

A Service of

ZBW

Leibniz-Informationszentrum Wirtschaft Leibniz Information Centre for Economics

Fischer, Björn; Haan, Peter; Salazar Sanchez, Santiago

Article — Accepted Manuscript (Postprint) The effect of unemployment on care provision

The Journal of the Economics of Ageing

Provided in Cooperation with: German Institute for Economic Research (DIW Berlin)

Suggested Citation: Fischer, Björn; Haan, Peter; Salazar Sanchez, Santiago (2022) : The effect of unemployment on care provision, The Journal of the Economics of Ageing, ISSN 2212-8298, Elsevier, Amsterdam, Vol. 23, pp. 1-31, https://doi.org/10.1016/j.jeoa.2022.100395

This Version is available at: https://hdl.handle.net/10419/307399

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



ND https://creativecommons.org/licenses/by-nc-nd/4.0/



WWW.ECONSTOR.EU

The effect of unemployment on care provision^{*}

Björn Fischer¹, Peter Haan², and Santiago Salazar Sanchez³

¹DIW Berlin; bfischer@diw.de ¹DIW Berlin and FU Berlin; phaan@diw.de ¹FU Berlin; santias93@zedat.fu-berlin.de

June 24, 2022

Abstract

In this paper we estimate the effect of unemployment on informal care provision. For the identification we use plant closures as a source of exogenous variation and combine difference-indifferences with matching based on entropy balancing. The analysis is based on data from the German Socio-Economic Panel (SOEP). We find that there is a time conflict between employment and informal care provision. Unemployment increases the probability of providing care by 2.9 percentage points while the daily hours of care provision rise by around 0.05 hours per week-day. Both men and women react with significant increases in care provision. We find the largest effects for women with low education.

JEL Classification: I11, I18, I38, J14, J21, J22

Keywords: Long-term care; Informal care; long-term care insurance; labor supply; unemployment; plant closure; entropy balancing

^{*}We would like to thank for financial support from the FNA of the Rentenversicherung and from JPI More Years Better Lives through the project PENSINEQ .

^{© &}lt;2024>. This manuscript version is made available under the CC-BY-NC-ND 4.0 license http://creativecommons.org/licenses/by-nc-nd/4.0

1 Introduction

Population ageing creates excess demand for long-term elder care (LTC). Therefore, one of the most pressing challenges for social policy is to increase the supply of formal and informal care (Geerts et al., 2012; Gusmano and Okma, 2018; van Groenou and De Boer, 2016). The extension of informal care is of particular importance since both the care dependent and policy makers prefer care provided by family and friends in the elder person's home (Blaise, 2018; Hajek et al., 2018; Lipszyc et al., 2012; Mentzakis et al., 2009). The majority of care providers is younger than 60 years old and is still in the work force. This suggests that informal care providers face a time conflict between care provision and gainful employment which might be an important restriction to further increase informal care. It is therefore important to document and understand the time conflict between employment and informal care provision. However, this is challenging as the identification of the effect of employment on the decision to provide informal care requires exogenous variation in employment.¹

In this paper we follow e.g. Halla et al. (2020) or Marcus (2013) and use plant closures as a source of exogenous variation for employment. This allow us to estimate the effect of unemployment on informal care provision. In more detail, for the empirical analysis we combine difference-in-differences with entropy balancing, similar to Everding and Marcus (2020). In addition, we analyze the effect of unemployment using an event study design. The analyses are based on data from the German Socio-Economic Panel (SOEP) which contains information on employment, informal care provision and other socio-economic variables such as income, heath and education.

Our results provide evidence for a time conflict between employment and informal care provision. In the main specification we find that after entering unemployment the probability of providing care increases on average by 2.9 percentage points while the daily hours of care provision rise by around 0.047 hours per weekday. The results are robust to various robustness checks including placebo tests. We further show that while the effect is present for both men and women, it is larger in absolute terms for women but larger in relative terms for men. When focusing on heterogeneous effects we can show that effects are largest for women with low education.

This study is related to several strands of the literature. A large number of previous studies focuses on the link between employment and informal long-term care provision. Carr et al. (2018), Heitmueller (2007), Jacobs et al. (2017), Niimi (2017), and Van Houtven et al. (2013), among others, find negative short term effects of providing informal care on labor market outcomes.² Other papers analyze the implications of employment on care provision. For example, He and McHenry (2016) find that working 10% more hours per week reduces the provision of informal care among US American women by around

 $^{^1 \}mathrm{See}$ Bauer and Sousa-Poza (2015) and Lilly et al. (2007) for reviews.

 $^{^{2}}$ Schmitz and Westphal (2017), Skira (2015) and Korfhage (2019) can point to long term consequences of informal care provision.

2 percentage points; Bergeot and Fontaine (2020), Carrino et al. (2019), Fischer and Müller (2020), Golberstein (2008), Mentzakis et al. (2009), Michaud et al. (2010), Moscarola (2010), Nizalova (2012), and Stern (1995), come to similar results but study different margins of labor supply.

Our study is also linked to the analyses by Mommaerts and Truskinovsky (2020) and Costa-Font et al. (2015). They show that informal care provision is affected by the business cycle. Interestingly, Mommaerts and Truskinovsky (2020) discover that informal care provision among adult sons reacts counter-cyclically to the business cycle. This suggests that higher unemployment rates and lower opportunity costs matter in son's choice to provide informal care. In contrast, adult daughters do not seem to react to unemployment rates. Costa-Font et al. (2015) find an increase in the availability of informal care following the Great Recession in Europe, suggesting that rising unemployment rates could increase informal care provision. While these papers point to a relevant link between the business cycle and informal care provision, a variety of possible channels can explain these results. Our approach focuses specifically on the effects of unemployment on informal care provision and can therefore shed more light on this important margin. Our paper is to the best of our knowledge the first to study the impact of isolated unemployment events on individuals' informal caregiving.

The remainder of this study is structured as follows: Section 2 describes the institutional setting of the long term insurance and unemployment insurance in Germany. Section 3 explains the identification strategy. Section 4 describes the data and variables used in the estimation. In Section 5 we present the results along with their interpretation and relates the findings to the effects of other studies. Lastly, section 6 concludes.

2 Institutional Background

Before we turn to the empirical analysis we provide a short overview about the relevant institutional setting in Germany: The LTC insurance system and benefit structure for LTC provision has an effect on the opportunity costs of providing informal care. This potentially reduces the conflict between LTC and employment and could lead to a smaller effect of unemployment on care provision. On the other hand, the unemployment insurance system in Germany provides financial support during unemployment which increases the potential to engage in informal care provision.

2.1 Long-term care insurance and care provision in Germany

Since 1995 the German social security scheme includes a long-term care insurance (LTCI). It provides benefits to those permanently (at least six months) impaired with at least two activities of daily living (ADL) and one instrumental activity of daily living (IADL). Depending of the care needs recipients are classified into care categories ranging from substantial need of care (Care Level 1) to most severe need of care (Care Level 5)³. Table 1 provides details about the five care levels with information about requirements, benefits and the share of recipients of the LTCI in the respective level.⁴

Care	Requirements	Benefits (monthly)	Share
level			
1	low impairment of in-	No entitlement for	9.44%
	dependence	cash benefits or in-	
		kind transfers for	
		home care; 125 Euro	
		earmarked benefits	
2	significant impairment	316 Euro cash benefits,	42.39%
	of independence	689 Euro in-kind; 125	
		Euro earmarked bene-	
		fits	
3	severe impairment of	545 Euro cash benefits,	27.93%
	independence	1289 Euro in-kind; 125	
		Euro earmarked bene-	
		fits	
4	highest impairment of	728 Euro cash benefits,	14.05%
	independence	1612 Euro in-kind; 125	
		Euro earmarked bene-	
		fits	
5	special cases (hard-	901 Euro cash benefits,	6.17%
	ship) , people with	1995 Euro in-kind; 125	
	exceptionally high	Euro earmarked bene-	
	maintenance effort ^{a}	fits	

Table 1: Care levels in Germany

^aIndividuals who have no cognitive impairments but are physically highly impaired; for them it is hard to reach the highest score on the list; therefore, the special case is constructed

Care recipients may choose between being cared at a nursing house or at home. If the recipient decides to be cared at home LTCI provides three options: receiving direct caring services (Pflegedienstein-kind transfer), pecuniary benefits for informal care, or a mixture of the two. The cash benefits are neither ear-marked nor means-tested but it is intended that the recipient uses the money for reimbursing a family member or a friend who provides informal care (Geyer and Korfhage, 2015). In addition, individuals providing 10 hours of care per week on at least two days for a care dependent with at least care level 2 can receive pension points. However, the cash compensation from the LTCI and the pension claims the informal caregiver can receive are far lower than potential labor earnings, specifically for individuals with high wage potentials (Geyer and Korfhage, 2015).

In 2019 the LTCI counted 4.1 million recipients of benefits from the care insurance, 3.3 million

 $^{^{3}}$ Formerly, there were only three care dependency levels, these were extended to five care dependency levels in 2017. The information in Table 1 refers to the definition of care levels from 2017 onward.

⁴Although the statutory LTCI in Germany is relatively broad and was designed to cover virtually the whole population. Geyer and Schulz (2014) point out that only about 32% of the people in need of long-term care fulfill the criteria for becoming benefit recipients. In these cases, no benefits are granted and family members providing informal care do not receive any compensation.

were cared for at home and 0.8 million in institutionalized care facilities. Around 51% (2.1 million) of all recipients were cared for exclusively informally in their own home, 23% (0.9 million) received care including some form of formal care.⁵ Thus, in Germany the largest share for frail elderly receives informal care.

According to the data of the Socio Economic Panel study $(SOEP)^6$ around 4.3 million people provided informal care to frail elderly in 2018, two third of which are women. While we find that among the group of 50-69 year old women around 11% provide some informal care, it is around 7% among the men in this age group. In the group of 40-49 year old women we find around 7% of women provide some informal care. The spike in the age group of 50-60 year old is connected to highest care demand from parents who reach ages of high care demand. Further, the SOEP data show that around 44% of care givers are already retired, while 17% are non employed, 18% are full-time employed and 13% are part-time employed.⁷

2.2 Unemployment benefits in Germany

Depending on their working history unemployed individuals either receive unemployment benefits (ALG I) or means-tested transfers (ALG II)⁸. Specifically, an individual who becomes unemployed receives unemployment insurance for an entitlement period which depends on previous employment and age. Unemployment insurance is equal to 60% of the individual's after-tax labor earnings in the year before she entered unemployment. For individuals with children the insurance amounts to 67%. Unemployed not eligible for ALG I receive ALG II which guarantees every individual a permanent minimum annual income.

3 Methodology

The aim of this paper is to empirically analyze how a transition into unemployment changes the provision of informal care. The identification of this relation is challenging since employment and care provision are jointly determined. Importantly, several studies (see e.g. Meng, 2012, Heitmueller, 2007, and Nguyen and Connelly, 2014) document an effect from informal care provision on labor supply.

To overcome this identification problem, we follow e.g. Halla et al. (2020) or Everding and Marcus (2020) and use plant closures as an exogenous source of unemployment in a difference in difference (DiD)

 $^{{}^{5}}$ See Bundesamt (2020) for information about care dependent individuals in Germany.

 $^{^6 \}mathrm{See}$ Section 4 for more information.

 $^{^7\}mathrm{Own}$ calculations based on SOEP data, see also Fischer and Geyer (2020).

⁸For a more detailed discussion, see e.g. Haan and Prowse (2015). The minimum amount of ALG II Germany in 2018 was 416 per month for a single person. Rent and heating payments are covered by another entity and vary with state and/or city of residence.

setting. In this context unemployment is not chosen by the individual but exogenously determined. To account for confounding factors which might vary over time we compare the changes in informal care provision before and after the plant closure to informal care provision of a control group. In more detail, we define a treatment group that is composed of individuals in the sample who became unemployed because their place of work closed (plant closure). In theory, the control group consists of all the individuals in the sample that work either full or part-time in the private sector. These are individuals who could potentially suffer from a plant closure. However, as discussed in Marcus (2013) and as documented in Table 2 the treatment group and a control group with this broad definition significantly differs in various dimensions. Therefore, we use entropy balancing to define a control group which is more suitable for the analysis. Specifically, we select individuals from the broad control group which are comparable to individuals in the treatment group before the plant closure took place.

Entropy balancing procedure

We apply entropy balancing as proposed by Hainmueller (2012). The entropy balancing algorithm focuses directly on making the covariate distribution of the control group as close as possible to the covariate distribution in the treatment group. The entropy balancing scheme calculates scalar weights in the control group such that the distribution of the first and second moment of the covariates matches those in the treatment group.⁹ In the main analysis we perform the balancing group specific. This means that we calculate balancing weights for the full sample, and for the heterogeneity analysis gender specific weights for men and women.

The entropy balancing scheme is designed to keep the estimated control weights (weights for the control units) as close as possible to the set of uniform weights. Uniform weights are the set weights where all the control units have the same relevance in the estimation, i.e. $q_i = 1/n_0$ where n_0 is the number of control units in the sample. Among the balancing covariates there are employment related variables such as: tenure, job worries, industry, labor income, company size, overall work-experience and number of years in unemployment.¹⁰ We match on pre-treatment values for the treated individuals and 1-year lagged values for control observations. Entropy balancing procedure calculates balancing weights that are non-negative and deviate least from uniform weights. In a robustness check we present results obtained applying propensity score weighting.

⁹For further details about the implementation see Hainmueller (2012). We perform entropy balancing using Stata's user-written program "ebalance" (Hainmueller and Xu, 2013) and applying the default tolerance level of 0.015.

¹⁰See Table 2 for a full list of balancing variables.

Difference-in-differences balancing estimator

In the DiD setting we estimate the effect of a transition into unemployment due to a plant closure on informal care provision for treated individuals and compare this to changes in care provision of the matched control group. First, consider a DiD-style equation in which we allow for a differential effect of the predetermined control variables before and after treatment:¹¹

$$Y = \beta + \nu POST + \gamma D + \delta (POST * D) + \eta X' + \kappa (POST * X') + \phi Year + \tau (POST * Year)$$
(1)

where Y is a measure of informal care provision. POST is an indicator that takes the value 1 in periods after plant closure and 0 otherwise, D is the indicator for the group of individuals that experience plant closure at some time, X' includes observable predetermined characteristics¹² and Year stands for year fixed effects¹³. The parameter of interest is δ . Due to the nature of the treatment (plant-closure induced unemployment) we do not observe individuals in the control group in the POST-state. Therefore, we follow Everding and Marcus (2020) and perform a first-difference transformation of Equation 1.¹⁴ The parameter of interest, δ , is identical to that of the resulting estimation Equation 4 in which we regress changes in caring behavior (ΔY) on the treatment indicator (D), controlling for X', the selected predetermined control variables and year-fixed effects (Year):

$$\Delta Y = \nu + \delta D + \kappa X' + \tau Y ear + u \tag{4}$$

Equation 4 is estimated by weighted least squares using the weights from the entropy balancing step. For the treated observations changes in the outcome variable, $\Delta Y^{Treatment}$, are the difference between the outcome variable in the year before the plant closure and the period(s) after: $\Delta Y^{Treatment} = Y_{POST}^{Treatment} - Y_{PRE}^{Treatment}$. For the control group we calculate the difference between

$$Y^{POST} = \beta + \nu + (\gamma + \delta)D + (\eta + \kappa)X' + (\phi + \tau)Year$$
⁽²⁾

and setting POST = 0 in Equation 1 which leads to:

$$Y^{\widehat{PRE}} = \beta + \gamma D + \eta X' + \phi Y ear \tag{3}$$

Subtracting the two equations yields Equation 4, with $\Delta Y = Y^{POST} - Y^{PRE}$. As X' and Year are predetermined they are identical in $\widehat{Y^{POST}}$ and $\widehat{Y^{PRE}}$ and cancel out.

¹¹We use predetermined control variables to avoid the problem of "bad" control variables which might be affected by the plant closure.

 $^{^{12}}$ We use the set of predetermined covariates also used in the entropy balancing step. For treated observations we use pre-treatment values, for control observations values from t - 1.

¹³Year fixed effects are also predetermined.

 $^{^{14}\}mathrm{First},$ we set POST=1 in equation 1 which leads to:

the year of observation, t, and the previous period, t - 1: $\Delta Y^{control} = Y_t^{control} - Y_{t-1}^{control}$. In the estimation sample we use all observations that give valid information on all outcome and control variables over at least 3 periods in the control group. Individuals who experience a plant-closure at some point are part of the control group up to 4 periods before plant-closure occurs if they respond in at least 3 consecutive waves and give valid information on all outcome variables and covariates. The treatment group consists of all treated observations. In the main analysis we focus on the exposure to the treatment over two periods, the period of the job loss and the next survey wave. Meaning that if the plant closure occurred in period t, the treatment indicator is equal to one in t and t + 1. First-difference outcomes for t + 1 are also constructed as differences between t + 1 and the period before treatment (t-1). In an additional analysis we also show effects if we only consider the treatment in period t and if we consider treatment also in t + 2. For treated individuals observations after the second period of treatment are not considered.

4 Data

For our analysis we use longitudinal survey data from the German Socio-Economic Panel (SOEP).¹⁵ Information on informal care provision has been collected yearly in the SOEP since 2001. Hence, we restrict the analysis to observations between 2001 and 2018. We further restrict the sample to individuals working in the private sector, aged 18 to 60 and who are observed for at least three periods. The SOEP includes as well detailed information about job loss. Based on this information we construct the treatment indicator which takes the value one if the person loses her job due to plant closure and is registered as unemployed.

Dependent variables

The SOEP contains information on daily hours spent on informal care for people in need on a normal weekday (excluding children).¹⁶ From the variable measuring daily hours spent on informal care, we construct two separate variables to measure the extensive and intensive margin. First, to capture the extensive margin we define a binary indicator equal to one if the person provides one or more hours of care per weekday. Second, for the intensive margin we focus on the number of daily hours spend on

¹⁵For more information about the SOEP, see Goebel et al. (2019).

¹⁶The exact question in the survey is: What is a typical weekday like for you? How many hours per normal workday do you spend on the following activities? Care and support of persons in need of care The answer is only related to hours spend on informal care for non-children (e.g. elderly and/or disabled individuals). There are two further distinct questions about hours of care provided on Saturdays and Sundays. These questions are only asked every two years. Therefore this information cannot be used in this analysis because it relies on differences in the outcome from one period to the next.

informal care.

4.1 Control variables

The SOEP contains a large set of information with variables such as health status, relationship indicators, age, perceived job security etc.¹⁷ which we use for entropy balancing and as covariates in the DiD estimation. In Table 2 we compare the control variables for the general control group (Column 1), the treatment group (Column 2) and the matched (weighted) control group (Column 3). All variables reported in Table 2 are used in the balancing step and as control variables in the DiD estimation as predetermined variables. above, treated individuals (Column 2) are less educated and have a lower income, on average, than individuals in the general control group (Column 1). Also, individuals in the treatment group are more often blue collars workers than in the control group: 24% vs. 44% respectively; this amounts to a difference of 18 percentage points. The most important difference between the two groups is the perceived job stability. Around 47% of individuals in the treatment group reported to be very concerned about their job security, this share is 11% in the control group. Comparing individuals in the treatment and the matched control we find no significant differences in the observable characteristics. After applying entropy balancing weights, the control group values are markedly closer to the treatment group values (Column 4).

A set variables that is used in the balancing step and as control variables in the regressions serves to control for differences in demand for informal care: cohabitation with a partner, the age of the individual, or variables about the family structure. Failing to control for these other causes of care provision would bias the effect of unemployment on informal caring. Everding and Marcus (2020), Halla et al. (2020), and Marcus (2013) report negative health effects of sudden unemployment on spouse's health. We control for partner health in order to rule out that a health shock endogenously induced by treatment leads to a care-demand shock and drives results. For the heterogeneity analysis we construct a binary indicator that is one if a person is low educated. This is constructed using SOEP's variable on the CASMIN-Classification.¹⁸ We define low education as category 1 in the CASMIN ranking (lower vocational education). Alternatively we provide results when choosing the ISCED97 classification, for which low education is defined as middle vocational education and lower.

Before we turn to the estimation results we provide first descriptive evidence of the effect of unemployment on informal care provision. Table 3 shows the mean of the outcome variables by gender for the broad control group, the matched control group and the treatment group before and after the treatment (plant closure). For women (last row) we find that 6.23% provide some care in the matched control group. In the treatment group the share is lower: 3.92% before the plant closure and 6.76%

 $^{^{17}\}mathrm{The}$ exact definition of the control variables is included in the Appendix Table A1.

¹⁸See Brauns et al. (2003).

Table 2:	Descri	ptive	statistics	-	covariates
TODIO 2.	DODOII	PULIC	0000100100		0010110000

$Variables^{a}$	Control group	Treatment group	Weighted control	Raw difference ^{b}
Age^{c}	44.89 (8.97)	45.79(9.45)	45.72(9.44)	0.07
Female	0.43% (0.49)	0.40% (0.49)	0.40% (0.49)	0.00
Migrant	0.16% (0.37)	0.26% (0.44)	0.26% (0.44)	0.00
Siblings	0.11% (0.31)	0.07% (0.26)	0.07% (0.26)	0.00
Alone	0.30% (0.46)	0.30% (0.46)	0.30% (0.46)	0.00
Labor income ^{d}	39644.75(31294.94)	26825.69(18225.23)	26198.94(16756.37)	626.75
$Tenure^d$	13.40(9.90)	11.44% (10.79)	10.87 (9.82)	0.29
Work experience	19.79(9.71)	21.39 (10.79)	21.36(10.78)	0.03
Unemployment experience	0.40(1.23)	0.90(2.00)	0.90(2.00)	0.00
Children	0.46% (0.50)	0.40% (0.49)	0.40% (0.49)	0.00
Blue collar	0.24% (0.42)	0.44% (0.50)	0.44% (0.50)	0.00
Concerned with job loss				
Very Concerned	0.11% (0.31)	0.47% (0.50)	0.47% (0.50)	-0.00
Somewhat Concerned	0.37% (0.48)	0.36%(0.48)	0.36% (0.48)	0.00
Not Concerned at all	0.52% (0.50)	0.17%(0.38)	0.17%(0.38)	0.00
Firm size				
Small	0.21% (0.41)	0.37% (0.48)	0.37% (0.48)	0.00
Small-Medium	0.26% (0.44)	0.33%(0.47)	0.33%(0.47)	0.00
Medium	0.22% (0.42)	0.16% (0.37)	0.16%(0.37)	0.00
Large	0.27% (0.44)	0.13%(0.34)	0.13%(0.34)	0.00
Occupation sector				
Primary Sector	0.02% (0.13)	0.02% (0.13)	0.02% (0.13)	-0.00
Manufacturing	0.25%(0.43)	0.31%(0.46)	0.31%(0.46)	0.00
Energy & Water	0.01%(0.11)	0.01% (0.09)	0.01%(0.09)	0.00
Construction	0.06% (0.23)	0.17%(0.37)	0.17%(0.37)	0.00
Wholesale & Retail	0.10% (0.31)	0.26% (0.44)	0.26% (0.44)	0.00
Hotel & restaurants	0.02% (0.13)	0.03%(0.18)	0.03%(0.18)	0.00
Transport	0.06% (0.23)	0.03%(0.18)	0.03%(0.18)	0.00
Banking & Insurance	0.05%(0.21)	0.03%(0.16)	0.03%(0.16)	0.00
Other services	0.31%(0.46)	0.11%(0.32)	0.11%(0.32)	0.00
Health services	0.13% (0.33)	0.02%(0.14)	0.02% (0.14)	0.00
Educational attainment				
Elementary	0.25% (0.43)	0.52% (0.50)	0.52% (0.50)	0.00
Secondary	0.45% (0.50)	0.38%(0.49)	0.38%(0.49)	0.00
Tertiary	0.30% (0.46)	0.10% (0.31)	0.10%(0.31)	0.00
Satisfaction with own health				
Very poor	0.01% (0.09)	0.03% (0.16)	0.03% (0.16)	0.00
Poor	0.05% (0.23)	0.11%(0.31)	0.11%(0.31)	0.00
Satisfying	0.26% (0.44)	0.26% (0.44)	0.26%(0.44)	0.00
Good	0.48% (0.50)	0.42% (0.49)	0.42% (0.49)	0.00
Very good	0.20% (0.40)	0.19% (0.39)	0.19% (0.39)	0.00
Hospital stay	0.08% (0.27)	0.13% (0.34)	0.13% (0.34)	0.00
Observations	101,462	374	101,462	

Source: SOEP v35; Notes:

a. We suppress the time and state dummies. For the complete table see the appendix.

b. The raw difference is the difference between treatment and weighted control values.c. For continuous variables standard deviation is displayed in parenthesis.

d. Values are presented in levels. In the regression these variables are included in their logarithmic transformation.

	Control	Weighted control	Pre-Treated	Post-Treated
Full sample				
Hours of care per day	0.08(0.54)	0.08(0.51)	0.03(0.25)	0.07 (0.36)
Care provider	4.34% (0.20)	4.41%(0.21)	2.29% (0.15)	4.81%(0.21)
Observations	101,462	101,462	261	374
Males				
Hours of care per day	$0.05 \ (0.39)$	$0.05 \ (0.37)$	$0.01 \ (0.11)$	$0.05 \ (0.31)$
Care provider	2.95% (0.17)	3.27% (0.18)	1.25% (0.11)	3.5% (0.19)
Observations	58,262	58,262	159	226
Females				
Hours of care per day	0.12(0.68)	0.12(0.68)	0.07(0.38)	0.10(0.42)
Care provider	6.22%(0.24)	6.23%(0.24)	3.92% (0.19)	6.76% (0.25)
Observations	43,200	43,200	102	148

Table 3: Descriptive statistics - outcome variables

Notes: For calculation of Post-Treated means we incorporate outcomes in periods t (first period of treatment) and t + 1 as in the baseline specification. The outcome variables are included in the regression in their DID transformation see Section 3 for further detail.

after treatment.¹⁹ For the number of provided hours we find a similar picture: the hours increase by 0.04 after the plant closure in the treatment group, but the overall level is slightly higher in the control group. For men the structure is similar but at a different level: 3.27% of men in the matched control group provide some care whereas for the treated men the share is lower before plant closure (1.25%) and increases to 3.5% after the treatment.

5 Results

In this section we present the estimation results. First, we discuss the findings of the main specification and heterogeneous effects by gender, education and age. Then, we turn to several robustness checks.

5.1 Main results

Table 4 presents the overall effects of the analysis. In the first two columns we show the results of the DiD estimates without entropy balancing weights and without (Column 1) and with covariates (Column 2). Column 3 includes the DiD results with entropy balancing weights but without covariates. Finally, in Column 4 we account for covariates - this is our preferred specification. We present effects on the probability to provide care and the hours of care provided in a normal weekday. In parentheses robust standard errors, clustered at the personal level, are reported.²⁰

 $^{^{19}}$ We do not match on the pre-treatment outcome variable.

²⁰We follow Everding and Marcus (2020) in clustering standard errors. Table A3 in the Appendix shows that significance and size of standard errors hardly change when calculating robust standard errors. Abadie and Spiess (2021) discuss calculation of standard errors taking into account entropy balancing. They advise to cluster on the level at which

Effects are positive for both outcome variables across all specifications. The simple DiD (Column 1) shows the smallest effects (2pp and 0.026 hours per week-day). After including control variables (Column 2), we find significant results of higher magnitude. When using the weighting scheme from the entropy balancing step (Column 3), size and significance of results are merely altered, the same is true when including control variables in addition to the weighing scheme (Column 4). The results show a clear picture: the change from employment to unemployed significantly increases the probability of becoming a caregiver. According to the preferred specification the probability increase by 2.9 percentage points (pp); which is a substantial relative increase of about 120% compared to a pre-treatment probability of providing care of 2.29%. The result for the number of daily hours of care-giving is similar. Care giving significantly increases by about 138% (an increase of 0.047 hours compared to a pre-treatment mean of 0.03).

Literature studying unemployment effects on caregiving is rare. He and McHenry (2016) find that 10% more working hours reduce informal caregiving probabilities by 2pp. Scaling up this result, unemployment is connected with a 20 pp increase in informal caregiving. Retirement- a 100% reduction in working hours - is connected to even bigger effect sizes (Bergeot and Fontaine, 2020; Carrino et al., 2019; Fischer and Müller, 2020). These results are difficult to compare to point estimates from this study as labor supply events are rather different in nature, groups of interest have different demand for care²¹ and research designs report different margins²².

To put the magnitude of our results in perspective, we investigate how other time activities are affected by plant-closure induced unemployment. Table A2 in the Appendix shows that a plant closure leads to a reduction in time spent on the job on average by 8.7 hours per weekday (Columns 1 and 2), and an increase in time spent in education (0.6 hours), running errands (1.7 hours), child care (1.0 hours) and on hobbies (1.0 hours). Changes in time spent in informal care are, therefore, relatively small. However, one has to take into account that relatively few individuals provide informal care or have to take this decision.

5.2 Heterogeneous effect by gender, education and marital status

The literature has documented that women provide most of the informal care (see as well Table 3). This might be related to their lower labor market attachment. Therefore, unemployment might increase informal care provision less for women than for men, who might have higher opportunity costs and time conflicts in employment. Mommaerts and Truskinovsky (2020) find that opportunity costs matter in men's decision to provide informal care, and gender specific unemployment rates on a state

balancing took place. When implementing this procedure we find even smaller standard errors. Thus we use clustered error at the personal level to obtain a conservative benchmark.

²¹Individuals who retire are in age groups in which demand for informal care is much larger.

 $^{^{22}}$ Fischer and Müller (2020) use an IV strategy, so that effects sizes are connected to LATE effects.

Outcome	(1)	(2)	(3)	(4)
Care provider	0.020	0.030^{***}	0.029^{**}	0.029^{***}
	(0.013)	(0.011)	(0.011)	(0.010)
Pre-Treatment mean	0.028	0.023	0.023	0.023
Hours of care	0.026	0.050^{**}	0.047^{**}	0.047^{***}
	(0.023)	(0.020)	(0.020)	(0.018)
Pre-Treatment mean	0.045	0.034	0.034	0.034
Controls	-		-	\checkmark
Weighting	-	-	\checkmark	
Observations	$129,\!637$	101,836	101,836	101,836

Table 4: Effect of unemployment on informal care provision

Notes: This table displays the effect of plant closure induced unemployment on the probability of being a care-provider (rows 1 and 2) and the hour of informal care provided on a normal week-day (rows 3 and 4). Controls: The set of control variables is reported in Table 2. Weighting: Estimated applying weights estimated from entropy balancing. The estimation rests on 374 treated observations. Cluster robust standard errors in parentheses (clustered at the personal level); *** p<0.01, ** p<0.05, * p<0.1

level cannot explain informal care provided by women. However, gender roles and culture might lead to women carrying the heavier burden of informal care provision. Then, we might still find higher effects for women than for men. To test for gender differences, we separately estimate the effects of unemployment on care provision for each gender. Specifically, we estimate gender-specific weights by running the entropy balancing algorithm for men and women separately to construct gender specific control groups (Table 5).

Table 5: Effect of unemployment on informal care by gender

	(1)	(2)	(3)	(4)
	Ma	ales	Fen	nales
Care provider	0.026*	0.026**	0.032*	0.032**
	(0.015)	(0.013)	(0.017)	(0.013)
Pre- Treatment Mean	0.013	0.013	0.039	0.039
Hours of care	0.045**	0.045**	0.053	0.052*
	(0.022)	(0.019)	(0.036)	(0.029)
Pre- Treatment Mean	0.013	0.013	0.068	0.068
Controls	-		-	
Weighting				, V
Observations	58,488	$58,\!488$	43,348	43,348

Notes: This table displays the effect of plant closure induced unemployment on the probability of being a care-provider (upper panel) and the hour of informal care provided on a normal week-day (lower panel) by gender. Controls: The set of control variables is reported in Table 2. Weighting: Estimated applying weights estimated from entropy balancing. Cluster robust standard errors in parentheses (clustered at the personal level); *** p<0.01, ** p<0.05, * p<0.1

The change in the probability of becoming a caregiver when entering unemployment is slightly lower for men than for women. While men increase the probability to be an informal care giver by 2.6pp, women show an increase of 3.2pp. The difference in the point estimates is not significantly different from zero, though. At the same time women increase the daily hours of care-giving by 74%. The effect for men is 450%. Thus men increase care-giving less in absolute terms, but given the low pre-treatment levels they increase care-giving more in relative terms.²³

	(1)	(2)	(3)	(4)	(5)	(6)
Group	roup Full samp		Μ	en	Women	
			Care p	rovision		
Low education	-0.007**	-0.017	0.000	-0.035*	-0.019***	0.015
Treatment	(0.003) 0.012	(0.018) 0.007	(0.005) 0.018	(0.019) -0.002	(0.007) 0.001	(0.032) 0.039
Treatment & low education	(0.036) 0.031^{***}	(0.036) 0.030^{***}	(0.048) 0.029^{**}	(0.041) 0.023^{**}	(0.051) 0.035^{**}	(0.059) 0.033^{**}
	(0.010)	(0.009)	(0.013) Hours	of care	(0.017)	(0.013)
			liouis	or care		
Low education	-0.012^{*}	-0.003	-0.001	-0.036^{*}	-0.036^{*}	0.029
Treatment	-0.020	(0.023) -0.002 (0.041)	(0.000) 0.019	(0.021) 0.009 (0.044)	-0.095	-0.019
Treatment & low education	(0.048) 0.063^{***} (0.021)	(0.041) 0.060^{***} (0.019)	(0.048) 0.054^{**} (0.025)	(0.044) 0.045^{**} (0.020)	(0.103) 0.079^{**} (0.036)	(0.092) 0.075^{***} (0.029)
	(0.021)	(0.019)	(0.025)	(0.020)	(0.050)	(0.029)
Controls	- ,		- ,		- ,	
Weighting	101.020	101.020		√ ►0.400	$\sqrt{12}$	12 240
Observations	101.836	101.836	28.488	28.488	45.548	45.548

Table 6: Effect of unemployment on informal care by education

Notes: This table displays the effect of plant closure induced unemployment on the probability of being a care-provider (upper panel) and the hour of informal care provided on a normal week-day (lower panel) for the full sample and by gender. Low education is defined as having lower vocational training and less. Controls: The set of control variables is reported in Table 2. Weighting: Estimated applying weights estimated from entropy balancing. Cluster robust standard errors in parentheses (clustered at the personal level); *** p < 0.01, ** p < 0.05, * p < 0.1

Further, we test if results vary by education by including an interaction term between low education and treatment.²⁴ Table 6 shows effects for both outcome variables, the probability of care provision and hours of daily care provision for the full sample (Columns 1 and 2), for men (Columns 3 and 4) and women (Columns 5 and 6). We find significant differences in the treatment effect by education for all groups. The increase of informal care seems to be driven by the lower educated. We find significant

²³Appendix Table A5 shows that results are similar when using the full sample with interactions by gender.

 $^{^{24}}$ As the number of treated individuals is limited in the sample, we can not stratify the sample into any given number of subgroups to perform the balancing step separately. We perform further heterogeneity tests using this interaction procedure for this reason.

effects only for the interaction of treatment and the low education indicator in the full sample. This is true for the effects on the probability of care provision as well as hours of care on a weekday. Lower educated individuals increase their probability to be a care-giver by 3.0pp when they become involuntarily unemployed. The same is true if we split the sample by gender. Lower educated men seem to react to involuntary unemployment in their care-giving significantly while higher educated men do not. The pattern is the same for women.²⁵ One reason for this pattern might be related to the treatment and the population (see as well Section 6). The large majority of individuals which face a plant closure have lower educated individuals tend to have lower labor income and only little non-labor income. Thus, for this group it is more difficult to reduce employment for informal care. This group might therefore face a harsher time conflict between labor and informal care provision.

Finally, we focus on heterogeneity by age and test for different effects for individuals younger and older than 50 years. In general, older individuals face a higher demand for informal care as parents and partners of these individuals reach ages of high incidence of care demand. Wetzstein et al. (2015) and others report that highest demand to care for a parent or another relative arises from the age 50 onward. This is supported by our findings. Table 7 reports that effect sizes in the full sample are significantly higher for individuals older than 50 years of age. This is driven by men, who show significantly higher effects in this age group. For women we do not find significant differences.

5.3 Robustness tests

In the following we provide several robustness analyses with supporting evidence for our empirical specification. First, in Table 8 we present the results of several placebo analyses. We use the same specification as above, but lag the treatment of the plant closure artificially by 1, 2 and 3 years. All effects are insignificant and the point estimates are smaller and negative in sign for the hours of care. In the next step we show that results do not depend on the balancing procedure. Instead of using entropy balancing, we calculate propensity score weights in the first step to construct the control group (Table 9).²⁶ We find a significant and positive effect of unemployment care provision. Point estimates are slightly larger than when using entropy balancing weights.

We show how results vary when we change the period length. As mentioned above, in the main

²⁵Appendix Table A4 shows results if we use the ISCED classification for the definition of low education. Effect sizes and significance levels are practically the same.

²⁶Control group weights are constructed as $PS(C_c)/(1-PS(C_c))$, where $PS(C_c)$ is the propensity score. For more information see Caliendo and Kopeinig (2008). Appendix Table A9 shows summary statistics of covariates using propensity score matching. Propensity score weighting also leads to a reduction in difference between the (plain) control group and the treatment group. However, the raw differences between the means in the weighted control group and the treatment group are larger in comparison to entropy balancing.

	(1)	(2)	(3)	(4)	(5)	(6)
Group	Full s	sample	М	en	Women	
			Care p	rovision		
Older than 50	0.004	0.023	0.005	0.043^{*}	0.007	-0.012
	(0.003)	(0.017)	(0.004)	(0.022)	(0.006)	(0.017)
Treatment	0.023^{*}	0.026^{**}	0.001	0.002	0.056^{**}	0.062^{***}
	(0.012)	(0.012)	(0.011)	(0.011)	(0.024)	(0.023)
Treatment & Older than 50	0.040^{*}	0.054^{*}	0.061^{**}	0.094^{**}	0.008	-0.017
	(0.021)	(0.030)	(0.030)	(0.042)	(0.022)	(0.027)
			Hours	of care		
Older than 50	0.010	0.053**	0.003	0.042*	0.021	0.053
	(0.007)	(0.027)	(0.007)	(0.024)	(0.018)	(0.043)
Treatment	0.035	0.035^{*}	0.010	0.012	0.075	0.079^{**}
	(0.021)	(0.021)	(0.018)	(0.017)	(0.047)	(0.040)
Treatment & Older than 50	0.071^{**}	0.111^{***}	0.092^{**}	0.126^{**}	0.043	0.068
	(0.035)	(0.043)	(0.044)	(0.051)	(0.057)	(0.063)
		,		,		,
Controls	- ,		- ,		- ,	\checkmark
Weighting						
Observations	101,836	101,836	58,488	58,488	43,348	43,348

Table 7: Effect of unemployment on informal care by age group

This table displays the effect of plant closure induced unemployment on the probability of being a careprovider (upper panel) and the hour of informal care provided on a normal week-day (lower panel) for the full sample and by gender for the group aged 50 and older. Controls: The set of control variables is reported in Table 2. Weighting: Estimated applying weights estimated from entropy balancing. Cluster robust standard errors in parentheses (clustered at the personal level); *** p<0.01, ** p<0.05, * p<0.1

Τ	abl	e	8:	ŀ)	lacel	bo '	tr	eat	$^{\mathrm{tm}}$	ent

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged treatment	1 y	ear	2 ye	ears	3 years	
Care provision	0.008	-0.000	0.003	0.001	-0.031	-0.028
	(0.057)	(0.037)	(0.025)	(0.017)	(0.029)	(0.020)
Hours of care	-0.039	-0.053	-0.009	-0.012	-0.058	-0.054
	(0.089)	(0.062)	(0.039)	(0.028)	(0.059)	(0.040)
a		,		,		,
Controls	-	\checkmark	-	\checkmark	-	\checkmark
Weighting	\checkmark		\checkmark	\checkmark	\checkmark	\checkmark
Observations	95,773	95,773	86,942	86,942	75,842	75,842

This table displays the effect of 1 (columns 1-2), 2 (columns 3-4) and 3 (columns 5-6)year-lagged plant closure induced unemployment (placebo treatment) on the probability of being a care-provider (upper panel) and the hour of informal care provided on a normal week-day (lower panel) for the full sample. Controls: The set of control variables is reported in Table 2. Weighting: Estimated applying weights estimated from entropy balancing. Cluster robust standard errors in parentheses (clustered at the personal level); *** p<0.01, ** p<0.05, * p<0.1

specification, we define the treatment indicator as 1 in period t, in which the plant-closure occurred (and the respondent is unemployed) and in period t+1 thereafter (if the respondent is still unemployed)

	(1)	(2)	(3)	(4)	(5)	(6)
Group	Full s	ample	Μ	Men		men
Care provider	0.054^{*}	0.059^{**}	0.042	0.057^{*}	0.064	0.072**
	(0.032)	(0.024)	(0.038)	(0.032)	(0.058)	(0.030)
Hours of care	0.075	0.086**	0.048	0.066**	0.099	0.123**
	(0.048)	(0.035)	(0.039)	(0.033)	(0.103)	(0.052)
Controls	-	\checkmark	-	\checkmark	-	\checkmark
Weighting	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Observations	101,836	101,836	58,181	58,181	$42,\!646$	$42,\!646$

Table 9: Effect of unemployment on informal care, propensity weights

This table displays the effect of plant closure induced unemployment on the probability of being a care-provider (upper panel) and the hour of informal care provided on a normal week-day (lower panel) for the full sample and by gender. Controls: The set of control variables is reported in Table 2. Weighting: Estimated applying weights estimated from entropy balancing. Cluster robust standard errors in parentheses (clustered at the personal level); *** p<0.01, ** p<0.05, * p<0.1

and had no other job in between). Figure 1 shows in addition point estimates and 95% confidence intervals on the probability to be a care-giver when only focusing on the current period (Period t) and when including the second period after the plant closure occurred, if the respondent is still unemployed and had no job in-between (Period t to t+2). While point estimates are similar across all specifications they are insignificant (at the 5% confidence level) when only considering the current period. The picture is similar for the effect on the hours of care provision (Figure 2).²⁷

In a further robustness check we further include caregiving variables, i.e. pre-treatment variables, in the balancing step. Table A7 shows that this does not strongly change the results: Controlling for pre-treatment caregiving leads to slightly higher point estimates. Finally, we vary the research strategy to understand how sensitive our estimates are to another approach. We apply an event study approach using a more homogeneous group: We limit the sample to individuals who experience a job loss due to plant closure at some point in time in the panel. Treatment is still plant-closure induced unemployment but in a group of individuals who all at some point in time experience plant closure induced unemployment, however the timing of the event differs (see Appendix A.1 for more details). Table A8 in the Appendix shows the estimation results. Overall the results are very similar to the results obtained in the DiD entropy balancing estimation. We find positive and significant (10% level) effects of plant-closure induced unemployment on the probability of being a care provider (2.1pp) as well as on the weekly hours of informal care (0.032 hours of care per weekday).

 $^{^{27}}$ We present the estimation results for this robustness check in Appendix Table A6.

Figure 1: Effect on informal care provision: Different treatment definitions



Source: SOEP v35, own calculations. Notes: This figure shows effects of plant closure induced unemployment on the probability to provide informal care by length of the treatment definition in periods. Period t is the period in which plant closure induced unemployment occurs.

6 Conclusion

This study documents a time conflict between employment and informal care provision: We show that a transition from employment into unemployment significantly increases the incidence of informal care provision and an increase in the number of hours of care provided. The effect of unemployment is estimated by a difference-in-differences matching research design based on entropy balancing using plant closure as quasi-exogenous variation. In more detail, we find that unemployment increases the incidence of providing care by almost 2.9 percentage points (a relative increase of about 120%) while the daily hours of care provision rise by around 0.047 hours per weekday, a 138% increase. These findings are robust to various changes in the empirical specification and placebo tests provide empirical support for the identification strategy. In the heterogeneity analysis we show that both men and women react with significant increases in care provision. Moreover we show that effects are larger for women with low education.

For the interpretation of these findings a discussion about the external validity of the empirical design is important. By design, studies which use plant closures as exogenous variation, exploit information of a specific group. As discussed in Table 2 the treated individuals differ for the general population. Amongst others on average they are less educated and have lower labor earnings. From a policy perspective this is a central group as these individuals are more vulnerable and more dependent

Figure 2: Effect on informal care hours: Different treatment definitions



Source: SOEP v35, own calculations. Notes: This figure shows effects of plant closure induced unemployment on the hours of informal care provision by length of the treatment definition in periods. Period t is the period in which plant closure induced unemployment occurs.

on public policy. However, results are difficult to generalize to the full population. Since we find that the effect of unemployment on the provision of long term care is stronger for individuals with low education, it is plausible that the effect for the general population would be lower as the fraction of low educated is lower.

Still, the results have important implications for the policy debate. Informal care provision plays an important role in the care-mix of many OECD countries and LTC systems try to encourage informal care provision by introducing economic incentives. Our findings, together with the literature which focus on different groups, however, show that there still exists a binding time constraint for working individuals. In our study, we assume that demand for informal care is present independent of treatment. As we find that informal care is increased irrespective of that, individuals in employment should face the same demand for informal care but cannot provide it. Similarly, Fischer and Müller (2020) find that received informal and overall care are reduced once females living in the same household are not able to retire anymore at former early retirement ages. This suggests that often, if no informal care is provided, less or no care is received by frail elderly in need. Mommaerts and Truskinovsky (2020) also finds that in economic booms, when less informal care is provided by adult children, less care is received by the frail parents. This can have detrimental health effects of frail elderly.²⁸

Thus, in order to increase supply of informal care and reduce the time constraint between labor and 28 See Hu and Li (2020), Wu and Lu (2017) and Chon et al. (2018) for further information.

informal care provision, policy has to strengthen opportunities for employed individuals to take time off work, provide informal care and return to their jobs afterwards. German policy has already started to address this by introducing the 'Familienpflegezeitgesetz' and 'Pflegezeitgesetz' which grant these opportunities. Wage replacement in times of informal care provision are however insufficient which is why so far only few individuals make use of these regulations.

References

- Abadie, A., & Spiess, J. (2021). Robust post-matching inference. Journal of the American Statistical Association, 1–13.
- Bauer, J. M., & Sousa-Poza, A. (2015). Impacts of informal caregiving on caregiver employment, health, and family. *Journal of Population Ageing*, 8(3), 113–145.
- Bergeot, J., & Fontaine, R. (2020). The heterogeneous effect of retirement on informal care behavior. *Health economics*, 29(10), 1101–1116.
- Blaise, M. (2018). The informal care provision: what are the genuine incentives of children? (Working Papers of BETA No. 2018-12). Bureau d'Economie Théorique et Appliquée, UDS, Strasbourg.
- Brauns, H., Scherer, S., & Steinmann, S. (2003). The casmin educational classification in international comparative research. Advances in cross-national comparison (pp. 221–244). Springer.
- Bundesamt, S. (2020). Pflegestatistik. pflege im rahmen der pflegeversicherung. deutschlandergebnisse. file:///D:/Temp/pflege-deutschlandergebnisse-5224001199004-1.pdf
- Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of economic surveys*, 22(1), 31–72.
- Carr, E., Murray, E. T., Zaninotto, P., Cadar, D., Head, J., Stansfeld, S., & Stafford, M. (2018). The association between informal caregiving and exit from employment among older workers: Prospective findings from the uk household longitudinal study. *The Journals of Gerontology:* Series B, 73(7), 1253–1262.
- Carrino, L., Nafilyan, V., Pabon, M. A. et al. (2019). Should i care or should i work? the impact of working in older age on caregiving (tech. rep.). HEDG, c/o Department of Economics, University of York.
- Chon, D., Lee, Y., Kim, J., & Lee, K.-e. (2018). The association between frequency of social contact and frailty in older people: Korean frailty and aging cohort study (kfacs). Journal of Korean Medical Science, 33(51), 332–339.
- Costa-Font, J., Karlsson, M., & Øien, H. (2015). Informal care and the great recession (CESifo Working Paper Series No. 5427). CESifo Group Munich.
- Everding, J., & Marcus, J. (2020). The effect of unemployment on the smoking behavior of couples. *Health economics*, 29(2), 154–170.
- Fischer, B., & Geyer, J. (2020). Pflege in corona-zeiten: Gefährdete pflegen besonders gefährdete.
- Fischer, B., & Müller, K.-U. (2020). Time to care? the effects of retirement on informal care provision. Journal of Health Economics, 73, 102350.
- Geerts, J., Willem'e, P., & Mot, E. (2012). Long-term care use and supply in europe: Projection models and results for germany, the netherlands, spain and poland (tech. rep.). European Network of Economic Policy Research Institutes (ENEPRI), ENEPRI Research Report No. 116.

- Geyer, J., & Korfhage, T. (2015). Long-term care insurance and carers' labor supply a structural model. *Health Economics*, 24(9), 1178–1191.
- Geyer, J., & Schulz, E. (2014). Who cares? die Bedeutung der informellen Pflege durch Erwerbstätige in Deutschland. *DIW Wochenbericht*, (14), 294–301.
- Goebel, J., Grabka, M. M., Liebig, S., Kroh, M., Richter, D., Schröder, C., & Schupp, J. (2019). The german socio-economic panel (soep). Jahrbücher für Nationalökonomie und Statistik, 239(2), 345–360.
- Golberstein, E. (2008). Essays on long-term care and aging (Doctoral dissertation). University of Michigan.
- Gusmano, M. K., & Okma, K. G. (2018). Population aging and the sustainability of the welfare state. *Hastings Center Report*, 48, S57–S61.
- Haan, P., & Prowse, V. (2015). Optimal social assistance and unemployment insurance in a life-cycle model of family labor supply and savings (DIW Discussion Papers No. 1468). Berlin, Deutsches Institut für Wirtschaftsforschung (DIW). http://hdl.handle.net/10419/110329
- Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political analysis*, 25–46.
- Hainmueller, J., & Xu, Y. (2013). Ebalance: A stata package for entropy balancing. Journal of Statistical Software, 54(7).
- Hajek, A., Lehnert, T., Wegener, A., Riedel-Heller, S. G., & König, H.-H. (2018). Langzeitpflegepräferenzen der älteren in Deutschland. Das Gesundheitswesen, 80(08/09), 685–692.
- Halla, M., Schmieder, J., & Weber, A. (2020). Job displacement, family dynamics, and spousal labor supply. American Economic Journal: Applied Economics, 12(4), 253–87.
- He, D., & McHenry, P. (2016). Does formal employment reduce informal caregiving? *Health Economics*, 25(7), 829–843.
- Heitmueller, A. (2007). The chicken or the egg? endogeneity in labour market participation of informal carers in England. *Journal of Health Economics*, 26(3), 536–559.
- Hu, B., & Li, L. (2020). The protective effects of informal care receipt against the progression of functional limitations among chinese older people. *The Journals of Gerontology: Series B*, 75(5), 1030–1041.
- Jacobs, J. C., Van Houtven, C. H., Laporte, A., & Coyte, P. C. (2017). The impact of informal caregiving intensity on women's retirement in the united states. *Journal of Population Ageing*, 10(2), 159–180.
- Korfhage, T. (2019). Long-run consequences of informal elderly care and implications of public longterm care insurance.

- Lilly, M. B., Laporte, A., & Coyte, P. C. (2007). Labor market work and home care's unpaid caregivers: A systematic review of labor force participation rates, predictors of labor market withdrawal, and hours of work. *The Milbank Quarterly*, 85(4), 641–690.
- Lipszyc, B., Sail, E., & Xavier, A. (2012). Long-term care: Need, use and expenditure in the eu-27 (tech. rep.). Economic Papers 469, European Commission, Directorate-General for Economic and Financial Affairs. Brussels.
- Marcus, J. (2013). The effect of unemployment on the mental health of spouses evidence from plant closures in germany. *Journal of Health Economics*, 32(3), 546–558.
- Meng, A. (2012). Informal caregiving and the retirement decision. *German Economic Review*, 13(3), 307–330.
- Mentzakis, E., McNamee, P., & Ryan, M. (2009). Who cares and how much: Exploring the determinants of co-residential informal care. *Review of Economics of the Household*, 7(3), 283–303.
- Michaud, P.-C., Heitmueller, A., & Nazarov, Z. (2010). A dynamic analysis of informal care and employment in England. *Labour Economics*, 17(3), 455–465.
- Mommaerts, C., & Truskinovsky, Y. (2020). The cyclicality of informal care. Journal of health economics, 71, 102306.
- Moscarola, F. C. (2010). Informal caregiving and women's work choices: Lessons from the Netherlands. LABOUR, 24(1), 93–105.
- Nguyen, H. T., & Connelly, L. B. (2014). The effect of unpaid caregiving intensity on labour force participation: Results from a multinomial endogenous treatment model. Social Science & Medicine, 100, 115–122.
- Niimi, Y. (2017). Does providing informal elderly care hasten retirement? evidence from Japan (tech. rep. No. 730). Tokyo: Asian Development Bank Institute.
- Nizalova, O. (2012). The wage elasticity of informal care supply: Evidence from the health and retirement study. *Southern Economic Journal*, 79(2), 350–366.
- Schmitz, H., & Westphal, M. (2017). Informal care and long-term labor market outcomes. Journal of Health Economics, 56, 1–18.
- Skira, M. M. (2015). Dynamic wage and employment effects of elder parent care. International Economic Review, 56(1), 63–93.
- Stern, S. (1995). Estimating family long-term care decisions in the presence of endogenous child characteristics. *Journal of Human Resources*, 551–580.
- Van Houtven, C. H., Coe, N. B., & Skira, M. M. (2013). The effect of informal care on work and wages. Journal of Health Economics, 32(1), 240–252.
- van Groenou, M. I. B., & De Boer, A. (2016). Providing informal care in a changing society. *European Journal of Ageing*, 13(3), 271–279.

- Wetzstein, M., Rommel, A., & Lange, C. (2015). Informal caregivers Germany's largest nursing service. *GBE kompakt. Facts and Trends from Federal Health Reporting*, 6(3), 1–11.
- Wu, H., & Lu, N. (2017). Informal care and health behaviors among elderly people with chronic diseases. Journal of Health, Population and Nutrition, 36(1), 40–47.

A Appendix

A.1 Event study design

In this section we describe the event study design to estimate plant-closure induced unemployment effects on informal caregiving. We limit the sample to all individuals in the main sample who experience plant-closure induced unemployment within the panel. Treatment is still unemployment through plantclosure but in this event-study design treatment is defined by timing of the lay-off. Equation 5 describes the estimation strategy. Y_{it} represents the outcome variable (care provision and hours of informal care per weekday), $Post_{it}$ is an indicator that is 1 if plant closure induced unemployment has occurred in the current or the previous period (and the individual is still unemployed). We introduce year-fixed effects (γ_t) in all specifications while individual fixed effects are introduced only in Column 1 of table A8. We also introduce D_{it} , a variable indicating the distance to the event (plant-closure) in years. We are interested in the effect of plant-closure induced unemployment α_1 and cluster standard errors at the individual level. We find 935 observations for individuals in SOEP in the years 2001-2018 who experience plant-closure induced unemployment at some time.

$$Y_{it} = \alpha_0 + \alpha_1 Post_{ti} + \sum_{\tau} D_{it}^{\tau} + \gamma_t + \gamma_i + \epsilon_{it}$$
(5)

Table A8 shows that within the group experiencing plant closure at some point the event itself increases informal care on the intensive and extensive margin significantly. The introduction of individual fixed effects reduces point estimates but does not alter significance severely.

A.2 Further tables

Demographics	
Age^a	age in years
Female	1 = female, $0 = $ male
Migrant	1 = individual (or parents) moved to Germany, $0 = $ everyone else
Siblings	1 = individual has at least one sibling, $0 = $ only child
Alone	1 = individual has no partner, $0 =$ everyone else
Children	1= individual has children under 18 in hh, $0=$ everyone else
Labor market	
Labor income	natural logarithm of individual yearly labor income
Tenure	natural logarithm of tenure years
Blue collar	1 = blue collar worker, $0 =$ everyone else
Job worries	3 categories (big worries, some worries, no worries)
Company size ^{b}	4 categories (small, small-medium, medium, large) c
Industry	10 categories
Education	4 categories (in school, elementary, secondary, tertiary)
Work experience	Years in full-time experience, part-time experience is counted
	as 0.5 years of work experience in full-time
Years in unemployment	Years that an individual spent in unemployment
Health	
Subjective health ^{a}	5 categories (very poor, poor, satisfying, good, very good)
Hospital stay	1 = individual spend at least one night in the hospital last year,
	0 = everyone else
Others	
State of residence	16 categories
Year dummies	from 2001 to 2017

Table A1: Overview of control variables

a Variable also included for partner;

b Extra category for missing values;

c "small" refers to less than 20 employees, "small-medium" to 20-199 employees, "medium" to 200-1999 employees and "large" to 2000 employees and more.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	La	bor	Educ	ation	Erra	ands	Chile	d care	Hol	obies
	-8.707^{***} (0.187)	-8.690^{***} (0.163)	0.629^{***} (0.124)	0.624^{***} (0.114)	1.702^{***} (0.155)	1.670^{***} (0.142)	1.074^{***} (0.206)	1.047^{***} (0.181)	1.003^{***} (0.157)	1.006^{***} (0.140)
Ν	100,530	100,530	101,528	101,528	101,286	101,286	101,711	101,711	101,523	101,523

Table A2: Effect of unemployment on other time-use categories

This table displays the effect of plant closure induced unemployment on several other time-use variables on a normal week-day for the full sample. Controls: The set of control variables is reported in Table 2. N: Number of Observations; Weighting: Estimated applying weights estimated from entropy balancing. Robust standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1

Outcome	(1)	(2)	(3)	(4)
Care provider	0.020^{*}	0.030^{***}	0.029^{***}	0.029^{***}
	(0.011)	(0.011)	(0.011)	(0.010)
Hours of care	0.026	0.050^{**}	0.047^{**}	0.047^{***}
	(0.020)	(0.019)	(0.020)	(0.018)
Controls	-	\checkmark	-	\checkmark
Weighting	-	-	\checkmark	\checkmark
Observations	129,637	101,836	101,836	101,836

Table A3: Effect of unemployment on informal care provision (non-clustered standard errors)

This table displays the effect of plant closure induced unemployment on the probability of being a care-provider and the hour of informal care provided on a normal week-day for the full sample. Controls: The set of control variables is reported in Table 2. Weighting: Estimated applying weights estimated from entropy balancing. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)	
Group	Full sample		Men		Women		
			Care provision				
Low education	0.002	0.002	-0.001	0.006	0.007	0.008	
	(0.003)	(0.006)	(0.005)	(0.008)	(0.006)	(0.009)	
Treatment	0.016	0.019	0.020	0.030	0.009	0.006	
	(0.036)	(0.034)	(0.055)	(0.050)	(0.041)	(0.031)	
Treatment & low education	0.034^{***}	0.033^{***}	0.027^{**}	0.031^{***}	0.044^{**}	0.046***	
	(0.011)	(0.010)	(0.013)	(0.011)	(0.018)	(0.016)	
	Hours of care						
Low education	0.005	-0.001	0.001	0.007	0.010	0.010	
	(0.007)	(0.011)	(0.007)	(0.011)	(0.013)	(0.017)	
Treatment	-0.013	-0.006	0.023	0.035	-0.066	-0.072	
	(0.049)	(0.044)	(0.055)	(0.051)	(0.085)	(0.068)	
Treatment & low education	0.070^{***}	0.062^{***}	0.053^{**}	0.054^{***}	0.091^{**}	0.091***	
	(0.021)	(0.019)	(0.025)	(0.021)	(0.038)	(0.032)	
Controls	-	\checkmark	-	\checkmark	-	\checkmark	
Weighting	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	
Observations	102,497	102,497	58,883	58,883	43,614	43,614	

Table A4: Effect of unemployment on informal care by education (ISCED1997 classification)

This table displays the effect of plant closure induced unemployment on the probability of being a careprovider and the hour of informal care provided on a normal week-day for the full sample and by gender interacted with low education (ISCED97 Classification). Controls: The set of control variables is reported in Table 2. Weighting: Estimated applying weights estimated from entropy balancing. Cluster robust standard errors in parentheses (clustered at the personal level) *** p < 0.01, ** p < 0.05, * p < 0.1

	(1)	(2)	(3)	(4)
		Care p	rovider	
Women	-0.001	-0.000	-0.002	0.007
	(0.001)	(0.001)	(0.003)	(0.009)
Treatment	0.024^{*}	0.029^{*}	0.028^{*}	0.026^{*}
	(0.014)	(0.015)	(0.015)	(0.013)
Treatment & Women	0.013	0.030^{*}	0.028^{*}	0.041^{**}
	(0.026)	(0.017)	(0.017)	(0.019)
		Care	hours	
Women	-0.006**	-0.001	-0.010	0.015
	(0.002)	(0.003)	(0.009)	(0.018)
Treatment	0.041^{**}	0.053^{**}	0.047^{**}	0.045^{**}
	(0.020)	(0.022)	(0.022)	(0.021)
Treatment & Women	-0.004	0.044	0.037	0.066
	(0.049)	(0.035)	(0.035)	(0.042)
Controls	-	\checkmark	-	\checkmark
Weighting	\checkmark	\checkmark	\checkmark	\checkmark
Observations	$129,\!637$	$101,\!836$	$101,\!836$	$101,\!836$

Table A5: Effect of unemployment on informal care by gender (interaction)

This table displays the effect of plant closure induced unemployment on the probability of being a care-provider and the hour of informal care provided on a normal week-day for the full sample and by gender (interaction with female-dummy). Controls: The set of control variables is reported in Table 2. Weighting: Estimated applying weights estimated from entropy balancing. Cluster robust standard errors in parentheses (clustered at the personal level) *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)
Group	Full sample	Men	Women	Full sample	Men	Women
Treatment]	Period t		Perio	od t to $t +$	2
Care provider	0.023	-0.012	0.075***	0.027**	0.028*	0.024*
	(0.015)	(0.015)	(0.021)	(0.012)	(0.016)	(0.013)
Hours of care	0.035	-0.002	0.081^{**}	0.039^{*}	0.050^{**}	0.026
	(0.025)	(0.020)	(0.041)	(0.021)	(0.023)	(0.035)
Controls	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Weighting	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark
Observations	101,438	58,250	43,188	101,896	58,519	43,377

Table A6: Effect of unemployment on informal care by treatment definition

This table displays the effect of plant closure induced unemployment on the probability of being a care-provider and the hour of informal care provided on a normal week-day for the full sample and by gender. t is the period in which the plant closure induced unemployment occurs. Controls: The set of control variables is reported in Table 2. Weighting: Estimated applying weights estimated from entropy balancing. Cluster robust standard errors in parentheses (clustered at the personal level) *** p<0.01, ** p<0.05, * p<0.1

Table A7: Effect of unemployment on informal care - balancing on pre-treatment caregiving

Variables	(1)	(2)	(3)	(4)	(5)	(6)	
Group	Full sample		М	Men		Women	
			Care pr	ovision			
Treatment	0.039***	0.039***	0.039**	0.038***	0.040**	0.040***	
	(0.011)	(0.010)	(0.015)	(0.012)	(0.017)	(0.014)	
	Hours of care						
Treatment	0.070***	0.070***	0.067***	0.067***	0.076**	0.076***	
	(0.020)	(0.018)	(0.023)	(0.019)	(0.036)	(0.029)	
Controls	-	\checkmark	-	\checkmark	-	\checkmark	
Weighting	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	\checkmark	
Observations	101,836	101,836	$58,\!485$	$58,\!485$	43,348	$43,\!348$	

This table displays the effect of plant closure induced unemployment on the probability of being a care-provider and the hour of informal care provided on a normal week-day for the full sample and by gender. Controls: The set of control variables is reported in Table 2. Weighting: Estimated applying weights estimated from entropy balancing. Cluster robust standard errors in parentheses (clustered at the personal level) *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)
Care provider	0.030^{**}	0.021^{*}
	(0.015)	(0.011)
Hours of care	0.050^{*}	0.032*
	(0.027)	(0.017)
Observations	935	935
Year fixed effects	\checkmark	\checkmark
Individual fixed effects		_

Table A8: Effect of plant closure induced unemployment on informal care - event study

This table displays the effect of plant closure induced unemployment on the probability of being a care-provider and the hour of informal care provided on a normal week-day for the full sample and by gender. In this table we use an event study design. The sample contains only individuals who experience plant-closure at some time while treatment is timing-specific. Cluster robust standard errors in parentheses (clustered at the personal level) *** p<0.01, ** p<0.05, * p<0.1

Variables ^a	Control group	Treatment group	Weighted control	Raw difference ^{b}
Age^{c}	44.89% (8.97)	45.79% (9.45)	44.51% (9.53)	-0.49
Female	0.43%~(0.49)	$0.40\% \ (0.49)$	0.43%~(0.50)	0.01
Migrant	0.16%~(0.37)	0.26%~(0.44)	0.21% (0.41)	0.06
Siblings	0.11%~(0.31)	0.07%~(0.26)	0.13%~(0.34)	0.03
Alone	0.30%~(0.46)	0.30%~(0.46)	$0.28\% \ (0.45)$	-0.02
Labor income ^{d}	39644.75 (31294.94)	26825.69(18225.23)	37122.70(28317.58)	-3192.04
$Tenure^d$	13.40% (9.90)	11.44% (10.79)	$11.93\% \ (9.80)$	-1.87
Work experience	19.79 (9.71)	21.39(10.79)	19.80(9.72)	-1.59
Unemployment experience	0.40(1.23)	0.90(2.00)	0.40(1.23)	0.5
Children	0.46%~(0.50)	0.40%~(0.49)	0.45%~(0.50)	-0.01
Blue collar	0.24%~(0.42)	0.44% (0.50)	$0.26\% \ (0.44)$	0.04
Concerned with job loss				
Very Concerned	0.11%~(0.31)	0.47%~(0.50)	0.13%~(0.34)	0.02
Somewhat Concerned	0.37%~(0.48)	0.36%~(0.48)	0.40%~(0.49)	0.03
Not Concerned at all	0.52%~(0.50)	0.17%~(0.38)	0.47%~(0.50)	-0.06
Firm Size				
Small	0.21%~(0.41)	0.37% (0.48)	0.25% (0.43)	0.04
Small-Medium	0.26%~(0.44)	0.33% (0.47)	0.27% (0.44)	0.00
Medium	0.22% (0.42)	0.16%~(0.37)	0.24% (0.43)	0.02
Large	0.27%~(0.44)	0.13%~(0.34)	0.22% (0.42)	-0.05
Occupation				
Primary Sector	0.02%~(0.13)	0.02%~(0.13)	0.03%~(0.16)	0.01
Manufacturing	0.25%~(0.43)	0.31%~(0.46)	0.27% (0.44)	0.02
Energy & Water	0.01%~(0.11)	0.01%~(0.09)	0.02%~(0.13)	0.01
Construction	0.06%~(0.23)	0.17%~(0.37)	0.05%~(0.21)	-0.01
Wholesale & Retail	0.10%~(0.31)	0.26%~(0.44)	0.13%~(0.34)	0.04
Hotel & restaurants	0.02%~(0.13)	0.03%~(0.18)	0.03%~(0.16)	0.01
Transport	0.06%~(0.23)	0.03%~(0.18)	0.06%~(0.24)	0.01
Banking & Insurance	0.05%~(0.21)	0.03%~(0.16)	0.04%~(0.19)	-0.01
Other services	0.31%~(0.46)	0.11% (0.32)	0.27% (0.44)	-0.05
Health services	0.13%~(0.33)	0.02% (0.14)	0.11%~(0.31)	-0.02
Education				
Elementary	0.25%~(0.43)	0.52%~(0.50)	0.24% (0.43)	-0.02
Secondary	0.45%~(0.50)	0.38%~(0.49)	0.48%~(0.50)	0.04
Tertiary	0.30%~(0.46)	0.10%~(0.31)	0.28%~(0.45)	-0.02
Satisfaction with own health				
Very poor	0.01%~(0.09)	0.03%~(0.16)	0.01%~(0.07)	-0.00
Poor	0.05%~(0.23)	0.11%~(0.31)	$0.07\% \ (0.25)$	0.02
Satisfying	0.26%~(0.44)	$0.26\% \ (0.44)$	0.24% (0.43)	-0.03
Good	0.48%~(0.50)	0.42% (0.49)	0.47%~(0.50)	-0.02
Very good	0.20%~(0.40)	0.19%~(0.39)	0.22% (0.42)	0.03
Hospital stay	0.08%~(0.27)	0.13%~(0.34)	$0.07\% \ (0.25)$	-0.02
Observations	101,462	$31 {}^{374}$	101,462	

Table A9: Summary statistics of covariates (balancing variables) in the plain control group, treatment group and weighted treatment group (propensity score weighting)

Source: SOEP v35; Notes:

a. We suppress the time and state dummies. For the complete table see the appendix.

b. The raw difference is the difference between treatment and weighted control values.

c. For continuous variables standard deviation is displayed in parenthesis.

d. Values are presented in levels. In the regression these variables are included in their logarithmic transformation.