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The effect of unemployment on the mental health of spouses - Evidence from plant closures in Germany

Jan Marcus¹

Studies on health effects of unemployment usually neglect spillover effects on spouses. This study specifically investigates the effect of an individual's unemployment on the mental health of their spouse. In order to allow for causal interpretation of the estimates, it focuses on plant closure as entry into unemployment, and combines difference-in-difference and matching based on entropy balancing to provide robustness against observable and time-invariant unobservable heterogeneity. Using German Socio-Economic Panel Study data the paper reveals that unemployment decreases the mental health of spouses almost as much as for the directly affected individuals. The findings highlight that previous studies underestimate the public health costs of unemployment as they do not account for the potential consequences for spouses.

JEL: I12, J65

Keywords: unemployment, mental health, plant closure, entropy balancing, matching, job loss

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1. Introduction

Apart from income, employment has many non-financial benefits, such as structured time, social status and identity, social contact, collective purpose, as well as activity (Jahoda 1979). Unemployment results in the loss of the pecuniary and non-pecuniary work benefits, and these losses also impact other household members. Spouses of newly unemployed individuals have to cope with reduced household income, a presumably more depressed partner, the partner’s unfamiliar presence at home as well as a reduced social status. For spouses, too, these negative consequences of unemployment might result in depressive symptoms and other mental health issues.

Yet, while there is a whole branch of literature on the health implications of job loss and unemployment for those individuals directly affected (see e.g. Browning et al. 2006; Brand et al. 2008; Eliason & Storrie 2009; Kuhn et al. 2009; Salm 2009; Sullivan & von Wachter 2009; Deb et al. 2011; Schmitz 2011; Browning & Heinesen 2012; Marcus 2012), few studies address the impact on their spouses. Not considering the potential negative externalities on spouses might result in underestimating the public health costs of job loss (e.g. Kuhn et al. 2009). This study contributes to our understanding of spillover effects of unemployment on other household members by estimating the effect of unemployment on the spouse’s mental health. In order to give the estimates a causal interpretation, this study applies a combination of matching and difference-in-difference that is robust against selection on observables and selection on unobservables with time-invariant effects. The matching part of the estimator constitutes one of the first applications of entropy balancing (Hainmueller 2012), which balances the conditioning variables more effectively than common propensity score methods. Furthermore, this study considers only unemployment resulting from plant closures. Other causes of unemployment might result from mental health issues and, hence, might be endogenous.

Using German Socio-Economic Panel Study (SOEP) data from 2002 through 2010, this paper finds that the unemployment of one spouse² similarly affects the mental health of both spouses. About one year after plant closure, unemployment decreased mental health by 27 % of a standard deviation for unemployed individuals themselves and by 18 % of a standard deviation for their spouses. In general, the decreases in mental health are larger when the male spouse enters unemployment. The results are robust over various matching specifications. Furthermore, this paper shows that changes in mental health do not differ between treated and matched controls before the plant

²The terms “partner” and “spouse” are used interchangeably in this paper.

closure, adding additional credibility to the identification assumption. Analyzing other reasons for unemployment and not just that connected to plant closures confirms the finding that unemployment decreases the mental health for spouses almost as much as for directly affected individuals. However, the effects for other reasons of unemployment are not larger than for unemployment due to plant closure, suggesting that selection issues with respect to entering unemployment might be less important than previously thought.

The structure of this paper is as follows. The next section discusses related literature in greater detail, section 3 illustrates the estimation strategy, section 4 introduces the data, describes the construction of treatment and control group, and provides descriptive statistics. The main results are presented in section 5, while section 6 performs further analyses. Section 7 concludes.

2. Related Literature

The literature on the consequences of unemployment is closely related to the literature on the consequences of job loss - especially when the focus is on the identification of causal effects. In the following, I discuss these two branches of literature together, bearing in mind that not all individuals who lose their jobs are unemployed afterwards and not every individual in the state of unemployment experienced the event of an involuntary job loss.

Previous studies provide some evidence for spillover effects of job loss and unemployment on other household members. For instance, [Winkelmann & Winkelmann \(1995\)](#) report decreases in subjective well-being following the partners' unemployment (without differencing between the reasons for unemployment). [Stephens \(2002\)](#), using U.S. Panel Study of Income Dynamics (PSID) data, provides evidence for the "added worker effect", that women increase their labor supply due to their husbands' job losses resulting from lay-offs or plant closures. Again with PSID data, [Charles & Stephens \(2004\)](#) show that job loss resulting from lay-off or plant closure increases the probability of divorce. Other studies indicate that children are also affected by their parents' loss of employment. For instance, using SOEP data, [Siedler \(2011\)](#) finds that experiencing parental unemployment (for any reason) increases the probability of children to support extreme right-wing parties. With data from the PSID, [Lindo \(2011\)](#) provides evidence for a reduction in children's birth weight following a father's experience of plant closing. This already indicates that the public health costs of job loss are underestimated if spillover effects

on other household members are not taken into account.³ Taken together, the findings on spillover effects on other household members lead to the expectation of negative consequences of unemployment for the spouse’s mental health.

Few studies explicitly analyze the causal relationship between unemployment and the partner’s mental health. Most of these studies focus on single plants or small geographic areas (e.g. [Liem & Liem 1988](#); [Penkower et al. 1988](#); [Dew et al. 1992](#)).⁴ To my knowledge only two studies use nationally representative data in this context ([Clark 2003](#); [Siegel et al. 2003](#)). However, both studies do not take into account the endogeneity of the treatment. Drawing on data from the British Household Panel Study, [Clark \(2003\)](#) finds partner’s unemployment to reduce mental health, but less so if the respondent is already unemployed. Yet, this study does not differentiate between the reasons for unemployment. With data from the U.S. Health and Retirement Study (HRS) [Siegel et al. \(2003\)](#) do not find a significant effect of husbands’ job loss on wives’ mental health in general. However, this study also considers individuals who lost their job due to layoffs, which might result from mental health issues. Furthermore, due to the sampling design of the HRS, this study only analyzes individuals over the age of 50. In contrast, the present study looks at the entire range of working-age individuals and includes in the treatment group only individuals who lost their job due to plant closure.

Previous studies document spillovers of other events in one spouse’s life on the other spouse’s mental health. For instance, [Bolger et al. \(1989\)](#) find that stress experienced by one spouse is associated with strain in the other spouse.⁵ With a sample of the elderly Dutch population, [Lindeboom et al. \(2002\)](#) provide evidence that a severe illness of the partner significantly decreases own mental health. They also find that the death of the spouse strongly increases the risk of developing a depression. Compared to the other life events they analyze (e.g. disability, severe financial problems, death of child, death of grandchild), conjugal bereavement has the largest effect on mental health.

³A further reason why the public health costs of unemployment might be underestimated is that often the focus is on short-term effects, and long-term consequences like potential scarring effects of unemployment ([Clark et al. 2001](#)) are not taken into account.

⁴[Dew et al. \(1992\)](#) provide an overview over earlier qualitative studies on this topic.

⁵[Jones \(1993\)](#) and [ten Brummelhuis et al. \(2010\)](#) come to similar conclusions. Though, it remains unclear whether the associations presented in these studies can be interpreted as causal effects.

3. Estimation Strategy

In order to estimate the effect of unemployment on the mental health of couples, this paper combines matching and difference-in-difference (DiD), which is regarded to be superior to pure cross-sectional matching estimators (Heckman et al. 1997). This estimator brings together the literature on selection on observables with the literature on selection on unobservables. The idea of the estimator is rather simple. In the matching part of the estimator, I take couples who are affected by unemployment and similar couples who do not experience unemployment. In the DiD part, I compare changes in mental health of these two groups. The DiD part eliminates time-invariant mental health differences between couples in the treatment and control group that result from unobserved variables (like personality traits and differences in the reporting behavior). In all analyses I focus on the average treatment effect on the treated (ATT), i.e. the unemployment induced change in mental health of those couples who are actually affected by unemployment as a result of plant closures.

The challenge is how to make treated couples (couples, where one spouse is affected by unemployment resulting from plant closure) and control couples (couples without job loss experiences in the period) similar. To increase similarity between the two groups, propensity score methods are often applied (Caliendo & Kopeinig 2008),⁶ where the control group observations are reweighted either by weights that depend directly on propensity score values (as in propensity score weighting) or by weights that depend on propensity score distances to treatment observations (as, for example, in nearest neighbor or kernel matching). However, I do not take the detour via the propensity score, but instead implement a reweighting technique, entropy balancing (Hainmueller 2011, 2012), that focuses directly on the balancing of conditioning variables (see appendix A.1). Entropy balancing is more effective in reducing covariate imbalance than propensity score methods as it reweights the control group observations in such a way that the control group satisfies pre-specified balancing requirements (here: same mean and variance of conditioning variables as in the treatment group). In the section on sensitivity analyses I also apply propensity score methods.

I perform entropy balancing separately for couples where the husband/wife enters unemployment.⁷ This is like exact matching on the gender of the directly affected

⁶The propensity score (Rosenbaum & Rubin 1983) is the probability to receive the treatment conditional on the covariates.

⁷For convenience, I refer to the male and female in a couple as husband and wife - independent of marital status.

spouse. Section 5 shows the results for all couples pooled and separately according to whether husband or wife enters unemployment.

Obtaining the weights from entropy balancing constitutes the first step in implementing the estimation strategy. This is the matching/reweighting step. The second step is the regression step, where the change in mental health is regressed on the treatment indicator with the sampling weights obtained in the first step. In the regression step, I additionally control for all conditioning variables used in the matching step. This does not alter the treatment effect as after weighting the treatment is mean-independent of all conditioning variables. However, the regression-adjustment decreases the standard errors of the treatment effect estimates because it reduces unexplained variance in the outcome. This is similar to including control variables in randomized experiments.

Hence, the ATT of interest can be obtained from

$$\hat{\beta} = (\mathbf{X}'\mathbf{W}\mathbf{X})^{-1}\mathbf{X}'\Delta y, \quad (1)$$

where Δy is the vector of mental health changes and \mathbf{W} a diagonal matrix with 1 in the diagonal cells for couples of the treatment group and entropy balancing weights in the diagonal cells for control group couples. \mathbf{X} is a n -by- $(k+2)$ matrix, in which the first column consists of a vector of 1s and the second column of the values of the treatment group indicator, D , for each couple. Additionally, \mathbf{X} contains one column for each of the k conditioning variables. The estimator is similar to the regression-adjusted semiparametric difference-in-difference matching strategy proposed by Heckman et al. (1997). It differs only with respect to the construction of the weights, which are computed by propensity score methods in Heckman et al. (1997).

In order to give the estimates a causal interpretation, the estimator has to assume that no unobserved variables exist that simultaneously influence *changes* in mental health and the probability of entering unemployment due to plant closure, i.e. in the absence of treatment (unemployment due to plant closure) the mental health of treated couples and matched control couples follows the same trend:

$$E[Y_0^a - Y_0^b | EB(X), D = 1] = E[Y_0^a - Y_0^b | EB(X), D = 0], \quad (2)$$

where $\Delta Y_0 = Y_0^a - Y_0^b$ refers to the change in mental health from before (b) to after (a) the treatment in the absence of treatment and $EB(X)$ refers to the weights from entropy balancing.

4. Data

This paper makes use of data from the German Socio-Economic Panel (SOEP, v27) from 2002 through 2010. The SOEP is among the largest and longest running household panel surveys in the world. Annually about 20,000 individuals participate in the SOEP. It consists of several subsamples and is designed to be representative of the entire population in Germany (Wagner et al. 2007). The SOEP hosts several features that make it particularly attractive for the present analysis. Firstly, the longitudinal nature of the data ensures that I can observe the mental health scores before and after the treatment. Secondly, its large sample size facilitates analysis based on relatively rare events like plant closures. Thirdly, the SOEP contains not only information on one household member but also data on cohabiting spouses. These data are directly provided by the spouses themselves. Fourthly, after household dissolutions the SOEP follows *all* household members and not just the household head. This is of particular importance for the present analysis as unemployment increases the probability of divorce (Charles & Stephens 2004) and, hence, household dissolution. Only considering couples that still live together after the treatment would result in a rather selective panel (though divorce related panel attrition might still occur in the SOEP; see below). Fifthly, the SOEP provides a wide range of information at the individual and the household level, including details about earnings, employment and living conditions. This enables me to include almost all conditioning variables used in related studies.

4.1. Outcome

This study uses the Mental Component Summary Scale (MCS), which was developed as a brief instrument to measure mental health in large scale surveys (Ware et al. 1996). It is found to be reliable and valid (e.g. Salyers et al. 2000), with high values of sensitivity and specificity compared to other brief scales of mental health (Gill et al. 2007). MCS is not a disease-specific measure focusing on a particular condition or disease, but a generic measure of mental health. MCS is used widely in the epidemiologic literature and a broad literature in economics uses this summary measure of mental health as well (e.g. Lechner 2009; Reichert & Tauchmann 2011; Schmitz 2011). It was included in the SOEP as *the* measure of mental health. It is not a measure of general life satisfaction although it correlates with life satisfaction.⁸

⁸The correlation in the used sample is $r = 0.4$.

The construction of MCS reverts to the SOEP version of the SF-12 questionnaire, which was first adopted in the SOEP in 2002 and ever since is included every two years. The SF-12 contains 12 health-related questions that encompass two dimensions: physical and mental health. All items reflect the *current* health status of the respondents, as they refer to the four weeks immediately prior to the interview (e.g. “How often did you feel run-down and melancholy in the last four weeks?”). Appendix A.2 provides an overview over the items of the SF-12 questionnaire and the answer categories. MCS is a weighted combination of the 12 items and provided by the SOEP Group. It is computed by means of explorative factor analysis and transformed to have mean 50 and standard deviation 10 in the 2004 SOEP sample (Andersen et al. 2007). Higher values indicate a better mental health status.

4.2. Treatment and Control Group

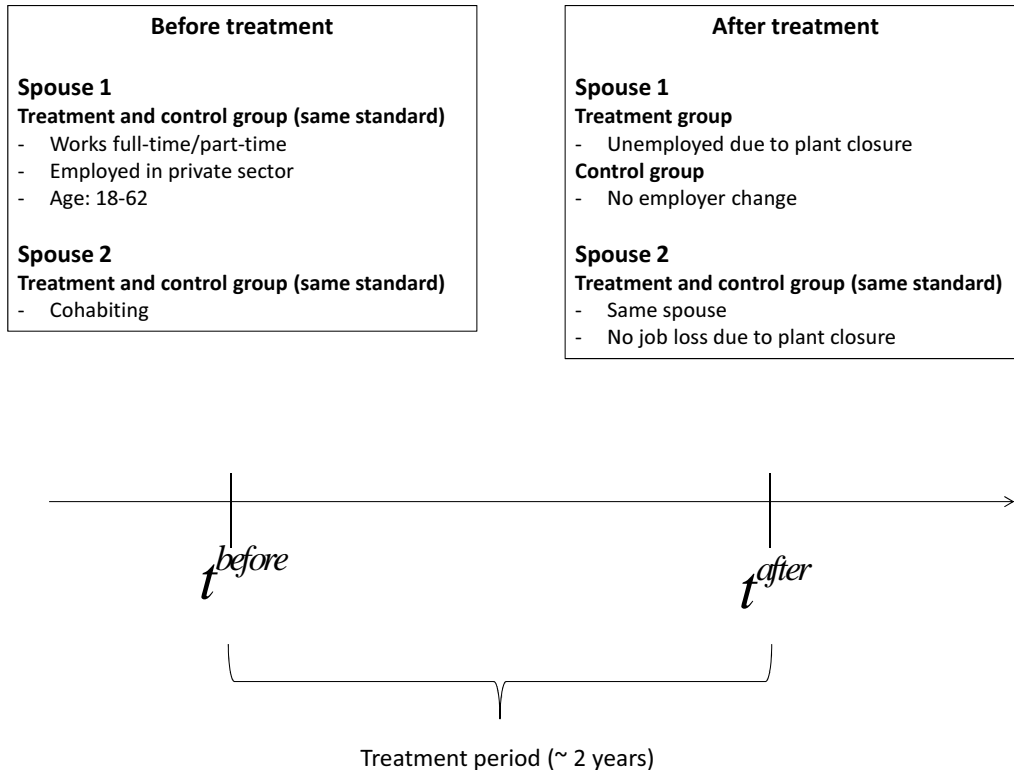
Treatment and control group consist of couples who live together in the same household before the treatment - irrespective of their marital status. Figure 1 provides an overview of the construction of treatment and control group, which the following paragraph describes in more detail.

I only include couples where both spouses participate in the survey before (t^b) and after (t^a) the treatment, and provide valid mental health information in both years. I do not consider same-sex couples as there are none in the treatment group.

The treatment group comprises couples in which one spouse (the “directly affected spouse”) enters unemployment due to plant closure between two survey waves with the SF-12 questionnaire. I construct the treatment indicator by combining information from the question on whether the respondent is officially registered as unemployed with information on the reason why the individual left the last job. I only consider plant closures since other reasons of unemployment might be endogenous, e.g. someone might be dismissed because of shrinking work productivity due to marital problems (and marital problems might decrease mental health). Before the plant closure the directly affected individual has to be employed either full-time or part-time in the private sector and has to be between the ages of 18 and 62. I include couples in the treatment group irrespective of age and employment status of the indirectly affected spouse (the partner of the directly affected individual). However, I do not consider couples in which the indirectly affected spouse experienced an involuntary job loss between t^b and t^a due to plant closure. That is done in order to prevent that own experiences deteriorate the mental health effect of the indirectly affected spouse. The plant closure experience of

one spouse is likely to be correlated with a plant closure experience of the other spouse since spouses might work in the same plant. Excluding couples in which indirectly affected spouses experience plant closures themselves reduces the treatment group by 7 %.

Figure 1: Construction of treatment and control group



Note: The figure presents an overview of the construction of treatment and control group. The boxes show the requirements that couples have to meet to qualify for treatment and control group, respectively. “Spouse 1” refers to the directly affected individual and “spouse 2” to the partner of “spouse 1”.

The control group consists of a potentially directly affected individual (who is of the same sex as the directly affected individual in the treatment group) and a potentially indirectly affected individual. For the potentially indirectly affected spouse the same restrictions apply as in the treatment group construction, both before and after the treatment. Similarly to the treatment group, at the pre-treatment interview the potentially directly affected individual has to be employed either full-time or part-time in the private sector and has to be between the ages of 18 and 62. However, couples qualify only for the control group, if the potentially directly affected spouse did not leave the previous employer during the treatment period (this excludes couples with any job loss

experiences; see figure 1). This leaves more than 14,000 couples for the control group, compared to 109 couples in the treatment group: 70 couples in which the husband enters unemployment and 39 couples in which the wife enters unemployment.

The plant closure can take place at any time between two survey waves that include the mental health questions. Hence, there are four treatment periods: 2002-2004, 2004-2006, 2006-2008 and 2008-2010. I estimate treatment effects pooled over all four treatment periods. On average, I observe the treatment group 11 months after the plant closure. This time, however, varies between 0 and 23 months, with a rather uniform distribution. Hence, the estimates are to be interpreted as averages over these different unemployment durations; an interpretation inherent also to most applications of fixed effects panel estimators.

4.3. Conditioning Variables

The set of conditioning variables, i.e. \mathbf{X} in equation (1), is selected following the screening of conditioning variables in other studies that analyze health effects of job loss and unemployment on the directly affected individual ([Browning et al. 2006](#); [Böckerman & Ilmakunnas 2009](#); [Eliason & Storrie 2009](#); [Salm 2009](#); [Sullivan & von Wachter 2009](#); [Schmitz 2011](#)). The richness of the SOEP data allows including almost all conditioning variables used in these studies. Also the job security perceived by the individuals is included, which can be seen as a variable that captures unobserved factors related to the plant closure. The conditioning variables include demographic, labor market related, educational and health data of the directly affected spouse. I include the same set of conditioning variables for the indirectly affected spouse as for the directly affected spouse - except for those variables that make only sense for working individuals (e.g. tenure with current firm, size of the company). The pre-treatment working status is only included for indirectly affected spouses. Therefore, conditioning variables can be divided into variables reported by the directly affected individual, variables reported by the indirectly affected individual and variables on the couple (i.e. household) level. All 72 non-collinear conditioning variables originate from the pre-treatment interview. As the conditioning variables also include the pre-treatment values of the mental health score, the applied regression-adjusted matching DiD estimator resembles a regression-adjusted matching estimator, where the outcome is the post-treatment mental health score ([Lechner 2010](#)). I use the terminology matching DiD, in order to emphasize that the estimator provides also some robustness against selection on unobservables. Table 1 provides an overview of the conditioning variables.

Table 1: Overview of the conditioning variables

Variable	Definition	D	I
Individual information			
<i>Demographic</i>			
Age	in years	✓	✓
Female	0=male, 1=female	✓	✓
Migrant	1=individual or parents moved to Germany, 0 otherwise	✓	✓
Non-German	0=German, 1=foreign citizenship	✓	✓
<i>Health</i>			
Physical health	based on SF12 questionnaire (see Andersen et al. 2007)	✓	✓
Mental health	based on SF12 questionnaire	✓	✓
Often melancholic	0=never/almost never, 1=always/often/sometimes; part of SF12	✓	✓
Self-rated health	3 categories (very good/good, satisfactory, poor/bad)	✓	✓
<i>Labor market</i>			
Labor earnings	annual nominal labor earnings in 1000 Euro	✓	✓
Never unemployed	0=ever unemployed, 1=never unemployed	✓	✓
Tenure	tenure with present employer (in years)	✓	
Years in full time	previous full-time experience in years	✓	
Company size	4 categories (< 20, 20-200, 200-2000, ≥ 2000 employees)	✓	
Perceived job security	3 categories (big worries, some worries, no worries)	✓	
Industry sector	10 categories	✓	
Working status	3 categories (full time, part time, not employed)		✓
<i>Educational</i>			
Secondary schooling	4 categories (no degree/basic school, intermediate/other school, academic school track (Abitur), technical school)	✓	✓
University	0=no university degree, 1=university degree	✓	✓
Vocational training	0=no vocational training, 1=vocational training	✓	✓
Couple information			
Children	1=children under 18 in household, 0 otherwise	✓	
Regional unemployment	yearly information on the state level	✓	
Residential district	4 cat. (< 2000, 2000-20 000, 20 000-100 000, ≥ 100 000 inhabitants)	✓	
Federal state	14 categories ⁹	✓	
Survey year	4 categories (2002, 2004, 2006, 2008)	✓	

Note: The table describes the coding of the conditioning variables and indicates whether the variable is included for the directly affected spouse (D), the indirectly affected spouse (I) or both. All conditioning variables originate from the pre-treatment interview.

⁹I group Bremen with Lower Saxony and Hamburg with Schleswig-Holstein due to few cases.

4.4. Descriptive Statistics

Table 2 presents summary statistics of selected conditioning variables separately for couples in the treatment and control group (before and after matching/reweighting). The table in appendix A.3 provides the means of other conditioning variables.

Table 2: Summary statistics for selected variables before treatment

Variable	Treated	Controls		(unmatched) Difference
		unmatched	matched	
Directly affected spouse				
Age	48.1	44.0	48.1	-4.1***
Female ⁺	35.8	43.6	35.8	7.9*
Non-German ⁺	22.9	12.4	22.9	-10.5***
Mental health	49.9	50.7	49.9	0.8
Tenure	11.0	12.4	11.0	1.4
Never unemployed ⁺	62.4	70.6	62.4	8.2*
Labor earnings	24.9	35.2	24.9	10.3***
Big job worries ⁺	39.4	15.1	39.4	-24.3***
No job worries ⁺	22.0	39.0	22.0	16.9***
University ⁺	8.3	23.3	8.3	15.1***
Indirectly affected spouse				
Mental health	49.3	50.4	49.3	1.1
Works full-time ⁺	49.5	52.2	49.5	2.7
Not working ⁺	31.2	22.7	31.2	-8.5**
N	109	14285	109	

Note: The first three columns present means of selected variables before treatment for treated, controls and matched controls, respectively. ⁺ indicates that the mean represents a percentage share. The last column displays the difference in means between treatment and control group before matching; stars indicate significant *t*-test differences between these two groups: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

The first two columns of table 2 display means of the conditioning variables for the treated and the control group couples, respectively. The last column displays differences in means between treatment and control group before matching and tests for the significance of these differences. Directly affected spouses differ in many respects significantly from their control group counterparts. For instance, they are older (48.1 vs. 44.0 years), are less likely to be female, more often do not have the German citizenship and earn annually on average 10,000 Euro less. Individuals in the control group are almost three times more likely to have a university degree than individuals who experience unemployment due to plant closure (23.3 % vs. 8.3 %). However, before the treatment there are

no significant differences with respect to tenure and mental health. The mental health score is only about 0.8 points (about 8 % of a standard deviation) lower for the directly affected spouses in the treatment group and the difference is not statistically significant from zero.

Similarly, the indirectly affected spouses do not differ significantly from their control group counterparts with respect to mental health (49.3 vs 50.4), but with respect to age, German citizenship, education and earnings (see appendix A.3). Of these indirectly affected spouses, 31.2 % of them do not work, compared to 22.7 % in the control group.

The third column of table 2 reports means for the matched controls. After the reweighting based on entropy balancing the means in the control group equal the means in the treatment group. The applied entropy balancing scheme not only balances the means but also the variances of the conditioning variables.

The table in appendix A.3 not only reports the means for other conditioning variables, but it also compares the matched control groups resulting a) from entropy balancing and b) the propensity score based kernel matching (Heckman et al. 1997). Kernel matching results rely on an Epanechnikov kernel and a bandwidth of 0.06, which improves the covariate balance particularly well compared to other propensity score based specifications.¹⁰ The table shows that also kernel matching works quite well. For all but one variable (technical college for the directly affected spouse) the standardized bias is below the value of 5, which is regarded to be low (Caliendo & Kopeinig 2008).¹¹ However, the table in appendix A.3 also depicts that entropy balancing clearly outperforms kernel matching as it better improves covariate balance between treatment and control group. Kernel matching even increases the standardized bias for some variables (e.g. for living in a small city).

5. Results

Table 3 shows the results for the effect of unemployment on the mental health of couples. The table shows the findings pooled for all couples and separately according to the sex of the directly affected spouse. It starts with a simple specification and then gradually incorporates more sophisticated procedures. The first specification provides a simple

¹⁰For propensity score methods I also include the squared terms of all cardinal conditioning variables to improve balance on the second moments.

¹¹The standardized bias is a measure of the matching quality, and defined as the difference between the means of treated and controls as a percentage share of the square root of the average of the variances in the two groups (see also appendix A.3).

comparison of the average mental health of treated and (all) controls *after* treatment. Since there might be fundamental differences between the treatment and control group (e.g. with respect to reporting behavior or the general mental health level), specification (2) uses the *change* in mental health as outcome. Hence, this specification resembles an ordinary difference-in-difference estimator without control variables. It might be that the mental health of treated couples follows a different trend than the mental health of other couples, i.e. even in the absence of treatment the mental health of the treated couples would change in a different way. The previous section shows that treated and control couples differ indeed in many respects. This makes it more likely that the treated are on a different mental health track. Matching ensures that only comparable couples are compared. Specification (3) displays the results for the matching DiD estimator. Specification (4) is the preferred specification as, in addition to specification (3), it includes the covariates in the outcome equation as well. This leaves the estimates of the ATT unchanged, because by construction of the entropy balancing scheme, the treatment indicator is mean-independent of all conditioning variables. However, including the covariates in the outcome regression reduces the variance in the outcome and, hence, makes the estimates more precise.

Specification (1), the simple mean comparison, shows in the first cell that the mental health score of spouses who entered unemployment due to plant closure is on average about 2.68 units lower than the mental health score of control group individuals. This implies a difference of about 26.8 % of a standard deviation since the mental health score is normed to have a standard deviation of 10. For the spouses of the directly affected individuals, mental health is on average 2.59 points lower. The second and third panel show that the mental health is worse for both spouses irrespective of the sex of the directly affected spouse. However, the difference between treated and controls is more pronounced for couples where the husband became unemployed, and not significant for couples where the wife entered unemployment. In general, the differences are of similar magnitude for own mental health and the spouse’s mental health, and not statistically significant from each other (as indicated by the p-values). This finding suggests that unemployment of one spouse similarly affects the mental health of both spouses.

The results for specification (2) are similar to the previous results, although the coefficient estimates decrease somewhat in magnitude (especially in the last panel). In the matching DiD estimator in specification (3) both standard errors and coefficient estimates slightly increase, t-statistics (not shown) marginally increase for most estimates. However, incorporating matching does not change the overall picture much.

Table 3: The effect of unemployment on mental health - main results

Outcome	Mean difference (1)	DiD (2)	Match (3)	Main specification (4)
All couples				
Own mental health	-2.68 ** (1.04)	-1.84 (1.12)	-2.68 ** (1.16)	-2.68*** (0.72)
Partner's mental health	-2.59 ** (1.01)	-1.47* (0.84)	-1.81 ** (0.88)	-1.81*** (0.66)
<i>p-value of difference</i>	0.94	0.78	0.53	0.32
Husband's unemployment				
Own mental health	-3.22 ** (1.35)	-2.70* (1.53)	-3.13 ** (1.56)	-3.13*** (0.88)
Partner's mental health	-2.66 ** (1.34)	-2.04* (1.04)	-2.01* (1.09)	-2.01*** (0.77)
<i>p-value of difference</i>	0.73	0.71	0.53	0.27
Wife's unemployment				
Own mental health	-2.02 (1.62)	-0.28 (1.49)	-1.86 (1.58)	-1.86*** (0.63)
Partner's mental health	-2.11 (1.45)	-0.46 (1.40)	-1.46 (1.50)	-1.46* (0.77)
<i>p-value of difference</i>	0.96	0.93	0.85	0.63

Note: The table presents the effect of one spouse's entry into unemployment on the mental health of both spouses. Each cell displays the ATT from a separate regression and its robust standard error in parentheses. Additionally, the table provides p -values for the t -tests whether unemployment differently influences directly and indirectly affected spouses. The upper panel considers all couples, while the two lower panels display results separately according to the sex of the directly affected spouse. The results rely on 109 couples in the treatment group (including 70 couples where the husband enters unemployment) and more than 14,000 couples in the control group. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. The first column refers to the mean difference in mental health after the treatment and "DiD" to the simple difference-in-difference estimator without matching and "Match" to the DiD results after entropy balancing. The last column presents results for the matching DiD estimator that includes the covariates in the outcome equation.

The last column displays the results for the preferred specification, which includes regression-adjustment. In specification (4) unemployment decreases mental health for the directly affected individuals by 2.68 points on average, or about 26.8 % of a standard deviation. This decrease is stronger when the husband enters unemployment (3.13 vs. 1.86 points). The impact of the spouse's unemployment is only slightly smaller for the indirectly affected spouse (1.81 points on average) and the difference in the effects is far from being statistically significant. Again, the effect is stronger if the husband enters unemployment (2.01 vs. 1.46 points). However, the effects of the wife's unemployment become significant in this last specification. These effects exhibit negative signs in all specifications but were not estimated precisely enough before. The results also suggest that the mental health decrease for wives whose husbands enter unemployment and for wives who enter unemployment themselves is very similar, and the difference is far from being significant. It has to be considered that the two effects are based on two rather different groups of women (working wives vs. wives of working men). Hence, one can not interfere that women are more/less affected by the spouse's unemployment than by their own unemployment. Similarly, one cannot say for sure that men are more affected by their own unemployment than by their spouse's unemployment. In general, the coefficient estimates of the preferred specification closely resemble the results of specification (1), the simple mean comparison. This implies that selection into treatment is not strong with respect to mental health, which might provide additional credibility for studies that evaluate the impact of plant closures but do not observe the pre-treatment outcome.

It would be interesting to investigate whether the effect of unemployment differs between subgroups. However, due to the rather small number of couples in the treatment group - especially when only considering couples in which the wife enters unemployment - I refrain from more detailed inspections of potential mechanisms and treatment effect heterogeneity.¹²

When including the post-treatment household net income as additional control variable in the regression step, in order to analyze potential channels, the estimated effects

¹²Tentative analyses indicate that effects tend to be larger when - before the plant closure - the directly affected individual provided a higher share of household income and when the indirectly affected spouse did not work full-time. Further tentative analyses do not find supportive evidence for the hypothesis that unemployment hurts less if individuals have more previous unemployment experiences (habituation hypothesis; [Clark et al. 2001](#)). On the contrary, some of these specifications suggest that unemployment has a more negative impact on mental health for those with previous unemployment times, particularly for those couples where the indirectly affected spouse has been unemployed before.

of unemployment on mental health only slightly decrease.¹³ This suggests that the drop in current household income is not the main channel for the estimated effects. However, the effects might work through the uncertainty about future income levels. Hence, it is not possible to conclude that income is irrelevant as potential channel.¹⁴

6. Further Results

This section consists of two parts. The first part performs sensitivity analyses. It applies different matching procedures (propensity score weighting, kernel matching), analyzes the sensitivity of the results to a redefinition of the treatment and runs a placebo regression to check the plausibility of the identifying assumption. The second part investigates the potential endogeneity of other reasons for unemployment. Table 4 presents the results for the various sensitivity analyses, table 5 for other reasons for unemployment.

6.1. Sensitivity Analyses

For the first two sensitivity checks I rely on propensity score methods instead of entropy balancing. Propensity score weighting (PSW) and kernel matching differ from entropy balancing with respect to the weighting matrix W in equation (1). Propensity score weighting assigns to each control observation a weight that equals $1/(1 - P(X))$, where $P(X)$ is the propensity score. Kernel matching matches to each treatment observation control observations that are close in terms of the estimated propensity score. However, it does not assign equal weights to all the matched neighbors but instead assigns weights according to distances in the propensity score.¹⁵ Specifications (5) and (6) present the results for propensity score weighting and kernel matching, respectively. The effects are similar to the results in the main specification. However, the effects for wife's unemployment slightly decrease, while the effects for husband's unemployment on husband's

¹³These results are available from the author upon request. The average monthly net household income is estimated to decrease by about 500 Euro due to one spouse's unemployment, applying the previously outlined estimation strategy to household income. This decrease accounts for less than 20 % of the pre-treatment household income.

¹⁴Couples tend to have stronger decreases in mental health due to unemployment, when the income of the directly affected spouse was more important for the couple's income. Also this finding from the tentative analyses underlines that income should not be excluded as moderator variable.

¹⁵As in appendix A.3, for kernel matching I use the linear index of the propensity score and an Epanechnikov kernel with a bandwidth of 0.06.

Table 4: The effect of unemployment on mental health - sensitivity analyses

Outcome	Main specification (4)	PS- weighting (5)	PS- matching (6)	All plant closures (7)	Placebo regress. (8)
All couples					
Own mental health	-2.68*** (0.72)	-2.60*** (0.70)	-2.73*** (0.74)	-0.76 (0.50)	-0.32 (0.64)
Partner's mental health	-1.81*** (0.66)	-1.83*** (0.61)	-1.64** (0.67)	-1.22** (0.48)	0.13 (0.63)
<i>p-value of difference</i>	0.32	0.36	0.23	0.44	0.53
$N_{Treated}$	109	109	109	288	62
Husband's unemployment					
Own mental health	-3.13*** (0.88)	-3.03*** (0.84)	-3.52*** (0.92)	-0.59 (0.60)	-0.91 (0.57)
Partner's mental health	-2.01*** (0.77)	-2.11*** (0.72)	-1.91** (0.79)	-0.96* (0.58)	-0.05 (0.52)
<i>p-value of difference</i>	0.27	0.34	0.14	0.62	0.14
$N_{Treated}$	70	70	70	194	33
Wife's unemployment					
Own mental health	-1.86*** (0.63)	-1.67*** (0.58)	-1.39** (0.63)	-1.12* (0.67)	0.36 (0.69)
Partner's mental health	-1.46* (0.77)	-1.30** (0.63)	-1.09* (0.64)	-1.76*** (0.65)	0.35 (0.75)
<i>p-value of difference</i>	0.63	0.61	0.69	0.40	0.99
$N_{Treated}$	39	39	39	94	29

Note: The table presents the effect of one spouse's entry into unemployment on the mental health of both spouses. Each cell displays the ATT from a separate regression and its robust standard error in parentheses. Additionally, the table provides the number of treated couples ($N_{Treated}$) and p -values for the t -tests whether unemployment differently influences directly and indirectly affected spouses. The upper panel considers all couples, while the two lower panels display results separately according to the sex of the directly affected spouse. Specification (4) is the main estimation specification as in table 3, specifications (5) and (6) display the results for propensity score weighting and propensity score (kernel) matching, respectively. In specification (7) the treatment group comprises *all* couples that experienced a plant closure and specification (8) performs a placebo regression that pretends that the treatment takes place two years earlier. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

and wife’s mental health get more similar for propensity score weighting and more different for kernel matching. Also these specifications do not reject the null-hypothesis that unemployment influences directly and indirectly affected spouses in the same way, as indicated by the p -values.

As outlined in section 2, research on the consequences of unemployment is closely intertwined with research on the consequences of job loss. In order to make the results comparable to other studies that solely analyze job losses (e.g. [Browning et al. 2006](#); [Brand et al. 2008](#); [Kuhn et al. 2009](#); [Salm 2009](#)), the treatment group in specification (7) comprises *all* couples that experienced a plant closure (irrespective of unemployment experiences).¹⁶ The results in table 4 indicate that plant closures per se do not have such negative impact on mental health. Rather, it is the unemployment experience that decreases mental health. Hence, failing to differentiate between job loss and unemployment might be a potential reason why existent studies do not find an effect of job loss on own mental health (e.g. [Browning et al. 2006](#); [Brand et al. 2008](#); [Salm 2009](#)). Own plant closure experiences significantly decrease own mental health for wives, but no longer for husbands. The decrease in the spouses’ mental health remains significant. Also the effects on the spouses’ mental health are smaller than in the main specification indicating that those with unemployment following a plant closure have larger drops in mental health.¹⁷ In specification (7), the mental health consequences are slightly larger for couples in which the wife experienced a plant closure.

To identify causal effects, all matching procedures assume that the conditioning variables include all variables simultaneously influencing changes in mental health and the probability of becoming unemployed due to plant closure. This assumption cannot be directly tested. In order to add additional credibility to this assumption, I perform a placebo regression. For this purpose, I pretend that the treatment takes place two years earlier. Accordingly, for the first step I compute the weights based on conditioning variables obtained in the last year with health data before the *placebo* job loss. Specification (8) shows that the placebo treatment does not influence changes in mental health. All estimated effects are insignificant and close to zero. This specification adds plausibility to the assumption that the mental health of treated and matched controls follows a

¹⁶Apart from this difference, the same rules for the selection of the treatment group apply as before (see figure 1 and section 4.2), in particular couples where both spouses experienced a plant closure are disregarded.

¹⁷Considering only couples that are included in specification (7) but not in specifications (1)-(6) indicates that only the effect of the wife’s plant closure on the mental health of the spouse is significant (results are not shown, but are available upon request).

similar trend before the treatment.

Despite the robustness of the results to different matching procedures, the ATT estimates might be downward-biased for several reasons. First, there might be selective panel attrition. Couples experiencing a greater negative impact from unemployment (e.g. with respect to finances or identity) might be more likely to drop out of the sample.¹⁸ These couples might also be more likely to experience greater decreases in mental health. Related to this argument for selective panel attrition is the finding that job loss increases the risk to commit suicide (Eliason & Storrie 2009), which is an extreme form of mental health problems. Similarly, also divorce increases the chances of panel attrition,¹⁹ and job loss increases the probability of divorce (Charles & Stephens 2004). Second, the *expectation* of the plant closure might already decrease mental health. Hence, for treated couples the pre-treatment mental health score would be lower than their “normal” mental health score. Using German SOEP data, Reichert & Tauchmann (2011) provide evidence that already the fear of becoming unemployed decreases mental health. Yet, specification (8) indicates that treated and matched controls do not differ with respect to their mental health trend before the treatment. One reason for this might be that the conditioning variables include also the perceived job security and that I, hence, compare only couples having similar risks of job loss.

Additionally, the effects might be biased since the analyses do not include couples where both spouses experience a plant closing. The direction of this bias is not clear. If both partners experience a plant closure, the drop in household income is even larger. This suggests larger decreases in mental health. However, findings in Clark (2003) suggest that unemployment hurts less when the partner is unemployed as well. When including the seven couples in the treatment group where both partners experienced a plant closure, the results do not change meaningfully.

As the present analysis focuses on the short-term impact of unemployment on mental health, it does not consider the full mental health consequences of unemployment. Long-term consequences like potential scarring effects (past unemployment has a negative impact even when the individuals have become reemployed; Clark et al. 2001) and the effects of future job insecurity (Stevens 1997; Knabe & Rätzel 2011) are not taken into account.

¹⁸For instance, Dorsett (2010) finds unemployment to be related to panel attrition when comparing survey and register data.

¹⁹Although the SOEP following rules should mitigate divorce related panel attrition, see section 4.

6.2. Other Reasons for Unemployment

In order to assess the endogeneity of other reasons for unemployment, table 5 presents the effects of different reasons for entering unemployment on the mental health of both spouses.²⁰ Similar to [Kassenboehmer & Haisken-DeNew \(2009\)](#), I differentiate between unemployment due to plant closure, dismissal, and further reasons.²¹ I also examine the effect of all reasons for unemployment jointly.²²

Many studies that analyze health consequences of job loss and unemployment do not differentiate between the reasons for unemployment/job loss (e.g. [Browning et al. 2006](#); [Eliason & Storrie 2009](#); [Kuhn et al. 2009](#); [Sullivan & von Wachter 2009](#); [Deb et al. 2011](#); [Browning & Heinesen 2012](#)). Those studies that differentiate, provide mixed evidence on the differential effects. [Salm \(2009\)](#) does not find any decreases in health for neither job loss due to lay-off nor for job loss due to plant closure in the U.S.; he observes a decrease only for those who left the job for health reasons. [Schmitz \(2011\)](#) does not find any effects of unemployment due to plant closure on health for Germany. However, he provides evidence that unemployment due to other reasons decreases health satisfaction, increases the number of hospital visits and reduces mental health. [Marcus \(2012\)](#) shows that job loss increases smoking initiation, irrespective of whether job loss due to plant closure or due to dismissal is considered. A study on subjective well-being ([Kassenboehmer & Haisken-DeNew 2009](#)) demonstrates that, in Germany, the subjective well-being decrease is even larger from unemployment due to plant closures than from unemployment due to dismissal.

Comparing the effects of all unemployment (first column in table 5) with the effect of unemployment due to plant closure (second column) shows that unemployment due to plant closure seems to hurt more than unemployment in general. Potentially the all unemployment category includes also cases of “voluntary” unemployment, which might be less detrimental for both spouses’ mental health. Therefore, the next column looks at unemployment due to dismissal, which is often regarded as involuntary unemployment (e.g. [Kassenboehmer & Haisken-DeNew 2009](#); [Marcus 2012](#)). Two arguments support the idea that unemployment due to dismissals is more detrimental for mental health

²⁰All specifications in table 5 base upon the procedure of the main specification (specification 4 in table 3), with the only difference that the treatment group varies between the columns.

²¹Further reasons include own resignation, mutual agreement, end of temporary contract and leave of absence/sabbatical.

²²I would like to thank the anonymous referee for drawing my interest in investigating the effect of other reasons for unemployment.

Table 5: Changes in mental health after different entries into unemployment

Outcome	Reason for unemployment			
	all	plant closure	dismissal	further
All couples				
Own mental health	-1.42*** (0.38)	-2.68*** (0.72)	-1.83*** (0.53)	-0.65 (0.53)
Partner's mental health	-0.91*** (0.35)	-1.81*** (0.66)	-0.83 (0.51)	-0.59 (0.48)
<i>p-value of difference</i>	0.25	0.32	0.11	0.92
$N_{Treated}$	761	109	323	329
Husband's unemployment				
Own mental health	-1.66*** (0.46)	-3.13*** (0.88)	-1.61*** (0.61)	-1.20 * * (0.61)
Partner's mental health	-0.98 * * (0.46)	-2.01*** (0.77)	-0.54 (0.64)	-0.92 (0.63)
<i>p-value of difference</i>	0.26	0.27	0.18	0.72
$N_{Treated}$	456	70	205	181
Wife's unemployment				
Own mental health	-1.08* (0.60)	-1.86*** (0.63)	-2.22*** (0.79)	0.02 (0.75)
Partner's mental health	-0.81 (0.50)	-1.46* (0.77)	-1.33* (0.70)	-0.18 (0.58)
<i>p-value of difference</i>	0.68	0.63	0.29	0.80
$N_{Treated}$	305	39	118	148

Note: The table presents the effect of different reasons for entering unemployment on the mental health of both spouses. Each cell displays the ATT from a separate regression and its robust standard error in parentheses. Additionally, the table provides p -values for the t -tests whether unemployment differently influences directly and indirectly affected spouses. The upper panel considers all couples, while the two lower panels display results separately according to the sex of the directly affected spouse. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

than due to plant closures. First, many researchers argue that poor health might cause unemployment (e.g. [Kuhn et al. 2009](#); [Schmitz 2011](#)). In line with this argument, some dismissals might result from deteriorating health.²³ Second, dismissals rather than plant closures might be attributable to own behavior. Therefore, dismissals might hurt more. Contrary, there are also arguments that unemployment due to plant closures is more detrimental for mental health than due to dismissals. Plant closures might make it more difficult to find a new job as others in the region (with similar qualifications) also lost their jobs due to the plant closure. Additionally, individuals staying with the firm until it finally closes, might be a group with the worst labor market prospects outside that firm, low flexibility and/or a high identification with the firm. Furthermore, some dismissals might actually be voluntary quittings in order to get compensation ([Kassenboehmer & Haisken-DeNew 2009](#): 453-454).

Table 5 shows that for wife's entry into unemployment the decreases in mental health are similar for plant closure and dismissal. However, for husband's entry into unemployment, plant closures are more detrimental than dismissals for the mental health of both spouses. The effect on the indirectly affected spouse is even insignificant in this specification. This comparison suggests that the mental health consequences of unemployment are not overestimated when considering dismissals as well. Either endogeneity issues with respect to the effect of dismissals on mental health are rather weak in Germany or the effects of different endogeneity mechanisms cancel out. When looking at the effect of unemployment that results from other reasons than dismissal and plant closure in the last column, the effects of wife's unemployment on mental health do not only turn insignificant but become virtually zero. For husband's own unemployment the decrease in mental health is smaller than before but still significant, while the effect on his partner is only slightly smaller but turns insignificant. However, this category might also include some cases of chosen unemployment.

Table 5 highlights that for each specification, the coefficients for the indirectly affected spouse is similar to that for the directly affected spouse. The two coefficients are not significantly different in any of the specifications. This confirms the conclusion that unemployment decreases the mental health of spouses almost as much as for the directly affected individuals.

²³Even controlling for pre-treatment mental health may not rule out reverse causality, as mental health might decrease between the last pre-treatment interview and the dismissal. Researchers could not distinguish this decrease *before* the dismissal from a decrease *due* to the dismissal.

7. Conclusion

This paper analyzes spillover effects of unemployment on other household members by estimating the causal effect of unemployment on spouse's mental health. Using data from the German Socio-Economic Panel Study (SOEP) from 2002 through 2010, this paper finds that unemployment of one spouse similarly affects the mental health of both spouses. About one year after the plant closure, unemployment decreases mental health by 27 % of a standard deviation for the unemployed individuals themselves and by 18 % of a standard deviation for their spouses. In general, the decreases in mental health are larger when the husband enters unemployment. The findings are robust over various specifications.

In order to give the estimates a causal interpretation, this study focuses on an exogenous entry into unemployment (i.e. plant closure), and applies a combination of matching and difference-in-difference estimation that is robust against selection on observables and selection on unobservables with time-invariant effects. The matching part of the estimator constitutes one of the first applications of entropy balancing ([Hainmueller 2012](#)), which balances the conditioning variables more effectively than common propensity score methods. The estimation strategy assumes that no unobserved variables exist that simultaneously influence changes in mental health and the probability of entering unemployment due to plant closure. This paper provides an indirect test to show that this identifying assumption is not violated, as mental health does not follow a different trend for treated and matched controls before the plant closure.

The findings highlight that unemployment has severe consequences not just for the directly affected individuals, but also for their spouses. Hence, previous studies underestimate the public health costs of job loss as they do not consider the consequences for spouses. When comparing costs and benefits of labor market policies to prevent unemployment, policy-makers should take into account that employment has non-financial benefits not only for the employed individuals themselves but also for their spouses.

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A. Appendix

A.1. Entropy balancing

Entropy balancing reweights the control group observations in such a way that the control group satisfies pre-specified balancing requirements (here: same mean and variance of conditioning variables as in the treatment group). Among the possible sets of weights that fulfill these balancing requirements, entropy balancing chooses the set of weights that deviates as little as possible from uniform weights (Hainmueller 2012).²⁴ Entropy balancing spares the need to check for covariate balance since balance according to the pre-specified balancing requirements is fulfilled by construction. This makes the burdensome procedure of propensity score methods unnecessary, where “researchers ‘manually’ iterate between propensity score modeling, matching, and balance checking until they attain a satisfactory balancing solution” (Hainmueller 2012: 25). Entropy balancing is more effective as it improves the balance reached by common propensity score methods for all covariates. Furthermore, while propensity score methods often decrease balance on some covariates, entropy balancing improves balance for all conditioning variables. In contrast to propensity score methods, entropy balancing is fully non-parametric.

In the present analysis, I require the control group to have the same mean *and* the same variance as the treatment group for all conditioning variables after entropy balancing. In applications of propensity score methods usually only the balance of the first moments is checked. Entropy balancing is implemented using the program “ebalance” (Hainmueller 2011) in Stata 11.2.

Besides the unconfoundedness assumption (see eq. 2), a further requirement of matching estimators is the overlap condition ($P(D = 1|X) < 1$). It ensures that for any given X , there are not just treated observations but also control observations. It is not clear how to impose common support conditions for entropy balancing. Most studies relying on propensity score methods exclude treated observations whose propensity score exceeds the maximum of the propensity score in the control group in order to implement the common support for the ATT (Caliendo & Kopeinig 2008). However, this common support condition is not binding in the present analysis since members of the control group have the highest propensity score values. Hence, the overlap condition seems to be satisfied in the present case. Furthermore, entropy balancing requires that there are more observations in the control group than moment restrictions.

²⁴To compare deviations from uniform weights, entropy weighting uses the entropy divergence (Kullback 1959) as distance measure. Hence the name entropy balancing.

A.2. Overview of the SOEP version of the SF-12 questions

99. How would you describe your current health?

- Very good
 Good
 Satisfactory
 Poor
 Bad

100. When you ascend stairs, i.e. go up several floors on foot:
 Does your state of health affect you greatly, slightly or not at all?

- Greatly
 Slightly
 Not at all

101. And what about having to cope with other tiring everyday tasks,
 i.e. when one has to lift something heavy or when one requires agility:
 Does your state of health affect you greatly, slightly or not at all?

- Greatly
 Slightly
 Not at all

102. Please think about the last four weeks.
 How often did it occur within this period of time, ...

Always Often Some- Almost Never
 times

- | | | | | | | | | | |
|---|--------------------------|---|--------------------------|---|--------------------------|---|--------------------------|---|--------------------------|
| ● that you felt rushed or pressed for time? | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> |
| ● that you felt run-down and melancholy? | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> |
| ● that you felt relaxed and well-balanced? | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> |
| ● that you used up a lot of energy? | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> |
| ● that you had strong physical pains? | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> |
| ● that due to physical health problems | | | | | | | | | |
| – you achieved less than you wanted to at work
or in everyday tasks? | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> |
| – you were limited in some form at work or in
everyday tasks? | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> |
| ● that due to mental health or emotional problems | | | | | | | | | |
| – you achieved less than you wanted to at work
or in everyday tasks? | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> |
| – you carried out your work or everyday tasks
less thoroughly than usual? | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> |
| ● that due to physical or mental health problems you
were limited socially, i.e. in contact with friends,
acquaintances or relatives? | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> | — | <input type="checkbox"/> |

A.3. Descriptive statistics - means and standardized bias

Variable	Means treated	Means controls			Standard. Bias (%)		
		raw	EB	kernel	raw	EB	kernel
Directly affected spouse							
Age	48.1	44.0	48.1	48.2	45.4	0.0	-1.7
Female ⁺	35.8	43.6	35.8	35.8	-16.1	0.0	0.0
Migrant ⁺	23.9	15.3	23.9	22.4	21.7	0.0	3.4
Non-German ⁺	22.9	12.4	22.9	21.8	27.8	0.0	2.8
Physical health	49.8	52.2	49.8	50.0	-28.0	0.0	-2.1
Mental health	49.9	50.7	49.9	50.0	-9.6	0.0	-1.2
Often melancholic ⁺	51.4	46.2	51.4	50.4	10.4	0.0	2.0
Bad health ⁺	14.7	9.3	14.7	13.2	16.4	0.0	4.2
Medium health ⁺	34.9	32.5	34.9	35.5	5.0	0.0	-1.4
Good health ⁺	50.5	58.1	50.5	51.2	-15.4	0.0	-1.5
Labor earnings	24.9	35.2	24.9	25.2	-46.3	0.0	-2.3
Never unemployed ⁺	62.4	70.6	62.4	62.5	-17.4	0.0	-0.3
Tenure	11.0	12.4	11.0	10.9	-14.6	0.0	0.6
Small company ⁺	33.9	19.9	33.9	32.1	32.0	0.0	3.9
Medium-small company ⁺	45.9	30.5	45.9	47.4	31.9	0.0	-3.0
Medium company ⁺	11.9	24.0	11.9	12.3	-31.8	0.0	-1.2
Large company ⁺	8.3	23.5	8.3	8.2	-42.5	0.0	0.2
Big job worries ⁺	39.4	15.1	39.4	39.9	56.6	0.0	-0.9
Some job worries ⁺	38.5	45.9	38.5	38.8	-15.0	0.0	-0.5
No job worries ⁺	22.0	39.0	22.0	21.3	-37.4	0.0	1.8
Years full-time	21.2	18.0	21.2	21.3	29.3	0.0	-0.4
Primary sector ⁺	0.0	1.3	0.0	0.0	-16.4	0.0	0.0
Manufacturing ⁺	39.4	30.0	39.4	38.8	19.9	0.0	1.4
Energy and water ⁺	0.0	1.3	0.0	0.0	-16.0	0.0	0.0
Construction ⁺	13.8	5.5	13.8	14.0	28.0	0.0	-0.6
Wholesale and retail ⁺	23.9	11.8	23.9	24.7	31.9	0.0	-1.9
Hotel and restaurants ⁺	0.9	1.4	0.9	1.1	-4.4	0.0	-1.5
Transport ⁺	1.8	5.3	1.8	1.7	-18.5	0.0	0.9
Banking and insurance ⁺	2.8	5.1	2.8	2.4	-12.3	0.0	2.0
Health services ⁺	2.8	11.7	2.8	3.0	-35.1	0.0	-1.7
Other services ⁺	11.0	23.3	11.0	11.2	-33.0	0.0	-0.7
Basic school ⁺	45.0	29.1	45.0	45.4	33.2	0.0	-0.8
Intermediate school ⁺	45.0	44.9	45.0	42.9	0.1	0.0	4.1
Technical college ⁺	2.8	6.8	2.8	3.7	-19.1	0.0	-5.3
Highest secondary ⁺	7.3	19.2	7.3	8.1	-35.4	0.0	-2.7
University ⁺	8.3	23.3	8.3	9.6	-42.2	0.0	-4.8
Vocational training ⁺	78.9	76.8	78.9	77.9	4.9	0.0	2.5

Variable	Means treated	Means controls			Standard. Bias (%)		
		raw	EB	kernel	raw	EB	kernel
Indirectly affected spouse							
Age	47.2	44.0	47.2	47.7	31.4	0.0	-4.1
Migrant ⁺	26.6	15.4	26.6	24.4	27.7	0.0	5.1
Non-German ⁺	22.9	12.4	22.9	21.2	27.7	0.0	4.1
Physical health	48.9	51.4	48.9	49.0	-29.1	0.0	-1.0
Mental health	49.3	50.4	49.3	49.4	-11.7	0.0	-0.7
Often melancholic ⁺	57.8	47.9	57.8	55.8	19.8	0.0	4.0
Bad health ⁺	17.4	11.7	17.4	17.6	16.1	0.0	-0.4
Medium health ⁺	38.5	32.0	38.5	37.0	13.6	0.0	3.2
Good health ⁺	44.0	56.2	44.0	45.5	-24.5	0.0	-2.9
Labor earnings	21.0	24.6	21.0	20.7	-14.4	0.0	1.3
Never unemployed ⁺	56.9	65.1	56.9	57.9	-17.0	0.0	-2.1
Works full-time ⁺	49.5	52.2	49.5	48.0	-5.4	0.0	3.0
Works part-time ⁺	19.3	25.1	19.3	20.4	-14.1	0.0	-2.9
Not working ⁺	31.2	22.7	31.2	31.6	19.3	0.0	-0.8
Basic school ⁺	36.7	28.1	36.7	38.3	18.5	0.0	-3.2
Intermediate school ⁺	48.6	46.1	48.6	47.6	5.0	0.0	2.0
Technical college ⁺	6.4	6.4	6.4	5.4	0.1	0.0	4.2
Highest secondary ⁺	8.3	19.4	8.3	8.7	-32.7	0.0	-1.5
University ⁺	11.9	22.4	11.9	11.8	-28.0	0.0	0.5
Vocational training ⁺	74.3	75.4	74.3	73.5	-2.4	0.0	1.9
Couple information							
Children ⁺	37.6	49.8	37.6	36.9	-24.7	0.0	1.4
Regional unemployment	9.6	10.2	9.6	9.7	-13.7	0.0	-1.9
Village ⁺	11.0	9.1	11.0	10.8	6.5	0.0	0.6
Small town ⁺	37.6	35.8	37.6	39.1	3.7	0.0	-3.0
Small city ⁺	27.5	28.1	27.5	25.6	-1.3	0.0	4.3
Big city ⁺	23.9	27.0	23.9	24.5	-7.2	0.0	-1.5
Year 2002 ⁺	40.4	28.4	40.4	39.4	25.3	0.0	2.0
Year 2004 ⁺	23.9	25.6	23.9	24.4	-4.1	0.0	-1.2
Year 2006 ⁺	11.9	24.6	11.9	10.8	-33.1	0.0	3.6
Year 2008 ⁺	23.9	21.4	23.9	25.5	5.9	0.0	-3.7
N	109	14285					

Note: Summary statistics for treated couples, all control couples and matched control couples. The first two columns present the means of selected variables before treatment for treated and controls. Third and fourth column show the means for the reweighted control group according to entropy balancing (EB) and kernel matching, a propensity score method. The last three columns display a measure for the quality of the matching process. The standardized bias is defined for each conditioning variable s as $SB_s = 100 \cdot \frac{\bar{s}_1 - \bar{s}_0}{\sqrt{\frac{1}{2}(\sigma_{s1}^2 + \sigma_{s0}^2)}}$, where \bar{s}_1 and \bar{s}_0 are the means of treated and controls, respectively, and σ_{s1}^2 and σ_{s0}^2 the corresponding variances. ⁺ indicates that the mean represents a percentage share.