A disadvantage of the alternative health shock definition is that health shocks for those at the very bottom of the distribution are ruled out by construction. This is why we regard our baseline specification as clearly preferable. Nevertheless, the health shock definition based on absolute changes in MCS and PCS does not drastically alter the estimated effects. The point estimates get somewhat smaller and occasionally turn insignificant. Yet the general pattern of MCS shocks adversely affecting relationship stability while no such effect is found for PCS

[20] For the limiting case that any reduction in MCS or PCS is regarded as a health shock (threshold value of zero) we get: MCS shock$_{♂}$ 0.005 (0.002), MCS shock$_{♀}$ 0.010 (0.005), PCS shock$_{♂}$ −0.002 (0.003), PCS shock$_{♀}$ −0.003 (0.003), MCS shock$_{♂♀}$ 0.022 (0.006), PCS shock$_{♂♀}$ −0.001 (0.003).

[21] MCS shock are slightly more and PCS shocks are slightly less frequent compared to the reference specification (see Table A3 in the Appendix and the corresponding entries in Table 1).

Table 7: ATE Estimates - Additional Covariates

	Big Five		Fam. Statisfaction		Big Five & Fam. Satis.	
	Est. Eff.	S.E.	Est. Eff.	S.E.	Est. Eff.	S.E.
MCS shock$_{♂}$	0.027***	(0.008)	0.023***	(0.008)	0.028***	(0.010)
MCS shock$_{♀}$	0.022***	(0.007)	0.024***	(0.008)	0.028***	(0.009)
MCS shock$_{♂♀}$	0.022	(0.015)	0.046**	(0.023)	0.043*	(0.022)
PCS shock$_{♂}$	0.007	(0.006)	0.014*	(0.008)	0.016*	(0.009)
PCS shock$_{♀}$	−0.004	(0.004)	0.002	(0.006)	0.002	(0.006)
PCS shock$_{♂♀}$	−0.024***	(0.001)	−0.023***	(0.001)	−0.023***	(0.001)
Big Five	✓				✓	
Satisfaction fam. life			✓		✓	

Notes: *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.1; clustered standard errors; for panel waves (biennially 2008–2014); propensity score weighting. **Source**: Own calculations based on SOEP data.

shocks, remains stable.

4.2.2 Additional Covariates

All so far discussed analyses do not condition on pretreatment satisfaction with family life or partner characteristics that are possibly related to partnership quality. Table 7 displays the key coefficients of three additional inverse probability weighting specifications, where we condition on the big five personality traits of each partner (column 1), satisfaction with family life (column 2) and both additional sets of covariates (column 3).

Controlling for satisfaction with family life and the big five personality traits does not change the overall pattern of results from their counterpart displayed in Table 5. However some small deviations occur. The coefficient of the joint MCS shock turns smaller and statistically insignificant in the specification where we additionally condition on the big five personality traits (column 1). It is larger in the specifications including family life satisfaction (column 2) or both sets of covariates (column 3). These deviations may be explained by the reduced sample size which increases the noisiness of estimation. There is a weak indication that physical health shocks to the male partner negatively affect relationship stability (columns 2 and 3).

All in all, conditioning on satisfaction with family live – as a proxy for relationship quality – and partner characteristics that are possibly related to partnership quality does not put the key result of adverse effects of MCS shocks into question. Although these results do not rule out effects of PCS shocks, they seem to be of much smaller relevance than shocks to mental health. Moreover, our results still suggest that there is a stabilizing effect of joint physical health shocks.[22]

[22] In a linear regression the coefficients attached to the additional control 'satisfaction with family life' are highly significant, negative and symmetric for the male and the female partner. Not surprisingly, relationships of partners who are happy with his or her family are less likely to be terminated. Including the partner-interaction of the satisfaction variable in this regression yields a quite telling pattern of coefficients. The coefficients of individual satisfaction in absolute terms get much bigger while the interaction term is positiv and highly significant. This can be interpreted such that the risk of separation already substantially increases if one partner is unhappy.

4.2.3 Sample and Roles within Partnership

A frequent question in the relevant literature (e.g. Pevalin and Ermisch, 2004; Kohn and Averett, 2014b) is whether marriage makes a difference in the interplay of partnership and health. In our analysis we address this issue by re-estimating the inverse probability weighting model only considering married couples. In a similar way we address the concern that institutionalization of partners in need of nursing care may generate technical separations that cannot be regarded as relationship break down. We hence restrict the estimation sample to relatively young couples (older partner's age ≤ 85, ≤ 75, and ≤ 65), for which moving to a nursing home is less likely than for couples with at least one partner of very advanced age. Table 8 displays the estimated coefficients for these models. Excluding unmarried and old couples from the estimation sample appears to make little difference. If at all, focussing on relatively young couples (≤ 65) yields somewhat stronger adverse effects of MCS shocks as compared to considering couples of all age groups.

Finally we examine results for analyses in which we distinguish the roles 'main breadwinner' and 'partner', rather than male and female partner. The estimated role specific health shock coefficients may partly capture different channels through which health affects partnership. We define the 'main breadwinner' as the partner with the higher personal income. If there is no difference in income we use the information about who acts as 'household head' as secondary and the partners' age as tertiary criterion. We interpret the 'main breadwinner' to be the (economically) stronger partner, even though this may not apply to all couples. Disengaging the analysis from the traditional man-woman model allows for including both hetero- and homosexual couples. Yet, due to the relatively small number of homosexual couples that are identified in the SOEP, this does not make a major difference in terms of the estimation sample.[23] Table 9 shows the estimated coefficients for the inverse probability weighting for heterosexuals (column 1) and hetero- as well as homosexuals (column 2). Neither altering the roles within partnerships nor including homosexual couples leads to a deviation from the familiar overall pattern of estimated coefficients. The estimated heterogeneity in the effects of MCS shocks is of the same moderate magnitude as in the model of reference and stays statistically insignificant. In terms of the point estimates, the risk of separation seems to be slightly smaller if the economically weaker partner is hit.

Taken together the results form various estimations using different samples and estimation techniques show a rather robust overall picture: Mental health shocks are detrimental to partnership stability. If one partner experiences a sharp decline in mental health over two years, the hazard for splitting up over the next two years roughly doubles. If both partners are hit by such a shock things are even worse. In terms of the point estimates, we see some heterogeneity with respect to the gender of the partner who is subject to the health shock and with respect to the partners relative economic position. More specifically, relationship breakdown seems to be less likely if the female or the economically weaker partner – roles that coincide for the majority of partnerships in the sample – experiences a

[23] Roughly 0.3 percent of the observed couples are all female and less than 0.2 percent are all male. This is for various reasons unlikely to be a meaningful estimate of the share of homosexuals in the German population.

Table 8: ATE Estimates - Unmarried and Old Couples Excluded

	Married		**Age ≤ 85**		**Age ≤ 75**		**Age ≤ 65**	
	Est. Eff.	S.E.	Est. Eff.	S.E.	Est. Eff.	S.E.	Est. Eff.	S.E.
MCS shock$_{♂}$	0.031***	(0.007)	0.030***	(0.007)	0.033***	(0.008)	0.040***	(0.009)
MCS shock$_{♀}$	0.026***	(0.006)	0.022***	(0.006)	0.024***	(0.006)	0.027***	(0.007)
MCS shock$_{♂♀}$	0.030*	(0.016)	0.027*	(0.015)	0.027*	(0.015)	0.032*	(0.018)
PCS shock$_{♂}$	0.001	(0.005)	0.007	(0.006)	0.006	(0.006)	0.006	(0.008)
PCS shock$_{♀}$	−0.002	(0.004)	−0.006	(0.004)	−0.006	(0.004)	−0.008	(0.005)
PCS shock$_{♂♀}$	−0.020***	(0.001)	−0.026***	(0.001)	−0.027***	(0.001)	−0.033***	(0.001)

Notes: *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.1; clustered standard errors; six panel waves (biennially 2004–2014); propensity score weighting. **Source**: Own calculations based on SOEP data.

Table 9: ATE Estimates - Main Breadwinner (⊙) and Partner (☾)

	Heterosexual Couples		**Homosexuals included**	
	Est. Eff.	S.E.	Est. Eff.	S.E.
MCS shock$_{⊙}$	0.030***	(0.007)	0.031***	(0.007)
MCS shock$_{☾}$	0.024***	(0.006)	0.024***	(0.006)
MCS shock$_{⊙☾}$	0.030**	(0.015)	0.030**	(0.015)
PCS shock$_{⊙}$	0.000	(0.005)	0.000	(0.005)
PCS shock$_{☾}$	0.000	(0.005)	0.000	(0.005)
PCS shock$_{⊙☾}$	−0.026***	(0.001)	−0.026***	(0.001)

Notes: *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.1; clustered standard errors; six panel waves (biennially 2004–2014); propensity score weighting. **Source**: Own calculations based on SOEP data.

loss of mental health. Our key finding challenges the notion of long term partnership as an effective informal insurance against mental health risks. It rather seems that the emotional support one may have expected to find in a relationship in case of such hardship is likely to be denied at the time, when it is needed most. Our results regarding physical health shocks are very different. There, we see very little evidence that a sharp deterioration in physical health increases the separation hazard. Although we cannot firmly rule out such an effect, it is almost certainly much smaller than the impact of a shock to mental health. Quite to the contrary, our results suggest that jointly experiencing a deterioration of physical health bonds partners closer together. In consequence, while long term partnership may fail as informal insurance against mental health shocks it seems to work as insurance against physical health risks.

Our analysis nevertheless has some limitations. First of all, identification is not based on a specific exogenous source of variation in health. Although we are confident that we have reduced the role endogeneity bias may play for the results, we cannot claim that we have completely eliminated it. The matching estimators do a reasonably good job in aligning treatment and control in terms of observables but unobservables may still jointly affect mental health and partnership stability. However, our results are robust to including satisfaction with family life as covariate. As a proxy for partnership quality one may regard this variable as key confounder, which if omitted generates a spurious correlation between (mental) health and partnership stability. Yet, this seems not to apply to our analysis.

5 Discussion and Conclusion

Using household level data from Germany and applying different matching estimators, we estimated the effects of shocks to physical and mental health on relationship stability. Our results reveal a robust pattern: a sudden and severe deterioration of mental health has a corrupting impact on relationships. The risk of separation over two years is roughly doubled by a mental health shock, irrespective of whether the male or the female partner is hit. We see some, yet statistically insignificant, asymmetry in this effect with respect to gender or with respect to the intra-family economic position of the partner who is hit by this shock. The results are quite different for shocks to physical health. There we do not find a destabilizing impact on marriage or long-term relationships. The data rather suggest that jointly experiencing a severe deterioration in physical health makes couples stay together.

Our results question whether marriage and long-term relationships are an effective informal insurance instruments against (non-monetary) consequences of sickness. How relationships react to health shocks appears to depend on the type of health shock and to a lesser extend on the economic position within the partnership. Mental health problems appear tobe a risk for which finding informal insurance in a relationship is difficult. One may speculate that the external effects of mental illness to the healthy partner are so strong that he or she decides to end a relationship, even if he or she is altruistic to the suffering partner. This argument is to some extent corroborated by the asymmetry regarding the economic position of the partners. For the (economically) weaker partner the gains from escaping from these external effects might to a greater extent be offset by the negative consequences of a separation. An alternative way of interpreting the strong adverse effect of a shock to mental health is that the gains from partnership are complements to mental health. That is, emotional support might not be found in a partnership when suffering from mental illness, even if it is not denied by the healthy partner. If the former explanation is more relevant, the asymmetry between shocks to mental and to physical health points to the latter being less stressful to the not directly affected partner or that physical illness is more likely to activate altruism. In any case, relationships seem to provide much better informal insurance against physical as compared to mental health risks.

Partnership as a genuinely private matter should not be subject to policy interventions. We nevertheless regard the empirical evidence yielded in this analysis as relevant for health policy makers. Our results suggest that mental illness generates substantial indirect costs through inducing relationship breakdown, which itself reduces the well being of two partners.

References

Andersen, H. H., Mühlbacher, A., Nübling, M., Schupp, J., and Wagner, G. G. (2007). Computation of standard values for physical and mental health scale scores using the SOEP version of SF12v2. Journal of Applied Social Science (Schmollers Jahrbuch), 127(1):171–182.

Averett, S. L., Argys, L. M., and Sorkin, J. (2013). In sickness and in health: an examination of relationship status and health using data from the canadian national public health survey. Review of Economics of the Household, 11(4):599–633.

Bang, H. and Robins, J. M. (2005). Doubly robust estimation in missing data and causal inference models. Biometrics, 61:962–972.

Booth, A. and Johnson, D. R. (1994). Declining health and marital quality. Journal of Marriage and Family, 56(1):218–223.

Brockmann, H. and Klein, T. (2004). Love and death in Germany: The marital biography and its effect on mortality. Journal of Marriage and Family, 66(3):567–581.

Bünnings, C. (2017). Health shocks and health behavior: A long-term perspective. Unpublished manuscript.

Caliendo, M. and Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. Journal of Economic Surveys, 22(1):31–72.

Cattaneo, M. D. (2010). Efficient semiparametric estimation of multi-valued treatment effects under ignorability. Journal of Econometrics, 155:138–154.

Charles, K. and Stephens, Jr., M. (2004). Job displacement, disability, and divorce. Journal of Labor Economics, 22(2):489–522.

Decker, S. and Schmitz, H. (2016). Health shocks and risk aversion. Journal of Health Economics, 50:156–170.

Dercon, S. and Krishnan, P. (2000). In sickness and in health: Risk sharing within households in rural Ethiopia. Journal of Political Economy, 108(4):688–727.

Destatis and WZB, editors (2016). Datenreport 2016 – Ein Sozialbericht für die Bundesrepublik Deutschland. Bundeszentrale für politische Bildung, Bonn.

Dolan, P., Peasgood, T., and White, M. (2008). Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being. Journal of Economic Psychology, 29(1):94–122.

Doyle, J. J. (2005). Health insurance, treatment and outcomes: Using auto accidents as health shocks. The Review of Economics and Statistics, 87(2):256–270.

Gill, S. C., Butterworth, P., Rodgers, B., and Mackinnon, A. (2007). Validity of the mental health component scale of the 12-item short-form health survey (mcs-12) as measure of common mental disorders in the general population. Psychiatry Research, 152(1):63–71.

Haisken-DeNew, J. P. and Frick, J. R. (2005). Desktop Companion to the German Socio-Economic Panel (SOEP). Technical report, DIW Berlin.

Huo, T., Guo, Y., Shenkman, E., and Muller, K. (2018). Assessing the reliability of the short form 12 (SF-12) health survey in adults with mental health conditions: a report from the wellness incentive and navigation (WIN) study. Health and Quality of Life Outcomes, 16(1):34.

Johnson, D. R. and Wu, J. (2002). An empirical test of crisis, social selection, and role explanations of the relationship between marital disruption and psychological distress: A pooled time-series analysis of four-wave panel data. Journal of Marriage and Family, 64(1):211–224.

Joung, I. M., van de Mheen, H., Stronks, K., van Poppel, F. W., and Mackenbach, J. P. (1998). A longitudinal study of health selection in marital transitions. Social Science & Medicine, 46(3):425–435.

Kessler, R. C., Walters, E. E., and Forthofer, M. S. (1998). The social consequences of psychiatric disorders, III: Probability of marital stability. American Journal of Psychiatry, 155(8):1092–1096.

Koball, H. L., Moiduddin, E., Henderson, J., Goesling, B., and Besculides, M. (2010). What do we know about the link between marriage and health? Journal of Family Issues, 31(8):1019–1040.

Kohn, J. L. and Averett, S. L. (2014a). Can't we just live together? New evidence on the effect of relationship status on health. Journal of Family and Economic Issues, 35(3):295–312.

Kohn, J. L. and Averett, S. L. (2014b). The effect of relationship status on health with dynamic health and persistent relationships. Journal of Health Economics, 36:69–83.

Li, L., Richter, A., and Steinorth, P. (2019). Mental health changes and the willingness to take risks. Mimeo, available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3352663.

Lillard, L. A. and Panis, C. W. A. (1996). Marital status and mortality: The role of health. Demography, 33(3):313–327.

Lipowicz, A. (2014). Some evidence for health-related marriage selection. American Journal of Human Biology, 26(6):747–752.

Manfredini, M., Breschi, M., and Mazzoni, S. (2010). Spouse selection by health status and physical traits. Sardinia, 1856-1925. American Journal of Physical Anthropology, 141(2):290–296.

Mastekaasa, A. (1992). Marriage and psychological well-being: Some evidence on selection into marriage. Journal of Marriage and Family, 54(4):901–911.

Merikangas, K. R. (1984). Divorce and assortative mating among depressed patients. The American Journal of Psychiatry, 141(1):74–76.

Negrusa, B. and Negrusa, S. (2014). Home front: Post-deployment mental health and divorces. Demography, 51(3):895–916.

Pevalin, D. J. and Ermisch, J. (2004). Cohabiting unions, repartnering and mental health. Psychological Medicine, 34(8):1553–1559.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70(1):41–55.

Rosenbaum, P. R. and Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. The American Statistician, 39(1):33–38.

Salyers, M. P., Bosworth, H. B., Swanson, J. W., Lamb-Pagone, J., and Osher, F. C. (2000). Reliability and validity of the SF-12 health survey among people with severe mental illness. Medical Care, 38(11):1141–1150.

Schmidt, L. (2008). Risk preferences and the timing of marriage and childbearing. Demography, 45(2):439–460.

Schoenborn, C. A. (2004). Marital status and health: United States, 1999-2002. In Advance Data from Vital and Health Statistics, number 351, Hyattsville, Maryland. National Center for Health Statistics.

Scully, J. A., Tosi, H., and Banning, K. (2000). Life event checklists: Revisiting the social readjustment rating scale after 30 years. Educational and Psychological Measurement, 60(6):864–876.

van den Berg, G. J. and Gupta, S. (2015). The role of marriage in the causal pathway from economic conditions early in life to mortality. Journal of Health Economics, 40:141–158.

Wade, T. J. and Pevalin, D. J. (2004). Marital transitions and mental health. Journal of Health and Social Behavior, 45(2):155–170.

Ware, J. E., Incorporated, Q., and Lab, N. E. M. C. H. H. A. (2005). How to score version 2 of the SF-12 health survey (with a supplement documenting version 1). Lincoln, R.I. : QualityMetric Inc. ; Boston, Mass. : Health Assessment Lab.

Weiss, Y. (1997). Chapter 3 the formation and dissolution of families: Why marry? Who marries whom? And what happens upon divorce. In Handbook of Population and Family Economics, volume 1, pages 81–123. Elsevier.

Wickrama, K. A. S., Lorenz, F. O., Conger, R. D., and Elder, G. H. (1997). Marital quality and physical illness: A latent growth curve analysis. Journal of Marriage and Family, 59(1):143–155.

Wilson, C. M. and Oswald, A. J. (2005). How Does Marriage Affect Physical and Psychological Health? A Survey of the Longitudinal Evidence. IZA Discussion Papers 1619, Institute for the Study of Labor (IZA).

Wood, R. G., Avellar, S., and Goesling, B. (2009). The Effects of Marriage on Health: A Synthesis of Recent Research Evidence. Nova Science.

Wooldridge, J. M. (2007). Inverse probability weighted estimation for general missing data problems. Journal of Econometrics, 141(2):1281–1301.

Wu, Z. and Hart, R. (2002). The effects of marital and nonmarital union transition on health. Journal of Marriage and Family, 64(2):420–432.

A Appendix

Table A1: Descriptive Statistics - Main Breadwinner-Partner Model

	Mean	S.D.	Med.	Min.	Max.
separation	0.026	0.16	0	0	1
MCS shock$_{\odot}$	0.059	0.236	0	0	1
MCS shock$_{☾}$	0.072	0.259	0	0	1
PCS shock$_{\odot}$	0.052	0.222	0	0	1
PCS shock$_{☾}$	0.063	0.242	0	0	1
MCS shock$_{\odot☾}$	0.012	0.109	0	0	1
PCS shock$_{\odot☾}$	0.006	0.077	0	0	1
MCS$_{t-2,\odot}^{\flat}$	0.518	0.091	0.533	0.101	0.794
MCS$_{t-2,☾}^{\flat}$	0.504	0.097	0.516	0.019	0.777
PCS$_{t-2,\odot}^{\flat}$	0.495	0.094	0.514	0.092	0.725
PCS$_{t-2,☾}^{\flat}$	0.489	0.098	0.507	0.101	0.781
age$_{\odot}$	54.310	13.920	54	20	98
age$_{☾}$	52.650	13.810	52	20	97
abs. age difference	3.759	3.596	3	0	37
education$_{t-2,\odot}$	12.740	2.873	11.5	7	18
education$_{t-2,☾}$	12.080	2.587	11.5	7	18
abs. educ. difference$_{t-2}$	1.707	1.916	1	0	11
east$_{t-2}$	0.253	0.435	0	0	1
home owner$_{t-2}$	0.615	0.487	1	0	1
child in hh$_{t-2}$	0.333	0.471	0	0	1
common child$_{t-2}^{\sharp}$	0.653	0.476	1	0	1
# of children$_{t-2}^{\sharp}$	1.666	0.776	2	1	8
min. age child$_{t-2}^{\sharp}$	7.899	4.832	8	0	16
married$_{t-2}$	0.889	0.314	1	0	1
partnership duration$_{t-2}$	8.892	7.217	7	0	28
censored couple info$_{t-2}$	0.741	0.438	1	0	1
employed$_{t-2,\odot}$	0.726	0.446	1	0	1
employed$_{t-2,☾}$	0.585	0.493	1	0	1
employed$_{t-2,\odot☾}$	0.533	0.499	1	0	1
income$_{t-2,\odot}$	2.960	2.625	2.5	0	99.99
income$_{t-2,☾}$	1.089	1.258	0.755	0	42
income share$_{t-2,\odot}$	0.725	0.230	0.724	0	1
homosexual	0.004	0.060	0	0	1
homosexual$_{♂}$	0.001	0.037	0	0	1

Notes: Statistics based on 25 210 couple-year observations; model that differentiates household head and partner including homosexual couples; six panel waves (biennially 2004–2014); $\odot$ household head; ☾ partner of main breadwinner; † not available for years earlier than 2008; $^{\sharp}$ conditional on children in household. **Source**: Own calculations based on SOEP data.

Table A2: Linear Regression with Controls explaining Separation

	without interact.		with interact.	
	Est. Coef.	S.E.	Est. Coef.	S.E.
MCS shock$_{♂}$	0.026***	0.006	0.027***	0.007
MCS shock$_{♀}$	0.021***	0.005	0.022***	0.006
MCS shock$_{♂♀}$			−0.006	0.016
PCS shock$_{♂}$	0.003	0.004	0.006	0.005
PCS shock$_{♀}$	−0.003	0.004	−0.001	0.004
PCS shock$_{♂♀}$			−0.023***	0.007
MCS shock$_{♂♀}$‡	0.047***	0.007	0.043***	0.014
PCS shock$_{♂♀}$‡	0.000	0.005	−0.018***	0.003
PCS$_{t-2,♂}$♭	0.020	0.012	0.020	0.012
MCS$_{t-2,♂}$♭	−0.034***	0.013	−0.034***	0.013
PCS$_{t-2,♀}$♭	−0.032***	0.012	−0.032**	0.012
MCS$_{t-2,♀}$♭	−0.017	0.012	−0.017	0.012
age$_{♂}$	−0.001**	0.000	−0.001**	0.000
age$_{♀}$	−0.000	0.000	−0.000	0.000
abs. age difference	0.002***	0.001	0.002***	0.001
education$_{t-2,♂}$	0.001	0.000	0.001	0.000
education$_{t-2,♀}$	−0.001**	0.001	−0.001**	0.001
abs. educ. difference$_{t-2}$	−0.000	0.001	−0.000	0.001
east$_{t-2}$	−0.005**	0.002	−0.005**	0.002
home owner$_{t-2}$	−0.008***	0.002	−0.008***	0.002
child in hh$_{t-2}$	−0.000	0.009	−0.000	0.009
common child$_{t-2}$♯	−0.011**	0.005	−0.011**	0.005
# of children$_{t-2}$♯	0.003	0.003	0.003	0.003
min. age child$_{t-2}$♯	0.001**	0.001	0.001**	0.001
married$_{t-2}$	−0.033***	0.006	−0.033***	0.006
partnership duration$_{t-2}$	−0.000***	0.000	−0.000***	0.000
censored couple info$_{t-2}$	−0.009**	0.004	−0.009**	0.004
employed$_{t-2,♂}$	−0.011***	0.004	−0.011***	0.004
employed$_{t-2,♀}$	−0.011**	0.004	−0.011**	0.004
employed$_{t-2,♂♀}$	0.008	0.005	0.008*	0.005
income$_{t-2,♂}$	−0.000	0.000	−0.000	0.000
income$_{t-2,♀}$	0.000	0.001	0.000	0.001
income share$_{t-2,♂}$	−0.019***	0.007	−0.019***	0.007
year 2006	−0.004	0.003	−0.004	0.003
year 2008	−0.003	0.003	−0.003	0.003
year 2010	−0.000	0.004	−0.000	0.004
year 2012	0.001	0.004	0.001	0.004
year 2014	−0.006*	0.003	−0.006*	0.003
N	25 119		25 119	

Notes:*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.1; clustered standard errors; ‡sum of regression coefficients; six panel waves (biennially 2004–2014). **Source**: Own calculations based on SOEP data.

Table A3: Desc. Stats. - Health Shocks def. in terms of Abs. Changes in MCS and PCS

	Mean	**S.D.**	**Med.**	**Min.**	**Max.**
MCS shock$_{♂}$	0.065	0.247	0	0	1
MCS shock$_{♀}$	0.076	0.265	0	0	1
PCS shock$_{♂}$	0.052	0.221	0	0	1
PCS shock$_{♀}$	0.057	0.231	0	0	1
MCS shock$_{♂♀}$	0.013	0.115	0	0	1
PCS shock$_{♂♀}$	0.005	0.073	0	0	1

Notes: Statistics based on 25 119 couple-year observations that are used in OLS estimations; model that differentiates between male and female partner ignoring homosexual couples; six panel waves (biennially 2004–2014); **health shocks** defined as ΔMCS and ΔPCS, respectively, smaller than −0.13; see Table 1 for corresponding statistics for health shock definition of reference. **Source**: Own calculations based on SOEP data.

Table A4: Linear Regression explaining Separation - Absolute Health Shocks

	without interact.		**with interact.**	
	Est. Coef.	S.E.	Est. Coef.	S.E.
MCS shock$_{♂}$	0.019***	0.005	0.016***	0.005
MCS shock$_{♀}$	0.017***	0.005	0.015***	0.005
MCS shock$_{♂♀}$			0.015	0.015
PCS shock$_{♂}$	0.000	0.005	0.000	0.005
PCS shock$_{♀}$	−0.006	0.004	−0.006	0.004
PCS shock$_{♂♀}$			0.001	0.014
MCS shock$_{♂♀}$‡	0.036***	0.007	0.046***	0.013
PCS shock$_{♂♀}$‡	−0.005	0.006	−0.005	0.013
PCS$_{t-2,♂}$$^{♭}$	0.019	0.012	0.019	0.012
CS$_{t-2,♂}$$^{♭}$	−0.039***	0.013	−0.039***	0.013
PCS$_{t-2,♀}$$^{♭}$	−0.031**	0.013	−0.031**	0.013
MCS$_{t-2,♀}$$^{♭}$	−0.022*	0.012	−0.022*	0.012
age$_{♂}$	−0.001**	0.000	−0.001**	0.000
age$_{♀}$	−0.000	0.000	−0.000	0.000
abs. age difference	0.002***	0.001	0.002***	0.001
education$_{t-2,♂}$	0.001	0.000	0.001	0.000
education$_{t-2,♀}$	−0.001**	0.001	−0.001**	0.001
abs. educ. difference$_{t-2}$	−0.000	0.001	−0.000	0.001
east$_{t-2}$	−0.005**	0.002	−0.005**	0.002
home owner$_{t-2}$	−0.008***	0.002	−0.008***	0.002
child in hh$_{t-2}$	−0.000	0.009	−0.000	0.009
common child$_{t-2}$$^{♯}$	−0.011**	0.005	−0.011**	0.005
# of children$_{t-2}$$^{♯}$	0.003	0.003	0.003	0.003
min. age child$_{t-2}$$^{♯}$	0.001**	0.001	0.001**	0.001
married$_{t-2}$	−0.033***	0.006	−0.033***	0.006
partnership duration$_{t-2}$	−0.000***	0.000	−0.000***	0.000
censored couple info$_{t-2}$	−0.009**	0.004	−0.009**	0.004
employed$_{t-2,♂}$	−0.011***	0.004	−0.011***	0.004
employed$_{t-2,♀}$	−0.011**	0.004	−0.010**	0.004
employed$_{t-2,♂♀}$	0.008	0.005	0.008	0.005
income$_{t-2,♂}$	−0.000	0.000	−0.000	0.000
income$_{t-2,♀}$	0.000	0.001	0.000	0.001
income share$_{t-2,♂}$	−0.019***	0.007	−0.019***	0.007
year 2006	−0.004	0.003	−0.004	0.003
year 2008	−0.003	0.003	−0.003	0.003
year 2010	0.000	0.004	0.000	0.004
year 2012	0.001	0.004	0.001	0.004
year 2014	−0.006*	0.003	−0.006*	0.003
N	25 119		25 119	

Notes:*** p-value < 0.01; ** p-value < 0.05; * p-value < 0.1; clustered standard errors; ‡sum of regression coefficients; six panel waves (biennially 2004–2014). **Source**: Own calculations based on SOEP data.

Table A5: PS Estimation - Logit Regressions explainig Mental Health Shocks

	MCS Shock Male		**MCS Shock Female**		**MCS Shock Both**	
	Est. Coef.	S.E.	Est. Coef.	S.E.	Est. Coef.	S.E.
PCS shock$_{♂}$	0.265**	0.129	0.081	0.115	0.434**	0.214
PCS shock$_{♀}$	−0.096	0.132	−0.088	0.125	0.203	0.228
PCS$_{t-2,♂}$	−4.139***	0.352	−0.707**	0.343	−3.879***	0.666
MCS$_{t-2,♂}$	4.067***	0.425	−2.425***	0.319	1.436*	0.756
PCS$_{t-2,♀}$	0.137	0.387	−3.842***	0.312	−3.251***	0.630
MCS$_{t-2,♀}$	−2.375***	0.331	4.070***	0.348	3.385***	0.744
age$_{♂}$	−0.033***	0.009	−0.024***	0.008	−0.024	0.016
age$_{♀}$	0.018*	0.009	0.003	0.007	0.002	0.016
abs. age difference	0.021*	0.011	0.027***	0.009	0.023	0.020
education$_{t-2,♂}$	−0.007	0.016	−0.001	0.014	0.013	0.032
education$_{t-2,♀}$	0.002	0.016	−0.021	0.014	−0.034	0.034
abs. educ. difference$_{t-2}$	−0.019	0.018	0.012	0.016	0.036	0.036
east$_{t-2}$	−0.058	0.080	0.030	0.067	−0.034	0.156
home owner$_{t-2}$	−0.076	0.068	−0.033	0.059	−0.266**	0.128
child in hh$_{t-2}$	0.006	0.201	0.235	0.170	0.018	0.393
common child$_{t-2}{}^{\sharp}$	0.172	0.114	0.022	0.095	0.134	0.237
# of children$_{t-2}{}^{\sharp}$	0.024	0.070	−0.023	0.060	0.090	0.129
min. age child$_{t-2}{}^{\sharp}$	0.004	0.012	−0.015	0.010	−0.023	0.024
married$_{t-2}$	−0.006	0.115	−0.097	0.095	−0.022	0.222
partnership duration$_{t-2}$	−0.001	0.005	−0.008*	0.004	0.005	0.010
censored couple info$_{t-2}$	−0.045	0.088	−0.046	0.078	−0.152	0.175
employed$_{t-2,♂}$	0.130	0.123	−0.117	0.110	−0.129	0.203
employed$_{t-2,♀}$	0.132	0.140	0.086	0.127	−0.212	0.256
employed$_{t-2,♂♀}$	−0.213	0.157	0.017	0.143	0.075	0.293
income$_{t-2,♂}$	−0.015	0.022	−0.015	0.014	0.017	0.023
income$_{t-2,♀}$	0.031	0.029	0.014	0.025	−0.104	0.081
income share$_{t-2,♂}$	−0.073	0.167	0.243	0.151	−0.271	0.319
year 2006	0.196**	0.097	0.165**	0.084	0.161	0.186
year 2008	0.030	0.101	−0.063	0.087	−0.197	0.202
year 2010	0.100	0.108	0.120	0.090	0.505***	0.185
year 2012	0.086	0.114	0.081	0.098	0.222	0.215
year 2014	−0.015	0.109	−0.090	0.095	−0.525**	0.240

Notes: *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.1; clustered standard errors; six panel waves (biennially 2004–2014). **Source**: Own calculations based on SOEP data.

Table A6: PS Estimation - Logit Regressions explaining Physical Health Shocks

	PCS Shock Male		**PCS Shock Female**		**PCS Shock Both**	
	Est. Coef.	S.E.	Est. Coef.	S.E.	Est. Coef.	S.E.
MCS shock$_{♂}$	0.330^{***}	0.120	0.011	0.123	0.118	0.324
MCS shock$_{♀}$	0.074	0.111	−0.054	0.120	0.442	0.279
PCS$_{t-2,♂}$	4.114^{***}	0.409	-1.204^{***}	0.351	1.386	1.124
MCS$_{t-2,♂}$	-2.321^{***}	0.350	0.898^{**}	0.356	−0.045	1.050
PCS$_{t-2,♀}$	-0.807^{**}	0.358	3.580^{***}	0.386	5.891^{***}	1.033
MCS$_{t-2,♀}$	0.233	0.364	-1.993^{***}	0.322	-2.241^{**}	0.895
age$_{♂}$	0.022^{***}	0.008	-0.015^{*}	0.008	0.037	0.027
age$_{♀}$	0.010	0.008	0.030^{***}	0.008	0.007	0.025
abs. age difference	0.019^{*}	0.010	0.023^{**}	0.009	0.009	0.030
education$_{t-2,♂}$	-0.081^{***}	0.016	−0.013	0.016	-0.145^{***}	0.050
education$_{t-2,♀}$	−0.009	0.017	-0.041^{**}	0.017	-0.099^{**}	0.050
abs. educ. difference$_{t-2}$	0.009	0.018	0.006	0.018	0.075	0.060
east$_{t-2}$	−0.071	0.074	-0.149^{**}	0.076	−0.250	0.223
home owner$_{t-2}$	-0.145^{**}	0.064	-0.123^{*}	0.064	−0.046	0.180
child in hh$_{t-2}$	0.159	0.238	−0.357	0.218	−0.207	0.821
common child$_{t-2}{}^{\sharp}$	0.170	0.123	-0.204^{*}	0.116	−0.503	0.405
# of children$_{t-2}{}^{\sharp}$	-0.167^{**}	0.083	0.096	0.072	0.248	0.233
min. age child$_{t-2}{}^{\sharp}$	−0.002	0.013	0.015	0.013	−0.024	0.053
married$_{t-2}$	−0.034	0.116	0.183	0.112	0.216	0.392
partnership duration$_{t-2}$	-0.011^{**}	0.004	−0.007	0.005	−0.001	0.011
censored couple info$_{t-2}$	−0.032	0.094	-0.166^{*}	0.088	0.024	0.302
employed$_{t-2,♂}$	0.019	0.114	−0.099	0.112	-0.513^{*}	0.311
employed$_{t-2,♀}$	0.079	0.127	-0.263^{**}	0.130	-1.003^{***}	0.379
employed$_{t-2,♂♀}$	−0.078	0.148	0.195	0.144	0.898^{**}	0.447
income$_{t-2,♂}$	-0.065^{***}	0.023	−0.025	0.019	0.041^{**}	0.019
income$_{t-2,♀}$	−0.021	0.033	−0.041	0.036	-0.415^{***}	0.131
income share$_{t-2,♂}$	−0.212	0.176	0.128	0.181	-1.428^{***}	0.385
year 2006	0.025	0.094	0.042	0.095	0.808^{***}	0.274
year 2008	−0.094	0.096	0.074	0.094	0.487^{*}	0.278
year 2010	−0.005	0.101	0.085	0.100	0.438	0.313
year 2012	−0.122	0.112	0.051	0.107	0.203	0.350
year 2014	−0.061	0.100	0.142	0.098	0.236	0.326

Notes: *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.1; clustered standard errors; six panel waves (biennially 2004–2014). **Source**: Own calculations based on SOEP data.

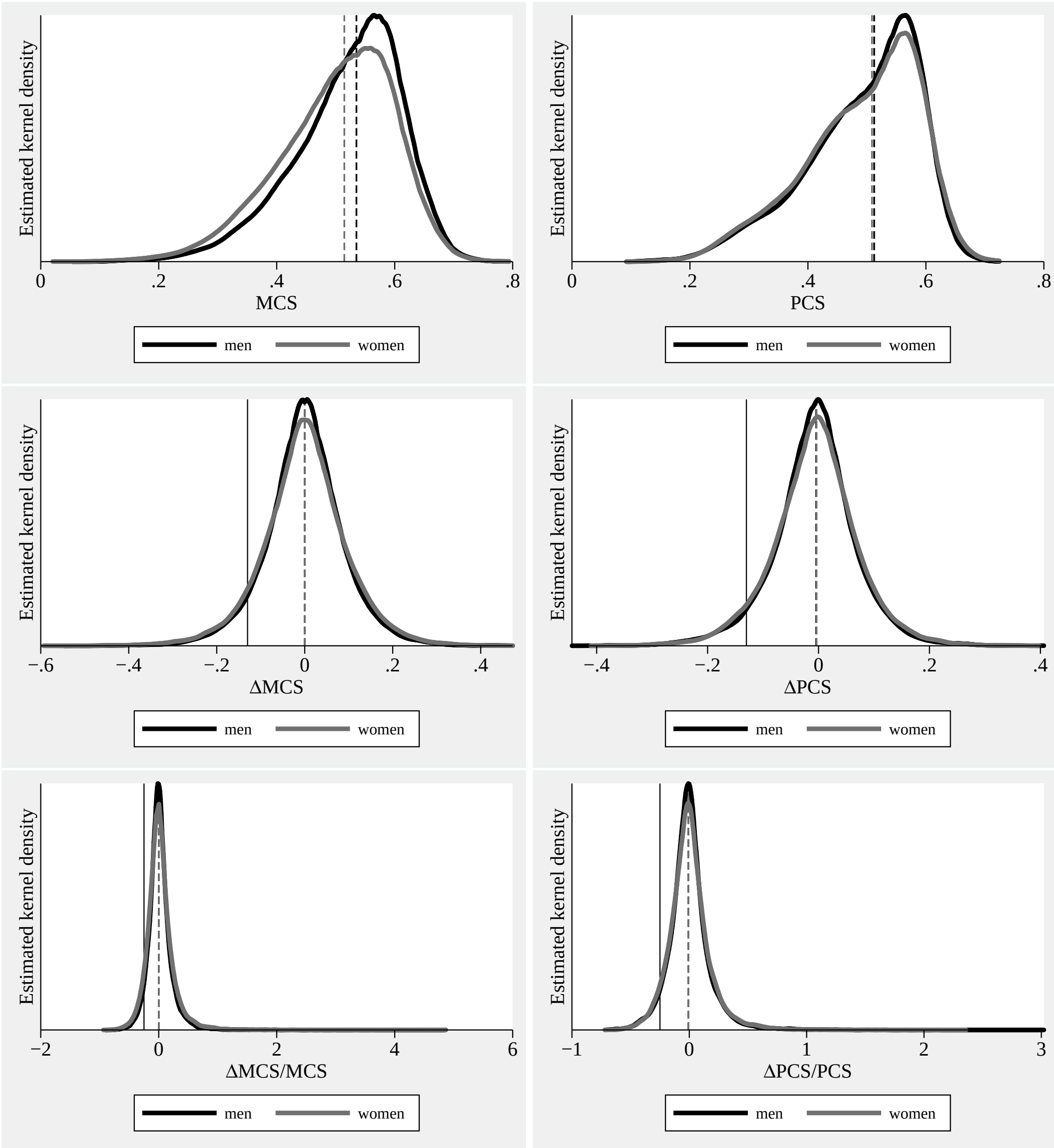

Figure A1: Estimated kernel densities of the level (first row), the absolute change (second row), and the relative change (third row) of MCS (left column) and PCS (right column). **Notes**: Based on estimation sample for the fixed effects model; dashed lines mark the respective median; solid vertical lines mark health-shock thresholds (−0.25 for relative and −0.13 for absolute change). **Source**: Own calculations based on SOEP data.