Essays on Pension and Long-Term Care policy

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Björn Fischer, MSc

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Dekan:
Prof. Dr. Dr. Giacomo Corneo

Erstgutachter:
Prof. Dr. Peter Haan, Freie Universität Berlin

Zweitgutachterin:
Prof. Dr. Pierre-Carl Michaud, HÉC Montreal

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Erklärung über Zusammenarbeit mit KoautorInnen und Vorveröffentlichungen

Kapitel 1

- In Zusammenarbeit mit Dr. Kai-Uwe Müller.
- Das Kapitel basiert in Teilen auf Vorarbeiten welche ich im Rahmen der Abschlussarbeit für den Master of Science an der Freien Universität Berlin durchgeführt habe (Fischer, 2017). Die Analyse wurde daraufhin substanziell erweitert.
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Kapitel 4

- In Zusammenarbeit mit Dr. Thorben Korfhage.
- Bislang unveröffentlicht.

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Preface

Demographic change is one of the major challenges for modern societies in most OECD countries. In Germany for every 100 people in the age group 20-65 years there were 23.6 people in pensionable ages (above 66 years) in 1991. This so called 'age quotient' increased to 26.8 in 2000, 33.8 in 2010 and 37 in 2020 (Bundesamt, 2019b, 2021). Projections show that the age quotient in Germany will rise to nearly 50 in 2038 (Bundesamt, 2019a). The reason for this development is the increase in average life-expectancy and a decreasing birth-rate especially since the mid-1960s. As the 'Baby-boomer' generations reach old age, the number of individuals older than 66 years is expected to grow by 22% from 16 million in 2020 to 20 million in 2035 (Bundesamt, 2021). A consequential development is the increase in the number of elderly individuals who are permanently dependent on care. This development is projected even though individuals tend to age more healthy (Colombo et al., 2011). In Germany, the number of care-dependent elderly is expected to rise from 4.1 million in 2019 to 5.9 million in 2050 (Jacobs et al., 2020). As a result, De la Maisonneuve and Martins (2013) project that public spending for Long-term care will double until 2060 from 1.7% of GDP across OECD countries in 2015 (OECD, 2017a).

Rouzet et al. (2019) suggest that policy makers in all OECD countries have to react to the upcoming challenges in several policy fields: the OECD calls for reforms of pension systems that improve its financial sustainability, reduce old-age poverty while ensuring a fair sharing of the burden across generations. Policy should further ensure higher labor market participation of several groups, especially women and the elder population. As the demand for Long-term care will rise dramatically the OECD suggests that policy finds efficient ways to sustain supply in order to facilitate healthy ageing.

Policy makers in many OECD countries and Germany have reacted to several of these challenges. Official retirement ages in Germany are rising and changes in social norms and improvements in child-care policy lead to an increase in female labor force participation in all age groups. Germany introduced a mandatory Long-term care insurance in 1995 to partially insure individuals against the risk to become permanently dependent on Long-term care in old-age. The German Long-term care insurance as well as families of care-dependent and the care dependent themselves favor family home care - often called informal care - over professional care services - often called formal care (Lipszyc et al., 2012; Blaise, 2018; Mentzakis et al., 2009; Hajek et al., 2018). Consequently, informal care amounts to 70-90% of the overall Long-term care provided (Fujisawa and Colombo, 2009; Geyer and Schulz, 2014). As informal care is fiscally less costly for the Long-term care insurance, policy intends to expand the informal care force.

These policy measures are often taken without regard to the other. Economic theory, however, suggests that individuals decide on their provision of labor hours and informal care simultaneously, considering respective opportunity costs (Becker, 1991). Ceteris paribus, employed individuals face higher opportunity costs of home production (including informal care). Therefore, people that are active on the labor market and depend on market income might refrain from taking on care activities (Al-Janabi et al., 2018). This argument leads to the hypothesis that increased retirement ages and labor market attachment of prime caregivers threaten the policy aim of increasing the informal care force. The fact that about two thirds of the 4-5 million informal caregivers in Germany are women, most often in the age-range around retirement (Wetzstein et al., 2015; Geyer and Schulz, 2014) - the same group that is expected to participate more in the labor market - intensifies this conflict. However, providing informal care to a frail family member can also be seen as a constraint, such that informal care activities are taken up regardless of opportunity costs (Al-Janabi et al., 2018). In this case, higher demand for informal care leads to higher take-up of informal caregiving and a reduction of time spent in employment. This, in turn, decreases labor market participation of those active as informal caregivers. Which of these arguments will predominate is ambiguous and ultimately an empirical question. In both cases, policy aims of the retirement and Long-term care systems are in conflict. It is crucial for policy makers to understand their potential to efficiently respond to challenges in both policy fields simultaneously.

The aim of this dissertation is to study the relationship of labor market, retirement and informal caregiving decisions in the context of changing policy regulations in Germany and the developments of demographic change. First, I investigate the causal link between the retirement system and informal caregiving. I assess whether reaching eligibility ages for retirement increases take-up of informal care and whether changes to retirement ages have an impact on informal caregiving. Second, I explore whether changes in labor market participation due to sudden unemployment increases informal caregiving. Third, I asses the policy maker's options in responding to challenges in Long-term care and retirement policy simultaneously.

In the first two chapters I examine whether retirement is causally linked to informal caregiving. Literature studies the impacts of informal care on labor supply and retirement decisions, partially finding negative links (Dentinger and Clarkberg, 2002; Van Houtven et al., 2013; Jacobs et al., 2017; Heitmueller, 2007). This suggests that reverse causality (Michaud et al., 2010) and selection on unobservables issues (He and McHenry, 2016) arise. Therefore, I need to circumvent these obstacles when studying causal impacts of retirement on informal care supply. The German retirement system includes institutional regulations that offer quasi-experimental variation in retirement behavior. I exploit these in chapters one and two.

In chapter one we use early retirement thresholds for Germany women as instruments for retirement behavior in a fuzzy regression discontinuity design. Together with Kai-Uwe Müller we apply this strategy to German survey data (the German Socio-Economic Panel Study, GSOEP) and find that as women use institutionalized early retirement thresholds they increase informal caregiving substantially and significantly. As one can assume that women around these early retirement thresholds differ only in the availability of retirement benefits, this suggests that retirement is used to solve time-conflicts between employment and informal care supply. Women might have wanted to provide informal care also before they were eligible for retirement benefits but were constrained by their labor supply. Results from the first chapter lead to the hypothesis that changes in the (early) retirement ages negatively impact informal caregiving.

I investigate this aspect in the second chapter by exploiting an increase in the early retirement age for German women from age 60 to 63. The abolishment of women's pension in the 1999 pension reform was thoroughly investigated with respect to labor market responses (Geyer and Welteke, 2019; Geyer et al., 2020). I use this exogenous variation in retirement behavior and study reactions in informal care supply twofold: First, I use the fact that the reform varies the early retirement age of women discontinuously along a woman's birth date in a regression discontinuity design. I find that as women can no longer retire before age 63 they provide less informal care in the ages 60-62. I can go one step further and show that on the household level the reform reduces informal care of women impacted by the reform but I find no substitution through formal care. Second, I use the reform as an instrument for retirement and confirm results from the first chapter: As women retired using an early retirement age before age 63 they increased informal care supply significantly.

The first two chapters contribute to literature twofold: They are among the first studies to credibly estimate a causal link of retirement on informal caregiving. They show that women make use of the institutionalized retirement ages to leave the labor market and take care of a frail family member. Bergeot and Fontaine (2020) and Carrino et al. (2019) find similar results. This suggests that before women are eligible for retirement benefits, time-conflicts between labor supply and caregiving partially prohibit them from taking up informal care. Further, the results demonstrate that increases in retirement regulations threaten the aims of the Long-term care insurance to insure supply of Long-term care by family members. As women might react to increased labor market attachment and higher retirement ages by providing less informal care, frail elderly that are dependent on care might suffer in terms of health behavior. This could have detrimental effects on progression of frailty (Wu and Lu, 2017; Chon et al., 2018). For a group of women, higher retirement ages mean that they have to combine informal care supply with labor. This double burden can have detrimental health effects for caregivers (Schmitz and Stroka, 2013).

In chapter three, we investigate a different margin in the connection between labor supply and informal caregiving. If the time-conflict between work and caregiving is also present at younger ages, women should also provide more informal care in unemployment. Simultaneity and selection on (un-)observables issues apply also in this research question. Together with Peter Haan and Santiago Salazar Sanchez we use plant closure induced unemployment in a difference-in-difference-matching procedure to estimate the causal link between unemployment and caregiving (Halla et al., 2020; Everding and Marcus, 2020). We find that both women and men increase provision of informal care after being laid off due to plant closure. We find highest impacts for women in low education. This chapter contributes to a body of literature investigating effects of labor supply on caregiving (Stern, 1995; Golberstein, 2008; Boaz, 1996; Doty et al., 1998; Nizalova, 2012; Carmichael et al., 2010) as well as impacts of the business cycle on caregiving (Mommaerts and Truskinovsky, 2020; Costa-Font et al., 2015). Results from this chapter establish that time-conflicts between labor supply and caregiving arise also at younger ages.

In chapter four (joint with Thorben Korfhage) we investigate the options of policy makers to simultaneously react to challenges of the retirement and Long-term care system. Chapters one and two establish that retirement has causal links with caregiving behavior and that changes to the retirement ages lead to reactions in caregiving. Chapters one to three exploit quasi-experimental settings to understand causal links in individual's decision-making regarding labor supply, retirement and caregiving and the impact of policy change. In contrast to that, in chapter four we build and estimate a structural dynamic life-cycle model to simulate policy changes and understand its effects on behavior, income and welfare for women in Germany. The model has two aims: First, we want to understand the impact of increased retirement ages also on formal care demand and inequality. Second, we study the effectiveness of Long-term care regulations in alleviating the implications of higher retirement ages for caregiving, formal care demand, inequality and welfare. We contribute to literature that uses dynamic models to understand long-term effects of caregiving on income and labor market outcomes (Skira, 2015; Korfhage, 2019). Our model is the first in this literature to incorporate formal care in the choice set of adult daughters who organize care for frail parents. We use the 1999 pension reform exploited in chapter two to validate our model. We can replicate effects of increased retirement ages on employment and informal caregiving. Further, we can show that the abolishment of women's pension impacts women who might have to take care of their parents in the future more as they may not be able to work longer. Our results suggest that the reform increased the demand for formal care which increases costs for the Long-term care insurance. Simulations of future policy changes show that further increases in the retirement ages have similar results for employment, caregiving and inequality. A combination of increased retirement ages with an increase in pension attainments through informal caregiving alleviate negative consequences of higher retirement ages. The same is true for a combination of higher retirement ages with the introduction of care-leave policies. While these combined reforms are welfare improving compared to only increasing retirement ages, they are accompanied with negative labor market and fiscal effects.

The chapters of this dissertation call on policy makers to react to challenges of demographic change with a comprehensive reform-strategy. Results show that time-conflicts between care provision and labor supply arise. People deal with these situations in various ways which mostly come with personal and economic disadvantages for those experiencing that a family member becomes dependent on care. Future developments in the age structure and participation in the labor market increase this tension. As shown in chapter four, policy has options to increase welfare and efficiency. Simultaneously improving care-leave models already in place when retirement ages rise might be a good starting point. Further, it might be vital to increase informal caregiving also by men. Results from chapter three show that also men face time-conflicts between family care and labor supply. As men are considered to depict lower labor supply elasticities different policy measures might be needed to boost a more equal sharing of the caregiving burden between both genders.

The results in this dissertation also call for future research. German policies include the possibility of care-leave already. It remains a question for future research why take-up of these possibilities remains low. Further, studies show a detrimental connection of caregiving with caregivers' health (Stöckel and Bom, 2022; Schmitz and Westphal, 2015; Hiel et al., 2015; Kolodziej et al., 2022). It is beyond the scope of the model developed in chapter four to study effects of changes to informal caregiving on fiscal costs of the health system. Further research should also study how men's informal caregiving decisions differ from that of women. Results can be useful to design policy to reduce the gender care-gap.

Chapter 1

Time to Care? The Effects of Retirement on Informal Care Provision

1.1 Introduction

Population aging creates problems for various pillars of modern welfare states. A higher life expectancy increases the age dependency ratio as well as the individual risk to become care dependent (Gusmano and Okma, 2018). The number of elderly persons in need of care grows faster than the group of potential care providers which puts pressure on the care system (Broese van Groenou and De Boer, 2016; Geerts et al., 2012). A rising age dependency ratio leads to increases in social security expenses and urges changes in pension schemes (OECD, 2017b; McGrattan and Prescott, 2017). In a prevalent reform strategy policy-makers aim to boost employment rates by prolonging working lives and increasing the labor market participation of underrepresented groups, most notably those of women. This could, however, create a conflict of objectives with the rising demand for private home care, often called informal care, that has been largely neglected so far.

Our paper tackles this looming trade-off as one of the first studies on the causal effect of the retirement decision on informal care provision. Informal is usually preferred over professionalized care by care recipients and their relatives. It is also favored within institutionalized long-term care (LTC) systems for cost reasons (Lipszyc et al., 2012; Blaise, 2018; Mentzakis et al., 2009). The German LTC insurance is an example (European Commission, 2016). Around 48% of currently care-dependent persons are cared for in their own homes exclusively by family and friends (Wetzstein et al., 2015). About two thirds of the 4 to 5 million informal caregivers in Germany are women. The highest shares of care providers are found around retirement (about 12% in the age group between 55-69 years vs. at most 8% in any other age group; see Wetzstein et al. (2015) or Geyer and Schulz (2014)). Age differences within marriages and the lower life-expectancy of men are explanations for the gender gap in the prevalence of informal care (Meyer, 2006). Men also rarely take on care responsibilities for close persons other than their wife.

In order to assess whether a conflict of objectives between retirement and care policy is indeed impending, our analysis is focused on women as primary caregivers. We investigate whether women increase informal care provision when retiring from their early retirement age (ERA). Women have not only used these thresholds extensively (Geyer and Welteke, 2019; Keck and Krickl, 2013). They also exhibit the highest care rates in this age range (Wetzstein et al., 2015). We estimate a causal effect employing the ERA of women as instruments for retirement behavior (Battistin et al., 2009; Eibich, 2015). From the causal effect of retirement on care we conclude whether gainful employment may crowd out informal care before retirement becomes a viable option. This is of great importance for the sustainability of LTC insurance systems in connection with future reforms to the retirement scheme. Policy makers would face a trade-off between policy goals: The prevalent reform strategy to extend the working life and increase female labor force participation threatens to diminish the supply of informal care.

Such a crowding out effect might occur when individuals who are confronted with the demand for care face a *time conflict*. This term refers to the decision problem between the supply of labor and informal care subject to a budget constraint. People may refrain from taking on care activities because they depend on their market income (Al-Janabi et al., 2018). Ceteris paribus opportunity costs of home production (including informal care) are higher for employed people. As soon as they are eligible for retirement benefits individuals may re-evaluate their care decision. There could be a positive causal effect of reaching the ERA on informal care provision. Alternatively, the supply of informal care may be inflexible and not adjusted upon early retirement. The time conflict would then be solved by reducing labor supply or time in other activities (leisure, other home production). Care activities are in this case taken up regardless of opportunity cost arguments. It is therefore an empirical question whether the described relationship exists.

This paper circumvents the endogeneity problem inherent in simultaneous decisions on the supply of labor and informal care by exploiting women's ERA thresholds as instruments for retirement (Battistin et al., 2009). Age cutoffs for early retirement are defined with the German pension legislation as one of different paths to go on pension. Depending on the cohort the ERA in Germany is 60 or 63. In 2000 about 37% of retiring women made use of ERA rules for women (Keck and Krickl, 2013). As the crossing of an cutoff is solely determined by age and thus exogenous, we can utilize related changes in the choice set and budget constraint within a fuzzy regression discontinuity design (RDD). A threshold serves as instrument for the individual retirement decision. This approach deals with reverse causality and selection on unobservables. The necessary assumption that individuals cannot select into one of the age groups (being older or younger than the cutoff) holds by definition.

We estimate the effect of this negative labor supply shock on informal care provision using data from the German Socio-Economic Panel (SOEP). The SOEP is one of very few data sets containing comprehensive information on the labor market status, the retirement age and state as well as the provision of informal care (Goebel et al., 2019). This allows us to assess changes in informal care activity as well as effect heterogeneity in terms of working hours, location of care provision and educational attainment of the care provider. To the best of our knowledge this is the first paper on the causal effect of retirement on care provision with clean identification based on retirement thresholds. We provide

evidence for this causal mechanism by showing theoretically consistent effect heterogeneity patterns. As the legal retirement age in Germany was increased recently, our results contribute to a discussion on the potential impact of such pension reforms for future supply of informal care.
We find a significant and robust increase of previously employed women's informal care provision upon retirement at their ERA. Care hours rise on average by about 0.8 hours and the caregiving probability by about 13 percentage points on a weekday. Effects are of similar magnitude, but more significant when care is provided within the own household. Women retiring from full-time employment and highly educated women react slightly stronger. The findings are consistent with underlying behavioral mechanisms and previous evidence on informal care provision in Germany. The time-conflict is larger for full-time employed women. Highly educated women have a higher labor market attachment and propensity to supply care.
The paper is organized as follows: After a brief outline of the related literature (section 1.2) we characterize the relevant institutional features of the system of formal and informal care as well as the state pension system in Germany (section 1.3). The data set is introduced and a description of the sample and variables is given in section 1.4. The identification strategy is presented in section 1.5. We sketch reasons for endogeneity and explain how retirement age cutoffs are utilized as instruments for the retirement decision in a fuzzy RDD. We discuss instrument relevance and validity as well as threats to identification. Empirical results are presented in section 1.6. We start with our main specification for women retiring at their respective ERA threshold. We then discuss effect heterogeneity, effects for a homogenous sample with a single cutoff at 60 years, various robustness tests, and a comparison with older women and men. Section 1.7 discusses these findings and concludes.

1.2 Related literature

This paper contributes to the empirical literature relating labor supply, retirement decisions, and the provision of informal care. Lilly et al. (2007) and Bauer and Sousa-Poza (2015) provide reviews on the impact of informal care on labor supply. Reverse causality (Ettner, 1995; Michaud et al., 2010) and selection on unobservables (He and McHenry, 2016) may arise. Thus, research designs have been developed and evidence has been provided for causal effects in both directions.
One line of research investigates whether the provision of informal care affects retirement. Dentinger and Clarkberg (2002) find retirement odds to be higher by a factor of 5 for caregiving wives, while caregiving husbands retire at a later age. Estimating the impact of caregiving on retirement in Germany, Meng (2012) shows effects for women are stronger and that men are affected only by care intensity. Schneider et al. (2013) show that the physical burden, not the time spent in care drives intentions to exit the labor market. Van Houtven et al. (2013), Jacobs et al. (2017), Carr et al. (2018) and Niimi (2017) report that informal care providers have ceteris paribus a higher probability to be in retirement in the U.S., the U.K. and Japan. Geyer and Korfhage (2018) make use of the introduction of the German LTC insurance system and point to the time conflict between informal care provision and gainful employment. A related branch of literature relying on instrumental variables estimates direct labor supply effects of informal care. Carmichael and Charles (1998), Carmichael and Charles (2003a),

Carmichael and Charles (2003b), Heitmueller (2007) and Schmitz and Westphal (2017) are prominent examples who all confirm a negative causal impact of care activities on gainful employment.
Evidence for an impact of informal care on retirement and thus on labor supply does not mean that the opposite effect holds. The aforementioned studies take the decision to provide informal care as exogenous. Informal caregivers tend to retire earlier. When facing the demand for care, individuals may decide irrespective of their labor force status and trade off informal care against other time uses. Besides, a transition into retirement is not only an adaption in the time spend on the labor market, but implies a status change. So underlying mechanisms could be different.
A smaller strand of the literature focuses on the reverse effect of labor market participation on informal care finding mixed results. Various methods are applied to deal with endogenous labor supply in a model for the provision of care. Stern (1995) uses employment histories as instruments for current labor supply without finding an effect on informal care. Golberstein (2008) exploits a policy reform with a Difference-in-Differences (DiD) estimator and finds negative effects of women's labor supply incentives on the probability of co-residing with a disabled parent. Boaz (1996) and Doty et al. (1998) use age, education and number of children as exclusion restrictions in simultaneous-equation models. Boaz (1996) finds substantial, Doty et al. (1998) only limited effects on care provision. Using regional unemployment rates and industry structure in an instrumental variables (IV) approach Nizalova (2012) finds high negative effects of wages on care provision. In a similar IV framework He and McHenry (2016) find that for women of prime caregiving age (40-64) an increase of weekly working hours by 10% is associated with a reduction in caregiving probability of 2%. Those studies are based on U.S. data.
Applying a dynamic probit model on Dutch data Moscarola (2010) finds that prior employment reduces the caregiving probability by 2.4%. Berecki-Gisolf et al. (2008) cannot show an impact of the employment status on later caregiving uptake on Australian women. However, caregiving women show a negative correlation between hours previously spent in paid employment and caring hours. Carmichael et al. (2010) analyze the effect for the UK and find that employment and earnings impact informal care provision negatively. Mentzakis et al. (2009) also report negative effects of employment on informal care, but a positive effect of income and wealth. Michaud et al. (2010) estimate both directions of the relationship between employment and care for England simultaneously uncovering a negative effect of employment on future co-residential and extra-residential caregiving.
A prominent strand of literature is concerned with the substitutability of formal and informal care (Hollingsworth et al., 2017). Findings support the interpretation that the decision to provide informal care is not only influenced by the budget constraint, but also by other factors, e.g. the necessity to provide this particular form of care. In terms of identification our work is also related to a broader research that exploits age thresholds in retirement legislation and estimates causal effects of (early) retirement. Outcomes include the individual health status (Eibich, 2015; Müller and Shaikh, 2018) or consumption decisions (Battistin et al., 2009; Moreau and Stancanelli, 2015).

1.3 Institutional setting

The German system of social insurances consists of five pillars: State Pension Insurance, Health Insurance, Accidence Insurance, Unemployment Insurance and since 1995 also State Long-time Care (LTC) Insurance. In the following we will sketch the features of the LTC and pension insurance systems that are most relevant for our empirical analysis.

1.3.1 The state system of formal and informal care provision

In 2016 around 2.7 million people received benefits from the Social Care Insurance (Soziale Pflegeversicherung), the German governmental care insurer. Nearly 2 million of those were outpatients (BMG, 2017). The governmental care insurer defines a strict priority of home care. Benefit eligibility is defined only with respect to individual care needs: If a person needs help with at least two activities of every day life (cooking, mobility, etc.) for not less than 45 minutes per activity a day and he or she additionally needs support in household maintenance, benefits are granted. In sum, a person has to be in demand of 90 minutes of care per day. Three levels of care dependency existed during the period of observation that were extended to five levels in 2017. Most recipients receive monetary benefits in order to support relatives who take on the responsibilities, so-called *informal care*.

It is possible to combine informal with external care bought from professional providers. Parts of the costs are covered by insurance. Those benefits start from 326€ in care level II and go up to 901€ in care level V.[1] Care receivers are free to spend the amount and can use it to reimburse family carers. Geyer and Schulz (2014) point out that many individuals in need of care do not meet eligibility conditions. Informal care is then provided privately without any state support and the budget constraint is not influenced by the insurance system.

A number of current laws (e.g. the 'Pflegezeitgesetz' or the 'Familienpflegezeitgesetz') promote the compatibility of informal care and gainful employment.[2] Conditions for the provision of informal care without having to quit employment have improved significantly in recent years (BMAS, 2017). However, the take-up of these rights and benefits seems to be very limited, although official statistics have not been published.[3] This paper only provides indirect evidence on the effectiveness of these policies. The different laws do not affect our identification strategy. Improvements in the institutional framework over time could, however, reduce the size of the estimated effects if take-up increases.

[1]The exact benefits can be accessed via BMG (2017, 2019).

[2]Since 2008 the 'Pflegezeitgesetz' guarantees anyone working in a firm with 15 or more employees to be released temporarily (6 months at the maximum) on a part- or full-time basis when the demand for care arises (BMJ, 2008). Introduced in 2012 the 'Familienpflegezeitgesetz' allows to further reduce the working time to a minimum of 15 hours per week for up to 24 months when employees perform care for close relatives (BMJ, 2011). It includes a loan-like instrument to absorb the related income shock. The 'Act to Strengthen Long-Term Care' from 2015 bolstered the financial basis of the LTC system and provides carers with the opportunity to take time off their care duty for holidays and in cases of illness. It secures a 10 day job leave with benefits in emergency situations to organize the caretaking arrangements.

[3]Firms are not obliged to register the take-up of these instruments which is why official statistics do not exist. According to the German government the take-up of benefits for the 'Familienpflegezeitgesetz' amounted to 219 persons between 1 January 2015 and 31 May 2016 (Bundestag, 2016).

1.3.2 The state pension system in Germany

The German old-age provisions system consists of three pillars: state, employer-based, and private pension insurance schemes. In spite of efforts to increase the prevalence of private schemes, the state pension system is by far the most important pillar. In 2015 the total sum of old-age provisions amounted to 278 billion €, 74% of which originate from the Statutory Pension Insurance Scheme (Gesetzliche Rentenversicherung, GRV). When private income (from interest, rentals etc.) is included, state pension plan benefits still make up 63% of overall net income in retiree households (BMAS, 2016). Certain paths into retirement through the German state pension that differ for men, women, and different cohorts are crucial for our identification approach.[4] Eligibility for retirement benefits mainly depends on the number of years with paid contributions including periods in employment, with voluntary contributions, or recognized non-income periods. The GRV states six paths into retirement differing in the defined normal retirement age (NRA) or early retirement age (ERA).[5] For identification of our main effect we refer to different ERA thresholds for women in the time period 2001-2015:

(i) People who have acquired 35 years of contributions can retire early at the age of 63, but face benefit reductions.[6]

(ii) Women born before 1952 could retire early at the age of 60 if they fulfilled the contribution criteria and were willing to accept benefit deductions.[7] In 2012 the last cohort was eligible for early old age pensions for women at 60.

(iii) People born before 1952 could retire from unemployment if they had 15 years of contributions. Cohorts born until 1945 could use this path into retirement from the age of 60. Those born from 1949 onwards were eligible from an age-threshold of 63. Eligibility age was raised in monthly steps from 60 to 63 for those born between January 1946 to December 1948 per one month of later birth.

Geyer and Welteke (2019) and Geyer et al. (2020) show that the abolishment of women's retirement at age 60 led to a drop in the retirement probability in the group of 60-62 year old women born in the cohorts 1951 and 1952 of around 20 percentage points (pp). Employment increased in the group affected by the reform, yet unemployment and inactivity were likewise raised.

The NRA is 65 for women in our dataset. It defines the reference age for the calculation of deductions under early retirement.[8] Our sample includes the years 2001 to 2015 (sub-section 1.4.1). All aforementioned age thresholds are relevant for early retirement of women. For our main specification we pool women born before 1952 with later-born cohorts. We define the ERA accordingly at 60 years or 63 years. In an alternative estimation with a smaller, but more homogenous sample, we use only women born before 1952 and the applicable threshold at age 60 as an instrument.

[4]See Boersch-Supan and Wilke (2004) for details on the German pension system. Geyer and Welteke (2019) provide an extended overview including the 1999 pension reform and alternative paths into retirement.

[5]An overview is given in GRV (2017).

[6]Since 2014 people who have been born before 1953 and have 45 years of contributions can retire without any deductions at the age of 63. This is not relevant for our observation period.

[7]These women need an accumulated 15 years of contributions, 10 of which have to be after their 40th birthday.

[8]Before 2012 the regular old age pension threshold for men was 65. Since then the regular old age pension threshold is gradually rising from 65 to 67 years for individuals born between 1949 and 1964.The data set contains no persons born after 1949 and aged 65 or older. The relevant old age pension age is 65 throughout our observation period.

1.4 Data, sample & variables

We use the German Socio-Economic Panel (SOEP). Since 1984 households and individuals have been followed on an annual basis to collect information on household structure and socio-demographic characteristics, working biography, income, attitudes, economic behavior, health etc. resulting in about 150 questions. Since 1990 East German households were added. The result is a representative panel study on about 44,000 individuals in around 13,000 households in 2016 (Goebel et al., 2019).

1.4.1 Sample construction

We identify retirement effects on the provision of informal care for women. We follow these women from 2001 to 2015 using SOEP wave v33. The underlying behavioral mechanism is the dissolution of an existing time conflict between labor supply and care as soon as the choice of retirement together with some form of pension benefits become available. If a person is non- or unemployed prior to retirement, there are no time (and/or potentially budget) constraints removed through the transition into retirement. We would not expect an impact on the supply of informal care under these circumstances. Therefore, we eliminate unemployed women who are not yet retired from our main sample. To avoid sample selection around retirement these individuals are removed completely and all of their spells in later stages of retirement are discarded as well. Disabled individuals are also discarded throughout the empirical analysis as they face different choice sets with respect to retirement and care provision. As one dimension of the heterogeneity analysis we only include women retiring from full-time employment into the estimation sample.[9] For the comparative analysis of men we apply the same sample restrictions.

1.4.2 Definition of variables

Outcomes

The SOEP questionnaire contains a question on the allocation of time on a weekday. Since 2001 individuals can report the time spent on taking care of an adult person[10] in need.[11] As the hours-variable is self-reported it is likely that the information is not perfectly accurate.[12] In order to capture the extensive margin of informal care we additionally collapse the hours information into a binary variable that is equal to one when a person spends time on care provision for the elderly and zero otherwise. To avoid linearity assumptions we also define a binary variable for intensive care. This variable is coded one when an individual provides more than 10 hours of informal care per week and zero otherwise. It is used in the heterogeneity analysis to assess whether the demand for intensive care induces a more severe time conflict.

[9] We define this as having worked on average 35 hours per week in the 3 years prior to retirement.

[10] Taking care of children is a separate question, so we can differentiate the two activities.

[11] The exact question is: "What is a typical day like for you? How many hours do you spend on care and support for persons in need for care on a typical weekday?"

[12] 47% of informal caregivers supply 1 hour, around 24% state 2 hours, about 10% provide 3 hours, and the remaining about 18% perform 3 or more hours. A relatively high number of people (1.5%) provide more than 20 hours of care.

Treatment

We use self-reported data to determine whether a person is retired or not. Individuals can state in which months of the previous year they received an old-age pension. This data is matched to the respective year and compared to the exact month of the interview. There are several definitions used in the literature to define retirement (Coe and Zamarro, 2011; Insler, 2014). A RDD becomes more adequate when the retirement information is precise. Given the type of information available in the SOEP, this is the optimal definition to realize a precise age measurement at retirement. Doing so we can use the retirement information until 2015 as it is reported retrospectively until 2016. We can likewise use information on informal caregiving until 2015.

1.4.3 Sample description

Different samples in our empirical analysis are a function of the bandwidth choices around the age-cutoffs for estimation. For our main analysis we employ the ERA as instrument and use a bandwidth of five years before and after the cutoff, respectively. The sample thus consists of women aged 55 (60 years minus 5) to 68 (63 years plus 5) who retire from employment. The resulting sample includes 16,908 person-year observations for 2,624 women (Table 1.1). Around 50.4% of these women are in retirement. The share of retired is higher among caregivers (54.1%) than non-caregivers (50.0%). 20.4% of women in the sample live in single-person households with a share of 7.9% providing informal care. In multi-person households the share of caregivers amounts to 10.8%. More than 84% of all female caregivers live in multi-person households. About 79.1% of women who do not provide informal care live in multi-person households.

Table 1.1: Summary statistics, main sample: women aged 55 to 68.

	Mean	S.D.	Minimum	Maximum
Outcomes				
Hours of Care	0.24	1.12	0	24
Caring Probability	0.10	0.30	0	1
Intensive Care	0.05	0.23	0	1
Covariates				
Retired	0.50	0.49	0	1
Age	61.45	3.89	55.08	68
Kids in HH.	0.13	0.43	0	5
Married	0.69	0.46	0	1
Education	12.16	2.82	7	18
Work. Hours	16.87	18.85	0	98
Health	2.71	0.84	1	5
Observations	16.908			

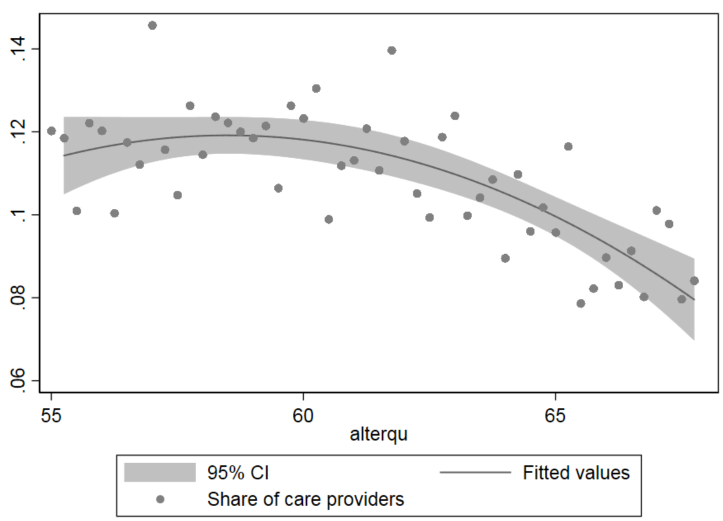
Notes: This Table shows summary statistics of outcome variables and important covariates. S.D.: Standard deviation; HH: Household; Work.: Working.

Source: SOEP v33, own calculations.

The mean age in our main sample is about 61.45 years (Table 1.1). Women provide on average about 0.24 hours of informal care per normal weekday. Around 10% of women in the sample supply positive care hours. About 47% of those informal caregivers supply 1 hour, around 25% state 2 hours, about

10% provide 3 hours, and the remaining about 16.5% perform more than 3 hours of care. A relatively high number of people (0.8%) provide more than 20 hours of care. The mean retirement age is 62.0 for women in the sample. A large standard deviation in the number of working hours shows that we observe individuals at a point of their employment biography when they experience substantial changes in their labor supply. We find that of those women that provide care 80% are married. However, only a significant 5 pp higher probability to be married exists for carers than for non-carers. The probability to provide care is around 2 pp higher for married individuals. The probability to still have a parent that is alive is not significantly different among care providers (49% vs. 50%, respectively). The probability to provide care is slightly lower if both parents are dead (1.7 pp).
The share of caregivers along with a quadratic trendline and a 95%-confidence interval is plotted for our main sample by age for women around the age cutoffs of interest (Figure 1.1). The percentages and relations are consistent with the findings of other descriptive studies on the provision of informal care that are based on alternative data sources (Wetzstein et al., 2015). The share of caregivers peaks between 60 and 65 and declines with higher ages. The graph confirms the considerable variance in the dependent variable. Besides the aforementioned changes in the labor supply status occurring at this point of employment biographies this may also point to some measurement error in the care variable. Figure A1 in the Appendix gives the mean of provided hours of care by quarters of age. The pattern is similar.

Figure 1.1: Share of female care providers by age (in bins of quarters of years of age)



Notes: This figure shows the proportion of care providers among women in the ages 55 to 70 in bins of quarters of years of age as well as a fitted quadratic trend and 95% confidence interval. *Source:* SOEP v33, own calculations.

1.5 Identification strategy

In this paper, we estimate the impact of retirement on informal caregiving activities. We conjecture that eligibility for pension benefits allows individuals to resolve the time conflict between employment and care. Labor supply and the provision of care are decided upon simultaneously. Endogeneity arises irrespective of incentives generated by pension and LTC insurance benefits. One underlying mechanism is selection on unobservables. Individuals' characteristics and preferences determine their behavior in terms of labor supply and retirement decisions as well as the provision of informal care. Another mechanism is reverse causality. Individuals retire (early) because demand for (informal) care arises when family members or close friends become care-dependent. In this case labor supply is adjusted as a consequence of care demand. We are interested in the causal effect in the opposite direction. Does (the dependence on) labor supply crowd out informal care? The identification strategy addresses both issues. We exploit retirement age thresholds in the German pension system that generate exogenous variation in labor supply.

1.5.1 Fuzzy regression discontinuity design

When women reach their ERA and fulfill the contribution criteria they become eligible for retirement benefits. This changes their choice set and budget constraint as retirement with pension benefits becomes available. Eligibility is determined solely through age, i.e. women's 'treatment status' is exogenous. Around ERA thresholds individuals differ only in benefit eligibility and are similar in all other aspects. We exploit this setting within a fuzzy regression discontinuity design (fuzzy RDD) (Battistin et al., 2009; Eibich, 2015; Müller and Shaikh, 2018)). The exogenous variation in retirement behavior created by these instruments is used to estimate local average treatment effects on the provision of informal care for compliers (Trochim, 1984; Lee and Lemieux, 2010; Hahn et al., 2001). We can thus identify the effect of retirement (the related reduction in labor supply) on the care provision for those individuals that react to changed incentives at a threshold.

Identification requires, first, that individuals cannot manipulate their age to select into treatment (i.e. being eligible to retirement benefits before actually reaching the defined age). Second, the potential outcome needs to be smooth around the threshold absent of treatment. There must not be any discontinuous change in the retirement probability by age in the absence of age cutoffs in the retirement rules. Under those assumptions effects of the instrumented retirement behavior on care provision can be causally attributed to the local treatment. In our setting the local average treatment effect (LATE) is specific to those women retiring at an age threshold. Under valid and relevant instruments this approach deals with simultaneity and selection on unobservables.

The institutional setting of the German state pension system strongly incentivizes individuals to retire at sharp cutoff ages (sub-section 1.3.2). ERA thresholds in Germany, set at age 60 for women born before 1952 and at age 63 for cohorts born later, are shown to be used frequently (see Geyer and Welteke (2019); Eibich (2015) and sub-section 1.5.2 below). We define cohort-specific ERA for all women in our main sample to estimate a Two Stage Least Squares (2SLS) model. Retirement (R_{it}) as the treatment variable is an endogenous regressor. The threshold variable I_{it} serves as instrument with $I_{it} = 1$ if $Age_{it} > c$. The cutoff c is defined for women born before 1952 as $c = 60$ and for women born from 1952 onwards as $c = 63$. The first stage captures the impact of the respective threshold on treatment assignment, i.e. the retirement decision:

$$R_{it} = \alpha + \beta_1 I_{it} + \beta_2(Age_{it} - c) + \beta_3(Age_{it} - c) * I_{it} + \epsilon_{it} \tag{1.1}$$

We allow the relationship between the treatment variable R_{it} and the forcing variable centered at the respective cutoff age c, $(Age_{it} - c)$ to be different on each side of the threshold.[13] The parameter β_1 measures the direct effect of crossing the threshold on the retirement probability. The second stage uses the predictions of treatment assignment from the first stage and regresses it on an outcome indicator for care-taking $Care_{it}$:

$$Care_{it} = \gamma + \delta_1 \hat{R_{it}} + \delta_2(Age_{it} - c) + \delta_3(Age_{it} - c) * I_{it} + \mu_{it} \tag{1.2}$$

We analyze different measures of caregiving $Care_{it}$, namely the extensive and intensive margin of informal care for the main analysis and a binary indicator for intensive care in the heterogeneity analysis (sub-section 1.4.2). The effect of interest is δ_1. For relevant and valid instruments the predicted retirement probability carries only exogenous variation and is independent of the error term. There is, thus, no endogeneity bias. In the main specification we estimate the effects for all women in our sample crossing their cohort-specific ERA. In an additional estimation we use solely women born until 1952 and define as threshold c only the ERA at 60 years that applied to this group. We perform a number of robustness checks in terms of bandwidth choice and using non-parametric estimators for the discontinuity (Gelman and Imbens, 2018).

1.5.2 Discontinuities in retirement behavior

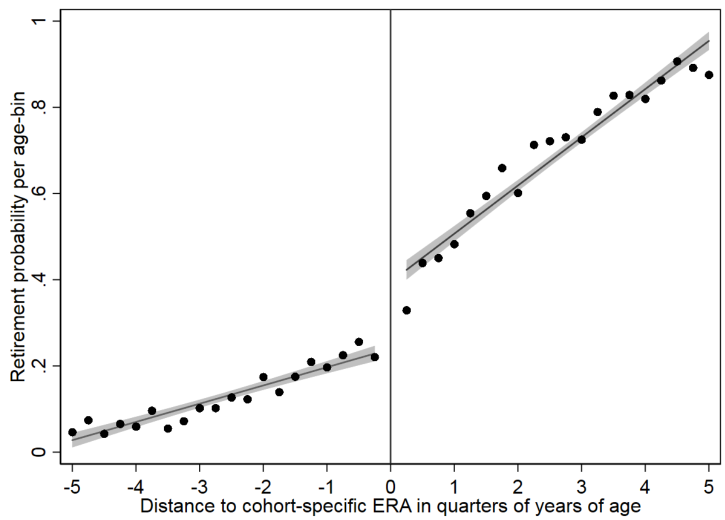
To serve as valid instruments age thresholds need to significantly affect retirement decisions. We therefore depict individual retirement behavior by age to check for jumps in the treatment variable, i.e. the retirement probability. We consider women at their cohort-specific ERA in our main sample. The retirement probability is calculated only on the basis of individuals that are in the labor force or that are retired. Retirement from unemployment is not included as there is no time conflict with informal care. Probabilities are depicted in bins of quarters of age (Figure 1.2). The graph depicts the jump in retirement probability at women's cohort-specific ERA including linear trends. The discontinuity is substantive and roughly amounts to 20 pp.

A similar discontinuity emerges in the graph that is based only on women born before 1952 with the ERA at 60 used as an instrument (Figure A2 in the Appendix). Less than 30% of women are retired before reaching the respective ERA. After crossing the threshold the retirement probability jumps to about 50%.

A look at first stage estimates largely confirms the graphical evidence. For cohort-specific ERA cutoffs with our main sample of all women retiring from employment a jump in the retirement probability of 16.6 pp results (Table 1.2, column 1). Women born before 1952 that retire from employment also exhibit a highly significant 18.9 pp jump in their retirement probability at the age-cutoff of 60 (Table

[13] We define the binary threshold variable as 1, if the individual is older than the respective age cutoff ($Age_{it} > c$). The first stage has more predictive power in comparison to the alternative specification with $D_{it} = 1$ if $Age_{it} \geq c$.

Figure 1.2: Retirement behavior by distance to the ERA



Notes: Each dot represents the mean of the outcome per bin (quarters of age difference to cohort-specific ERA); Linear trend and 95% confidence interval included. *Source:* SOEP v33, own calculations.

1.2, column 4). We find reduced effects of crossing the cohort-specific ERA with a 3-year bandwidth of 11.8 pp and a 16.5 pp jump in the retirement probability when introducing several control variables with a 5-year bandwidth (Table 1.2, column 3).

Table 1.2: First stages estimates - effect of ERA on retirement behavior.

	(1)	(2)	(3)	(4)
Instrument	ERA	ERA	ERA	Age 60
	0.172***	0.121***	0.165***	0.187***
	(0.022)	(0.030)	(0.024)	(0.024)
Observations	10095	5573	10095	8379
Controls	-	-	YES	-
Bandwidth—years	5	3	5	5

Notes: This Table shows effects of crossing the cohort specific early retirement threshold (ERA) on the probability to be retired among women using several bandwidths. Standard errors in parentheses; YES: controls for year of observation, number of children in the household, and marital status; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: SOEP v33, own calculations.

Our main analysis is based on a 5 year bandwidth around the ERA thresholds. Reducing the bandwidth for the main sample with cohort-specific ERA decreases these jumps in the retirement probability. A bandwidth of 2 years results in a discontinuity estimate of 9.7 pp, a further reduction to a 1 year bandwidth leads to an increase of 13.6 pp at the threshold (Table A1 in the Appendix). This pattern is confirmed in the same exercise with the reduced sample of women born before 1952 with ERA at age 60 as single instrument (Table A3 in the Appendix). Statistical significance is reduced only for 1 and 2 year bandwidth estimates due to the smaller sample size. The graphical evidence and the strong and robust coefficients from the first stage estimates confirm that ERA thresholds used here are indeed relevant instruments for the retirement decision.

1.5.3 Validity of identification

One identification condition for the effect of interest is that individuals cannot manipulate the forcing variable that selects them into treatment. Age is an exogenous factor, therefore this assumption holds by construction. Histograms do not exhibit discontinuities in the number of women by age (Figure A3 in the Appendix, upper left picture). A related identification condition is that no apparent discontinuities exist in the number of individuals in the sample and for important covariates that drive the outcome at a threshold. In the age range of interest no jumps in any of the population variables (share of married women, mean of years of education, and children in the household, plotted by age respectively) become apparent for women (Figure A3 in the Appendix).

When women reach their cohort-specific ERA they face the choice to retire, reduce labor supply and claim benefits or keep on working. As stated, many individuals actually use their earliest possible pathway into retirement (Geyer and Welteke, 2019; Keck and Krickl, 2013). Still, retiring is a choice variable opening up the possibility that people select into retirement according to care demand and their willingness or ability to supply informal care takes. This does not threaten identification, changes, however, the interpretation of our estimates slightly: We would still identify the effect of retirement on informal care provision for women retiring at their ERA. However, external validity for later retirement ages is reduced, if the demand for informal care changes at these other cut-off ages. It could also be that those individuals facing a demand for and are willing to provide informal care go into retirement at the ERA because of this reason. The remaining group of women retiring at later thresholds does not face a time conflict between work and care to the same degree. This leads to an upward bias in the estimated parameters in comparison to the underlying parameters for the overall population of women.

Last, we need to presume that independent of treatment (if there were no age cutoffs and no transition to retirement observed for a given individual) there would be no discontinuity in the outcome variable. We therefore need to assume a smooth function of care demand for the individual in the absence of retirement. If there are natural jumps in care demand at official retirement ages, we would simply identify this discontinuity, instead of changes in the provision of informal care that are driven by an exogenous shock in labor supply under a smooth function of care demand.

1.6 Results

First, we discuss 2SLS results for our main sample of women using the cohort-specific ERA as instrument presenting graphical evidence (sub-section 1.6.1) and main regression results (sub-section 1.6.2). We analyze effect heterogeneity in terms of type of previous employment (full-time vs. part-time) and type of care (within vs. outside the household; see sub-section 1.6.3). After a number of robustness checks (sub-section 1.6.4), we conclude this section with a comparison to low-intensity carers (sub-section 1.6.5). In the main specification and the heterogeneity analysis we use a 5 year bandwidth (i.e. a 10 year estimation window around the thresholds). All results include heteroskedasticity-consistent standard errors clustered at month of age level (Lee and Card, 2008).

1.6.1 Graphical evidence on informal care provision

The identification strategy in our ERA discontinuity analysis is essentially a fuzzy RDD estimation. A simple graphical analysis can be informative about discontinuous changes in outcome variables at the thresholds used as instruments.

We show, how the main outcome variables behave around the ERA threshold, introducing a trend line, as well as a 95% confidence interval around that trend line (Figure 1.3). We find that, while the means of respective outcomes per bin are quite dispersed, a small increase in the mean hours of daily care provision occurs at the ERA. Note that few women per bin perform informal care, and that this graph discards the dimension of retirement. We therefore turn to the results from our 2SLS (ERA discontinuity analysis) estimation to get a clearer picture of these effects.

1.6.2 Main estimation results

Results for women retiring from employment at the cohort-specific ERA reveal positive and significant effects of retirement on overall informal care hours. Daily care hours increase on average by 0.8 hours upon retirement (Table 1.3, upper panel). The coefficient is significant at the 1% level. Employed women aged 55-60, i.e. before crossing an ERA threshold, provide on average about 0.2 hours of informal care per week. Thus, the effect is substantial and and driven by women who take up informal care or increase hours of care. The other columns refer to similar estimates based on models with (2) an optimally chosen bandwidth (Calonico et al., 2014), (3) additional control variables (year of observation, number of children in the household, years of education, marital status), and (4) using only age 60 as instrument for retirement behavior in a group of women born before 1952, respectively. We find comparable positive effects on the hours of daily care provision in all of those robustness checks with only some variation in effect size. The effect size increases slightly with an optimal bandwidth, but is less precisely estimated (column (2)). Using only a single ERA threshold yields virtually an identical estimate (column (4)).

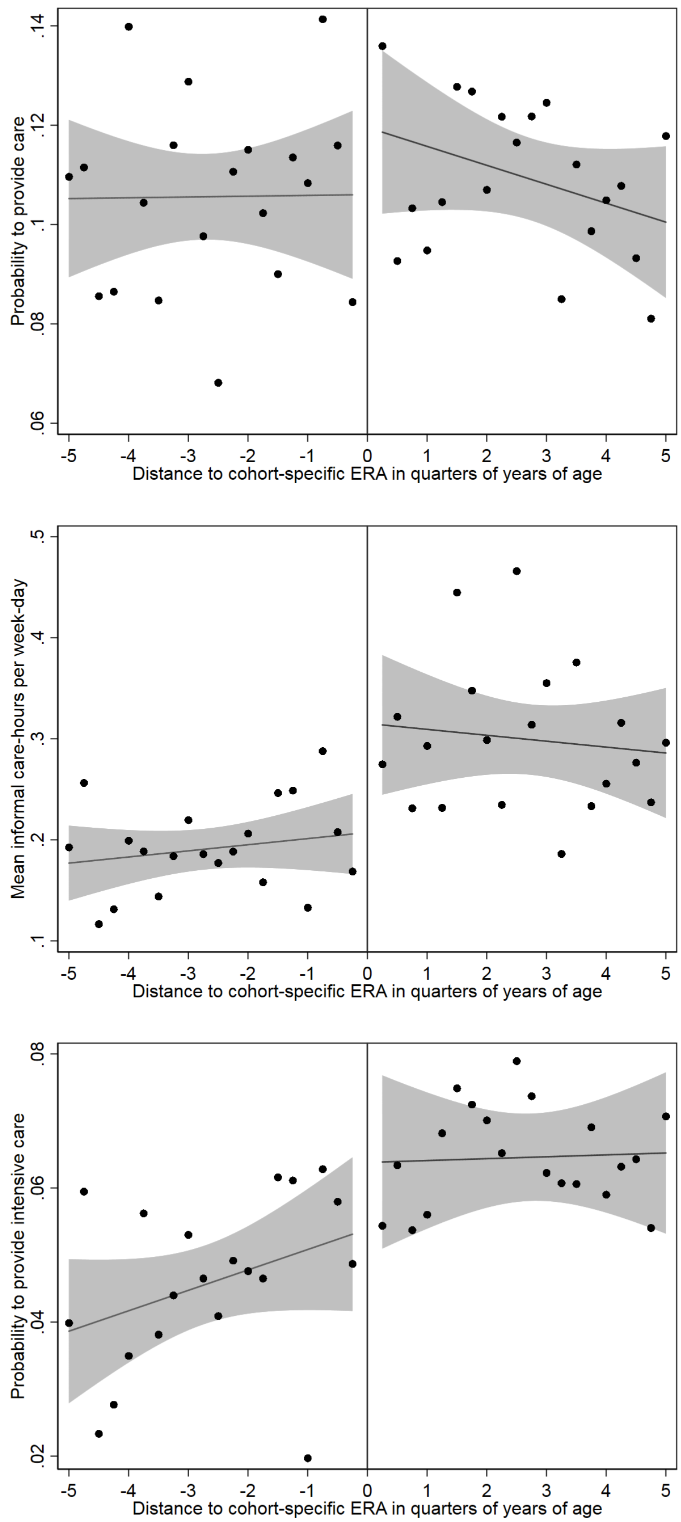
The hours effect is substantially higher for the group of women who already provide some care before they reach their ERA: The provision of informal care increases on average by 5.4 hours per day (Table 1.4). Before crossing their ERA thresholds caregiving women in our main sample provide about 1.7 hours of informal care.

This number almost triples indicating a resolution of a time conflict through retirement. Due to the smaller sample size we are not able to identify a significant effect with an optimal bandwidth (column (2)). Similar to the estimates for the whole sample, we find a slightly larger effect size. Adding controls and using a single cut-off as instrument yields robust results (columns (3) and (4)).

According to our estimates for the extensive margin of care the probability to be a caregiver increases through retirement by 13 pp (Table 1.3, middle panel).[14] The baseline probability to be a caregiver for employed women in the age-range 55-60 is around 9%. The group of caregivers more than doubles through early retirement. Note that this increase is estimated for a specific group of women retiring at their ERA. The substantial effect sizes for care hours and the care probability could be partially

[14]The parameter estimate holds at the mean of the distribution in linear probability models (LPM). Predicted probabilities based on LPM estimates are not bound between 0 and 1.

Figure 1.3: Care provision around the ERA



Notes: This Figure shows the informal care-giving behavior of women around their cohort specific early retirement age (ERA). Each dot represents the mean of the outcome per bin (quarters of age difference to cohort-specific ERA); Linear trend and 95% confidence interval included. Source: SOEP v33, own calculations.

Table 1.3: 2SLS effects of retirement on informal care provision.

	(1)	(2)	(3)	(4)
Instrument	ERA	ERA	ERA	Age 60
	Hours of care provision			
	0.772***	0.898*	0.813***	0.695***
	(0.252)	(0.460)	(0.264)	(0.248)
Observations	10095	6189	10095	8379
Bandwidth—years	5	3.282	5	5
Pre-Treatment mean	0.159	0.159	0.159	0.151
	Probability to provide care			
	0.131*	0.163	0.146*	0.118
	(0.075)	(0.165)	(0.078)	(0.076)
Observations	10095	5484	10095	8379
Bandwidth—years	5	2.935	5	5
Pre-Treatment mean	0.091	0.087	0.091	0.085
	Intensive care			
	0.096*	0.092	0.102*	0.075
	(0.050)	(0.083)	(0.053)	(0.052)
Observations	10095	6705	10095	8379
Bandwidth—years	5	3.562	5	5
Pre-Treatment mean	0.038	0.038	0.038	0.035
Controls	-	-	YES	-
KL.Paap	58.75	-	46.73	63.22

Notes: Main effects and robustness checks, women retiring from employment, women observed in 2001-2015; ERA: cohort-specific early retirement age (all women), Age 60: only age 60 as instrument (women born before 1952); (2): optimally selected bandwidth; Cluster robust (clustered on the month of age level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; YES: controls for year of observation, number of children in the household, and marital status; Kl.Paap: Kleibergen-Paap statistic.

Source: SOEP v33, own calculations.

Table 1.4: 2SLS estimates on the hours of care provision, only care providers before retirement.

	(1)	(2)	(3)	(4)
Instrument	ERA	ERA	ERA	Age 60
Retired	5.434*	8.133	5.592**	4.555*
	(2.785)	(8.474)	(2.817)	(2.429)
Observations	1082	735	1082	887
Controls	-	-	YES	-
Bandwidth—years	5	3.568	5	5
Pre-Treatment mean	1.743	1.759	1.743	1.779
KL.Paap	6.118	-	6.181	6.722

Notes: This Table shows the 2SLS effects of retirement on the hours of provided informal care in the group of women who provide some informal care already before they cross the cohort-specific early retirement age (ERA) Standard errors in parentheses; (2): optimally selected bandwidth; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; YES: controls for year of observation, number of children in the household, and marital status; Kl.Paap: Kleibergen-Paap statistic.
Source: SOEP v33, own calculations.

due to selection into early retirement: The group of women using the ERA could be selective with respect to the demand for and, or their willingness to supply informal care (section 1.5.3). Robustness checks yield similar patterns as for hours of informal care. The effect increases slightly with an optimal bandwidth, but is no longer statistically significant (Table 1.3, column (2)). Including control variables and using a single ERA cut-off does not alter effect sizes or significance (columns (3) and (4)).
The probability to be an intensive caregiver increases by 9.6 pp (Table 1.3, lower panel). With a baseline probability of 4% the effect size of intensive is comparable to overall care. Parameters are only slightly altered in the robustness checks (columns (2)-(4)).
Selecting the optimal bandwidth again yields a coefficient of comparable magnitude that is not statistically significant (column (2)). Extensive margin parameters are in general less precisely estimated with our data than the hours coefficients.

1.6.3 Effect heterogeneity

We analyze effect heterogeneity for our main sample along the following dimensions: informal care provided to people living within the same household, women who were full-time employed before retirement, for highly educated women, the combination of care within the own households with the latter two dimensions (Table 1.5) and by marital status. We discuss effects for overall care hours, the probability to be a caregiver, and the probability to provide intensive care. The sample size for women who provided informal care before retirement is too small for the heterogeneity analysis.
When a caregiver lives in the same household as the recipient, care decisions could potentially be different. People might also have a more precise conception of their own care activities when it takes place within their household.[15] Point estimates are slightly smaller for average care hours and for the extensive margin compared to the main effects. They are also slightly smaller for the probability to be an intensive caregiver. Yet, estimates turn out to be statistically more significant at the intensive and extensive margin (Table 1.5, column (2)).
When estimating effects for women who were full-time employed before retirement we check whether the time conflict between employment and care is more binding. This should yield larger point estimates. Women retiring from full-time employment on average increase their care-provision by about one hour. Their probability to be a caregiver increases by 14.1 pp and their probability to provide intensive care by 14.4 pp upon retirement through the ERA (Table 1.5, column (3)). Compared to the main effect estimated increases are larger for all margins. The same pattern holds when we look specifically at women providing care for people living in their household and retiring from full-time work (Table 1.5, column (5)). Consistent with our expectations women retiring from full-time employment show more substantive increases in the provision of informal care and coefficients become more significant. The time conflict between labor supply and informal care indeed seems to be more binding for full-time employed women.
A further exercise breaks down the main effect by level of education. Descriptive studies have shown that informal care varies substantially by education (Wetzstein et al., 2015). In addition, highly

[15] We discard observations, if care provision is reported in a period, but this person lives in a household which at no point in the observed time span is inhabited by a person in need for care.

Table 1.5: 2SLS estimates: heterogeneous effects of retirement on informal care provision.

	(1)	(2)	(3)	(4)	(5)	(6)
	Hours of care provision					
	0.772***	0.636***	0.984***	1.657***	0.832***	0.998**
	(0.252)	(0.233)	(0.319)	(0.484)	(0.289)	(0.471)
Pre-treatment mean	0.159	0.042	0.137	0.180	0.038	0.056
	Probability of care provision					
	0.131*	0.101**	0.141	0.403***	0.132**	0.155*
	(0.075)	(0.047)	(0.087)	(0.140)	(0.060)	(0.082)
Pre-treatment mean	0.091	0.019	0.084	0.105	0.018	0.026
	Probability of intensive care provision					
	0.096*	0.118***	0.144**	0.279***	0.153***	0.165***
	(0.050)	(0.037)	(0.065)	(0.088)	(0.049)	(0.062)
Pre-treatment mean	0.038	0.012	0.031	0.042	0.009	0.014
Observations	10095	9303	6057	6127	5593	5555
KL.Paap	58.75	63.11	52.19	23.54	55.09	22.48

Notes: Women retiring from employment, cohort-specific ERA, women observed 2001-2015, 5-year bandwidth; (1): main effect – cohort-specific ERA, (2): care within the own household, (3): retiring from full-time employment, (4): highly educated women, (5): care within the own household & retiring from full-time employment, (6): care within the own household & highly educated women; Cluster robust (clustered on the month of age level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Kl.Paap: Kleibergen-Paap statistic.

Source: SOEP v33, own calculations.

educated women exhibit significantly greater employment rates and thus a higher probability to be eligible for retirement at their ERA. All early retirement paths condition on a certain number of contribution years. We use years of schooling and separately estimate the 2SLS model for those who have at least 11 years of schooling. Higher educated women show markedly larger and also more significant effects for all margins of care (Table 1.5, column (4)). This heterogeneity pattern can be replicated for women that care only within their own household (Table 1.5, column (6)).

The final heterogeneity exercise looks separately at married and unmarried women. Effects are more precisely estimated for married women (Table A5 in the Appendix). Validity of the instrument does no longer hold in the smaller sub-sample of unmarried women (Table A6 in the Appendix).

1.6.4 Robustness tests

We perform a two placebo test before we follow the common practice in RDD analysis and test whether the choice of bandwidth around the age cutoff drives our results. We also check the robustness of findings by including several covariates in the estimation procedure. Finally, we show results based on local linear and local polynomial estimators choosing rectangular, triangular and Epanechnikov kernels.

First, we conduct a placebo test. We analyze a sample of women who are unemployed in the relevant age window. This group also uses ERA thresholds for retiring but does not face a time conflict between care provision and labor supply. The instrument still works fine in this sample, without yielding significant effects on informal care provision (Table A7 in the Appendix).

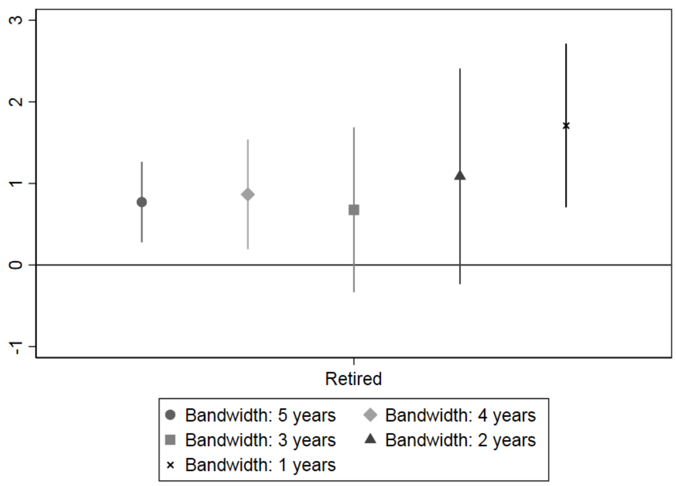
A related robustness check also revolves around the theoretical concept of a time conflict: we use the measure of informal care provided on weekends. We find that hours of care are impacted positively when women retire at their ERA. However, the point estimate is less than half the size compared to weekday estimates and not statistically significant (Table A8 in the Appendix). Neither the probability of care provision, nor intensive care provision are impacted significantly. These results support the interpretation that the main effects are indeed driven by a time conflict between labor supply and informal care provision.

All of the aforementioned results are based on a bandwidth choice of five years. Individuals in the age range of five years around the cutoff age are used for estimation. We check whether narrowing the bandwidth to 4, 3, 2 and 1 years produces different results. This is also interesting for substantive reasons. The 5 year bandwidth for the specification using cohort-specific age thresholds includes besides the ERA at 60 also the ERA at 63 for women born before 1952 as well as the NRA at 65 years which applies to all women in the main sample. Estimating similar models with narrower bandwidths rules out that the paths into early retirement are influenced by other thresholds at higher ages. The trade-off is that identification is based on less observations which produces noisier estimates.

Figure 1.4 graphs point estimates and 95% confidence intervals for women's hours of care provision upon retirement at an ERA for 5 different bandwidth choices. Narrowing the bandwidth from 5 to 2 years does hardly alter point estimates. Confidence intervals are increasing with lower sample sizes. A zero effect is within the boundaries of the confidence interval for the 2 and 3 year bandwidths. A one-year bandwidth, however, not only widens the 95% confidence interval. It also increases the point estimate markedly leading to a statistically significant effect of almost 2 hours of informal care per week.

Robustness tests for the binary outcome, i.e. the extensive margin of informal care, reveal that for all bandwidths between five and two years the 95% confidence intervals include a zero effect (Figure 1.5). For bandwidths between five and 3 years the point estimate virtually does not change. A bandwidth of two years and particularly a bandwidth of one year lead to substantially larger point estimates. The coefficient for the one year bandwidth seems to be upward biased. An increase in the care probability of about 80 pp in this rather small sample does not seem plausible.

Figure 1.4: 2SLS estimates: robustness checks for bandwidth choice, daily hours of informal care, cohort-specific ERA.

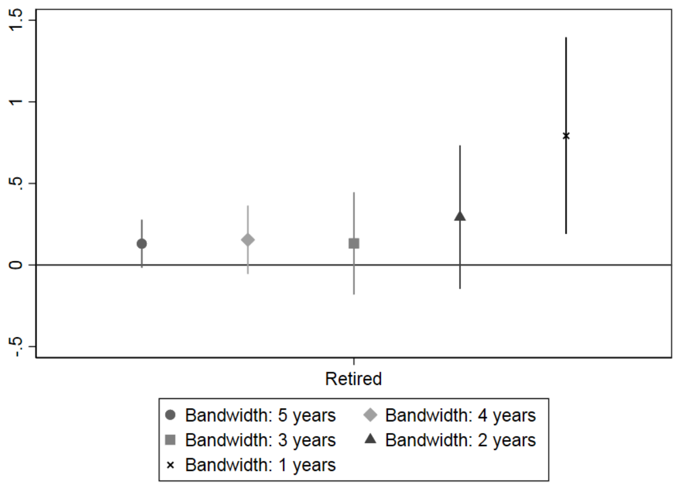


Notes: This figure shows 2SLS estimates of retirement on daily hours of informal care provision by bandwidth choice. ERA: early retirement age. *Source:* SOEP v33, own calculations.

We repeat the robustness tests and limit the analysis to informal care within the household. Point estimates and the 95% confidence intervals for extensive and intensive margin estimates vary less when the bandwidth is reduced (Figures A4 and A5 in the Appendix). Results are significantly different from zero for a 4 year bandwidth. Confidence intervals include a zero effect for all narrower estimation windows. The graphs look very similar when the sample includes only women born before 1952 for whom the ERA at 60 applied (Figures A6 and A7 in the Appendix). Confidence intervals are slightly wider due to the decreased sample size.

In another robustness test a local linear estimator is used and a triangular kernel is chosen for our main sample and bandwidth of 5 years. Results are not sensitive to choosing a different estimator (Tables A9 in the Appendix, column (1)). We also include local quadratic and local cubic polynomials in the specification. Results are sensitive to this specification test (Tables A9 in the Appendix, column (2) and (3)). The magnitude of parameters increases in most cases. However, these increases are not statistically significant. Standard errors also increase which leads to only few statistically significant point estimates. Using an Epanechnikov kernel for our standard bandwidth of 5 years produces results for women in our main sample that are comparable in size and significant for overall informal care and

Figure 1.5: 2SLS estimates: robustness checks for bandwidth choice, probability of informal care, cohort-specific ERA.



Notes: This figure shows 2SLS estimates of retirement on the probability of informal care provision by bandwidth choice.ERA: early retirement age. *Source:* SOEP v33, own calculations.

informal care within the household (Tables A9 in the Appendix, column (4)). The same holds when these robustness checks are done for care provided within the household (Tables A10 in the Appendix). The exclusion restriction in our IV setting holds if only those women that use the institutional setting to retire at the ERA show a discontinuous jump in the respective outcome variables. Women who do not retire at, but either before (never-takers) or after (always-takers) the threshold must not show this discontinuity when they cross the ERA threshold. Figure A8 in the Appendix depicts caring behavior of women retiring from the next retirement thresholds onwards (never-takers, i.e. their retirement age is above 65 or 63, respectively). We do not find any discontinuities for this group. Then, we look at individuals retiring before their ERA (always-takers). No jumps in either of the three outcomes for this group are visual (Figure A9 in the Appendix). In contrast, discontinuities at the ERA cutoff appear, when informal care outcomes are plotted by age for those women who use their ERA threshold for retiring (see Figure A10 in the Appendix). These patterns are confirmed when we look at reduced-form effects of crossing the age threshold (ERA threshold) on care giving behavior in the respective groups (Table A11 for never-takers, Table A12 for always-takers, Table A13 for the whole group of women retiring from employment).[16]

1.6.5 Comparison with low intensity caregivers

We argue that the mechanism behind the effect of early retirement on informal care is an underlying time conflict between employment and care activities before eligibility for pension benefits is reached. The main analysis is focused on employed women as main caregivers in Germany and ERA thresholds are used for identification. According to previous evidence women provide informal care most

[16]We provide additional robustness checks in Appendix A.1.

frequently in the age range around early retirement (Wetzstein et al., 2015; Geyer and Schulz, 2014). Evidently the effect should be weaker for groups with a lower care propensity and completely absent for individuals with an inelastic supply of informal care. We therefore compare our findings with similar estimates for older women at their second possible ERA of 63 years[17] and at their NRA of 65 years. In addition, we analyze men at their ERA of 63 and at their NRA of 65 years.

The ERA at 63 is a valid instrument for women, although the 4.0 pp increase in their early retirement probability is clearly smaller compared to the first early retirement options. The NRA at 65 is a weak instrument for women as shown by the insignificant 1.3 pp jump in their retirement probability (Table A14, columns (1) and (2) in the Appendix). We do not find significant effects for any of the outcomes, neither care hours nor the probability of care overall or intensive care at the ERA 63. The same holds for different margins of informal care at the NRA 65, although results need to be interpreted carefully because of the weak first stage (Table A17 in the Appendix). Most of the point estimates exhibit a negative sign. It seems that we pick up the negative trend in the caregiving probability along the forcing variable (see Figure 1.1 above).

For men, the ERA cutoff at 63 (11.5 pp increase) and the NRA at 65 (16.5 pp increase) turn out to be valid instruments for the retirement decision (Table A14, columns (3)-(5) in the Appendix). We do not find significant effects at any margin of informal care for men, either at the ERA 63, nor at the NRA 65 (Table A18 in the Appendix). Contrary to older women, point estimates are close to zero throughout. To sum up, the comparison with groups of individuals that exhibit a lower care intensity did not yield significant retirement effects on informal caregiving. There is no evidence for a time conflict between employment and care activities for these groups.

1.7 Discussion and conclusion

Causal effects between informal care provision and labor supply have been investigated in both directions of influence. We argue that implications from an increase in life-cycle labor supply in connection with population aging and structural changes on labor markets are potentially important as they may threaten future supply of informal care. Women provide the majority of informal care in Germany as in most other countries. This paper thus focuses on the effect of women's early retirement on their informal care provision. As the share of care providers in the population is highest around their ERA, the question arises whether a transition from employment to retirement induces an increase in the provision of informal care to close relatives and friends. The mechanism behind this potential retirement effect on informal care is argued to be a time conflict between the supply of labor and care as long as eligibility for retirement benefits is not reached.

The endogeneity problem inherent in these simultaneous labor supply and care decisions is addressed within a fuzzy RDD. We exploit a quasi-experimental set-up generated by German retirement legislation. Women are incentivized to retire early at ages 60 and 63. These ERA thresholds serve as instruments for retirement in a 2SLS framework. We estimate the local effect of retirement on indi-

[17] Note that we do not use women born from 1952 onwards for this comparison as the ERA at 63 is their only early retirement path. We only us women born earlier for whom the ERA at 63 is the second option to retire early. Most of those women were already eligible for early retirement at the ERA 60, albeit with larger deductions.

viduals complying to these rules (women retiring at an ERA threshold) for informal care hours per weekday, the probability of caregiving and the probability to provide intensive care. We document instrument relevance and discuss identifying assumptions for this framework. Although applied in other contexts this approach has not been used in the literature on the effects of employment on care provision.

We find positive effects for informal care of women retiring from employment at their ERA. Increases in the provision of informal care are estimated at the intensive and extensive margin and robust to various sensitivity checks. The overall hours effect of about 0.8 hours per normal weekday and increases of about 13 pp in the probability of caregiving overall and 10 pp for intensive care are of plausible magnitude given care statistics for women in that age range. These effects turn out to be robust to a number of robustness checks varying the estimation window, specification and type of estimator as well as a more homogeneous sample with a single ERA threshold.

Based on our rich panel data we are able to analyze effect heterogeneity along several dimensions. Women who supply informal care at home exhibit effects of similar magnitude that are estimated more precisely. This confirms that heterogeneity and measurement error in the care variable is smaller for this sub-sample. Women retiring from full-time employment and highly educated women react markedly stronger. The hours effect of women that already provided some care before retirement is also substantially larger. These findings are consistent with the assumed behavioral mechanisms and confirm previous descriptive evidence on the structure of informal care in Germany. The time-conflict is larger for full-time employed women. Highly educated women have a higher labor market attachment and propensity to supply care. The lack of an effect for groups with low care intensity – older women at their second possible ERA or NRA and men at both age thresholds – fits this behavioral interpretation. We conclude that labor supply indeed puts time restrictions on caregiving activities for women.

What are implications for pension and care policies? Induced by societal change and promoted through equal opportunities policies female labor market participation is on the rise. Women's early retirement threshold at age 60 has been abolished to cope with demographic ageing. Problems for informal care provision seem unavoidable. As shown women increase caregiving significantly through retirement at their ERA. With early retirement options no longer available, it is not clear how this additional care gap will be filled. Coming retirement reforms need to take this into account. Future research needs to assess whether particular care receivers profit from the group of informal caregivers analyzed in this paper. When early retirement is not an option, our findings could also be valid for older age groups. Prevalent increases of the pensionable age would then have similar implications for care supply.

On the other hand, policy-makers started to react to increased employment-related barriers to informal care provision by introducing care-times for employees. Parts of these reforms were not yet enacted in the observation period of this paper. Further research should also focus on the question whether such new LTC policies can effectively diminish the negative relationship between care provision and labor supply around retirement by dissolving the time conflict. Another margin for policy action could be to make the care supply of men more elastic.

Chapter 2

Retirement and informal care provision - Effects of the 1999 pension reform in Germany

2.1 Introduction

Societal aging puts pressure on several pillars of the social security system. The long term care system as one of these pillars is especially affected as experts expect that the group of care dependent elderly individuals growths by up to 45% from 2020 to 2050 in Germany (Jacobs et al., 2020; Rothgang et al., 2012). This group of care dependent as well as the family members often favor informal care[18] (Lipszyc et al., 2012; Blaise, 2018; Mentzakis et al., 2009; Hajek et al., 2018). Additionally, informal care is also often viewed as cost-saving in comparison to stationary care in nursing homes as well as formal home care. Therefore, policy intends to expand the informal care force. Consequently, informal care amounts to 70-90% of the overall care provided to frail elderly (Fujisawa and Colombo, 2009; Geyer and Schulz, 2014). However, the number of care dependent elderly individuals in the society growths faster than the potential supply of informal caregivers. This development threatens the LTC policy objective.[19] Contemporaneously, retirement policy in many OECD countries aims at delaying retirement and prolong working lives while female labor supply is enforced to increase in all age-groups. Retirement policy is supposed to reduce the pressure that demographic changes put on old age provision systems.

While retirement and care policies are mostly conducted without regard to the other, research proposes that counteracting objectives might exist. These counteracting objectives emerge due to a time conflict

[18]The term informal care describes personal care in the homes of the frail person provided by family members or close friends.

[19]See Bundesamt (2017); Wetzstein et al. (2015); Geerts and Willemé (2012) for calculations and statistics on the demand and supply for informal care in Germany and internationally.

on the individual level. As prospective informal care givers are active on the labor market they have to juggle responsibilities on the labor market and informal care provision and not seldom chose only one or the other. For many individuals the availability of retirement benefits can resolve this conflict. Therefore, retirement can lead to an increase in informal care activity and delayed retirement would consequently decline the supply of informal care providers.

This paper is among the first to analyze the impending conflict. I exploit a sizable exogenous shift in the early retirement age (ERA) for German women to estimate consequential reform effects on informal care provision applying a regression discontinuity design (RDD)(Manoli and Weber, 2016; Mastrobuoni, 2009). I exploit variation in retirement behavior that is induced by the 1999 pension reform in Germany. The reform effectively increased the early retirement age (ERA) by up to three years and is therefore well suited for this analysis (Geyer and Welteke, 2019; Geyer et al., 2020). Further, applying an IV estimation I contribute an elasticity parameter between retirement and care provision using the same exogenous policy variation (Nielsen, 2019). Using German SOEP (Socio-Economic Panel) data I can point to differential effects in interesting sub-groups (by education, labor market attachment). Further, I make use of the household dimension of SOEP to identify how changes in care activities of a household member might lead to substitution with other types of care. To cross-validate point-estimates and improve instrument validity I include German SHARE data.

I find that the reform induces a 23 percentage points decrease in retirement probability for German women aged 60-62. The reform leads to a 5 percentage points decrease in the probability that women in the group provide any informal care. This substantive and significant reduction is not severely sensitive to several robustness checks. In a multinomial logit analysis, I find that women less often provide small amounts of care (less than 10 hours per week) while they do not reduce intensive care provision (more than 10 hours per week). Also, I find that in households, that require care of any kind and are inhabited by more than 2 individuals the probability that care from within the household is provided sinks significantly as a woman impacted by the reform inhabits the household. Interestingly, I find no increase in care provided from outside the household in the group. It therefore seems that as women prolong their working lives they reduce the provision of low-intensity care. However, as intensive care is required, women seem to provide the care without regard to the double burden arising.

In the IV strategy I estimate a significant positive elasticity between retirement and informal care provision in the group. The effect size is in line with the parameters estimated in the RDD strategy and points to the fact that a further delay of retirement ages can lead to a problematic reduction in informal care supply.

In both estimation routines I find that women who are more attached to the labor market react stronger. This is probably driven by the fact that this group is most likely to prolong working lives beyond the age 60 due to the reform. As I estimate increased and more significant reactions in groups of women that I proxy to be eligible for women's pension the pattern is confirmed.

This paper contributes to two strands of research. Studies have put focus on the causality between labor supply and informal care activity in the middle part of an individual's working career.[20] Results

[20]Carmichael and Charles (1998, 2003a,b); Heitmueller (2007); Schmitz and Westphal (2017) find negative effects of informal care provision on labor supply. Golberstein (2008); Boaz (1996); Doty et al. (1998); Carmichael et al.

indicate that individuals provide less care if they are active in the labor market but also that care providers supply less labor. Jacobs et al. (2017), Van Houtven et al. (2013), Carr et al. (2018) and Niimi (2017) study the effect of care provision activities on retirement behavior. Their results support the notion that informal care provision hastens retirement. As women in age-groups around retirement (55-69 years old) are the most active informal care providers this is an important margin (Wetzstein et al., 2015; Geyer and Schulz, 2014). Fischer and Müller (2019) show that as women reach their cohort specific early retirement age (ERA) they retire and causally provide more informal care. This paper therefore adds to this line of research as I also estimate retirement effects on informal care provision. Importantly this is the first paper to point to effects of an increase in the ERA on informal care supply. This margin is particularly interesting for policy makers in the design of future pension policy. Secondly, a prominent strand of literature is concerned with the substitutability of formal and informal care (Hollingsworth et al., 2017; Van Houtven and Norton, 2004; Bonsang, 2009; Karlsberg Schaffer, 2015; Bell et al., 2007). As mixed results are found, it remains a question for further research whether formal and informal care are substitutes or complements. I can give further insights into the puzzle using exogenous variation. I contribute results suggesting that formal and informal care are rather complements.

This paper structures as follows: section 2.2 gives an overview of the German public pension scheme, explains how the reform of interest affects eligibility for benefits and briefly introduces the German state system of formal and informal care provision. I describe the identification strategy in section 2.4 and introduce the used data-set in section 2.3. After that I present the results in section 2.5 and conclude in section 2.7.

2.2 Institutional Background

In the following I present the relevant aspects of the German LTC insurance system and the German pension system including the specifics of the 1999 pension reform used for identification.

2.2.1 The state system of formal and informal care provision

Since the introduction of the German mandatory social insurance program for long term care (LTC) in 1995 the financial and social risk to become permanently (at least 6 months) dependent on care is partly socially insured. The Federal Ministry of Health reports that in 2016 around 2.7 million people received benefits from Social Care Insurance. The governmental care insurer defines a strict priority of home-care, consequently nearly 2 million of the benefit recipients were outpatients (BMG, 2017). If a care dependent person fulfils the criteria[21] benefits, which are not means-tested, are granted.[22] Most

(2010); Michaud et al. (2010); Dautzenberg et al. (2000); He and McHenry (2016); Nizalova (2012); Moscarola (2010); Berecki-Gisolf et al. (2008); Mentzakis et al. (2009); Carrino et al. (2019) study the reverse causal effect.

[21]Need for help with at least two activities of every day life (Cooking, mobility ect.) for at least 45 minutes per activity a day and additionally support in household maintenance. In sum a person has to be in demand of 90 minutes of care per day

[22]Benefits in cash for individuals cared informally start from €316 in care level II and go up to €901 in care level V. Three degrees of care dependencies were defined until 2016. A reform introduced a more fine grained system since 2017, defining 5 degrees.

recipients receive monetary benefits in order to support relatives taking on the care responsibilities (informal care). It is also possible to combine informal care with external formal care. Benefits in kind for formal care are generally more generous as the insurance system pays for formal care arrangements directly.[23] These benefits, however don't fully cover the risks of care dependency. Consequently, if a person in need of care wants to live in their own home, informal care often has to be provided alongside the organized formal care arrangements. Some individuals in need of care are still not covered by the care insurance system as they don't fulfill criteria mentioned above to receive benefits of either sort (Geyer and Schulz, 2014). Therefore, informal care is in demand in most settings that require assistance for a permanently impaired person.

Around 4-5 million people are active as informal care providers in Germany, nearly two thirds are women and we observe a trend along the age distribution such that highest amounts of care are provided in the years leading up to retirement (ages 55-69). Still, carers are most often in working ages so that they have to coordinate labor supply and informal care activities. Informal care providers face short term risks including health costs, reduced labor income and mental stress.

The conflict that arises between labor supply and informal care is targeted by the insurance system further by introducing care leave so that employed individuals can take care of relatives' care needs.[24] Further, individuals providing care are granted additional contribution points to their social retirement insurance records which leads to increased benefits. These laws in connection with the benefits granted for informal care activities are supposed to enlarge informal care supply by diminishing conflicts between care provision and gainful employment. Still, the conflict still exists as benefits can not replace income from employment. Individuals facing care demand from relatives or close friends have to deal with a stressful and difficult choice whether and to what extent to provide care. This decision is most often also influenced by the labor market situation.

2.2.2 The state pension system in Germany and the 1999 pension reform

The German pay-as-you-go (PAYG) statutory public pension system is the most important pillar in the German old-age provisions system, insuring 85% of the working age population (Boersch-Supan and Wilke, 2004).[25] The German insurance system defines a normal retirement age (NRA) as well as an early retirement age (ERA), which both differ along an individual's birth cohort, length of the working biography and sex.[26] A pension reform from 1999 introduced a change to the ERA for German women abolishing women's pension.[27] While women born until Dec 31st 1951 could use women's pension to retire early at age 60 if they fulfilled the contribution criteria[28], this pathway into retirement was no longer available for women born from 1952 onward. For them the ERA was effectively raised to at least 63 years as can be seen in Figure 2.1. The contribution criteria for claiming retirement benefits

[23] Those range from €468 up to €1,612 per month.

[24] Employed caregivers are granted the right to take unpaid leave of up to 6 months and in addition an emergency leave for medical reasons of up to 10 days per year is possible. Also, caregivers can take a leave from caregiving of up to 4 weeks per year.

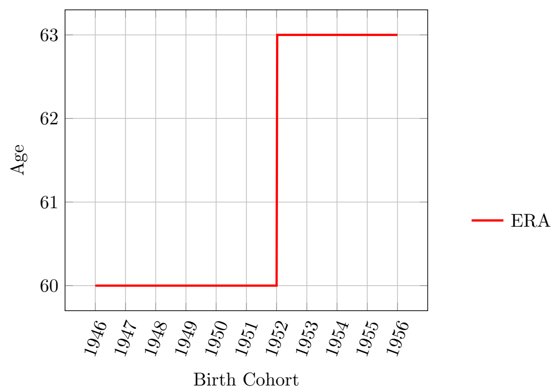
[25] Civil Servants and self-employed are exempted from compulsory retirement insurance.

[26] See Börsch-Supan et al. (2004) for further information on the German pension system.

[27] The Law was announced on December 16, 1997.

[28] Required were 15 years of pension contributions 10 of which had to be accumulated after the age 40

Figure 2.1: Female eligibility ages along birth cohorts



at age 63 (Retirement for long term insured) did not change and as Geyer and Welteke (2019) argue, those retirement paths could be claimed by very similar groups of women. They calculate that around 60% of women born in 1951 were eligible for women's pension at age 60.

Retirement benefits are associated with permanent pensions deductions that correspond to the respective NRA defined in the retirement pathway.[29] Women who used age 60 to retire through women's pension faced higher deductions compared to women who retired through invalidity pension or women claiming pension for long term insured at age 63.[30]

Women born from 1952 onward lose the most important option to exit the labor market and receive benefits before age 63. The only pension type they can claim before age 63 is invalidity pension. As Geyer and Welteke (2019) argue, invalidity pension, while being preferable to women's pension at age 60 due to lower deductions, is characterized by several eligibility criteria that are hard to fulfill. Claiming unemployment benefits, going into inactivity or disability pensions are the remaining options to leave the labor force at age 60. The reform therefore affects women's retirement behavior especially in the ages 60-62, as those born before 1952 could retire at 60 years but for most women born later the earliest retirement age is 63.

[29]Until 2012, individuals could claim pensions through the regular pension (for which 5 years of contributions are required) and 4 additional paths: (1) Pension for women; (2) Invalidity pension; (3) Pension after unemployment or old-age part-time work; (4) Pension for the long-term insured. While pension for women as well as invalidity pension define age 60 as ERA, they define the NRA differently: 65 and 63, respectively. The defined NRA for claiming early retirement at age 63 is increasing from 65 to 67 for cohorts born between 1946 and 1964.

[30]Retiring at age 60 through the pension for women leads to a 18% decrease in benefits compared to using the NRA of 65. It amounts to 10.8% for invalidity pension and 9% for women claiming early retirement at age 63 if born on Jan 1 1952.

2.3 Data set and definition of variables

For my analysis I use the Socio-Economic-Panel-Study (SOEP).[31] Using the SOEP waves 2009-2016 I construct a panel of women born between 1949 and 1954 (the birth years around the cut-off date 1.1.1952) and aged 60-62 (the ages in which women are affected by the reform). To test for heterogeneous effects I look at women who report no unemployment or inactivity spells between the ages 55 and 60. Women in this sample can still go into inactivity or unemployment at age 60. However, this group is most likely to prolong their working lives until the age 63. Further, I can use the rich panel dimension of SOEP to construct a sample of women who collected enough contribution points until age 60 to be eligible for women's pension. In this sample, all women are treated by the reform if born from 1952 onward.

Outcome variables As main outcome variable, I use information from the SOEP on time spend on informal care provision on a normal week-day. This is reported in the main personal questionnaire.[32] I use this information to construct a binary variable, indicating whether an individual provides any informal care or not and an indicator, whether an individual spends more than 10 hours per week on care provision, labeled 'intensive care provision'. For an additional analysis I construct a categorical variable, coded as 0 if no care is provided, 1 if one hour per week-day is provided and 2 is more or equal to two hours are provided.

Further variables Individuals are defined as retired according to the self reported working status information. Most interesting covariates like marital status, educational attainment and whether a child lives in the household can easily be used from reported data in the SOEP. I define high education as reporting a degree of 5 or higher on the ISCED 1997 scale.[33] Also, in SOEP I find information whether the individual cohabits with a care dependent person.

2.3.1 Summary statistics

Table 2.1 reports summary statistics on SOEP data on some important covariates as well as the outcome variables. The constructed SOEP-sample contains 3569 person year observations on 1390 women. Women report to provide a mean of 0.26 hours of care per normal weekday and 10% provide care. The mean age in the sample is 61.47 years and 29% of person year observations are reported as retired, 68% as married. Table B1 in the Appendix shows the number of women in respective ages by birth cohort. The data set is balanced along age and year of birth.

[31] Since 1984 households and individuals in Germany have been followed on an annual basis to collect information on household structure, working biography, labor and non labor income, education and more resulting in about 150 questions. The result is a representative panel study on yearly about 30,000 individuals in around 11,000 households. For more information see Wagner et al. (2007); Goebel et al. (2019). SOEP version v34 (available online: 10.5684/soep.v34) is used.

[32] The exact question in SOEP is: What is a typical day like for you? How many hours do you spend on care and support for persons in need for care on a typical weekday?

[33] This includes Bachelor's degrees from an university or an university of applied science.

Table 2.1: Summary statistics of outcome variables and covariates for women born 1949-1954, aged 60-62.

	N	Mean	Std. Dev.
	Outcome variables		
Hours of Care	3569	0.26	1.26
Caring Probability	3569	0.10	0.30
Intensive caring Probability	3569	0.06	0.23
	Covariates		
Retired	3569	0.29	0.45
Reform	3569	0.49	0.50
Age	3569	61.47	0.87
High education	3569	0.21	0.41
Children in household	3569	0.06	0.23
Care need in the household	3569	0.04	0.19
Married	3541	0.69	0.46

Notes: This Table shows the summary statistics of the main outcome variables and important covariates in the main estimation sample. N: Number of observations; Std. Dev.: Standard deviation.
Source: SOEP v34, own calculations.

2.4 Identification strategy

Estimating effects of retirement on informal care supply the researcher can a priori not distinguish whether informal care is increased due to a decrease in labor supply or whether labor supply is diminished as a consequence of informal care activities. I circumvent this fundamental endogeneity issues by exploiting variation induced in retirement behavior by the 1999 pension reform. In a first step this paper estimates effects of the reform on informal care provision. After applying this regression discontinuity (RDD) setting (Hahn et al., 2001) I use the reform to access retirement effects on care provision, using the the reform as an instrument. The second step allows me to estimate an elasticity between retirement and care provision

2.4.1 Regression Discontinuity analysis

I use the institutional difference between women that are born on either side of Jan 1st 1952 and aged 60-62 to estimate the causal effect of an increase in the ERA on care giving of these women in a RDD approach. Formally, individual care activity is regressed on a binary treatment variable (D_i)- being 0 if the person was born before 1952 and 1 otherwise.

$$Care_{it} = \gamma_0 + \gamma_1 D_i + \gamma_2(z_i - c) + \gamma_3(z_i - c) * D_i + \delta X_{it} + \nu_{it} \tag{2.1}$$

I allow for a trend of the outcome with respect to the running variable - the individual birth-date z_i, exact to the month- centered at January 1, 1952 (c), ($z_i - c$), which can break at the cut-off. The parameter of interest in this specification is γ_1, which estimates an intention to treat effect (ITT) as not all women would have been eligible for women's pension at age 60. I include the year of reporting of each observation in the data-set as well as the exact age of the women as control variables (X_{it}).[34] This RDD procedure identifies the causal reform effect on informal care provision as individuals are not able to manipulate their birth date and therefore select into or out of being eligible for retirement with age 60. Further, one has to assume that absent of the policy the cohorts 1951 and 1952 do not discontinuously differ in retirement behavior or care-taking behavior. Additionally no break in demand for informal care is expected to occur. Geyer and Welteke (2019) argue that other policy changes can not explain differences in retirement behavior between the cohorts. Also I check whether the groups around the cut-off differ significantly on observable characteristics (see section 2.4.3).

2.4.2 Instrumental variable approach

I can make use of the reform in a second setting to explicitly estimate retirement effects on care provision directly. This analysis allows to estimate an elasticity parameter between retirement and informal care. The reform is used as an instrument for retirement behavior.[35] In a first stage I regress retirement (R_{it}) on the binary reform indicator D_i, being 0 if a women is born before 1952 and therefore eligible for retirement with 60 and 1 if not. In the group of women aged 60-62 the treatment dummy should have high explanatory power for retirement behavior.

$$R_{it} = \alpha_0 + \alpha_1 D_i + \alpha_2(z_i - c) + \alpha_3(z_i - c) * D_i + \beta X_{it} + \mu_{it} \tag{2.2}$$

Again, two separate trends of retirement with respect to the running variable (birth date, z_i), centered at the cut-off (1.1.1952, c) are allowed with a break in the trend at the cut-off. In the second stage I regress care activity ($Care_{it}$) on instrumented retirement behavior ($\hat{R_{it}}$) and the same included trends.

$$Care_{it} = \delta_0 + \delta_1 \hat{R_{it}} + \delta_2(z_i - c) + \delta_3(z_i - c) * D_i + \epsilon X_{it} + \omega_{it} \tag{2.3}$$

The parameter of interest (δ_1) estimates the effect of retirement on care provision as a Local Average Treatment Effect (LATE). This parameter gives the average effect of retirement on care provision in the group of women that respond to a change in the instrument- the reform. In this specific case the group of so-called compliers are those women that retire between the ages 60 and 62 as they still face the old legislature. I will throughout the analysis check whether the excluded instrument (the binary cohort indicator D_i) is valid, meaning that its impact on retirement behavior has to be sufficiently large.

2.4.3 Assumptions and Data

The density plot in the Appendix contributes to the argument that women do not select into treatment (see figure B1 in the Appendix). Table 2.2 reports the results from the main RDD analysis using important covariates (marriage status, high education, children in the household and care need in the household) as outcome variables. On a 24 month of birth year bandwidth (BW) I find that women born

[34] I include further control variables to check for sensitivity.
[35] This estimation procedure is similar to a fuzzy RDD estimation, see Lee and Lemieux (2010).

from 1952 onward show positive estimation parameters on all covariates. Only the probability that a care dependent lives in the household is significantly higher in the treated group. In the Appendix in tables B2, B6, B4, B8 one finds the same estimation on 3 different outcomes including also quadratic month-of-birth trends. Further I perform the estimation on a group of women aged 55-60 (Appendix tables B3, B7, B5). Concluding, one can state that as differences between treatment and control group occur, they are largely due to cohort effects and not behavioural reactions to the reform.[36] I will still include these covariates in the main estimation procedures to test robustness of my results. The probability that one cohabits with a care dependent person can potentially be a reaction to the reform and will therefore not be controlled for.

Table 2.2: Reform effects on important covariates (RD-effects).

	(1)	(2)	(3)	(4)
Variables	Marital status	High education	Children in HH.	Care need in HH.
Reform	0.134	0.083	0.015	0.029*
	(0.077)	(0.061)	(0.018)	(0.016)
Observations	2,397	2,412	2,412	2,412
Controls	YES	YES	YES	YES
BW—months	24	24	24	24
Pre treat. pred.	0.721	0.332	0.204	0.0230

Notes: This table show the effects of the reform on important covariates. Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses;* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; HH.: Household.
Source: SOEP v34, own calculations

2.5 Results

Following, I show graphs depicting first insights on the potential effect in the RDD analysis. Thereafter, I discuss results from the multivariate estimation strategies, starting with RDD estimation results. The results from the IV estimation follow.

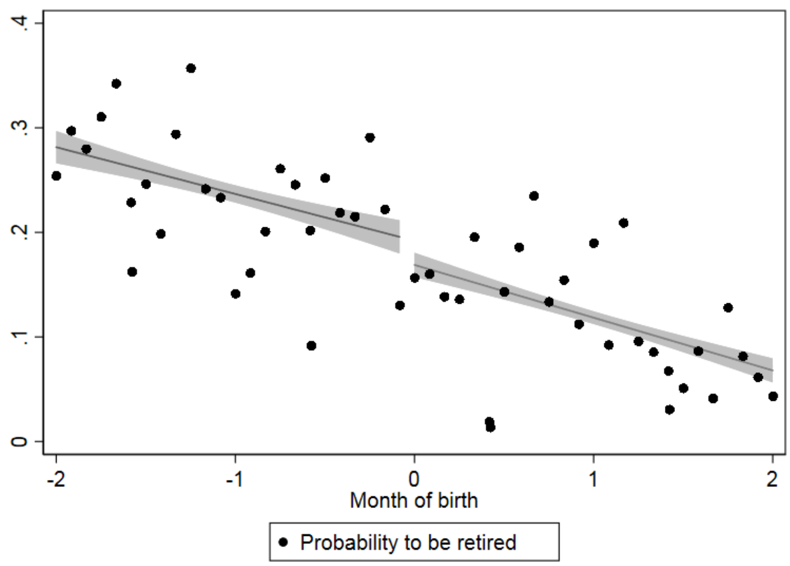
2.5.1 Graphical evidence

The effect assumed in this paper is hypothesized to occur as the reform induces a reduction in the probability of women aged 60-62 to be retired if they are born from 1952 onward. Consequently, I expect, building up on results from Geyer and Welteke (2019) and Geyer et al. (2020), that the probability to be employed increases in the group. Figure 2.2 shows retirement behavior of women in the group of interest along their month of birth. The graph shows a break in the linear trend of the probability to be retired after crossing the cut-off date. A reduction in retirement probability occurs. In the Appendix in figure B3 one can see that while women show an increase in the probability to be

[36]As similarly significant differences (of similar size and sign) between the groups in the three covariates of interest occur in the age group affected by the reform (60-62) as well as in the group not affected by the reform (women aged 55-60), I am confident that I find differences between the cohorts that are no reactions to the reform. The three main covariates can therefore be seen as predetermined.

unemployed, the probability to be employed is not positively impacted by the reform on first sight. Figures 2.3, 2.4 and 2.5 present care taking behavior of women in the group of interest along their birth date in bins of birth-months. I include a linear trend of the respective outcome with the birth date separately before and after January 1st 1952 on a 24 month BW and a 90% confidence interval for the figures. One sees a small drop in the probability to be a care provider that seems borderline significant in this picture. No changes appear in the other two outcome variables. This is unsurprising as one sees that the outcome variable is rather noisy. This occurs as only small amounts of women perform care and I therefore find them dispersed in the bins that rest on small sample sizes per se. This analysis therefore heavily rests on the multivariate RDD estimation procedure.

Figure 2.2: Share of retired women in the ages 60-62 by birth month.



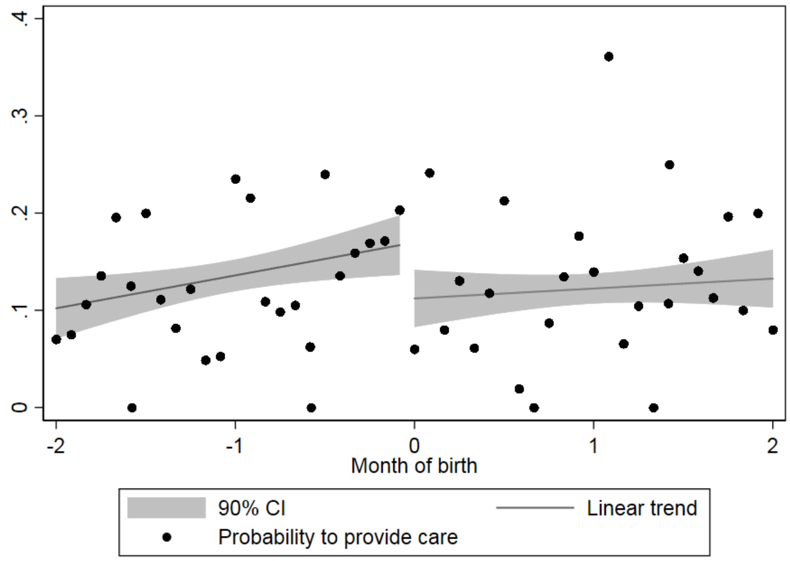
Notes: This Figure shows the probability to be retired for women aged 60-62 who are born around the reform cut-off (0 represents the 1.1.1952) Linear trend and 95% confidence interval included. *Source:* SOEP v34, own calculations.

2.5.2 RD-effects on care activity

I present results from the RDD setting, in which effects of the increase in the ERA on care provision are estimated in a parametric and a non-parametric estimation procedure. The key parameter of interest that is shown in the tables measures the effect of being born from January 1 1952.[37] I include the exact age of the individual and year of reporting as covariates in all specifications and further I control for marital status, cohabitation with a child and educational attainment. In the baseline I use a 24 month BW, which accumulates to a 48 month window of birth-months around the cut-off (women born from Jan 1, 1950 -Dec 31, 1953). In the main tables I show parameters obtained from using an OLS procedure (upper row) and a local polynomial estimation. In columns 1 and 3

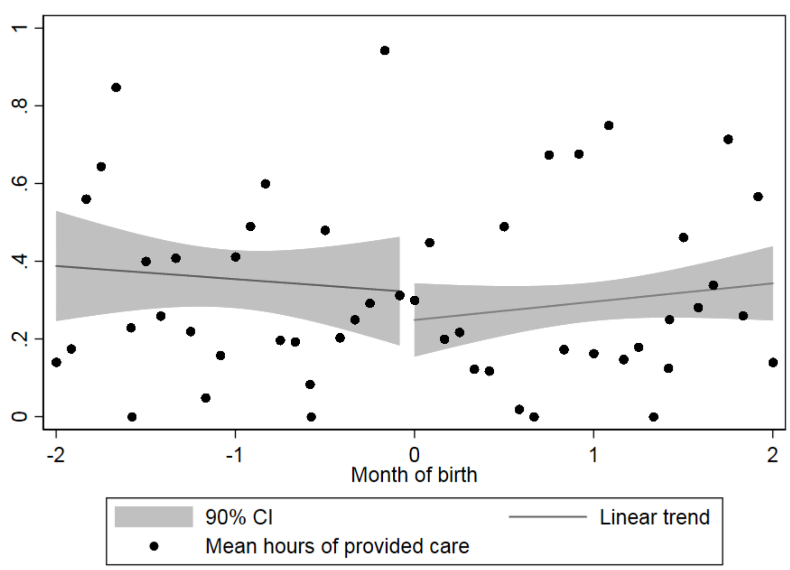
[37] I use STATA's *rdrobust* package to estimate the non-parametric local polynomial procedure , see Calonico et al. (2017)

Figure 2.3: Probability to provide care for women in the ages 60-62 by birth month.



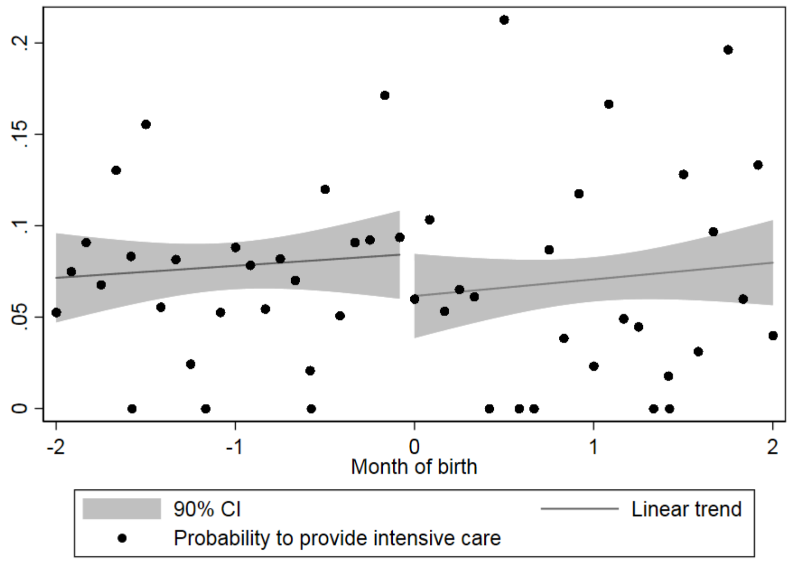
Notes: This Figure shows the probability to provide informal care for women aged 60-62 who are born around the reform cut-off (0 represents the 1.1.1952) Linear trend and 95% confidence interval included. *Source:* SOEP v34, own calculations.

Figure 2.4: Mean hours of care provided per weekday by women in the ages 60-62 by birth month.



Notes: This Figure shows the hours of informal care provision for women aged 60-62 who are born around the reform cut-off (0 represents the 1.1.1952) Linear trend and 95% confidence interval included. *Source:* SOEP v34, own calculations.

Figure 2.5: Probability to provide intensive care for women in the ages 60-62 by birth month.



Notes: This Figure shows the probability to provide hingh intensive informal for women aged 60-62 who are born around the reform cut-off (0 represents the 1.1.1952) Linear trend and 95% confidence interval included. *Source:* SOEP v34, own calculations.

I include the additional covariates and in columns 3 and 4 I include quadratic global (OLS) or local (local polynomial) trends.[38] All estimations are performed employing robust standard errors that are clustered on a quarter of year-of-birth level to take into account the panel dimension of the data.[39]

2.5.2.1 Baseline effects

Using a 24 month BW I estimate a significant (5% level) 5.8 pp decrease in the probability to be a care giver in the group of women born from Jan 1 1952 in comparison to women born before (table 2.3, columns 1, row 1). This parameter is not significantly altered when employing the non-parametric procedure, including further covariates and a quadratic trend (table 2.3, columns 2-4, rows 1 and 3). Effect sizes are slightly bigger in the robustness tests. The hours of informal care activity are reduced due to the reform by around 0.073 hours per normal week-day (see Table 2.3 columns 5-8) and the probability to be an intensive care giver decreases in the group by 2.3 pp (see Table 2.3 columns 9-12). Those two parameters, however, are not significantly different from zero, which does not change in the various robustness checks. Effect sizes, however are largely not sensitive to the checks. The estimated effect sizes make up less than one third or one fourth of a standard deviation on the extensive margin, while they exhibit a 25% decrease in the extensive margin in reference to the pre reform prediction.[40]

[38] In the baseline local polynomial estimation I employ a triangular kernel. Further robustness checks toward employing a epanechnikov kernel and different BWs are performed.

[39] I therefore follow Lee and Card (2008). Cluster robust standard errors are calculated according to Calonico et al. (2014) in the non-parametric estimations.

[40] I estimate the model on a sample of women not affected by the reform and predict the probability to be a care giver for women born at the cut-off.

Appendix Table B9 shows the effect size using a 12 and Appendix Table B10 a 36 month BW. In a 12 month BW the probability to be a care taker is also reduced significantly (10%-level) while effect sizes and significance is more sensitive in the smaller sample size. Using a 36 month BW effects on the binary main outcome are very similar to the 24 month bandwidth. I still find no convincing significant effects on the hours of daily care provision and the provision of intensive care. Sign and size of the estimates are however not altered much.

The fact that the inclusion of further control variables does not alter effects in the main specifications is a sign for high robustness as differences between the group in these covariates were shown to arise. In order to find out where the effect estimated on the extensive margin originates I construct a categorical variable, stating whether no care, non-intensive (1 hour per normal weekday) or intensive (at least 2 hours per normal weekday; at least 10 hours per week) is provided. Estimating a multinomial logit model using the RDD estimation strategy outlined in equation (1) on a 24 month BW, I estimate that women born from 1952 onward show a 5.5 pp higher probability to provide no care but a 3.1 pp lower probability to provide 1 hour of care per weekday. Table 2.4 gives the estimated marginal effects of switching from being born before 1952 to being born from 1952 onward on the 3 categories in rows 5 and 6.[41] The probability to provide intensive care is reduced rather little and the parameter is not significant.

2.5.2.2 Heterogeneity analysis

Further, heterogeneity checks are reported in Table 2.5 in columns (2)-(6). I progress as before, reporting results obtained from OLS estimations in the upper rows and results from local linear (non-parametric) estimations in the lower rows. The heterogeneity checks are performed with age of the individual and year of reporting as controls, I include linear trends on a 24 month BW. I Split the sample with respect to the following traits: High versus low education; women with high vs. women with lower labor market attachment;[42]

I find that highly educated women react stronger (a 11 pp decrease) to the reform on the extensive margin while the parameter is vaguely statistically significant (10%-level), as the sample size is strongly reduced (table 2.5, columns 2). Lower educated women do not react to the reform. Geyer et al. (2020) find that highly educated women have a higher probability to stay in the labor market due to the reform, which according to my results leads them to experience higher effects on their care provision. Women that are more attached to the labor market show slightly increased effects with comparable standard errors. The respective counter group shows again, no effects (column 4). In column 6 I estimate the effect of the reform on a group of women that are proxied to be eligible for women's pension at age 60 regardless of the birth cohort. With a 7 pp reduction I find a slightly bigger effect in this group which reflects what is closest to an average treatment effect (ATT).

Results on the hours of care provision (middle panel of Table 2.5) and intensive care provision (lower panel of Table2.5) are more unclear. I find that highly educated women react stronger and significantly

[41] Table 2.4 shows the estimation output from the multinomial logit regression in rows 3 and 4. The parameters can only be interpreted in sign. The base category is no care provision.

[42] Women with high labor market attachment are those that report no unemployment spells in their ages 55-60 while the rest is women with lower labor market attachment.

Table 2.3: Main RD-effects on informal care provision (24 month BW).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Probability to provide care				Daily hours of care				Probability to provide intensive care			
OLS	-0.058**	-0.055**	-0.069**	-0.067**	-0.073	-0.068	-0.107	-0.105	-0.023	-0.021	-0.035	-0.032
	(0.022)	(0.023)	(0.028)	(0.031)	(0.101)	(0.103)	(0.151)	(0.147)	(0.017)	(0.020)	(0.023)	(0.026)
Local polynomial	-0.062**	-0.061**	-0.083***	-0.083**	-0.086	-0.091	-0.175	-0.175	-0.027	-0.025	-0.049**	-0.047*
	(0.026)	(0.027)	(0.031)	(0.032)	(0.101)	(0.107)	(0.150)	(0.157)	(0.018)	(0.020)	(0.023)	(0.026)
Observations	2,412	2,397	2,412	2,397	2,412	2,397	2,412	2,397	2,412	2,397	2,412	2,397
Data	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP
Polynomial	1	1	2	2	1	1	2	2	1	1	2	2
Controls	YES	YES+	YES	YES+	YES	YES+	YES	YES+	YES	YES+	YES	YES+
BW—months	24	24	24	24	24	24	24	24	24	24	24	24
Pre treat. pred.	0.170	0.170	0.184	0.184	0.310	0.310	0.385	0.385	0.0822	0.0822	0.112	0.112

Notes: This Table shows main RD effects of the 1999 pension reform on informal care provision. Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses;* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy).
Source: SOEP v34, own calculations

Table 2.4: RD- effects on informal care provision- Multinomial logit estimation categorical variable.

Category	(1) No care	(2) Non-intensive care	(3) Intensive care
Estimation parameters			
Reform		-0.647*	-0.389
		(0.352)	(0.245)
Marginal effects			
Reform	0.056***	-0.032*	-0.024
	(0.021)	(0.018)	(0.018)
Observations	2,412	2,412	2,412
Controls	YES	YES	YES
BW—months	24	24	24

Notes: This Table shows reform effects on informal care provision using a categorical outcome variable. Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Non-intensive care: 1 hour of care per weekday, Intensive care: at least 2 hours of care per weekday; BW.: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire)
Source: SOEP v34, own calculations

to the reform in their probability to provide care intensively. Labor market attachment seems to be an important driver in the reform effect on the care taking decision. I perform these estimations on 12 and 36 month BWs as well as on a specification in which I include quadratic trends. On a 12 month BW (table B11) the main pattern is the same, while some standard errors are increased due to reduced sample sizes. In the group of women more attached to the labor market I estimate a more significant effect. The ATT is not significant in this specification. On a 36 month BW the pattern is similar to the baseline heterogeneity check. I estimate a significant 0.5 hours reduction for highly educated women on a 12 months BW, while the rest of the parameters are not heavily impacted. On a 36 month BW no parameter is significant any more. The 12 and 36 month BW specifications support the notion that in the subgroups of highly educated women and those more attached to the labor market intensive care provision is reduced significantly (tables B11, B12). Including quadratic month of birth trends I find that the main pattern stays the same on all three outcomes (table B13). However, I find an increased parameter on the binary indicator of care provision in the group of women more attached to the labor market. Also, intensive care provision is reduced more in this specification in the group of highly educated women as well as those attached to the labor market. Parameters are highly significant. The same changes occur when including a quadratic month of birth trend in the 12 and 36 month BW specification (tables B14, B15).

2.5.2.3 Robustness checks

In the following I report several robustness checks. First I perform placebo estimations before I use another data set to enrich the analysis. Then I show how results differ I I chose a different kernel estimator and change the estimation specification.

Table 2.5: Heterogeneous RD- effects on informal care provision by education, labor market attachment and eligibility.

	(1)	(2)	(3)	(4)	(5)	(6)
Subgroup	All	High Educ.	Low Educ.	Ret. from empl.	With unempl.	Eligible
	Probability to provide care					
OLS	-0.058**	-0.110*	-0.033	-0.069**	-0.012	-0.070**
	(0.022)	(0.054)	(0.028)	(0.027)	(0.096)	(0.028)
Local polynomial	-0.062**	-0.133**	-0.024	-0.086***	0.045	-0.080***
	(0.026)	(0.058)	(0.032)	(0.023)	(0.119)	(0.029)
Pre treat. pred.	0.170	0.183	0.166	0.179	0.146	0.201
	Daily hours of care					
OLS	-0.073	0.083	-0.115	-0.166	0.304	-0.084
	(0.101)	(0.276)	(0.130)	(0.095)	(0.332)	(0.128)
Local polynomial	-0.086	-0.112	-0.032	-0.204**	0.440	-0.136
	(0.101)	(0.205)	(0.120)	(0.102)	(0.375)	(0.141)
Pre treat. pred.	0.310	0.0647	0.401	0.374	0.0876	0.371
	Probability to provide intensive care					
OLS	-0.023	-0.082**	0.006	-0.034	0.023	-0.031
	(0.017)	(0.039)	(0.028)	(0.024)	(0.067)	(0.024)
Local polynomial	-0.027	-0.118***	0.021	-0.048**	0.066	-0.044*
	(0.018)	(0.034)	(0.024)	(0.023)	(0.078)	(0.026)
Pre treat. pred.	0.0822	0.0994	0.0760	0.0904	0.0489	0.0972
Observations	2,412	735	1,677	1,873	539	1,878
Data	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP
Polynomial	1	1	1	1	1	1
Controls	YES	YES	YES	YES	YES	YES
BW—months	24	24	24	24	24	24

Notes: This Table shows heterogeneous results of the 1999 pension reform on informal care provision. Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Educ.: Education; Ret.: Retirement; empl.: employment; BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire).
Source: SOEP v34, own calculations

Table B16 in the Appendix show results from 4 different placebo tests, using only SOEP data: Column 1 shows parameters from an RDD estimation in a group of women aged 63-65, columns 2 in a group of women aged 57-59 (women not impacted by the reform). In columns 3 and 4 I use Jan 1st 1951 and Jan 1st 1953 as cut-off points for estimation. No reform occured at that birth date cut-off's. I find that in neither of the placebo age groups nor on any of the placeo cut-offs is the probability to provide care impacted significantly. The same holds for the probability to provide intensive care. The hours of daily care provision are positively and very significantly impacted in the group of women aged 63-65. This parameter is difficult to interpret. I am most probably picking up some coincidence in the data here.

In a further step I can use data from the Survey of Health, Aging and Retirement in Europe (SHARE) which contains German information on care provision to enrich my sample and cross-check results obtained so far.[43] In the combined data set I find similar negative parameters on the probability to provide care. The reform leads to a 5 pp decrease in care provision on a 24 month BW, which is significant (5%-level) and not severely sensitive to the introduction of further control variables, quadratic trends or the usage of a non-parametric local polynomial estimator (table B26). Going to a 12 month BW I find slightly more sensitive results (table B27). While the parameter size is not impacted much, significance is partly reduced. On a 36 month BW I report slightly reduced point estimates with smaller significance levels (table B28). The heterogeneity checks show similar patterns as the ones reported above: I find higher and mostly similarly or more significant negative parameters in groups of women that are highly educated, more attached to the labor market or eligible for women's pension. When introducing SHARE data, these heterogeneous results are more stable and significant (see tables B31, B30, B32, B34, B33, B35).

As a next step I employ the local linear estimator choosing a triangular kernel and estimating the effect of interest on a BW as selected by the optimal bandwidth selection procedure proposed by Calonico et al. (2014) and implemented in STATA's *rdrobust* package (table B17, column 1). Further I choose an epanechnikov kernel to estimate the procedure on a 12, 24 and 36 moth BW (same tables, columns 2-4). I find that on the optimally selected BW of 16.94 months the probability to be a care provider is reduced by 7.5 pp and highly significant (1% level). Employing an epanechnikov kernel I find that the effect sizes are very similar and highly significant. I find no significant effects on the hours of daily care provision on either of these tests. The probability to be an intensive care provider increases significantly on a optimally chosen 19.97 month BW and on a 12 month BW employing an epanechnikov kernel (10% and 5% level respectively).

At last, I estimate the main effects re-specifying the RDD model from equation (1). In this test I suppress the trend break occurring at the cut-off.[44]. I find that the parameters on the probability to provide care are not altered on a 24 month BW and significant on a 5% level (see table B18). Estimating these procedures on the hours of daily care provision and intensive care provision I find no significant effects, while point estimators are not altered (see table B18).

[43]See Appendix C for an introduction into the data set and a description of its handling.

[44]I set γ_3 equal to 0.

2.5.2.4 Substitutability and demand for formal care

Several studies have looked into the question whether informal and formal care can be viewed as substitutes, finding mixed results. Van Houtven and Norton (2004) find that informal care reduces the utilization of formal home health care and potentially delays the entry into nursing homes for frail elderly individuals. Bonsang (2009) shows that informal care may substitute formal paid domestic help. However, the relationship gets weaker as the health status of the frail person deteriorates. Informal care is a substitute for formal care only when tasks require low skills. According to Bell et al. (2007) and Karlsberg Schaffer (2015) who exploit a reform in Scotland that introduced free formal care, informal and formal care are no substitutes. In this section I assess the reform effect on care provision in care households. SOEP provides information on the household level whether a household is inhabited by a care dependent person and how care is provided in this household- from within or from outside the household.[45] This information on care activity comes from another question in SOEP than the source of information that I use in the above estimation and therefore I can validate effects obtained above using answers from the household questionnaire. Further I can see whether I find substitution effects toward care provided from outside the household.

For this purpose I look at all individuals who live in care households[46] which are also inhabited by a women aged 60-62 and born between 1947 to 1956. Importantly this woman can not be the care dependent person herself. I then compare those households which are inhabited by a woman born pre 1952 (born from 1947-1951 and aged 60-62) with those inhabited by a women born from 1952 onward (born 1952-1956 and aged 60-62). The information on care dependency in the household as well as the outcome variables of interest (care provided from within or without the household) are given on a household level, however I perform the estimation on an individual level to gain more observations.[47] The idea of this estimation is the following: As care households are inhabited by women affected by the reform it should be more probable that no care is provided from within the household but more care is provided from outside the household. Table 2.6 therefore depicts the effect of the reform on the composition of provided care in care households.[48] The results can also give insights on the substitutability of care provided within and from outside the household. Column 1 shows that I find slight negative but insignificant effects of the reform on the probability that care from outside the household is provided. No significant differences appear by household composition (column 2: Households inhabited by more than 2 people; columns 3: Households inhabited by 2 people). However, in column 4 one sees that the probability that care from within the household is provided sinks through the reform by nearly 10 pp, starting from a mean of 90% in the group. This result is driven by households in which more than 2 persons cohabit (see column 5) while no significant effect is found in households inhabited by 2 persons (column 6). First, this result supports the effects

[45] Care from within the household can be provided informally by a household member or formally by a professional care taker living in the household. The same is true for care provided from outside the household. It can be family member living outside the household or care services.

[46] Care households are those inhabited by a care dependent person.

[47] I have to assume that treated and non-treated households (those inhabited by a women born 1952 vs. those inhabited by a women born before 1952) do not differ in household size and composition.

[48] I regress the household specific outcome on the binary indicator whether the women in the household was born before or after Jan 1st 1952 as well as the number of household members and the age of the care dependent individual. Further I include the distance in birth months to the birth cut-off of the woman of interest in the respective household.

shown above on a household level. Second, in this small sample I find no hints that outside care is substituted for reduced inside care. It might more be the case that less care is provided and/or provided more efficiently.

Table 2.6: Effects of the reform on care-mix in households with care-demand.

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome		Outside care			Inside care	
Houshold size	All	>2 Person	2 Person	All	>2 Person	2 Person
Treated	-0.018	-0.144	0.097	-0.093**	-0.132**	-0.022
	(0.076)	(0.099)	(0.135)	(0.046)	(0.057)	(0.081)
Observations	404	215	189	404	215	189
BW—months	60	60	60	60	60	60
Mean of outcome	0.250	0.247	0.254	0.903	0.898	0.910

Notes: This Table shows effects of the 1999 pension reform on care used in households inhabited by a care dpeendent person. Cluster robust (clustered on the household level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
All: Individuals from all households as described; > 2 Person: Only Households as described with more than 2 members; <= 2 Person: Only Households as described with less or equal than 2 members; Outside care: Outside (formal or informal) care provided within the household; Inside care: Inside (informal) care provided within the household; Informal care: Inside or outside care provided by family member or friend; Health: self-reported health status (5 levels, 5: bad, 1: very good); BW: Bandwidth; Data: SOEP data; Further covariates: Distance in birth months to cut-off (treated person in the household)
Source: SOEP v34, own calculations

2.5.3 IV-effects on informal care

In this section I discuss the results obtained in the instrumental variable (IV) approach. I use the reform to instrument retirement behavior and access an elasticity between retirement and care provision.

2.5.3.1 First stage performance

Table 2.7: RD- effects on retirement and employment.

	(1)	(2)	(3)	(4)
Variables	Retired	Employed	Unemployed	Inactive
Reform	-0.230**	0.093	0.069**	0.036
	(0.072)	(0.057)	(0.021)	(0.053)
Observations	1,547	1,547	1,547	1,547
Controls	YES	YES	YES	YES
BW—months	12	12	12	12
Pre treat. pred.	0.378	0.415	0.0310	0.127

Notes: This Table shows effects of the 1999 pension reform on retirement and employment. Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: Yes (Age of individuals and year of questionnaire)
Source: SOEP v34, own calculations

In section 2.5.1 I already portrayed that retirement probabilities sink discontinuously as women aged 60-62 are born from 1952 onward. Table 2.7 shows the effect of the reform on retirement as well as employment probabilities. In a 12 month BW I find an effect on retirement behavior of -23 pp. This as well as the employment and unemployment effects are similar to those found by Geyer et al. (2020) and Geyer and Welteke (2019) which is encouraging as I make use of survey data set that additionally has a lower number of observations. While the probability to be unemployed increases significantly by 6.9 pp due to the reform in this group of women, the probability to be employed increases insignificantly by 9.3 pp.[49] While Geyer et al. (2020) and Geyer and Welteke (2019) find an equal split between effects on unemployment, employment and inactivity they find significant parameters.
For both estimation strategies the first stage effect is vital to identify the effects of interest. In the Appendix in Table B19 one can see how the effect of the reform on retirement changes using different BW sizes. I estimate a 23 pp drop in retirement probabilities for women aged 60-62 on a 12 month BW while the effect decreases to a 12 pp drop on a 24 month BW and a 13 pp drop on a 36 month BW. I find very small and insignificant effect using 2 different placebo cut-off dates (Jan 1 1951 and Jan 1 1953). No discontinuous difference in retirement behavior occurs for women born from 1951 (1953) in comparison to women born in the year(s) before. The reform therefore is a valid instrument for the IV analysis in general. To validate this point I include the first stage F-value in the 2SLS estimation tables as in some subgroups the instrument can have weak instrument properties.

2.5.3.2 Baseline effects

Baseline results are estimated using a parametric 2SLS procedure on a 24 month BW choosing a uniform kernel.[50] Additionally the main tables report results obtained in a local polynomial estimation (lower rows). For both estimators I report parameters on a 24 month BW including several additional covariates (columns 2 and 4) and including quadratic trends with the running variable (columns 3 and 4).
I find that the probability to be an active care giver increases by 47.6 pp due to retirement (5% level significance) on a 24 month BW (see table 2.8 column 1). Neither including further control variables leads to a stark reduction in significance nor does the inclusion of quadratic trends (2SLS estimator, table 2.8 columns 2-4). The point estimate is increased when including covariates and reduced when including quadratic tends. The local linear estimator reports a comparable but less significant point estimate. I find a positive 0.6 hours effect of retirement in the baseline (table 2.8, columns 5-8) that is insignificant and a 19.3 pp increase in the probability to be an intensive care giver (table 2.8, columns 9-12). Those parameters are however not statistically significant from zero. It appears, however that even if the reform has significant effects on retirement behavior that in these samples I face a weak instrument problem as in all specifications on a 24 month BW the first stage F-value is below 12. The same holds for the estimations on a 12 month BW (see table B20 in the Appendix). Estimated 2SLS parameters are smaller on the 12 month BW (25 pp, 0.4 hours and 13.5 pp on intensive care

[49] Appendix Figure B3 shows these outcomes by month of birth in a 24 month BW.
[50] Tables on the 2SLS estimation report, additionally to the parameters and standard errors of the second stage the F-vale of the first stage. As a rule of thumb one should be cautious about 2SLS results when the first stage F-value is below the value of 12.

provision). Using a 36 month BW I obtain first stage F-values around 12 when I include linear trends only. I estimate a 38.4 pp increase in care provision due to retirement in the baseline (table B21, columns 1). Inclusion of further covariates increases the point estimate to 52 pp. I find no reportable and significant IV effects on the daily hours of care provision or intensive care provision in the further BW checks (see tables B21 in the Appendix). Reason for the weak instrument problem could be the small sample size. I therefore turn to two possibilities to increase my sample size: Including SHARE observations into my data set and estimate the same specification as described here;[51] staying within the SOEP data and increase the age group to women aged 57-62 and use a difference-in-difference (DiD) estimator.[52] Including SHARE data I find that the instrument is valid on a 12, 24 and 36 month BW as long as I do not include quadratic trends (see tables B38, B37, B39). I find that the probability to provide care is increased by 34 pp (24 month BW; 23.6 pp on a 12 month BW and 24.5 pp on a 36 month BW). These parameter estimates are highly significant. They are only slightly altered and not less significant when including covariates. Including quadratic trends does not alter significance or parameter size much. However, as stated, the instrument is weak in these cases. Very similar parameters are estimated when employing the local polynomial estimator.

Parameters estimated in this section are local average treatment effects (LATE). The size of parameters has to be interpreted within the linear probability model. The parameter means that in the group of women complying to the reform the proportion of women providing care increases by 47 pp. We can scale this parameter to fit the whole group of interest- women aged 60-62 and born in the year 1950-1953. The reform decreases the probability to be retired in this particular group by 12 pp (24 month BW). Scaling down the parameter from the 2SLS estimation, this corresponds a 5.7 pp[53] reduction in the probability to provide care which is parallel to the results gathered in the RD estimation above. The parameters I obtain in this section are therefore helpful in two ways: First I can verify that the effect size estimated in section 2.5.2 are also obtained in the 2SLS estimation. Second, one can (disregarding the locality of the effect) use the estimated parameter to make an educated guess about reactions in informal care activity to changes in retirement legislature.

In the DiD specification all first stage F-values are well around or above 12 (except on a 12 year BW). In tables B22 I report 2SLS results on a 12, 24 and 36 month BW, for both, the whole sample (columns 1-3) and the group of eligible women (columns 4-6). I find that retirement as induced by the reform, age and cohort thresholds in the group of women aged 57-62 increases care provision by 19.5 pp (12 month BW; 15.6 pp on a 24 month BW and 14.7 pp on a 36 month BW). These point estimates

[51] I can only estimate effects on the probability to provide care when including SHARE data. See Appendix C for further information on SHARE data and the combination of data sets.

[52] This procedure is helpful as it enlarges the sample size for estimation. Also the point estimator on instrumented retirement behavior in the second stage has a slightly different interpretation: It measures the effect of women retiring in the ages 60-62 as they still could do so in comparison to women who can not retire in either policy state (as they are too young) and women who can not retire in the ages 60-62 due to the policy shift. The interaction between being born from 1952 onward and being aged 60-62 is the estimator of interest. I then assume that the difference in retirement behavior that occurs between the age groups is constant absent the reform. The first stage is specified as: $R_{it} = \alpha_0 + \alpha_1 Age(>= 60)_{it} + \alpha_2 Born(>= 1952)_i + \alpha_3 Age(>= 60)_{it} * Born(>= 1952)_i + \alpha X_{it} + \mu_{it}$; The second stage is specified as: $Care_{it} = \delta_0 + \delta_1 \hat{R_{it}} + \delta X_{it} + \omega_{it}$; $Born(>= 1952)_i$ indicates whether a women is born from 1952 onward, $Age(>= 60)_{it}$ indicates that a women is aged 60-62 (while the other group is aged 57-59), X_{it} includes the age of the individual as a running variable as well as the year of observation.

[53] I apply a simple rule of proportion. The reform induces a -12 pp increase in retirement probability. Therefore I need to divide the parameter obtained in 2SLS (0.476) by -8.33 (100/12) to retrieve the estimate of 0.057.

Table 2.8: Main IV- effects of retirement on informal care provision.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Probability to provide care				Daily hours of care				Probability to provide intensive care			
2SLS	0.476**	0.597**	0.328**	0.376*	0.601	0.731	0.506	0.591	0.193	0.223	0.167*	0.181
	(0.215)	(0.301)	(0.166)	(0.219)	(0.737)	(0.960)	(0.561)	(0.656)	(0.126)	(0.174)	(0.095)	(0.125)
Local polynomial	0.389*	0.486*	0.388	0.437	0.537	0.720	0.817*	0.926*	0.171	0.202	0.228***	0.249***
	(0.214)	(0.280)	(0.238)	(0.273)	(0.568)	(0.714)	(0.448)	(0.527)	(0.111)	(0.137)	(0.071)	(0.078)
Observations	2,412	2,397	2,412	2,397	2,412	2,397	2,412	2,397	2,412	2,397	2,412	2,397
Data	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP
Polynomial	1	1	2	2	1	1	2	2	1	1	2	2
Controls	YES	YES+	YES	YES+	YES	YES+	YES	YES+	YES	YES+	YES	YES+
BW—months	24	24	24	24	24	24	24	24	24	24	24	24
First stage F-value	7.546	5.410	4.723	4.080	7.546	5.410	4.723	4.080	7.546	5.410	4.723	4.080

Notes: This table shows the main IV effects of retirement on informal care provision using the 1999 pension reform cut-off as instrument. Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
2SLS: Two stages least square estimation; BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy).
Source: SOEP v34, own calculations

are significant on a 5%-level (12 month BW) or a 10%-level (24 and 36 month BW). In the group of women eligible for women's pension I find comparable estimates that are all significant on a 5%-level. Point estimates on daily hours of care provision are only significant on a 36 month BW and for the group of eligible women on a 12 and 36 month BW. I find that intensive care provision is increased by retirement by 13 pp on a 12 month BW (significant) or 10 pp (12 month BW, group of eligible).

2.5.3.3 Heterogeneities

I perform the same heterogeneity checks as in the reduced form estimation. Table 2.9 depicts the results. I find that only in the group of eligible women the instrument is valid. In this group I find that women increase the probability to provide care by 40 pp (1% significance level.) Further results in the subgroups are not interpretable. The same holds for the effects of retirement on the daily hours of care provision and intensive care provision. No significant effect is estimated. Going to a 36 month BW I find that as women eligible for women's pension retire they increase care giving by 45 pp (significant on a 1% level). The first stage F-value is above 12 in this group. When I include SHARE data (see above and Appendix C) I find that the the instrument is valid in the groups of women with low education and the group of eligible women. In these groups I find that eligible women also show a 40.7 pp increase in care giving probability due to retirement (24 month BW) (see table B40). On a 12 months BW I find that the reform is a valid instrument and retirement increases care taking by more than 90 pp (see table B41). On a 36 month BW I find that women that are eligible for women's pension increase care giving by 45 pp (1 % significance level) due to retirement (see table B42). Including quadratic trends most first stage F-values fall way below the value of 12 (see tables B44, B43, B45).u

2.5.3.4 Robustness

As already discussed above, the results from the IV estimation suffer from weak instrument problems if I only include SOEP data. Including SHARE data, results are more stable and first stages become more valid.

Additionally I perform checks employing optimal BW selection procedures on local linear estimations. I find that on a 32.56 month BW retirement leads to a 44.6 pp increase in care taking (10% significance level) (table B23), while the optimal BW is 18.75 months for the daily hours of care provision (table B23). No significant results are estimated in this specification. On a 17.37 month BW I find that intensive care provision is increased by 20.8 pp (1% significance level) (table B23). On neither outcome I find that choosing an epanechnikov kernel changes results much.

2.6 Implications for caregivers and care receivers

My main empirical results have further implications for caregivers and care receivers. First, I established that employed women indeed face a time conflict, when they are (suddenly) confronted with demand for informal care. The RD results revealed that when women are forced to work longer, they provide mostly less low-intensive care. Women providing high-intensity care do either not want to, or

Table 2.9: IV- effects of retirement on informal care provision. Heterogeneity by education, labor market attachment and eligibility.

	(1)	(2)	(3)	(4)	(5)	(6)
Subgroup	All	High Educ.	Low Educ.	Ret. from empl.	With unempl.	Eligible
				Probability to provide care		
2SLS	0.476**	2.361	0.217	1.117*	0.030	0.407***
	(0.215)	(3.968)	(0.209)	(0.658)	(0.224)	(0.130)
Local polynomial	0.389*	1.123**	0.140	0.825**	-0.101	0.391***
	(0.214)	(0.462)	(0.213)	(0.383)	(0.284)	(0.121)
				Daily hours of care		
2SLS	0.601	-1.773	0.766	2.690*	-0.750	0.491
	(0.737)	(8.541)	(0.822)	(1.453)	(0.883)	(0.642)
Local polynomial	0.537	0.944	0.184	1.956***	-0.986	0.665
	(0.568)	(1.235)	(0.689)	(0.514)	(0.959)	(0.579)
				Probability to provide intensive care		
2SLS	0.193	1.764	-0.039	0.550	-0.056	0.183
	(0.126)	(3.195)	(0.180)	(0.337)	(0.163)	(0.120)
Local polynomial	0.171	0.993	-0.120	0.458**	-0.147	0.215**
	(0.111)	(0.639)	(0.150)	(0.187)	(0.189)	(0.103)
Observations	2,412	735	1,677	1,873	539	1,878
Data	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP
Polynomial	1	1	1	1	1	1
Controls	YES	YES	YES	YES	YES	YES
BW—months	24	24	24	24	24	24
First stage F-value	7.546	0.222	9.242	1.681	7.685	13.98

Notes: This table shows heterogeneous effects of retirement on informal care provision. Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
2SLS: Two stages least square estimation; Educ.: Education; Ret.: Retirement; empl.: employment; BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire).
Source: SOEP v34, own calculations

cannot reduce care hours (Tables 2.3 and 2.4). Consequently, more, high-intensity caregivers face a double burden of labor supply and informal care provision. Demographic trends, structural change on the labor market, and pension reforms, aggravate this problem. Previous literature has shown that this enlarged double burden has negative health consequences for caregivers. Schmitz and Stroka (2013) investigate the consequences that the provision of informal care in combination with labor supply has on caregivers' health. They find that the double burden of informal care provision and full-time work increases the intake of drugs. They conclude that informal care may have deteriorating health effects for caregivers, if they need to work and generate labor earnings at the same time. Bremer et al. (2015) and Hiel et al. (2015) come to similar conclusions. Unfortunately, the identification of health effects that result from a double burden is beyond the scope of this paper. The research design does not allow to also identify health effects. I cannot disentangle the impact of the double burden from the direct effect of retirement on health (Eibich, 2015).

Findings from the RD and IV results confirm that women who are not allowed to retire early and must work until later ages provide less informal care. I also find that low-intensive informal care is not compensated by care from outside the household. This means that care-dependent persons receive less overall informal care. Increased labor market participation and prolonged working lives of women in combination with less early retirement options reinforce this effect. Several studies point out the importance of (low-intensity) informal care for health outcomes of care recipients. Hu and Li (2020) document that the supply of informal care may reduce the progression of functional limitations among elder people. Especially low intensity care is found to have these effects. Wu and Lu (2017) show furthermore that informal care can also improve the health behavior of the elderly, especially among those with chronic diseases. This in turn has important positive health effects, especially for chronically ill persons. Chon et al. (2018) find that social interaction is beneficial for the health outcomes and the progress of frailty among elders. Similarly, the well-being of care receivers may suffer, when low intensity informal care is not available. Social interactions with known persons seem to play a particularly important role.

2.7 Conclusion

In this paper I investigate the causal effect of retirement behavior on informal care activity using a large increase in the early retirement age for German women. In a first step I estimate a regression discontinuity design to uncover effects of the retirement reform on informal care provision. I then use the reform to instrument endogenous retirement behavior. Using this identification I can access an elasticity parameter between retirement and informal care giving. I provide evidence on conflicting objectives in care and retirement policy showing that as retirement is mechanically delayed, affected women provide less care. This is one of the first papers to tackle retirement effects and pension reform effects on informal care activity.

I apply the estimation strategies to SOEP-data and find that the reform significantly decreases the probability of women aged 60-62 to be informal care givers by around 5 pp. As in the reform group of interest around 12% are active as informal care providers this change is substantive. It amounts to a third of a standard deviation of the outcome variable. I find no conclusive and significant effects on the daily hours of informal care provision in the standard specification. The variation in care behavior appears to stem from a reduced probability of women to provide non-intensive (one hour of care per weekday) care. Women that are more attached to the labor market show more pronounced effects of higher significance. This shows that on the one hand the underlying mechanism is a time conflict that is stronger for women with a lower labor supply elasticity. Further, highly educated women have proven to react stronger in their employment probability to the reform. Consequently, this group shows a higher reduction in informal care provision. As the reform effectively impacts only the group of women who fulfill contribution criteria I estimate an intention to treat (ITT) effect. Using SOEP data I can proxy eligibility for women's pension on both sides of the threshold to estimate what is closest to an average treatment effect (ATT). I estimate a slightly bigger effect of 7 pp that is equally significant. Further robustness checks reveal that the estimated parameters are not sensitive to standard changes in the specification. I find a significant reduction in the probability that care is provided from within the household in those households cohabited by a care dependent person and a women affected by the reform. As no increase in out-of household care provision is found, it seems that less care is provided. Further I uncover that retirement leads to increased informal care activity in the local environment of the treatment by around 40 pp. This effect size corresponds to the estimates obtained in the RD analysis. It reveals that as one reduces the opportunities for women to leave the labor market via the state pension system in this particular age-group their informal care activity is reduced. All results show that retirement seems to affect the informal care decision. As higher labor market attachment leads to higher effects in both specifications I suggest that these findings point to effects of the labor market status on informal care provision.

The findings contribute to research in several ways: First, I uncover that the increase in ERA that was introduced in Germany leads to unintended behavioral responses. As women have to delay retirement they react by decreasing their informal care provision. As care policy is designed to increase the supply of informal care, this effect is alarming for the policy maker. Care policy and retirement policy can not be conducted without regard to one another. The underlying research question on effects of labor supply on informal care provision is concerned with causality with regards to the decision making process. Using this retirement reform I uncover that at the later part of an individual's working career labor supply acts as a barrier to care activity and reaching eligibility criteria for retirement benefits solves this time conflict and informal care provision is increased. As I find that mostly non-intensive care provision is reduced, it seems that non-vital care responsibilities are abolished as women prolong their working lives. These are important to the care receiver as human interaction has an important effect on well-being. The point is stressed as no out-of household care substitution is found in the group that shows reduced in-household care provision. Intensive care provision, that is vital to health and livelihoods of sick and frail elderly is, however taken on irrespective the labor supply status. This points to the fact that individuals take on very burdensome care demand as they either see no substitution possibilities or they feel responsible. However, as on average also this group's labor supply is increasing the developments in retirement reforms induces more stress and hardship for the group.

Chapter 3

The effect of unemployment on care provision

3.1 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 (Gusmano and Okma, 2018; van Groenou and De Boer, 2016; Geerts et al., 2012). 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 (Lipszyc et al., 2012; Blaise, 2018; Mentzakis et al., 2009; Hajek et al., 2018). 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.[54]

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 use a difference-in-differences matching estimation procedure, similar to Everding and Marcus (2020). The analysis is 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. 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

[54]See Bauer and Sousa-Poza (2015) and Lilly et al. (2007) for reviews.

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. Heitmueller (2007); Jacobs et al. (2017); Van Houtven et al. (2013); Carr et al. (2018); Niimi (2017) among others find negative short term effects of providing informal care on labor market outcomes.[55] 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 2 percentage points; Mentzakis et al. (2009); Michaud et al. (2010); Moscarola (2010); Nizalova (2012); Stern (1995); Golberstein (2008); Fischer and Müller (2020); Bergeot and Fontaine (2020); Carrino et al. (2019), 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 no 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. Methodologically, our paper is related to studies that exploit variation in employment induced by involuntary job loss, see e.g. Halla et al. (2020), Marcus (2013) or Everding and Marcus (2020).

The remainder of this study is structured as follows: Section 3.2 describes the institutional setting of the long term insurance and unemployment insurance in Germany. Section 3.3 explains the identification strategy. Section 3.4 describes the data and variables used in the estimation. In Section 3.5 we present the results along with their interpretation and relates the findings to the effects of other studies. Lastly, section 3.6 concludes.

3.2 Institutional Background

Before we turn to the empirical analysis we provide a short overview about the relevant institutional setting in Germany which is important for the interpretation of the results: 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

[55] Schmitz and Westphal (2017), Skira (2015) and Korfhage (2019) can point to long term consequences of informal care provision.

Germany provides financial support during unemployment which increases the potential to engage in informal care provision.

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3.2.1 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)[56]. Table 3.1 provides details about the five care levels with information about requirements, benefits and the share of recipients of the LTCI in the respective level.[57]

Table 3.1: Care levels in Germany

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

a. Individuals 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 (Pflegedienste-in-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 are far lower that 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 were cared for at home and 0.8 million in institutionalized care facilities. Around 51% (2.1 million) of all

[56] Formerly there were only three care levels, these were extended to five levels in 2017

[57] Although 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.

recipients were cared for exclusively informally in their own home, 23% (0.9 million) received care including some form of formal care.[58] Thus, in Germany the largest share for frail elderly receives informal care.

According to the data of the Socio Economic Panel study (SOEP)[59] 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, SOEP data shows 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.[60]

3.2.2 Unemployment benefits in Germany

Depending on their working history unemployed individuals either receive unemployment benefits (ALG I) or means-tested transfers (ALG II)[61]. 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.

3.3 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 (Meng, 2012; Heitmueller, 2007; 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) 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 3.2 the treatment group and a control group with this broad definition

[58] See Bundesamt (2020) for information about care dependent in Germany.
[59] See Section 3.4 for more information.
[60] Own calculations in SOEP data, see also Fischer and Geyer (2020).
[61] For a more detailed discussion, see e.g. Haan and Prowse (2015)

significantly differ in various dimensions. Therefore, we use matching techniques 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.

Matching procedure

We apply the entropy matching scheme proposed by Hainmueller (2012). The entropy matching 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 match those in the treatment group.[62] 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 matching scheme calculates balancing weights that are non-negative and 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 matching covariates there are employment related variables such as: Tenure, Job worries, Industry, Labor income and Company size.[63] As mentioned above, we only match on pre-treatment values for the treated individuals. In a robustness check we present results obtained applying propensity score weighting.

Difference-in-differences matching 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. We first present the model in levels

$$Y_{it} = \beta + \nu POST + \gamma D_{it} + \delta(POST * D_{it}) + \eta X_{it} + \kappa(POST * X_{it}) + \phi Time + \tau(POST * Time) + u_{it} \tag{3.1}$$

where Y_{it} 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_{it} includes observable characteristics.[64] and $Time$ stands for years fixed effects. The parameter of interest if δ.

We estimate the model in first differences. For the treated observations ΔY is the difference in the outcome variable in the year before the plant closure and the periods after while for the control group

[62]For 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.

[63]See Table 3.2 for a full list of matching variables.

[64]We use the set of covariates also used in the matching step.

it is the difference over the same time period. The final estimation equation therefore is:

$$\Delta Y_{it} = \nu + \delta D_{it} + \kappa X_{it} + \tau Time + uit \tag{3.2}$$

.

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 $t+1$. For treated individuals observations after the second period of treatment are not considered. In an additional analyses we also show effects if we only consider the treatment in period t and if we consider treatment also in $t+2$.

3.4 Data

For our analysis we use longitudinal survey data from the German Socio-Economic Panel (SOEP).[65] 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 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 spend on informal care for people in need on a normal weekday (excluding children).[66] From the variable measuring daily hours spend 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 informal care.

3.4.1 Control variables

The SOEP contains a large set of information with variables such as health status, relationship indicators, age, perceived job security etc.[67] which we use for the matching and as covariates in the DiD estimation. In Table 3.2 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

[65]For more information about the SOEP, see Goebel et al. (2019).

[66]The 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.

[67]The exact definition of the control variables is included in the Appendix Table C1.

reported in Table 3.2 are used in the matching step and as control variables in the DiD estimation. As mentioned above, treated individuals (Column 3) 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 collar 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 matching, the control group values are markedly closer to the treatment group values (Column 4).

A set of predetermined variables that is used in the matching 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. Halla et al. (2020); Marcus (2013); Everding and Marcus (2020) 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 variabel on the CASMIN-Classification.[68] 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 3.3 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% after treatment.[69] 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.

3.5 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. Table 3.4 presents the overall effects of the analysis. In the first two columns we show the results of the DiD estimates without matching and without (Column 1) and with covariates (Column 2). Column 3 includes the DiD results with matching but without covariates. Finally, in Column 4 we account for

[68] See Brauns et al. (2003).

[69] We do not match on the pre-treatment outcome variable.

Table 3.2: Descriptive statistics - covariates

Variables[a]	Control group	Treatment group	Weighted control	Raw difference[b]
Age[c]	44.89% (8.97)	45.79% (9.45)	45.76% (9.44)	0.03
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 (31294)	26825 (18225)	26512 (17496)	313
Tenure[d]	13.40 (9.90)	11.44% (10.79)	11.16 (10.32)	0.29
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	101,836	

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.

Table 3.3: Descriptive statistics - outcome variables

	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

Notes: This Table shows statistics of the main outcome variables in the (un-)weighted control group and in the treatment group differentiated by treatment timing. 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 3.3 for further detail.
Source: SOEP v35, own calculations.

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 cluster robust standard errors, clustered at the personal level, are reported.[70]

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). About 80% of all care providers report 1 or 2 hours of care provision on a normal week-day. This means that a change in the caring status is most often a change from no care to 1 hour per weekday. This explains why the effect sizes for both variables are in the same range.

[70]We follow Everding and Marcus (2020) in clustering standard errors. Table C3 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 the matching step. They advise to cluster on the level at which matching 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.

Table 3.4: Effect of unemployment on informal care provision

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	-	√	-	√
Weighting	-	-	√	√
Observations	129,637	101,836	101,836	101,836

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 3.2. 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
Source: SOEP v35, own calculations.

3.5.1 Heterogeneous effect by gender, education and marital status

The literature has documented that women provide most of the informal care (see as well Table 3.3). 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 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 impacts 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 matching algorithm for men and women separately to construct gender specif control groups (Table 3.5).

The change in the probability of becoming caregiver when entering unemployment is lower for men than for women. While men increase the probability to be an informal care giver by 2.7pp, women show an increase of 3.1pp. At the same time women increase the daily hours of care-giving by 68%. The effect for men is 360%. Thus men increase care-giving less in absolute terms, but given the low pre-treatment levels they increase care-giving more in relative terms.[71]

Further, we test if results vary by education by including an interaction term between low education and treatment.[72] Table 3.6 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

[71] Appendix Table C5 shows that results are similar when using the full sample with interactions by gender.

[72] 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 matching step separately. We perform further heterogeneity tests using this interaction procedure for this reason.

Table 3.5: Effect of unemployment on informal care by gender

	(1)	(2)	(3)	(4)
	Males		Females	
Care provider	0.027*	0.027**	0.031*	0.031**
	(0.015)	(0.013)	(0.017)	(0.013)
Pre- Treatment Mean	0.013	0.013	0.039	0.039
Hours of care	0.046**	0.045**	0.048	0.048*
	(0.022)	(0.019)	(0.036)	(0.029)
Pre- Treatment Mean	0.013	0.013	0.068	0.068
Controls	-	√	-	√
Weighting	√	√	√	√
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 3.2. 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
Source: SOEP v35, own calculations.

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 3.4pp 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. The effects for higher educated groups (full sample, men and women) are still positive but insignificant.[73] One reason for this pattern might be related to the treatment and the population (see as well Section 3.6). The large majority of individuals which face a plant closure have lower education (77% of all treated are lower educated). Another reason might be related to credit constraints: 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 3.8 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.

[73] Appendix Table C4 shows results if we use the ISCED classification for the definition of low education. Effect sizes and significance levels are practically the same.

Table 3.6: Effect of unemployment on informal care by education

	(1)	(2)	(3)	(4)	(5)	(6)
Group	Full sample		Men		Women	
	Care provision					
Low education	-0.001	-0.005	-0.002	-0.011	-0.004	0.003
	(0.003)	(0.006)	(0.004)	(0.007)	(0.006)	(0.009)
Treatment	0.018	0.018	0.010	0.014	0.026	0.022
	(0.018)	(0.017)	(0.027)	(0.026)	(0.024)	(0.019)
Treatment & low education	0.038***	0.034***	0.038**	0.026**	0.033	0.045**
	(0.013)	(0.012)	(0.017)	(0.013)	(0.021)	(0.018)
	Hours of care					
Low education	0.004	-0.007	0.005	-0.008	-0.013	-0.014
	(0.007)	(0.011)	(0.006)	(0.011)	(0.019)	(0.023)
Treatment	0.014	0.015	0.015	0.014	0.008	0.003
	(0.026)	(0.023)	(0.027)	(0.027)	(0.046)	(0.036)
Treatment & low education	0.082***	0.072***	0.075**	0.062**	0.085	0.091**
	(0.029)	(0.026)	(0.034)	(0.028)	(0.055)	(0.044)
Controls	-	√	-	√	-	√
Weighting	√	√	√	√	√	√
Observations	102,497	102,497	58,883	58,883	43,614	43,614

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 3.2. 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
Source: SOEP v35, own calculations.

3.5.2 Robustness tests

In the following we provide several robustness analyses with supporting evidence for our empirical specification. First, in Table 3.9 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 matching procedure. Instead of using entropy matching, we calculate propensity score weights in the first step to construct the control group (Table 3.10).[74] We find again a significant and positive effect of unemployment care provision. Points estimates are slightly larger than when using entropy balancing weights.
Finally, we show how results vary when we change the period length. As mentioned above, in the main specification, we define the treatment indicator as 1 in period t, in which the plant-closure

[74]Control 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 C7 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.

Table 3.7: Effect of unemployment on informal care by marital status

	(1)	(2)	(3)	(4)	(5)	(6)
Group	Full sample		Men		Women	
	Care provision					
Married	0.001	-0.009	0.002	-0.017*	-0.001	-0.002
	(0.003)	(0.006)	(0.005)	(0.010)	(0.006)	(0.008)
Treatment	0.022	0.018	0.002	0.001	0.042	0.039**
	(0.014)	(0.013)	(0.005)	(0.011)	(0.028)	(0.020)
Treatment & Married	0.032**	0.024*	0.036*	0.017	0.023	0.024
	(0.015)	(0.012)	(0.020)	(0.016)	(0.021)	(0.017)
	Hours of care					
Married	-0.005	-0.019*	-0.003	-0.022	-0.014	-0.021
	(0.008)	(0.011)	(0.007)	(0.016)	(0.017)	(0.021)
Treatment	0.023	0.022	-0.001	0.003	0.043	0.044
	(0.015)	(0.016)	(0.006)	(0.016)	(0.030)	(0.029)
Treatment & Married	0.051*	0.037	0.056*	0.036	0.035	0.028
	(0.027)	(0.024)	(0.029)	(0.029)	(0.053)	(0.040)
Controls	-	✓	-	✓	-	✓
Weighting	✓	✓	✓	✓	✓	✓
Observations	101,572	101,572	58,356	58,356	43,216	43,216

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. This table shows differential effects by marital status. Controls: The set of control variables is reported in Table 3.2. 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
Source: SOEP v35, own calculations.

occurred (and the respondent is unemployed) and in period $t+1$ thereafter (if the respondent is still unemployed and had no other job in between). Figure 3.1 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 3.2).[75]

3.6 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 matching difference-in-differences research design using plant closure as quasi-exogenous

[75] We present the estimation results for this robustness check in Appendix Table C6.

Table 3.8: Effect of unemployment on informal care by age group

	(1)	(2)	(3)	(4)	(5)	(6)
Group	Full sample		Men		Women	
	Care provision					
Older than 50	0.004	0.024	0.004	0.044**	0.008	-0.011
	(0.003)	(0.017)	(0.004)	(0.022)	(0.006)	(0.018)
Treatment	0.023*	0.026**	0.002	0.003	0.055**	0.061***
	(0.012)	(0.012)	(0.011)	(0.011)	(0.024)	(0.023)
Treatment & Older than 50	0.040*	0.055*	0.061**	0.096**	0.007	-0.018
	(0.021)	(0.030)	(0.030)	(0.042)	(0.022)	(0.027)
	Hours of care					
Older than 50	0.010	0.054**	0.002	0.048**	0.024	0.056
	(0.007)	(0.026)	(0.006)	(0.024)	(0.016)	(0.043)
Treatment	0.035	0.035*	0.010	0.012	0.072	0.076*
	(0.021)	(0.021)	(0.018)	(0.018)	(0.046)	(0.039)
Treatment & Older than 50	0.071**	0.113***	0.091**	0.130**	0.040	0.065
	(0.035)	(0.043)	(0.044)	(0.052)	(0.057)	(0.063)
Controls	-	√	-	√	-	√
Weighting	√	√	√	√	√	√
Observations	101,836	101,836	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) for the full sample and by gender for the group aged 50 and older. Controls: The set of control variables is reported in Table 3.2. 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
Source: SOEP v35, own calculations.

Table 3.9: Placebo treatment

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged treatment	1 year		2 years		3 years	
Care provision	0.004	-0.005	0.003	0.001	-0.030	-0.028
	(0.057)	(0.039)	(0.025)	(0.017)	(0.029)	(0.020)
Hours of care	-0.044	-0.061	-0.010	-0.012	-0.056	-0.052
	(0.089)	(0.064)	(0.039)	(0.028)	(0.059)	(0.040)
Controls	-	√	-	√	-	√
Weighting	√	√	√	√	√	√
Observations	95,773	95,773	86,942	86,942	75,842	75,842

Notes: 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 3.2. 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
Source: SOEP v35, own calculations.

Table 3.10: Effect of unemployment on informal care, propensity weights

	(1)	(2)	(3)	(4)	(5)	(6)
Group	Full sample		Men		Women	
Care provider	0.051*	0.054**	0.041	0.055*	0.071	0.073**
	(0.031)	(0.024)	(0.038)	(0.032)	(0.061)	(0.031)
Hours of care	0.071	0.080**	0.047	0.064*	0.108	0.126**
	(0.046)	(0.035)	(0.038)	(0.033)	(0.107)	(0.053)
Controls	-	√	-	√	-	√
Weighting	√	√	√	√	√	√
Observations	101,836	101,836	58,181	58,181	42,646	42,646

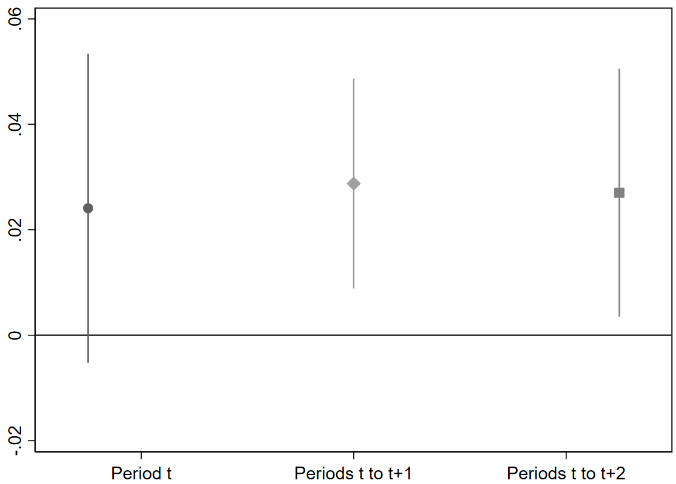
Notes: This table displays the effect of plant closure induced unemployment on the probability of being a care-provider (upper panel) and the hour of informal care provided on a normal week-day (lower panel) for the full sample and by gender. Controls: The set of control variables is reported in Table 3.2. 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
Source: SOEP v35, own calculations.

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 3.2 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 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)

Figure 3.1: Effect on informal care provision: Different treatment definitions

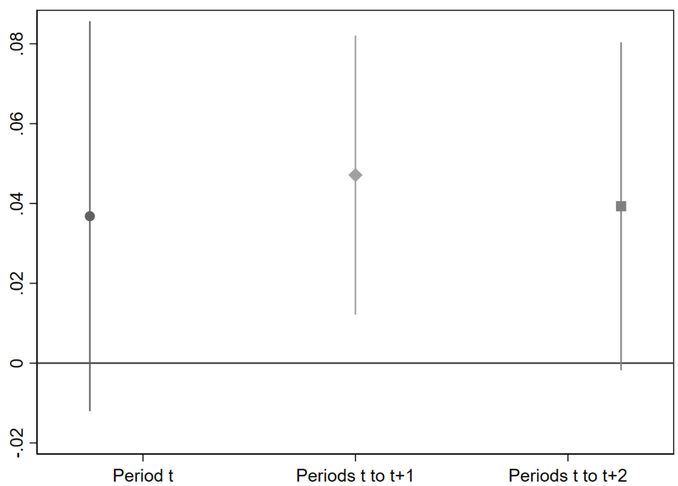


Source: SOEP v35, own calculations. *Notes:* This figure shows effects of plant closure induced unemployment on the probability to provide informal care by length of the treatment definition in periods. Period *t* is the period in which plant closure induced unemployment occurs.

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.[76]
Thus, in order to increase supply of informal care and reduce the time constraint between labor and 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.

[76]See Hu and Li (2020), Wu and Lu (2017) and Chon et al. (2018) for further information.

Figure 3.2: 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.

Chapter 4

Increasing employment and family care? A structural analysis of pension and long-term care policy reforms

4.1 Introduction

Most OECD countries, including Germany, expect a 45% increase in the number of long-term care-dependent individuals between 2020 and 2050 (Jacobs et al., 2020). Currently, two-thirds of all individuals in need of Long-Term-Care (LTC) receive primarily care from family members (informal care). Thus, many societies react to higher demand for LTC by supporting informal care provision. At the same time, pension schemes face challenges to its financial sustainability as the age dependency ratio rises. However, increasing retirement ages intensifies time-conflicts between paid employment and informal care provision. Therefore, pension and LTC policy aims are in conflict. It is crucial for policy makers to understand options that can solve pressing conflicts between these policy fields.

In this paper, we evaluate a comprehensive policy mix to simultaneously react to challenges in LTC and pension policies. Specifically, we study behavioral responses as well as welfare and distributional implications. For this purpose, we build and estimate a dynamic structural model in which agents can decide on labor supply, retirement, as well as formal and informal care provision for a frail parent. We improve on earlier models in two ways. First, we incorporate the choice for adult children to organize formal care for a frail parent. This is important as we want to understand the implications of changes to the retirement system also on demand for formal care. Further, in order to understand the preferences and considerations of adult children in case a parent becomes sick, the model needs to include the full choice-set. Second, we model the care provision decision conditional on an exogenous care demand process. In this important aspect we improve on earlier models as we incorporate parental age and health as well as distance to parents and existence of siblings in the care-demand function. This allows us to obtain structural parameters that reflect preferences for LTC provision to parents conditional on demand for care. Our model incorporates further restrictions. Individuals can only decide to provide labor hours if they receive a job offer. They understand that after periods of unemployment, the probability of a job offer is reduced.

Each choice comes with short and long-term payoffs as well as costs. We model the German tax and transfer system, including the pension system. Importantly, we incorporate the incentive structure of the German LTC insurance (LTCI). Further, agents receive labor and spousal income alongside income from their assets. Agents consider the implications of current actions for the future. We solve this dynamic modelling problem by backward induction.

The model is estimated using individual level data from the German part of the Survey of Health Ageing and Retirement in Europe (SHARE) and data from the German Socio-Economic Panel (SOEP). The SHARE data set includes unique information about parental health, age, the distance to them, and the existence of siblings that we use to estimate care demand. Further, SHARE respondents inform on informal care given to parents specifically. Concentrating on women aged 55 to 69, we estimate structural parameters by Maximum-Likelihood. Our model fits important dynamics of the data well. To understand the dynamics of the model we then simulate the consequences of a 10% higher female labor force participation at age 54. We find decreases in informal care provision mostly on the intensive margin. Formal care demand shows only low immediate responses. We can validate the model out of sample by simulating an increase in the early retirement age (ERA) for German women as introduced in the 1999 pension reform. The reform increases time-conflicts in the ages 60-62 for women born from 1952 onward compared to women born before. Our model replicates decreases in informal care supply and employment responses from this quasi-experimental setup (Geyer and Welteke, 2019; Fischer and Müller, 2020). In contrast to reduced form evidence we can point to a 25% increases in demand for formal care and differential effects of the reform by care-demand.

In a next step we leverage the structural model and simulate potential future policy changes. First, we raise retirement ages for all women to 67 (NRA) and 65 (ERA). Individuals in Germany born from 1964 onward face an NRA at age 67. Additionally, in Germany and other OECD countries, further increases to pensionable ages are being discussed. Our policy simulations can point to important dynamic side-effects not yet discussed in the literature. Those women who react with higher employment rates reduce informal care provision. Formal care demand increases as a consequence. As the retirement age increases to 67, we find a reduction in informal care hours by 5.12%, driven by decreasing high intensive informal care. We can show that women who have at least one living parent increase employment less than those without a parent who is alive. The group of women choosing unemployment as a reaction more often choose to provide informal care. Opportunity costs of informal care supply are lower in unemployment than in retirement, holding age constant. We then investigate the role of labor market frictions in the decision to provide informal care. Care-leave rules give the opportunity to return to the job after a leave, during which one provides informal care to a family member. We find that agents incorporate labor market frictions in their decision to supply informal care. Therefore, giving women the opportunity to return to their jobs after spells of informal care supply incentivizes more informal care provision and affects the care mix as well. Employment is reduced as a consequence. When we combine the introduction of care-leave with increased retirement ages we find that the combined reform leads to lower losses in life-time earnings and welfare for women with at least one parent who is alive. In the German LTCI, individuals providing long-term care to a frail elderly while not working full-time can collect pension points that will increase subsequent retirement benefits. We further investigate the role of this dynamic incentive to provide informal care in an additional simulation and find that these long-term incentives are important for high intensive informal care. We show that an increase in collectable pension points can alleviate detrimental effects on earnings and welfare brought about by higher retirement ages. Our results support the notion that pension and LTC policy aims are in conflict, which the incentive structure of the LTC policy is able to alleviate. We show that the increase in retirement ages has positive fiscal effects while the LTCI faces higher costs. The increase in collectable pension points in care-provision has favorable fiscal effects over the introduction of care-leave while both are worse than the sole increase in retirement ages from a fiscal standpoint.

Our paper contributes to several strands of the literature. Various papers investigated the simultaneous decision between informal care provision and labor supply that causes time-conflicts on the individual level (see Bauer and Sousa-Poza (2015) and Lilly et al. (2007) for reviews). There is a growing literature focusing on the care decision itself and the role of labor market attachment as well as retirement rules.[77] These papers show that the care decision is negatively influenced by labor market attachment which makes clear that informal care is not taken up unconditionally. Mommaerts and Truskinovsky (2020) and Costa-Font et al. (2015) show that informal care provision is connected to the business cycle, thus showing that opportunity costs of informal care provision matter. Fischer and Müller (2020), Carrino et al. (2019) and Bergeot and Fontaine (2020) point to the fact that the availability of retirement benefits can positively impact informal care provision, which, in turn, leads to the conclusion that an increase in retirement eligibility ages can reduce informal care supply. This threatens the aim of many OECD countries to meet growing demand for care for elderly informally through family and friends. Whereas this aspect has been investigated in reduced form analysis, the dynamic long-term considerations are yet to be understood. We contribute to this strand of literature by building a structural dynamic model investigating the interaction between the retirement system and the LTC system. Further, we aim to uncover the role of the dynamic incentive structure of the retirement system and LTC system for the negative impacts of increasing retirement ages on informal care supply.

Further papers focus on short term effects of informal care on labor market outcomes as well as retirement, finding negative effects.[78] Schmitz and Westphal (2017), Skira (2015) and Korfhage (2019) point to long term consequences of informal care provision. As papers on short-term effects of informal care supply show, there exists a time-conflict between gainful employment and care provision that is often solved by a reduction of working hours or a hastening of retirement. Due to labor market frictions as well as the organization of the pension system, this often leads to lower chances of future employment or a dropping-out of the labor force. Even if the job can be kept, human capital accumulation is interrupted, which has consequences for future earnings and pension income. Skira (2015) and Korfhage (2019) estimate structural models to analyze long term labor market costs of informal care supply.

[77] Berecki-Gisolf et al. (2008); Boaz (1996); Carrino et al. (2019); Carmichael et al. (2010); Doty et al. (1998); He and McHenry (2016); Mentzakis et al. (2009); Michaud et al. (2010); Moscarola (2010); Nizalova (2012); Stern (1995); Golberstein (2008); Fischer and Müller (2020); Bergeot and Fontaine (2020)

[78] Carmichael and Charles (1998, 2003a,b); Heitmueller (2007); Jacobs et al. (2017); Van Houtven et al. (2013); Carr et al. (2018); Niimi (2017)

Both emphasize the importance of labor market frictions, institutional incentives, and long-term consequences of informal care supply for wages and pension benefits. In contrast to their work, we focus on the caring decision in light of changing labor market attachment of elderly women and increasing retirement ages. While models by Skira (2015) and Korfhage (2019) incorporate informal care choices to understand consequences for informal care providers' future outcomes we also allow for children to choose formal care for their parents or combine formal and informal care.

Barczyk and Kredler (2018) build and calibrate a model of inter-generational non-cooperative decision making between a frail parent and a child. They want to understand the potential impact of LTC benefits on caring decisions and costs for Medicaid in the US. They build a rich model in which agents decide on formal and/or informal care and savings in a dynamic setting and find that subsidies for informal care can decrease reliance on Medicaid. Mommaerts (2015) builds a model of informal care provision and formal care organization for frail parents trying to understand the link between the availability of informal care and demand for private long-term care insurance in the U.S.. The focal point of Mommaerts (2015) is the demand for private long-term care insurance. Parents and children take a cooperative decision on care organization. In our model, adult children decision making is the focal point. We focus on their trade-off, which includes the public LTC system in Germany and utility of parental care.

The German LTCI supports both informal and formal care. Thus, the decision to provide informal care or organize formal care is greatly impacted by the various institutional incentives that have short term and long-term consequences. Therefore, it is important to understand the several aspects of the choice set of potential informal care providers to model care choices. A body of literature discusses whether formal and informal care are rather substitutes or complements, finding mixed results.[79] We contribute to that literature by investigating the role of LTC incentives in the choice between formal and informal care.

Further, we enlarge literature by contributing simulations on important policy reforms. Increasing the retirement age is discussed in many OECD countries in order to uphold the sustainability of the public pension system. Many papers investigate potential side effects of those increases with regards to fiscal consequences.[80] We contribute by showing dynamic consequences on informal care supply that can simultaneously impact formal care usage. This has not only side effects for the care market but also brings negative fiscal consequences for the LTCI. Further, we look at heterogeneous labor market reactions of individuals with and without care demand to reforms of the retirement age.

The paper structures as follows: In section 4.2, we present the institutional setting before presenting the data in Section 4.3. We then outline the behavioral model, discuss exogenous and endogenous processes, the solution of the model and explain the estimation in section 4.4. In section 4.5, we present main estimation results and discuss the model-fit. We then present simulations results in section 4.6 before we conclude in section 4.7.

[79] Hollingsworth et al. (2017); Van Houtven and Norton (2004); Karlsberg Schaffer (2015)

[80] Müller and Shaikh (2018); Battistin et al. (2009); Moreau and Stancanelli (2015); Eibich (2015); Fischer and Müller (2020); Staubli and Zweimüller (2013)

4.2 Institutional setting

Our model captures the incentive structure of the German pension system, social security system, tax system and LTCI. As we want to analyze the importance of the dynamic incentive structure of both, the pension and LTCI our model needs to capture those in detail.

4.2.1 LTC system

The German LTCI was introduced in 1995 in order to partially insure individuals against the risk to become permanently care dependent in old age. 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). The severity of impairment is graded by independent institutions - the Medical Service of the Health Funds - and benefits are granted regarding the individual classification in one of the five possible care dependency levels.

Table 4.1: Care levels in Germany

Care level	Requirements	Benefits (monthly)	Share	Costs of formal care in Euro (SD)[81]
1	low impairment of independence	No entitlement for cash benefits or in-kind transfers for home care; 125 Euro earmarked benefits	9.44%	79.31 (203.54)
2	significant impairment of independence	316 Euro cash benefits, 689 Euro in-kind; 125 Euro earmarked benefits	42.39%	70.77 (110.44)
3	severe impairment of independence	545 Euro cash benefits, 1289 Euro in-kind; 125 Euro earmarked benefits	27.93%	176.16 (451.62)
4	highest impairment of independence	728 Euro cash benefits, 1612 Euro in-kind; 125 Euro earmarked benefits	14.05%	224.26 (474.65)
5	special cases (hardship) ,people with exceptionally high maintenance effort[82]	901 Euro cash benefits, 1995 Euro in-kind; 125 Euro earmarked benefits	6.17%	
Total				122.38 (319.27)

Notes: This Table shows requirements (column 2) and benefits (column 3) for the five care-levels of the German LTCI. Column 4 shows proportions of individuals in LTC benefit receipt in the care levels and column 4 shows overhead costs of formal care usage as given in SHARE data.

Benefits are granted to enable frail elderly to be cared for either informally, formally or in a mix of the two. While informal care takes place in the home of the care dependent, mostly by family members, formal care can either be provided in an institutionalized old-age care home or by professional care providers in the person's home.[83] Table 4.1 gives information on requirements and benefits in the 5 care levels in Germany. It also reports the share of individuals in the 5 care levels among those receiving any payments from the German LTCI. The cash benefits (coloumn 3) are neither means tested nor earmarked. Individuals who are cared for in their own homes can either choose cash payments if they choose informal care or in-kind payments for formal care or a mix. In 2019, cash benefits for home

[83] In this model we discard the option to move into old-age homes as the information given on this is too sparse.

care range from 316 Euro in care level 2 to 901 Euro in level 5. This money can be used to pay for appliances assuring life at home or it can be paid to an informal care provider (e.g. family member). In-kind payments are used to pay for formal care. Benefits range from 689 Euro in care level 1 to 1995 Euro in level 5.[84] If a combination of in-kind formal care benefits and monetary benefits is chosen, the monetary benefit for informal care is reduced accordingly. In Table 4.1 (coloumn 4), we show the proportions of care benefit recipients in the 5 care levels.[85]. The majority of the 3.7 million individuals receiving benefits in 2019 are in care level 2 (42.39%) and care level 3 (27.93%). Statistics show that 1.8 million (49%) receive cash benefits for informal care, 153,000 (4%) received in-kind benefits and 514,000 (13%) make use of the option to use a combination of cash and in-kind benefits.

In SHARE data[86] we find that individuals using formal care face on average costs of 122.38 Euro per month which are not covered by the LTCI. Table 4.1 (coloumn 5) shows the overhead costs for the household if formal care is used by number of ADL's of the care dependent person. As benefits increase with rising care dependency, overhead costs seem to increase as well.

Further, the LTCI gives the opportunity to collect pension points (see section 4.2.2) for intensive informal care supply. These increase later pension benefit receipt. This is possible if: (1) care providers give care to a relative who is eligible for benefits from LTCI, (2) if care is provided for at least 14 hours a week, (3) if the care dependent person lives at home, and (4) if care givers spend less than 30 hours a week in payed employment. If these four conditions are satisfied, individuals collect 0.27 up to 0.8 pension points for each year of informal care-giving. If individuals are retired, they do not benefit from this regulation.

In the German part of the SHARE[87], individuals give information on care received formally and informally (from within or outside the own household). We plot care received by age in Figure 4.1. Looking at all individuals reporting some kind of received help, we find that while 65% report only to receive informal care, 21% are cared for in a combination of informal and formal care and 12% receive only formal care. However, care receipt differs greatly among several covariates: The proportion of individuals who need some kind of care grows with age (20% at age 60 vs. 40% at age 80, 68% at age 90). Formal care receipt, however, increases stronger with age than informal care receipt.[88] Table 4.2 shows the care mix (care from outside the household) of individuals from age 70 in SHARE by health status (Good, medium, bad).[89] In the upper panel, we find that with decreasing health higher percentages of individuals receive outside care; most striking is that formal care proportions increase dramatically as people report worse health. Informal care, while also in higher demand with worse health shows a less drastic increase. In the lower part, we show the care mix by health for those who receive outside care. We find again, that as health worsens, individuals receive more formal care.

[84] In the model we specify the year specific monetary values for cash benefits and in-kind payments.

[85] See BMG (2020) and Destatis (2022).

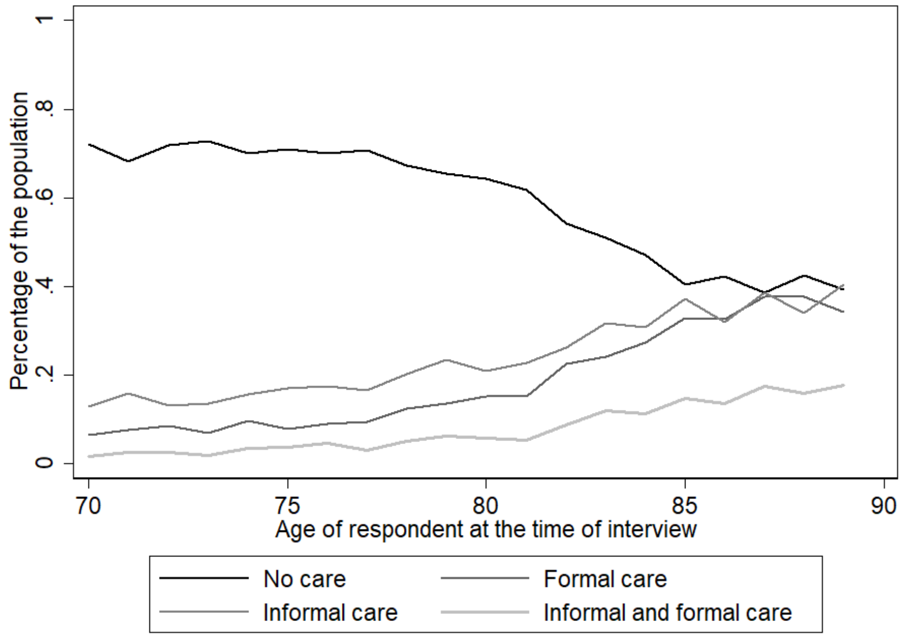
[86] See section 4.3.

[87] See section 4.3 for information on the SHARE data-set. Here, we look at all observations in the German part of SHARE

[88] While at the age 69 80% need no care, 16% receive informal care and small portions receive a mix (1.6%) or only formal care (1.7%), at the age of 80, nearly 40% receive some care (21% informal care, 9.6% a mix and 7.4% only formal care). At the age of 90, only 32 % receive no care at all, with 17.9% receiving only informal care, 35.8% receiving a mix and 13.4% receiving only formal care.

[89] We incorporate only care from outside the household to understand which role care received from children might play. Care from a spouse or another household member is discarded.

Figure 4.1: Care mix by age of parent generation (SHARE data)



Notes: This figure shows proportions of LTC usage by age. *Source:* SHARE, own calculations.

One reason could be that while elderly people in good health might still need assistance with several activities in the household, only those in bad health need formal care.[90]

Individuals with children receive less formal care; the same is true for those who have at least one child living close by. Those without children have a 9 percentage points (pp) lower probability to receive informal care if they receive any care. Further, we find that 39% of individuals reporting any kind of care receive some care from their children, while 17% receive some care from a spouse. Married individuals receive overall much less outside care. However, if married individuals receive care, higher proportions (31% vs. 22%) receive formal care than non-married individuals. The reason is that as married individuals need care, informal care tasks can often be performed by the spouse and if outside care is needed, care tasks often performed by professionals are demanded.[91]

4.2.2 Pension benefits

The public pension benefit system in Germany is a pay-as-you-go system. Benefits are linked to the labor market history and are calculated according to the German pension formula:

$$pension_t = (\sum PenP_t) * AF * PV_t \tag{4.1}$$

[90] Figure C1 in the Appendix depicts the proportions.

[91] Figure C2 in the Appendix shows care usage by existence of at least 1 child (upper left), distance to children (upper right) and marriage status (lower panels). We look at the care mix by children and distance to a child on any outside care received; the care mix by marriage status is shown conditional on care received (lower right) and unconditionally (lower left).

Table 4.2: Care mix by health

	Good Health	Medium health	Bad health
Unconditional			
No Care	79.96%	65.69%	46.87%
Formal care	3.62%	8.87%	20.53%
Informal care	14.00%	17.01%	14.27%
Informal and formal care	2.42%	8.44%	18.33%
Conditional on care received in the household			
Formal care	18.08%	25.84%	38.64%
Informal care	69.87%	49.57%	65.50%
Informal and formal care	12.05%	24.60%	34.50%

Notes: This Table shows proportions of LTC usage by self-reported health. The upper panel shows unconditional information while the lower panel shows proportions conditional on care received in the household from outside the household.
Source: SHARE data, own calculations

$PenP_t$ are so called pension points that are accumulated per year over the life cycle. They depend on the individual labor earnings and the mean gross labor earnings in Germany. An individual earning exactly the mean gross labor earnings of any given year collects 1 pension point for that year. For earnings below or above this benchmark, collected pension points are adjusted proportionally.[92] Additionally, individuals can collect pension points for example through child care or informal elder care, as described above (section 4.2.1).

The retirement age factor AF is 1 if the individual retired at the normal retirement age (NRA). Per month of early retirement with respect to the NRA, the factor is decreased by 0.003; per month of later retirement, the factor is increased by 0.005. If an individual retires at age 63, while the corresponding NRA is at age 65, the AF is 0.072 and the pension is 7.2% lower than if the person had retired at age 65.[93] The deductions for early retirement stay constant over the life span. The timing of retirement, therefore, is crucial for benefit size which leads to dynamic incentives to work longer. Our model incorporates this incentive structure. The deductions are often not considered actuarial fair. Therefore, it is often argued that the system provides an incentive for individuals to retire at the earliest convenience (Börsch-Supan et al., 2020).

The NRA is subject to change due to several reforms in the previous years. Therefore, the NRA for each individual depends also on the birth year. Further, depending on the number of waiting years[94] accumulated, a different NRA can apply. The same is true for potential early retirement ages (ERA). Table C14 in the Appendix gives an overview of requirements and possible ERA and NRA that exist. Women's pension, a specific pension path with an ERA at age 60 and a NRA at age 63 was abolished by the 1999 pension reform and effectively increased the earliest retirement age for German women from age 60 to age 63.[95]

The pension value PV_t changes each year and reflects the development of wages, inflation and demo-

[92] Pension points are calculated as $min\{H_t w_t / \overline{H_t w_t}, Max_t\}$, where $\overline{H_t w_t}$ is the region specific mean gross labor earning in period t and Max_t denotes a year specific cap on pension points which varies roughly around two.

[93] The highest value for AF possible is 1.3 which is reached 5 years after the NRA.

[94] Waiting times are the number of years that any person is active on the regular labor market and pays into the public pension system.

[95] This pension reform is investigated at length by Geyer and Welteke (2019); Geyer et al. (2020); Fischer and Müller (2020).

graphic trends in Germany. Each pension point accumulated during the lifetime is worth 34.19 Euro of retirement benefits in 2021.

Women in Germany heavily use the incentivized discrete retirement ages. Using the GSOEP[96] we find jumps in the probability to be retired of 13 percentage points (pp) at age 60, 10pp around the threshold age 63 and at the threshold age 65 a jump of about 16 pp. The earliest possible retirement age for many women is age 63. We find that about 61% of women are retired by age 63.5, showing that high amounts of women use their earliest possibility to retire.

4.2.3 Income tax, SSC contributions and unemployment insurance

Our model further includes key features of other elements of the German tax-and transfer system. Income taxation in Germany follows a progressive smooth tax function. Net income is further reduced through payment of social security contributions (SSC) to the public health insurance, LTC, unemployment insurance and pension contributions. The contributions total to about 20% of gross earnings. Pensions benefits are also subject to SSC but only for health and LTC insurance. Further, the SSC is capped. The German system distinguished between two kinds of unemployment benefits: After loosing a job, one receives ALGI, which is around 67% of the previous net earnings for approximately 12 months. After that, ALGII comes into play. ALGII payments are not dependent on previous earnings anymore.[97]

4.3 Data sets

In this paper we make use of two data sources that are both representative of the same German population: For estimation of the main structural parameters and exogenous care demand we use SHARE[98]. Further, we estimate certain exogenous processes (income processes and health transitions) using SOEP[99]. Both data sets have specific strengths. The main advantage of SHARE is the availability of individual level information on care provided, hours worked, retirement behavior and many socio-economic variables. Among those, we find information on parental health and age which is very valuable information considering the issue at hand. SOEP data on the other hand incorporates richer income information and is a yearly panel with more waves and more observations per wave.[100]

4.3.1 Construction of data sets

We make use of all German SHARE waves (1-7) including the SHARElife questionaires in waves 3 and wave 7. We construct two data sets using SHARE which each fulfill specific purposes: For the

[96]Figure C4 in the Appendix depicts retirement behavior of women. For this analysis we look at all women in SOEP-data from SOEP v35. We discard observations before 2001 in order to understand current retirement behavior. See section D.6 and section 4.3.

[97]In the model we abstract form ALGI and assume that agents directly fall back to low ALGII payments if they become unemployed.

[98]See Boersch-Supan and Wilke (2004),Börsch-Supan and Malter (2015), Malter and Börsch-Supan (2017) for further information on SHARE

[99]See Goebel et al. (2019) for further information on SOEP data.

[100]For definitions of SOEP variables, see section D.6.

structural estimation, we construct a data set containing all women aged 55 to 68 who give valid responses on all important variables. The final estimation data set contains 5,468 observations on 2,664 women.[101]

Second, we construct the parent-child data set. Starting from all observations in SHARE aged 65 and older we use the full information given on all living children of household members (gender, birth year, labor market status, distance to parent, frequency of visits to parents, martial status) and expand the data set along the children; we end up with a data set which has at heart the information on each child but contains the full information on parent's LTC usage. This data set then contains 19,963 observations on 3,582 parents.[102] For descriptions on the SOEP data set, see the corresponding sections on the estimation of the wage function (section D.8), non labor income (section D.9), partner income (section D.10), and health transitions (section D.7).

4.3.2 Summary statistics of SHARE data-estimation data set

Tables 4.3 and 4.4 gives summary statistic on the estimation data set. The mean age is 61.52 years and we observe individuals from the years 2004-2017.[103] 76.2% of the respondents have a partner in the same household. We find that 40.9% are retired, 39.5% are active in the labor market. The mean working hours among the ones active in the labor market is 31.73 hours per week. We find that 8.4% provide some kind of informal care, with 5.4% providing low-intensive informal care and 3% providing high intensive informal care. We do not observe the formal care choice for one's parent in the estimation data-set. Therefore we use the parent-child data set to estimate the probability of formal care usage among elderly dependent on parent as well as child information. We then use this information to impute the formal care choice in the estimation data-set.[104] Resulting from this imputation, we find that 15.7% of all observed women in the estimation data-set organize formal care for a parent. This proportion differs along age of children. Further, the probability of a parent being alive decreases with age. Therefore the probability of formal care organization peaks at age 58 with 18.21% and decreases from there to 6.4% at age 68 (see Figure C5 in the Appendix, left panel). Conditional on one parent being alive the probability rises monotonically with age of the observed individual, starting at 27% at age 55 and peaking at age 68 with 72.3% (see Figure C5 in the Appendix, right panel).

Table C15 shows that proportions of provided care differ only slightly along labor market status. However, informal care provision is highest among part-time employed women.

4.4 The behavioral model

In order to assess the policy makers' options to simultaneously react to increased demand for informal care and delay retirement we develop a structural model of informal and formal care provision and female employment. Women make decisions in the ages 55 to 68, are forced to retire and not to provide any care at age 69 and incorporate utility derived until the end of life at age 85. In each period, agents

[101] See section D.1 for a description of the main variables in SHARE

[102] See section D.2 for a descriptive Table on the parent-child data set.

[103] The SHARE questionnaire is asked in the years 2004, 2006, 2007, 2011, 2012, 2013, 2015 and 2017.

[104] See section D.3 for further information.

Table 4.3: Summary statistics of SHARE data- estimation data set

Covariate	Mean	Standard deviation
Age	61.52	(3.962)
High Education	0.350	(0.477)
East Germany	0.189	(0.392)
Number of children	1.476	(1.309)
Work Experience	26.33	(12.07)
Years since retirement	1.706	(3.161)
Married	0.762	(0.426)
Experience in informal care provision	0.306	(0.624)
Mother alive	0.317	(0.466)
Age of mother	84.40	(5.052)
Health of mother	1.839	(0.773)
Father alive	0.110	(0.313)
Age of father	84.31	(4.600)
Health of father	1.874	(0.774)
Parents live close by	0.724	(0.447)
Worked last period	0.448	(0.497)
Death of parent since last period	0.109	(0.311)

This Table shows means and standard deviations of important covariates and variables used in the behavioral model in the main SHARE data set: Women aged 55-68. This data set is used for estimation of the main structural parameters.
Source: SHARE-data, own calculations

decide between unemployment, part- and full-time employment and - if they are eligible - retirement. Agents who have a least one parent that is alive face the option that a parent needs LTC. Adult daughters can decide whether to provide care informally, either low, or high intensive. Importantly, we also incorporate the decision to organize formal care for a parent into this model. Agents can combine informal and formal care. If care demand arises agents can still decide not to provide or organize any care for a parent. They make a decision that jointly incorporates utility of the potential care giver and the potential care receiver-a parent. In that way the decisions takes into account utility derived from leisure and consumption directly and utility derived through care provision indirectly. We concentrate on the choice of care providers (a daughter), not on that of a care receiver (a parent).

Agents are restricted in several ways: First, they can only supply labor if they receive a job offer. The probability to receive a job offer is one if the agents has worked in the last period and decreases after spells of unemployment. Agents can only provide care to a parent if a parent is in need of care. We model demand for formal and informal care separetely. Both processes are estimated exogenously. Further, individuals face time and monetary budget constraints. We model the German tax- and transfer system, incorporating the pension benefit system and the LTC insurance. Agents receive income from labor, spousal income and income from assets. We abstract form savings decisions as the savings profile of individuals in the age range is rather flat. While savings are important in inter-temporal decision making in general, the German insurance system covers big parts of old age income and costs from care provision. Income from private savings make up only around 8% of old age income in Germany in 2015 (see BMAS (2021)), while income from the pension system make up around 65% and therefore play the biggest role in retirement decisions in Germany. Health transitions of parents and income processes are estimated exogenously and then used in the model. Processes that

Table 4.4: Main choices in SHARE data- estimation data set

Choice	Mean	Standard Deviation
Caring choice (1-3)	1.114	(0.401)
Providing informal care	0.084	(0.277)
Providing low intensive informal care	0.054	(0.227)
Providing high intensive informal care	0.03	(0.171)
Formal care (imputed)	0.157	(0.364)
Working choice (0-2)	0.576	(0.778)
Labor market participation	0.39	(0.489)
Working hours (among labor market participants)	31.73	(12.70)
Retired	0.409	(0.492)

This Table shows means and standard deviations of the choice variables used in the model in the main SHARE data set: Women aged 55-68. This data set is used for estimation of the main structural parameters.
Source: SHARE-data, own calculations

depend on past and current choices, like job offer rates and transitions of job experience are modelled endogenously.

As standard, individuals make forward looking rational decisions observing current utility of all options and incorporating consequences of these options for the future.

4.4.1 Choices

In each period agents can make choices between labor supply (no work/part-time/full-time work) and retirement.[105] Due to the exogenous procresses, agents face the risk to be confronted with demand for informal and/or formal care. In periods with care demand agents then have to choose whether to provide informal care themselves (non-intensive/high-intensive care) and/or organize formal care for the care dependent parent or not provide or organize any care. Informal and formal care are modelled as independent. Consequently, agents are faced with six discrete care options once care demand arises: Organize formal care (FC), provide informal care (IC) (either non-intensive informal care (LIC) or intensive informal care (HIC)), combine either LIC or HIC with FC or not provide any care. All combinations between work and care provision are feasible. The outside care option (neither provide IC nor organize FC once care demand arises) captures that siblings, the more healthy parent or others organize or provide care to the parent.

Women, who provide IC choose between 7 hours (LIC) and 21 hours (HIC) of IC provision per week.[106] In the model 40 labor hours per week corresponds to the full-time choice, 20 hours a week corresponds the part-time choice. These discrete hours values correspond to the 25% and 75% percentile of weekly labor hours for women in SHARE.

[105]Few individuals work after they retire in Germany. In 2018 SOEP data we find that of those individuals who report receiving benefits from the pension system only 5.87% report to be marginally employed.

[106]From SOEP data we know that the 25% and 75% percentile in the care hours distribution are 7 and 21 hours per week in a comparative sample. We use these discrete mass-points as discrete choices of non-intensive and intensive IC. In SHARE, respondents inform about the frequency with which they provide IC. We use this information to proxy the care provision in the data.

4.4.2 Flow utility

In each period agents take decisions that lead to immediate utility derived from a random utility function, given in Equation 4.2. Following Rust (1994) flow utility combines a non-stochastic part with a random component $e_t(d_t)$.[107] Individual utility U_t of an agent is derived from consumption C per period, leisure L_t and from care provision.[108] Utility from caring is of interest only, if a parent is in need of care (care demand CD_t). We can therefore separate flow utility U_t into two parts: Direct utility from income and leisure (U_{it}^A) and utility from IC_t and FC_t (U_t^B).

$$U_t(s_t, d_t, m, \theta) = U_t^A(C_t, L_t, \theta) + U_t^B(IC_t, FC_t, \theta) * \mathbb{1}(CD_t > 0) + \epsilon_t(d_t) \tag{4.2}$$

Utility[109] from income and leisure (Equation 4.3) is derived through a trans-log utility function:

$$U_t^A(C_t, L_t, \theta) = \theta_C ln(aC_t) + (\theta_{L_m} + \theta_{L_{AGE}}(AGE - 55))ln(bL_t) \tag{4.3}$$

The utility parameter θ_C defines the curvature of the decreasing marginal utility with consumption while θ_{L_t} gives the curvature of utility derived from leisure by two unobserved types. The unobserved types $m \in \{1, 2\}$ are allowed to differ in their preference for leisure. $\theta_{L_{AGE}}$ incorporates age specific utility from leisure. Age is a proxy for health impacting the taste for free-time.(e.g., Heyma, 2004; French and Jones, 2011)

Utility from care provision, as given in Equation 4.4 depends on the type of care as well as the unobserved type. HIC_t and LIC_t give different utility (θ_{LIC_m} and θ_{HIC_m}) as does FC_t (θ_{FC_g} with $g \in \{1, 2\}$). If a combination of formal and IC is chosen, the combined utility parameters from informal and FC are impacted by the parameter θ_{CC}. We let the caring parameters vary by unobserved types $m \in \{1, 2\}$ to allow for differing preferences for caring.

$$\begin{aligned} U_{it}^B(IC_t, FC_t, \theta) =& \theta_{LIC_m} LIC_t + \theta_{HIC_m} HIC_t + \theta_{FC_m} FC_t + \\ & \theta_{CC}(IC_t \& FC_t) \end{aligned} \tag{4.4}$$

Whether utility from providing informal and/or FC is positive or negative is ambiguous. On the one hand providing care can be burdensome physically, especially as we deal with individuals aged 55 and above.[110] This would lead to negative utility from providing IC. On the other hand, one might feel obliged to provide IC for a frail parent, which would correspond with altruistic motives (Johnson and Sasso, 2000). FC organization can in the same way lead to positive and negative utility. From an altruistic perspective, one might feel relief that the parent is being taken care of in a professional way. However, one might feel guilt that care is not being provided by oneself (Li et al., 2010; Mommaerts, 2015). If utility from both informal and FC are positive, altruistic motives might lead to higher utility

[107] For simplicity we abstract from individual indexing in all equations.

[108] As our model abstracts from savings, yearly consumption equals disposable income Y.

[109] We use the OECD equivalence scale and use $a = \frac{1}{(1+0{:}7x)}$, where x represents the number of additional persons in the household. This adjustment reflects economies of scale in consumption and follows e.g. Adda et al. (2017). L_t is normalized by dividing by $b = \frac{1}{4160}$, the maximum amount of hours of leisure available per year.

[110] Bom et al. (2019) among others discusses direct and indirect health effects of care-giving for the care-giver.

parameters from informal than FC due to preferences of parents to be cared for by their children (HCHE, 2017). The same is true for the parameter θ_{CC} on the combination of informal and FC. This parameter incorporates the fact that FC takes away part of the burden of IC provision. The combination of informal and FC can also create an extra amount of organization. The parameter θ_{CC} can therefore be positive or negative. Other motives to provide IC can be monetary benefits through the LTC system or forgone FC costs.

The vector of parameters to be estimated is θ; $s_t \in S$ contains state variables which affect individual decisions in each period t, and S represents the state space of all feasible realizations of the state variables.[111] $d_t \in D(s_t)$ represents the decision made by the individual from a set of different feasible actions $D(s_t)$ in period t. The choice specific error term $\epsilon_t(d_t)$ can be interpreted as an unobserved state variable (Rust, 1994; Rust and Phelan, 1997; Aguirregabiria and Mira, 2010).

Heterogeneity in utility comes from several sources: We implement preference heterogeneity in the utility of leisure by assuming two unobserved types $m \in \{1, 2\}$ which comprise a fixed proportion of the population (Heckman and Singer, 1984). We also allow the preferences of IC and FC to differ by the same groups. By modeling the probability of belonging to type m as a function of the employment history at the initial age, we also account for non-random initial conditions (Wooldridge, 2005). For further details on the initial conditions, see section D.13. Further, agents differ in their education level, work experience, the existence of a partner and years spend in retirement. These aspects lead to differences in income through the income processes (see Appendix Section 4.4.6). Education is a proxy for wealth accumulated by parents and children.

4.4.3 Budget Constraints

Agent's decisions are subject to a time budget constraint as given in Equation 4.5. Individuals have 80 hours of leisure per week by default which is reduced by their time spend in employment (part-time or full-time) or IC provision (high intensive or low intensive; see equation 4.5). FC, retirement and unemployment do not reduce leisure time.

$$L_t = L_{max} - IC_t - H_t \tag{4.5}$$

Consumption C is derived from gainful employment ($H_t * w_t$), non-labor income (A_t), income of the spouse (SI_t), pension benefits if retirement is chosen (PB_t), unemployment benefits if unemployment is chosen when retirement is no option yet (UB_t), cash benefits from IC provision if IC is chosen (CB_t). Income per period is reduced by tax payments (Tax_t), social security contributions (SSC_t) and potential costs of FC organisation (see Equation 4.6). Apart from labor income, non labor income and spousal income, we calculate the components using a full simulation of the German Tax and Transfer System. The hours choice H_t and the hourly wage w_t define labor income. Hourly wages depends on labor market experience and education. Spousal and non-labor income depend on the existence of a spouse, own education and age.

[111]See section D.11 for a list of all variables carried in the state space.

$$\begin{aligned} C_t =& H_t w_t + A_t + SI_t + IH_t + \mathbb{1}(R_t = 1)PB_t + \mathbb{1}(R_t = H_t = 0)UB_t + \\ & SA_t - Tax_t - SSC_t + \mathbb{1}(C_t > 0)CB_t \end{aligned} \tag{4.6}$$

Our model also incorporates the fact that dependent on the care dependency status of a parent, the several caring option impact the budget differently. As pointed out in Section 4.2 and Table 4.1, benefits from the LTCI are neither earmarked nor means-tested but depend on the care dependency level of the respective benefit receiver. Individuals in the model receive benefits only if the care dependent parent is expected to be eligible for pension benefits. Using information on health and age of the parent, we predict the number of limitations with ADL (see Appendix Section D.4.). If at least 2 limitations with ADL and one limitation with IADL are expected, individuals receive 316 Euro in cash benefits per month. We imply that the care depended person needs at least the minimum criteria of care, amounting to 90 minutes per day for care level 2. In the non-intensive care option individuals provide 30.1 hours of care per month, 67% of the needed care and are reimbursed with 67% of the respective benefits. In intensive care, the care-giver provides 90.3 hours of IC per month. If the care dependent person is predicted to be in care level 2, less time than 90.3 hours is required. Therefore, only the highest amounts of benefits in care level 2 are granted (316 Euro in 2020). If higher care levels are predicted, benefits in intensive care are increased, while in non-intensive care, amounts stay constant.

Accordingly, agents face costs connected with the organization of FC. Even though the LTCI offers benefits for FC (see section 4.2), often individuals have to pay parts of the costs out of their own pockets. In this case, later inheritances are reduced. In some cases, children partly help financing the care needs of parents. In the model, we assume lump-sum costs of FC organisations that depend on care-dependency. Costs for FC in the model follow the pattern from the SHARE data (see Section 4.2.1). If a combination of formal and IC is chosen, costs rise as the benefits are reduced accordingly.

4.4.4 Care demand

IC provision or organisation of FC is only possible if care demand exists. The care dependent person is a parent. Depending on the states, agents are faced with no care demand (if no parent is alive) or a continuous probability that demand for informal and (or) FC is necessary for their parents. As outlined above, FC and IC are utilized in different circumstances. While elderly parents in relatively good health often still get some informal help from children or other people, elderly parents in bad health often require some additional formal help. Therefore, we separate the FC and IC decision and accordingly also include separate care demand probabilities for informal and formal help.

Both demand functions depend on health and age of both parents as well as on martial status (of the parent), distance to parents and existence of siblings. We estimate these functions outside the model using the child-parent SHARE data set on different outcome variables, though. In this way, the inputs into the function impact demand for FC and IC differently. The outcome variable for IC demand is the usage of IC (except IC from the spouse) in the household of the parent. For FC demand we use usage of any kind of FC in the parent's household. In order to account for care demand to differ by marital status of the parent we estimate the regression separately on three groups: Mothers who have no partner, fathers who have no partner and parents who are married and live together. The regression equations do not incorporate the existence of a sibling or distance to a parent in the equation. We use predicted probabilities of care-demand in a second step and estimate the impact of distance to parents and existence of siblings on the probability that any given child provides IC or organizes FC for their parents.[112]

$$\begin{aligned} P(CD_{t,formal}) &= P(health_{father}, health_{mother}, age_{father}, age_{mother}, sibl_t, pdist_t, mar_t) \\ P(CD_{t,informal}) &= P(health_{father}, health_{mother}, age_{father}, age_{mother}, sibl_t, pdist_t, mar_t) \end{aligned} \tag{4.7}$$

4.4.5 Job offer

Individuals can only work on the labor market if they receive a job offer. In our model, retirement is an absorbing state, meaning that no job offers are possible once retirement is chosen. Agents who worked in the previous period have a job offer probability of 1. Agents who chose unemployment previously get a job offer with a continuous probability between 0 and 1. Following Korfhage (2019) job offer rates after unemployment depend on education, unobserved type and age. Individuals above the legal retirement age of 65 have a reduced job offer probability.[113]

4.4.6 Further processes

In this Section we describe how further important processes are modelled. The evolution of years of work experience and care experience is important for the wage process and the collection of pension points in times of IC supply. The transition of health of parents is important as this drives agents' expectations of demand for care. Income processes define income from various sources. In our model, some variables evolve independently from agent's choices. Among them are mother's and father's age, parental health and survival and the own age. Some factors are constant throughout the model: education, type, distance to parents and existence of siblings. Some evolve deterministically with decisions of the agents: work experience, care years, years in retirement.

Work and Care Experience Part time employment in the current period increases work experience by 0.5 years while full-time employment increases work experience by 1 year. The number of care years provided increases only with IC provision; by 1 year through intensive care provision and 0.5 years through non-intensive care provision.

Health Transitions and Survival Rates of Parents Parental health follows a function depending on

[112] See Appendix Section D.5 for regression equations and results.

[113] The job offer probability after unemployment is estimated following this equation 4.8.

$$P(JO_t = 1 | H_{t-1} = 0 \& R_{t-1} = 0) = \frac{exp(\lambda Z_{t-1})}{1 + exp(\lambda Z_{t-1})} \tag{4.8}$$

Parameters λ are calibrated using estimates from Korfhage (2019). The following equation defines the job offer rates:

$$Z_t = -1.3927 - 0.1704\mathbb{1}(Age >= 65) + 0.2916Educ + 0.5263Type_2 \tag{4.9}$$

current health, age and gender of the parent. Agents form believes about the future health which follow the observed transitions, estimated on SOEP data.[114] Children, therefore, have perfect understanding of the health processes and survival rates of their parents. Future health of parents is not impacted by current choices. We do not let health transitions be endogenously dependent on the type of long term care because LTC, as Mommaerts (2015) points out is not meant to impact health but is meant to uphold the ability to perform basic personal tasks. This is also in line with Applebaum et al. (1988), Card et al. (2008) and Finkelstein and McKnight (2008) finding no effect of the type of LTC on mortality or health transitions in later life. Survival rates of parents and agents are taken from official statistical life tables provided by European Statistics (Eurostat)[115]. Survival in this way does not depend on the type of care or the health status. It only depends on gender and age.

Income Processes Each period agents observe their income in all possible choices depending on the realized state variables. These are important for flow utility. Wages, non-labor income and spousal income follow a functional form which is estimated outside the model using SOEP data. Income from different aspects of the social security system are calculated as outlined above.

The wage is determined by human capital which is approximated by work experience, level of education and age (see Appendix Section D.8). If a person is married, potential income from a spouse increases household income, dependent on education and age of the agent (see Appendix Section D.10).

The last part of household income is non-labor income. This can contain e.g. assets, rental, and private retirement insurance income. Non-labor income depends on education, the existence of a spouse and age (see Appendix Section D.9).

4.4.7 Solution of the model

Each period agents observe their state vector s_t and make choices d_t that maximize their expected discounted lifetime utility given by Equation 4.10. Agents take into account the future which they discount with the factor β and additionally they take into account their age specific survival probability p_t. According to Bellman's principle of optimality agents take into account only today's (t) flow utility and tomorrows ($t+1$) expected discounted utility (Bellman, 1957). According to Rust (1987) if we assume that the utility function is additively separable in observable and unobservable components, the elements in the error ϵ_t are conditionally independent so that $F(s_{t+1}, \epsilon_{t+1}|d_t, s_t, \epsilon_t) = G_\epsilon(\epsilon_{t+1})F_s(d_t, S_t)$ and have an extreme value type 1 distribution agent's value function has the closed form solution given in Equation 4.11. We can solve this by backward induction, so $p_t()$ is a Markov transition probability function representing agent's beliefs about future states. λ and ψ represent the parameters in the job offer and care demand probabilities that we set. Following, we can calculate choice probabilities for feasible choices d_t as given in Equation 4.12. $d_t^{'}$ represents the other feasible choices.

$$\underset{d_t \in D(s_t)}{max} E_d \left\{ \sum_{j=t}^{T} \rho_t \beta^{j-t} u_j(s_j, d_j, \theta) | d_t, s_t, m, \epsilon_t \right\} \tag{4.10}$$

[114]See Appendix Section D.7 for details on the estimation and results.
[115]See http://ec.europa.eu/eurostat/data/database.

$$
\begin{aligned}
&v_t(s_t, d_t, m, \theta, \lambda, \psi) = u_t(s_t, d_t, \theta) + \\
&\rho_t \beta \sum_{(s_{t+1})} log \Bigg[\sum_{d_{t+1} \in D(s_t+1)} exp\{v_{t+1}(s_{t+1}, d_{t+1}, m, \theta)\} \Bigg] p_t(s_{t+1}|s_t, d_t, \lambda, \psi)
\end{aligned}
\tag{4.11}
$$

$$
P(d_t|s_t, m, \theta, \lambda, \psi) = \frac{exp\{v_t(s_t, d_t, m, \theta, \lambda, \psi)\}}{\sum_{d'_t \in D(s_t)} exp\{v_t(s_t, d'_t, m, \theta, \lambda, \psi)\}'}
\tag{4.12}
$$

The discount factor β is not estimated but defined as 0.98 which is in line with the literature (see e.g. Cooley and Prescott (2021)).

4.4.8 Estimation of structural parameters

We estimate the model applying a Maximum Likelihood (ML) estimation approach comparable to the ones formulated in Rust (1994) and Rust and Phelan (1997).[116] Our approach diverges from theirs as we do not observe job offers and care demand in the data. While Korfhage (2019) estimates both variables inside the likelihood function exploiting variation in the observed data we take parameters for both functions from exogenous estimations (see above). Applying an approach similar to the one in Iskhakov (2010) we use the probability functions in Equations 4.8 and 4.7 to integrate over the unobservables. Hence, the likelihood incorporates the probability distribution of $\{JO, CD\}$ and takes the following form:

$$
L(\theta, \lambda, \psi, \alpha) = \prod_{i=1}^{I} \left[\sum_m P(m|s^i_{T^i_0 - 1}, \alpha) \prod_{t=T^i_0}^{T^i} \sum_{JO,CD} q_t(jo, cd|s^i_{t-1}, d^i_{t-1}, \lambda, \psi) P(d^i_t|s^i_t, m, \theta) \right]
\tag{4.13}
$$

$P(d_t)$ represents the choice probabilities 4.12 which are derived in the dynamic model. q_t is the probability of being in any combination of job offer (JO) and care demand CD, which is derived from functions 4.7 and 4.8. As individuals are observed for different time spans, T^i_0 indicates the first observation period and T^i her last observation per individual. $P(m)$ represents the agent's probability to be in one of the two unobserved types m. We let women differ permanently in their taste for free-time and caregiving due to unobserved variables. These unobserved variables are correlated to observed initial conditions. T^i_0 indicates the first observation per individual as observed in SHARE data, T^i the last. The parameter vector $\{\theta, \alpha\}$ will be estimated within the ML estimation, the parameters for λ and ψ come from exogenous estimations.[117]

[116]The authors would like to thank the HPC Service of ZEDAT, Freie Universität Berlin (10.17169/refubium-26754), for computing time.

[117]See Sections 4.4.5 and 4.4.4. For more information on the estimation, see Appendix Section D.12

4.5 Results

Table 4.5 presents structural model parameters as estimated in the maximum likelihood estimation.[118]

The structural parameters are all of the expected size and direction. Agents experience positive

Table 4.5: Structural model parameter estimation results

Description	Parameter	Coefficient	Standard Error
Consumption	θ_Y	2.40	0.01
Leisure hours (type 1)	θ_{L1}	0.78	0.01
Leisure hours (type 2)	θ_{L2}	4.54	0.01
Leisure age trend	$\theta_{L_{AGE}}$	0.36	0.01
Light informal care (type1)	θ_{C1}	1.92	0.02
Intensive informal care (type1)	θ_{C2}	2.46	0.02
Formal care (type1)	$\theta_{C_{FC}}$	2.89	0.01
Light informal care (type 2)	θ_{C1}	2.06	0.04
Intensive informal care (type 2)	θ_{C2}	1.82	0.07
Formal care (type 2)	$\theta_{C_{FC}}$	0.18	0.01
Combination care	θ_{CC}	-1.33	0.02

Notes: This Table shows results for the main utility parameters as estimated using Maximum-Likelihood estimation.
Source: SHARE data, own calculations

marginal utility from consumption. Further, utility from leisure depends on one's own age and type. Leisure yields positive utility for all individuals. Leisure becomes increasingly valuable with age, according to the result on $\Theta_{L_{Age}}$. Therefore, as age increases, so does disutility of labor and time spend in IC provision. Utility from care-giving depends on the combination of formal and IC and also on the interaction with utility from income (through benefits) and leisure (time spent in IC). The direct utility from care can be seen in Table 4.6. We find altruistic utility from only providing IC

Table 4.6: Utility from formal and informal care

	Type 1		Type 2	
	No formal care	Formal care	No formal care	Formal care
No informal care	0	2.89	0	0.18
Low intensive informal care	1.92	3.48	2.06	0.91
High intensive informal care	2.46	4.02	1.82	0.67

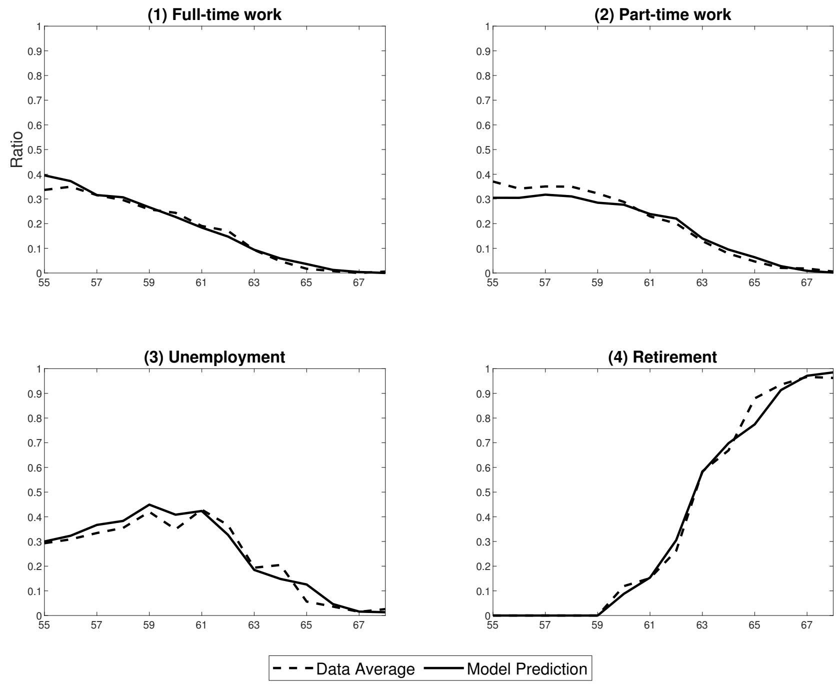
Notes: This Table shows direct utility derived by women of the two heterogeneous types by informal and formal care provision. The numbers do not include utility from leisure or consumption.
Source: SHARE data, own calculations

which is lower than if FC is included. HIC always yields higher altruistic utility than LIC. In contrast to estimates from (Korfhage, 2019) and (Skira, 2015) we find positive utility from providing IC. There are several reasons why this difference occurs. First, we include exogenous processes for care demand and therefore model care demand more accurately. Second, in contrast to Korfhage (2019), we include levels of FC and IC benefits and costs that differ by care dependency of parents. This impacts the opportunity costs of caring. Further, we find that women of unobserved type 1 have lower utility from leisure and they receive more utility from providing HIC. Utility gains from FC organization are higher for women of type 1 than type 2.

[118] Estimates for the probability to belong to one of the two unobserved latent types is given in Table C13 in the Appendix. Other estimation results of the exogenous processes are also presented in the Appendices.

Figure 4.2 shows the fit of the model in key outcomes with respect to labor market choices and retirement by age and educational status. To compare data averages and model predictions, a data

Figure 4.2: Model fit: labor supply and retirement decisions by age



Notes: This Figure depicts the model fit by comparing employment choices in the data with those from baseline model simulations by age. *Source:* SHARE, own calculations.

set was constructed using the dynamic model and utility parameters as described above. To ensure comparability with the original data, decisions are simulated for all observations only for the states (e.g. age, education etc.) in which they are observed in the data. Figure 4.2 depicts means of labor market choices by age in the data (dotted line) and simulation (solid line). The model fits the labor outcomes and retirement decisions of the data well. Our model correctly simulates the relationship between part- and full-time work by age where full-time work shows a starker decline with age in both, data and simulation. Our model also matches the development of unemployment. Women first show increased unemployment percentages before they can retire and unemployment rates fall drastically. Retirement behavior is also matched. Few individuals in the data can retire before age 63. Our model matches the fact that retirement proportions increase dramatically from age 63 onward. Nearly all women are retired by age 68 in the data and simulation alike. To understand caring choices, Table 4.7 shows portions of all possible caring choices among those with at least one living parent in the data and the simulated data. Overall, the model is able to fit the broad picture of care provision well. We see a light over-prediction of caring, especially of LIC without FC. The prediction of FC is overall very good, if slightly too high.[119]

[119]Figure C10 in the Appendix depicts provision of FC and IC in the overall sample. We depict the model fit of caring decisions by age and education in Appendix Figures C6 and C7.

Table 4.7: Care provision in data and model predictions

	Data average	Model prediction
No formal care		
No informal care	52.29%	48.07%
Low intensive informal care	9.62%	15.52%
High intensive informal care	4.15%	3.87%
Formal care		
No informal care	22.22%	25.03%
Low intensive informal care	6.80%	4.55%
High intensive informal care	4.92%	2.97%

*Notes:*This Table shows proportions of care provision (combination of informal and formal) as observed in the main estimation data set and as simulated by the behavioral model.
Source: SHARE-data, own calculations

Further, the model fits the main transition probabilities in work status and care provision.[120] The model matches high persistence of non-employment well, while it lightly over-predicts transitions from employment into non-employment and vice versa. The same holds for IC-giving. The model, however over-predicts the transitions from FC to non-FC organization and under-predicts the persistence in FC.

4.5.1 Validation: Effects of the abolishment of women's pension

In this section we show dynamic effects of abolishing women's pension applying the dynamic model. As mentioned above (Section 4.2), German women born until 1951 could retire early at age 60 if they fulfilled certain criteria.[121] This possibility was abolished in the 1999 pension reform. Women born from 1952 onward can only retire early at age 63. Geyer and Welteke (2019) and Geyer et al. (2020) show that this reform leads to an increase in labor market participation at ages 60-62 for women born just above the cut-off compared to those born before. They also show increases in unemployment. Fischer and Müller (2020) use this reform to show decreased FC activities for the women affected by the reform. We do not use this variation in the data for identification of structural parameters. This exercise is therefore interesting not only to show effects of increased retirement ages on caring behavior itself. It also shows that the model is able to simulate effects of policy changes that already took place but that are not directly contributing to identification.

In our sample of women aged 55, only 16.95% are born before 1952. As we only use women aged 55 for simulations, we go about as follows: We first simulate behavior for women aged 55 until age 68 pretending that all women are born before 1952 and treat outcomes as the baseline behavior. Then, we pretend all women are born from 1952 onward and repeat the simulation. This will be the simulation data-set. We then compare behavior in these two groups.

Table 4.8 compares parameters from reduced form evidence to the analogous parameters resulting from the simulation. Column 1 shows mean differences between women born in 1951 and those born in 1952 while column 2 shows regression discontinuity (RDD) effects from literature.[122] Columns 3-5 give

[120]Table C16 in the Appendix summarizes the transitions in observed and simulated data.
[121]In the model we abstract from the eligibility criteria for women's pension.
[122]In the model we do not track birth month. Therefore, we can not include birth cohort trends in the estimation

information on the specification from the parameters obtained in reduced form literature. We find that retirement and employment effects are similar to those from Geyer and Welteke (2019). We can not differentiate between unemployment and inactivity in the model. Therefore we report the combined non-employment effect. This effect is slightly bigger than in the literature. We find a reduction in the probability to be a caregiver by 7.2 percentage points (pp), which is 1.4 pp higher effect than in Fischer and Müller (2020). Our estimate on intensive care provision is very close to that of Fischer and Müller (2020). We find a reduction in care hours per month of 3.856 hours, which is an approximate 0.12 hours per day effect.[123] Literature finds a slightly smaller effect. All in all, our model matches the reduced form estimates very well.

Table 4.8: Validation: Comparison of parameters from model prediction and reduced form evidence

	(1) Model	(2) Reduced form	(3) Source	(4) BW	(5) Control Variables
Retirement	-0.299***	-0.276*** (0.02)	G&W	12 months	YES
Employment	0.135***	0.135*** (0.04)	G&W	12 months	YES
Non-employment	0.165***	-	-	-	-
Unemployment	-	0.052*** (0.01)	G&W	12 months	YES
Inactivity	-	0.062*** (0.01)	G&W	12 months	YES
Caring	-0.072***	-0.058** (0.02)	F&M	24 months	Age, year
Hours of care	-3.856***	-0.073 (0.10)	F&M	24 months	Age, year
Int. Care	-0.028***	-0.023 (0.02)	F&M	24 months	Age, year

*Notes:*This Table shows parameters from regression discontinuity regression using the 1999 pension reform for German women from literature and the model prediction. We look at women aged 60-62. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
G&W: Geyer and Welteke (2019); F&M: Fischer and Müller (2020);YES: month fixed effects, income group, having children, and western Germany dummies, and linear trends in the running variable (month of birth) on both sides of the policy cutoff; Int. Care: Intensive care
Source: SHARE-data, own calculations

Reduced form evidence could not investigate impacts on demand for FC. In the simulation, FC organization increases by 3.38pp (25.1%). Further, we can use the model to show how employment responses to the reform differ by care-demand: We compare women with at least one parent alive at age 55 with those, who have no parent who is still alive. Women with care demand have a higher probability to go into part-time work or unemployment as they can no longer retire at age 60. Among women with care-demand the probability to work full-time at age 60 rises by 15.91pp while it rises by 8.49pp for women without care-demand.

4.5.2 Effects of an increase in female labor force participation

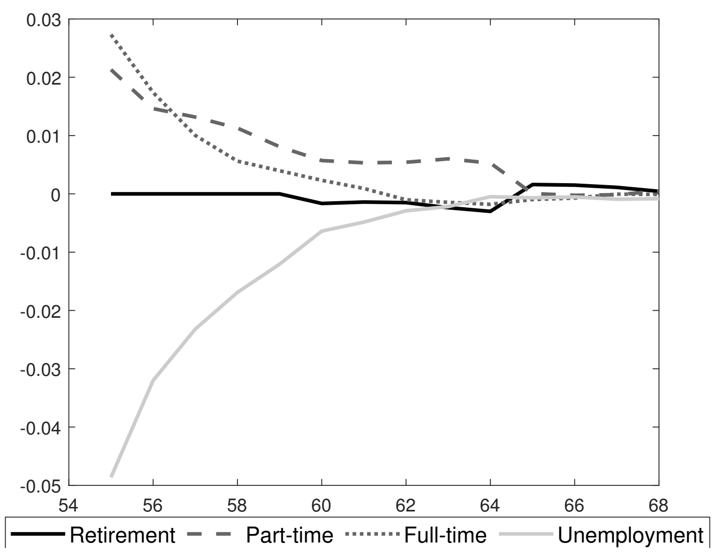
In this section we show how an hypothetical increase in female labor force participation impacts employment and caring behavior in the model. Firstly, this exercise helps us to understand the dynamics of the model and we can estimate baseline elasticities for caring behavior with changes in labor market outcomes. Secondly, as female labor supply is expected to increase in the future in all age groups irrespective of retirement rules this exercise is helpful to understand issues for policy makers.

and do not claim to estimate a RDD in the model. We simply compare differences in mean outcomes between the birth cohorts in the group of women born in the two years and ages 60-63.

[123]In the model we do not differentiate between weekdays and days on week-ends; Fischer and Müller (2020) estimate hours effects for time spent on weekdays.

We simulate behavior of individuals as observed in the data in the age 55 until the end of the model period (age 68). First, we do this for all individuals observed at age 55 given the current states and reported labor market participation- the baseline simulation. Then, we do the same exercises but artificially increase labor force participation of women at age 54 from currently 74.09% to 81.54% (a 10% or 7.45pp increase in labor force participation).[124] Figure 4.3 depicts labor market responses by age and education. The solid black line depicts differences in the probability to be retired by age between baseline and scenario. The solid grey line shows differences in part-time employment while the dotted grey line shows reactions in full-time employment. The light line shows unemployment differences. We find that at age 55, as 7.45pp (10%) more women are active in the labor market at age 54, labor force participation rises by 4.87pp (16.65%) with an increase by 2.31pp (6.89%) in part-time employment and 2.73pp (6.85%) increase in full-time employment. We find an immediate response in care provision: A shift from HIC (0.47pp or 5.67% decrease) to LIC (0.3pp or 2.71% increase) and a decrease in FC (-0.24pp or -1.41%). Overall at age 55, we find a decrease in IC given (0.11pp or 0.12%).

Figure 4.3: Effects of a 10% increase in female labor force participation at age 54 on employment



Notes: This Figure shows employment effects of a 10% increase to female labor market participation at age 54. *Source:* SHARE, own calculations.

Over the full life cycle we find a 1.13pp (1.89%) increase in employment, a 0.07 (0.91%) decrease in low intensive IC, a 0.19pp (9.0%) decrease in high intensive IC and a 0.26pp (2.01%) decrease in FC demand. All in all, we find a 13.5% decrease in labor hours and a 0.55% decrease in hours spend in IC. The amount of women who face a double burden of work and IC provision is increased by 0.63pp at age 55.

As we perform the opposite exercise (a 10pp decrease in female labor force participation at age 54) patterns are reversed. As labor hours are decreased by 2.61%, IC hours are increased by 0.07%. The

[124]For both simulations, the value function iteration is the same. The dynamic programming is not altered between the scenarios.

model is therefore able to capture the time conflict between paid employment and IC provision. We see that while women shift from high intensive to low intensive IC, the overall amount of IC provided is impacted less. As this is the first model to incorporate FC choices it is of great interest to understand the dynamic responses in FC demand. In this scenario, FC demand does not rise as IC giving decreases. This could partly appear as costs for FC play a role. Further, we model demand for formal and IC independently. FC is no perfect substitute for IC.

4.6 Policy simulations

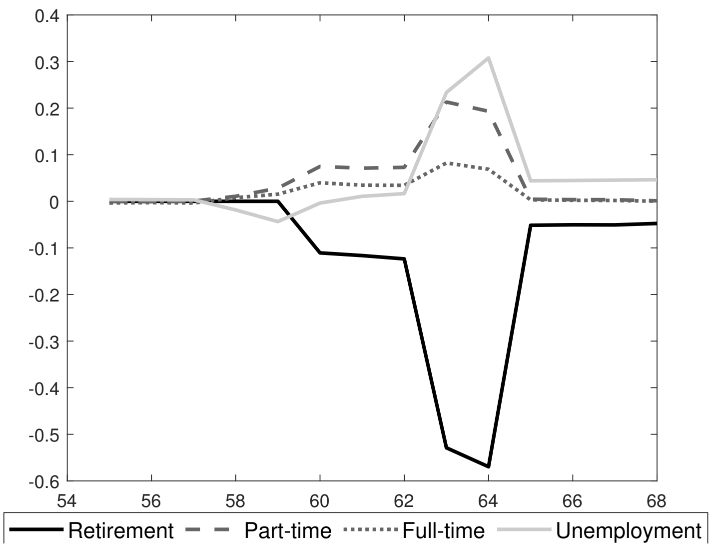
In this section, we show results of simulated potential future policy changes. Estimating a structural dynamic models we uncover the underlying behavioral parameters. We use them to asses efficiency of potential policy reforms. We first perform simulations in which we alter the retirement system and look at impacts on employment and caring behavior. This reform is of great policy relevance as women born from 1964 onward face a NRA at age 67. Our simulation can show side-effects of this reform. Then, we investigate the role of dynamic incentives of the LTC system in caring and employment decisions and combine them with changes to the retirement system. The LTC system is in place to alleviate negative impacts of possible dependency on care and increase provision of IC. Our simulations help to understand the effectiveness of these policies and understand its mechanisms. For each simulation scenario we create a new data set using the dynamic model employing the estimated parameters. First, we solve the model for each individual in the model in the baseline starting from age 55. States and choices in the following ages follow from the predictions from the model. Then, we change parameters and simulate the choices and states for the same set of individuals.

4.6.1 Effects of increased retirement ages

In this section we show effects of changes to the pension system on employment and caring choices. We compare the status quo baseline with a scenario in which the early retirement age (ERA) is set to age 65 and the NRA is at age 67 (scenario 1). This scenario is of interest as in Germany the NRA will be at age 67 for birth cohorts 1964 and thereafter; women will face this new NRA first in the year 2031. We first present behavioral responses by sub-groups before we analyse impacts on income and welfare.

All women experience an increase in the NRA to 67 and an increase in the ERA to 65. Agents understand this from age 55 on and can adjust behavior before the actual change in legislature impacts them (at ages in which they could formerly retire). At the ages in which the impact occurs agents face a decrease in non-employment income. For those with care-demand this reduction in non-employment income at higher ages increases the opportunity costs of time spent in IC provision. Also, if the knowledge on a later retirement age increases the utility of working in lower ages, the opportunity costs of IC provision increases in these ages. The effects for FC are not clear ex-ante. First, costs of FC are an important aspect. If higher retirement ages lead to a decrease of income (e.g. in higher ages or also in life-time income for those without a job-offer), then, due to the concave utility in consumption FC becomes more costly. The opposite occurs if the change in legislature increases income due to an increase in labor supply. This might therefore differ by income groups.

Figure 4.4: Employment responses to increased retirement ages



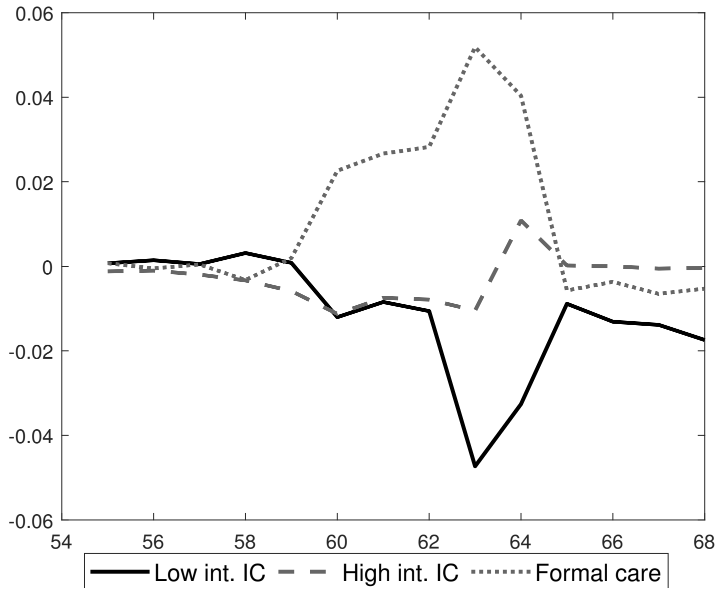
Notes: This Figure shows employment effects to an increase in retirement ages. *Source:* SHARE, own calculations.

Figure 4.4 shows average responses in employment decisions by age. Main retirement responses are shown in solid black lines; as the retirement ages are shifted to ages 65 and 67, individuals mechanically delay retirement. Women react by increasing full- as well as part-time employment and unemployment. We find that employment responses are highest at age 63 with a 21.31pp increase in part-time employment, a 8.23pp increase in full-time employment. Unemployment increases by 23.35pp at age 63 and peaks at age 64 with a 30.8pp increase compared to the baseline. The model therefore predicts that 56% of the women that can no longer retire are employed at age 63 while 44.2% go into unemployment. Employment effects differ by education: Lower educated women show a 49.3pp reduction in retirement at age 63, 44.19% of which go into unemployment, 39.78% shift into part-time and 16.01% into full-time; for highly educated women the relation is: 58.82pp reduction in retirement, 44.07% into unemployment, 40.9% into part-time and 14.98% into full-time. The model does not incorporate that leisure preferences might follow a shift in social norms as official retirement ages are increased. Also, labor market opportunities for women in the respective age groups might be better. In reality, employment responses might be bigger. The model predicts anticipation effects in employment. Agents seem to react to longer work horizons by increasing employment before retirement ages. At age 59, full time employment is increased by 1.53pp, part-time employment by 2.83pp and unemployment decreased by 4.36pp. Overall, we find a 15.66% increase in hours worked, and while female labor force participation increases by 6.84% at age 59, it increases by 114% at age 63.

Further, we can investigate employment responses by potential care-demand. Care-demand here is defined as having at least one living parent at age 55. Women with care-demand go into retirement faster in the baseline. In the simulation, at age 64, women with care-demand increase part-time employment by 26.6pp (116%) and women without care-demand by 16.46pp (153%), full-time employment at age

64 increases by 3.62pp (160%) for women with care-demand and by 8.15pp (93.7%) for women without care-demand. Unemployment increases by 29.67pp (129%) for women without care-demand and by 33.55pp (203%) for women with care-demand. We therefore find that women with care-demand have overall similar increases in labor force participation but show lower increases in hours worked. This might be due to higher opportunity costs of working when women have to think about providing IC to a parent.

Figure 4.5: Caring responses to increased retirement ages



Notes: This Figure shows caring effects to an increase in retirement ages. *Source:* SHARE, own calculations.

Figure 4.5 shows reactions in IC and FC provision due to the changes in retirement ages. It is interesting to see, that reactions occur in anticipation of later retirement ages also before agents are impacted directly. Further, we see that while low intensive IC is decreased parallel to retirement responses from age 60 onward and stays negative throughout the ages, high intensive IC decreases also in ages before retirement is an option and returns to pre-reform levels from age 64 onward. FC organization increases from age 60 onward and reactions return to 0 from age 64 onward. Overall, the sum of provided IC hours is decreased by about 5.12%. Low intensive IC decreases by 0.9% and high intensive IC decreases by 6.72% before age 62. FC provision stays constant before age 62. After age 62, high intensive IC decreases by 3.67% and low intensive IC decreases by 8.9%. The model captures counteracting incentives. While time in retirement is reduced, pension points that can be collected in IC times are less valuable. Further, time-conflicts are increased. In times of unemployment, benefits from IC provision are worth relatively more than in retirement. This is the reason why we find a small increase in high intensive IC at age 64, where unemployment increases are biggest.
Due to the increases in labor supply and partly low intensity IC provision, we find that more women face a double burden of IC and labor supply. We find an increase by about 0.9 pp at age 63. While in the baseline around 2.56% of women work and provide IC at the same time, it is 2.58% after the

introduction of the reform, a 0.78% increase. The double burden can have detrimental health effects for these women.

Table 4.9: Response in lifetime earnings to increased retirement ages

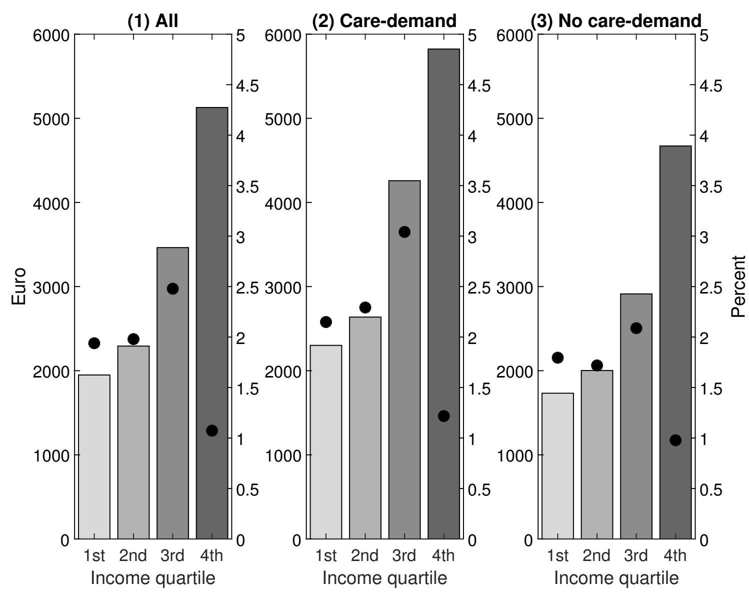
	(1) Euro (All)	(2) % (all)	(3) Euro (CD)	(4) % (CD)	(5) Euro (NCD)	(6) % (NCD)
	in 1000		in 1000		in 1000	
			Δ NPV of labor earnings			
total	13.9	14.61	14.3	15.57	13.2	13.82
1st quartile	13.5	18.92	14.4	21.57	12.4	17.27
2nd quartile	13.8	19.53	14.0	20.34	13.5	18.80
3rd quartile	16.2	17.79	16.0	17.74	16.3	17.83
4th quartile	12.0	8.16	12.8	8.95	10.8	7.53
			Δ NPV of Retirement benefit			
total	-11.0	-24.67	-11.4	-24.54	-10.4	-24.78
1st quartile	-13.3	-37.39	-14.1	-38.82	-12.2	-36.35
2nd quartile	-11.8	-27.04	-12.1	-27.58	-11.4	-26.52
3rd quartile	-10.9	-24.24	-10.9	-23.20	-10.9	-25.39
4th quartile	-7.94	-14.71	-8.57	-14.94	-6.98	-14.49
			Δ NPV of total earnings			
total	2.88	2.07	2.92	2.13	2.84	2.00
1st quartile	0.21	0.20	0.25	0.27	0.16	0.15
2nd quartile	2.01	1.76	1.95	1.70	2.12	1.81
3rd quartile	5.28	3.89	5.15	3.67	5.48	4.10
4th quartile	4.04	2.01	4.19	2.10	3.80	1.93

Notes: This Table shows differences in net-present-value of earnings and retirement benefits between the baseline and the policy simulation (increase in retirement ages). NPV: net present values; CD: Care-demand; NCD: No Care-demand.
Source, SHARE, own calculations.

Income and pension benefits are of course directly impacted by this reform. Our model calculates pension benefits collected until age 85, therefore individuals collect pension benefits for a shorter time horizon due to the reform. On the other hand, individuals who work longer and gather more pension points, experience higher pension benefits per period. We do not compensate agents for lost pension benefits. In that sense our pension reform leads to a surplus in the pension insurance system. Income from labor increases as women work more. Table 4.9 shows impacts on the net-present value (NPV) of labor earnings (or unemployment benefits), pension benefits and total earnings by income quartile, and the existence of a parent at age 55. Earnings and retirement benefits are calculated until the terminal age 85 and discounted by the discount factor β and survival probability ρ. NPV effects in Euro are depicted in columns 1,3 and 5, while in columns 2,4 and 6 we calculate the effects relative to baseline values. We find that for all groups effects on labor earnings are positive and retirement benefits are decreased, the total income effect of the reform is positive for all parts of the distribution. Further, women in the third income quartile increase labor income the most, the lowest quartile can compensate for lost pension benefits the least by working more. Women in the highest income quartile experiences a 2.01% increase in NPV of total earnings while women in the lowest income quartile experiences a 0.20% increase. In a further step, we differentiate the effects by care-demand. We define care-demand as above: Women with a least one parent who is alive at age 55 potentially face care-demand. In

columns 1 and 2 we depict effects for the full sample, in columns 3 and 4 we show effects only for those women with care-demand and in columns 5 and 6 we show effects only for those without care-demand. Be aware, that differential income effects by care-demand are a lower bound.[125] We find that women with care demand show higher reductions in retirement benefits. The reason is that they can less often work until their new higher retirement ages. On the other side women with potential care-demand react with higher increases in labor earnings and in sum, show higher effects on NPV of total earnings. This might be because women who might have to organize care for a relative often face costs of FC and thus need to earn more to compensate. This calculation does not include the total household effects on net income (including non-labor income and benefits and costs of IC and FC provision).
In a last step we analyze welfare effects of the increase in retirement ages. We follow Skira (2015) and Coe et al. (2018) and calculate the cost of welfare as a lump-sum amount of money that is necessary to equal welfare between the two scenarios. To do this we use the two simulations as above and compare the agent's life-cycle value function between the two scenarios. We can then use our knowledge on the agent's utility function and calculate the amount of money that is necessary to make agents as well off in the policy scenario as in the baseline scenario. Welfare is affected through the scenario as agents can no longer retire before age 65 and receive less pension benefits. On the other hand, as individuals potentially work more, life-time income could be positively impacted. As seen above, the reform leads to a decrease in life-time income and welfare is most probably impacted negatively. Figure 4.6 depicts

Figure 4.6: Welfare effects to increased retirement ages



Notes: This Figure shows welfare effects to an increase in retirement ages by potential care demand and income. *Source:* SHARE, own calculations.

the sums of money necessary to compensate for lost welfare in the grey bars by income quartile. The

[125]We only look at the existence of a parent at age 55; women might never experience high care-demand probabilities and therefore never provide care. Further, it is possible, that parents die at age 56 and no care-demand remains.

dots represent the changes relative to NPV of lifetime income. We find that as women can no longer retire before age 65 they loose welfare in all income quartiles. Highest losses in welfare in absolute terms are found in the fourth income quartile. The changes are largest in relative terms in the third income quartile. Women in the lowest income quartile often loose income but as they are often unemployed as a consequence, they do not loose utility from leisure. Women in the lowest income quartile need a lump-sum transfer of 1,949 Euro to be compensated for the loss in welfare, which is about 2.3% of their NPV of lifetime-income. The second and third income quartiles have lower losses in income but loose leisure time. The relative losses are smaller in comparison to their income. Figure 4.6 depicts effects for the whole population in the left panel. In the medium panel we present welfare effects for the group of women who can have care-demand and in the right panel we depict welfare effects for the group of women who cannot experience care-demand after age 55. We find that welfare losses are bigger for women with potential care-demand than for women without care-demand. Differences are biggest for women in the second and third income quartile. The reason is that women in these groups have good chances to be employed before age 65. Therefore, care-demand leads to a double burden or to a further lower increase in employment and hence income. Women in the lowest income quartile often react by unemployment and will therefore be impacted less by care-demand. We therefore see that the reform does lead to low differences in earnings between groups that might have care-demand in the future and those that might not. The inclusion of costs and benefits from care-provision and the value of income, leisure and care provision, however, shows that women who might have to take care of a parent in the future suffer more from the increase in retirement ages.

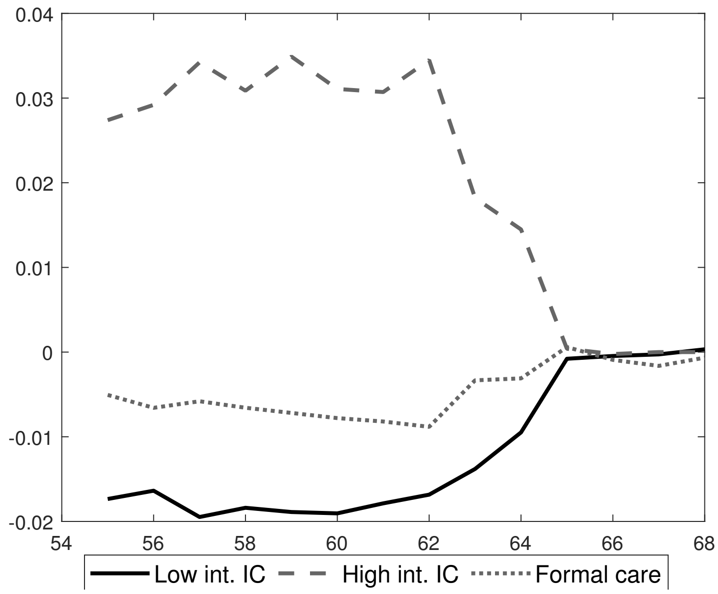
4.6.2 Impacts of changes to the LTC insurance

In this section we show the effects of changes to the dynamic incentive system of the LTC insurance in Germany. First, we simulate an increase in the pension points that IC givers can collect. Then, we introduce the opportunity to reenter the job after having spent time in IC provision and reducing labor hours to zero, which we call 'care-leave'.

4.6.2.1 Increase in pension points collected in informal care provision

In the baseline, the model incorporates the current policy rule: Individuals who provide IC can collect half a pension point if they do not work more than 30 hours per week. In the scenario we increase this to 1 pension point. This reduces the opportunity costs of high intensity IC provision. One can therefore expect an increase in high intensity IC provision. This impact is important especially before individuals go into retirement. Further, this simulation can impact labor force participation and retirement behavior through changes in the time budget (via increased IC provision) but also as people partly provide labor hours in order to collect pension points. Figure 4.7 shows impacts on caring behavior. In the full sample we find an increase in high intensive IC provision for women in the ages before retirement (55-61) of 1.57pp (50.21%) and a decrease in low intensive IC provision by 0.91pp (11.8%). Overall, we find an increase in IC provision before retirement ages by 0.73%. FC is reduced by 0.33pp (2.3%). Impacts from age 62 onward are smaller. While high intensive care is increased by 25.5%, low intensive care is decreased by 3.13% and overall, IC is increased slightly by 0.14%. FC

Figure 4.7: Care responses to increased collectable pension points



Notes: This Figure shows caring responses to the increase in collectable pension points in informal care provision. *Source:* SHARE, own calculations.

form age 62 onward is reduced by only 0.65%. If we look at impacts by education we find that lower educated women react stronger to this increased incentive. The difference in care provision effects by education emerge as the potential increase in pension benefits through IC provision is higher for lower educated women. Due to the decreasing marginal utility from consumption, increases in pension benefits are a greater incentive for women with lower income.

Overall, employment is reduced only slightly (-1.8% full-time and -0.34% part-time employment). Women with at least one parent alive reduce employment by 1.68%. Employment reactions are stronger for lower educated women. Overall supplied hours of work are reduced by 1.15%. Employment reactions appear as women partly work in order to increase pension benefits in later ages in the model. They can now increase pension benefits in earlier ages by providing IC. Further, increased high intensive IC leads to time conflicts and working becomes relatively less favourable.

In a next step, we combine the increase in collectable pension points with an increase in the retirement ages (see Section 4.6.1). Again, especially lower educated women are incentivized to increase high intensive IC. High intensive IC is increased by 44.1% before age 62 while low intensive IC is decreased by 12.8%. Before age 62 slightly more IC is provided and demand for FC is decreased only slightly. This shows that the increase in retirement ages leads to a reduction of the incentive to provide IC induced by collectable pension points. This emerges as individuals potentially work longer and spend less time in retirement. Individuals increase intensive IC by 41.1% from age 62 onward and reduce low intensive IC by 13.86%. Overall IC is reduced by 0.36% from age 62 onward. Demand for FC is increased by 2.53%. This shows a more pronounced shift from low to high intensive IC in later ages than if retirement ages are kept constant. Further, we find only a very small reduction in IC provision compared to the sole increase in retirement ages. This shows that as we increase the incentive to provide high intensive IC, individuals react also when the time-conflict between work and caring is present in later ages.

Employment responses in the combined scenario are very similar to the one without the increase in collectable pension points.[126] Women increase full-time employment by 55.2% and part-time employment by 64.4% from age 62 onward. This is a slightly smaller employment effect of increased retirement ages than if collectable pension points are not increased. Before age 62, women also increase employment less than if collectable pension are not increased (6.35% vs. 11.19%). The mean retirement age increases by 1.59 years.

Further, we analyze impacts of the combined increase in retirement ages and increase in collectable pension points on labor earnings. We show effects only for those individuals, who have at least one parent who is alive at age 55. Women who experience no care-demand during the time span of the model are not impacted differently from scenario 1, in which only the retirement age is increased. Increases in employment are smaller when we combine the increase in retirement ages with the increase in collectable pension points in IC provision. Therefore, Table C17 in the Appendix shows that consequential increases in labor earnings are smaller than in scenario 1. While in scenario 1, women increased labor earnings by 14.81% due to the increase in retirement ages, in our combined scenario, the increase is 14.37%. Decreases in retirement benefits are comparable to the ones shown in scenario 1 but slightly bigger. The reason is that in the combined scenario, increases in collectable pension points due to IC times lead to increased retirement benefits. This cannot offset the slightly lower increase in employment and consequential lower increase in employment experience and wage increases. The NPV of total earnings, consequentially is increased less than in the scenario in which only the retirement ages are increased.

Finally, we find that reductions in welfare are higher for the first two income quartiles but lower for the upper two if the increase in retirement ages is accompanied by an increase in collectable pension points. Figure 4.8 shows monetary values necessary to offset losses in welfare induced by the combined reform.

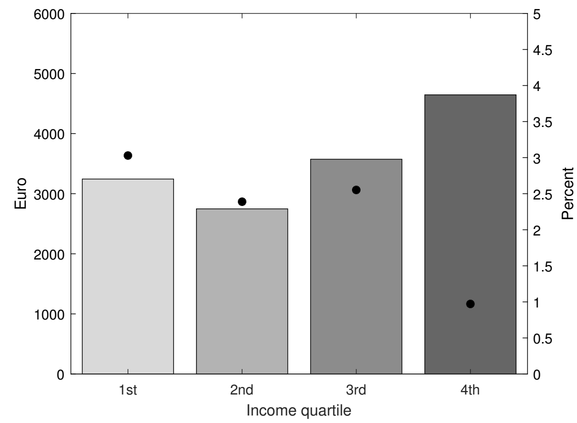
While on average, women require 1.2% of their NPV of earnings to off-set the loss in welfare created by the increase in retirement ages, it is 0.97% if one includes increased collectable pension points in IC. Highest relative losses in welfare can now be found in income quartile 1, showing that the second and third income quartile profit relatively more from the increase in collectable pension points in terms of welfare. This shows that for low income women the disincentive to work introduced by the increase in pension points off-sets the potential increase in pension benefits. For upper income women it is the other way around.

4.6.2.2 Introduction of 'care-leave'

Germany has already introduced policies that make it possible to reduce labor hours while providing care for a close relative and returning to the job after a short leave. This policy is not introduced into the model in the baseline. This simulation therefore gives a measure of the importance of labor market

[126] Figure C14 in the Appendix shows employment effects to the combined reform.

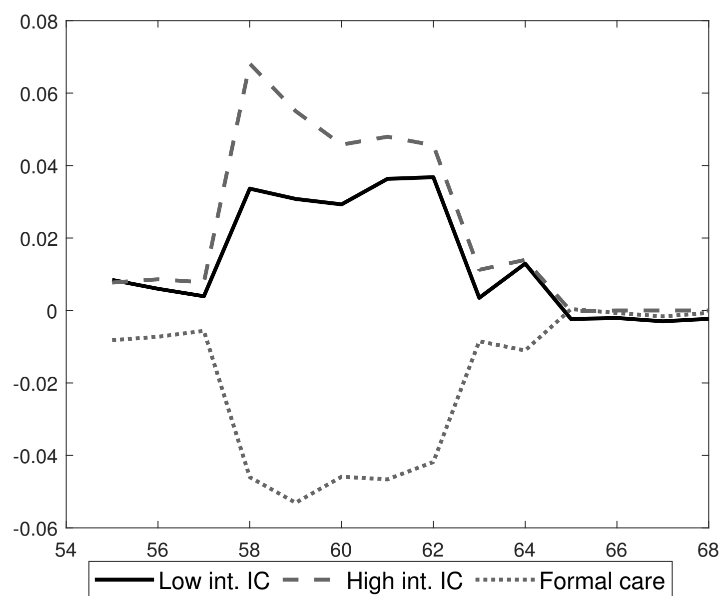
Figure 4.8: Welfare effects to increased retirement ages combined with increased collectable pension points



Notes: This Figure shows welfare effects to an increase in retirement ages combined with increased collectable pension points in times of informal care provision for women who may face demand for care by income. *Source:* SHARE, own calculations.

frictions in the uptake of IC provision. Figure 4.9 shows responses in care provision by age. We see

Figure 4.9: Care responses to the introduction of care-leave



Notes: This Figure shows caring effects to the introduction of a care-leave reform. *Source:* SHARE, own calculations.

that as labor market frictions are removed for IC provision, high and low intensive IC are increased while demand for FC is reduced. These responses are important especially until age 63 when most women hit retirement ages. We find that high intensive IC is increased by 1.48pp (52.5%) and low intensive IC is increased by 0.93pp (12.2%) before age 64. FC provision is reduced by 1.3pp (8.9%).

FC demand is decreased by 1.67pp (8.68%) for highly educated women and by 1.07pp (9.09%) for lower educated women. We find increases in high intensive IC in retirement ages (ages 64 and older) by 0.07pp (7.48%) and low intensive IC (0,04pp; 0.62%). FC is not impacted much in ages from age 64 onward. Overall, we find that through the introduction of care-leave, 17.43% more IC and 26.2% more IC hours are provided.

We find increases in part and full-time employment and increases in unemployment.[127] Before age 64 we find a 3.13pp (9.4%) decrease in part-time employment and a 1.08pp (4.15%) decrease in full-time employment and a 4.21pp (10.29%) increase in non-work. The increase in unemployment before age 64 is 4.7pp (13.7%) and retirement behavior is hardly impacted (0.07pp or 0.75% decrease in the probability to be retired by age 63). We still find reductions in part-time (-0.17pp, -3.64%) and full-time (-0.05pp, -2.69%) employment from age 64 onward. Retirement probabilities are decreased slightly (-0.26%) while unemployment is increased by 2.53%. The mean retirement age is increased slightly (by 0.016 years) and overall, working hours are decreased by 6.24 hours.

In the next step we combine the increase of retirement ages to 67 (ERA to 65) with the introduction of care-leave. We do this in order to understand whether the introduction of care-leave can absorb the detrimental care effects of increased retirement ages. Individuals react to the introduction of care-leave and decrease full- and part-time employment and increase unemployment.[128] Decreases in employment are however smaller than when we only introduce care-leave. At age 58, women reduce employment by 6.41pp (compared to a 7.31pp reduction if care-leave is introduced without altering the retirement ages). The reason is that the increased retirement age induces a further incentive to work. While changes to retirement are similar to the increase in retirement ages without introducing care-leave, employment is increased less in this combined scenario. At age 63, we find a 29.5pp increase in employment in scenario 1, while in this combined scenario, we find a 23.5pp increase in employment. Especially part-time employment is increased less than in scenario 1. The result is a stronger increase in unemployment if we combine the increased retirement age with the introduction of care-leave. Further, we find a 5.96% decrease in the demand for FC in the combined scenario while in scenario 1, demand for FC is increased by 2.9% overall.

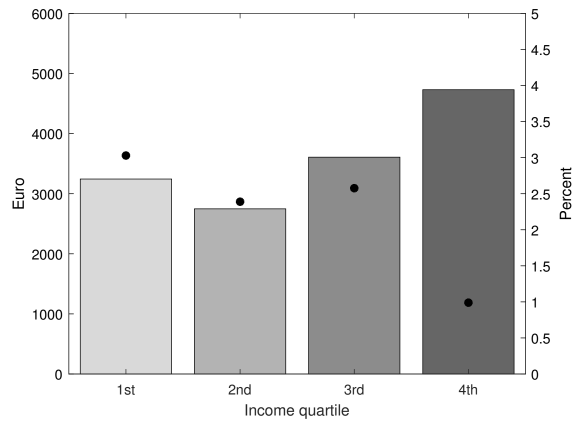
We can further analyze the impact of the combined reform on the NPV of labor earnings, retirement benefits and total earnings. We find that for the group of women who have at least one parent that is alive at age 55, labor earnings increase less if we introduce care-leave in combination with increased retirement ages in comparison to the sole increase in retirement ages. While the NPV of labor earnings increase by 14.81% if retirement ages are increased, the combined reform leads to an increase by 11.5%. The reason is that due to the introduction of care-leave, women with care-demand more often go into unemployment before retirement ages. Reductions in retirement benefits are also higher. Total earnings are even reduced if we combine higher retirement ages with the introduction of care-leave.

Figure 4.10 shows welfare effects in monetary terms and in percent of earnings if we combine increased retirement ages with the introduction of care-leave. The figure shows effects for women with potential

[127] Figure C15 in the Appendix shows employment responses to the introduction of care-leave for women who have at least one parent alive at age 55.

[128] Appendix Figure C17 shows employment effects of the combined reform.

Figure 4.10: Welfare effects to increased retirement ages combined with the introduction of care-leave



Notes: This Figure shows welfare effects to an increase in retirement ages combined with the introduction of care-leave for women who may face demand for care by income. *Source:* SHARE, own calculations.

care-demand. We see that the negative consequences of increased retirement ages on welfare are reduced due to the introduction of care-leave. Negative consequences are reduced from 1.2% of total earnings to 0.99%. This effect is very close to the reduction in negative welfare effects by the increase in collectable pension points in IC (see Figure 4.10). Lower income quartiles experience a higher reduction in income through reduced incentives to work. Therefore, the introduction of care-leave rather favours higher income groups.

4.6.3 Fiscal effects

In this section we describe fiscal effects of the important counterfactual policy reforms. In order to asses the efficiency of policy reforms one needs to understand its fiscal implications. We calculate fiscal implications in all aspects of the tax and transfer system that we model: Pension system, Social security benefits, LTC insurance benefits, social security contributions and taxes. Table 4.10 shows results. Positive values represent a surplus for the respective entity (state or insurance), while negative values represent losses. We calculate differences between the scenario of interest and the baseline simulation and report mean differences over all observations and relative results. In columns 1 and 2 we show results of increased retirement ages (see Section 4.6.1) after which we show implications of combined reforms: In columns 3-4 we show fiscal effects of combining increased retirement ages with increases in collectable pension points (see Section 4.6.2.1) and in columns 5 and 6 we show effects if increased retirement ages are combined with the introduction of care-leave (see Section 4.6.2.2).
We find that the pension payout is reduced in all three scenarios. As retirement ages are delayed, pensions are paid out in less periods on average. On the other hand agents collect more pension points and thus receive higher pension benefits which reduces the surplus of the pension system. The increase in the retirement age to 67 (ERA to 65, columns 1 and 2) leads to 9,140 Euro lower NPV of pension payouts (irrespective of taxes and social security contributions or non-labor income) on average which

is a 4.43% reduction relative to the average total pension payout. Due to increased unemployment, we find a 19.16% increase in payout of social security benefits (unemployment benefits) in this scenario which relates to an increase of 5,670 Euro on average per agent. In this scenario we find a reduction in IC and an increase in demand for FC. Thus LTCI cash-benefits are reduced while the LTCI pays out more in in-kind benefits (for FC). As the average costs for FC are higher than for IC, the LTCI pays out 200 Euro more in benefits on average and effectively has higher costs due to this reform scenario. Due to the increase in employment both social security contributions as well as income tax payments increase. The net effect of all social security systems for the scenario in which retirement ages are increased is still positive. On average the state saves 14,700 Euro in this scenario.

As we combine an increase in retirement ages with an increase in collectable pension points (see Section 4.6.2.1, columns 3 and 4 in Table 4.10) we find that pension payouts are reduced by 9,520 Euro which is very close to the impact if only retirement ages are increased. In the combined scenario we find reduced incentives to work which leads to a higher reduction in employment and thus social security benefits are impacted more than if only retirement ages are increased. The impacts on the LTCI is very different. As in the scenario agents are incentivised to provide more IC we find an increase in LTCI cash-benefit payout and a reduction in in-kind benefit payout. In total the LTCI faces slightly higher costs. As stated before, employment rises less in this scenario which is why social security contributions and income taxes are both increased less than in the scenario in which only retirement ages are increased. The net effect of this combined scenario is also positive while the state saves less in total than in the above scenario.

The last scenario that we asses from a fiscal standpoint is describes in Section 4.6.2.2: We combine an increase in the retirement ages with the introduction of a care leave policy. As a result agents work less than if only retirement benefits are increased. Therefore agents collect less pension points and pension payout is reduced more than in both scenarios above. Further, as individuals use times of unemployment to provide IC for a parent more often, the state faces a higher increase in unemployment benefits. The LTCI sees a surplus in this combined scenario as we find a shift from FC to IC. Regarding social security contributions and income taxes we find that the higher increase in unemployment in this combined scenario leads to only a small increase in social security contributions and even a decrease in tax payments. Overall this scenario leads to a small surplus of the state of 2,330 Euro.

As stated before we can see that as costs of FC are higher than costs of IC for the LTCI. Therefore the LTCI profits in monetary terms if reforms lead to a reduction of FC usage. This analysis does, however, not take into account that costs of pension points collected in times of IC might be taken over by the LTCI system. As they, again could be cross-financed by other state budgets, it is most informative to compare net effects.

4.7 Conclusion

In this paper we analyse the effects of increased labor market participation of women on informal and formal care-giving to frail parents and the role of the pension system and long-term care insurance in Germany therein. Concentrating on women in the ages 55-68, we build a dynamic structural model

Table 4.10: Fiscal effects of increasing retirement ages

	Increased retirement ages					
			Pension points		Care-leave	
	Euro in 1000	%	Euro in 1000	%	Euro in 1000	%
Pension payout	9.14	4.43	9.52	4.61	11.9	5.74
Social security benefits	-5.67	-19.16	-6.80	-22.96	-10.6	-35.73
LTCI cash benefits	0.08	4.53	-0.09	-5.59	-0.37	-22.13
LTCI in-kind benefits	-0.28	-1.39	0.08	0.41	0.86	4.23
Social security contributions	8.89	13.22	7.33	10.90	2.91	4.33
Income tax	2.59	2.82	1.28	1.39	-2.34	-2.55
Net effect	14.7	0.04	11.3	0.03	2.33	0.01

Notes: This Table shows fiscal effects of increased retirement ages (columns 1-2), combined with increased collectable pension points (columns 3-4) or the introduction of care-leave (columns 5-6). Positive values represent a surplus, negative values losses for the insurance or state.
Source: Own calculations.

to incorporate the dynamic nature of labor market and retirement decisions as well as the long-term care incentive structure. We estimate the model using data from the German part of the Survey of Health, Ageing and Retirement in Europe (SHARE) as well as the German Socio-Economic Panel (GSOEP) applying maximum likelihood. We use a quasi-experimental setting in the German pension system to validate our model. We can replicate effects of an increase in the ERA for German women on employment and informal care provision. Using the estimated structural parameters we simulate policy changes and compare outcomes with a baseline simulation. In these policy simulations, we analyse how an increase in the retirement ages, induced by an increase of the normal and early retirement ages can impact the decision for provide informal care as well as formal care organization. We then explore the role of labor market frictions and pension points collected in informal care demand in the decision to provide informal care and the care-mix.

When increasing the labor force participation of women at age 54, women work more in the short and long-term. This leads to increased time-conflicts between paid employment and informal care provision. As a result, especially high intensive informal care provision is reduced and we see a shift toward low intensive care provision. Demand for formal care is not increased as a consequence. Further, our model points to the fact that employment responses toward increased retirement ages can vary by care-demand. As women have elderly parents they increase employment less and have a higher probability to be unemployed compared to women who have no parent that is still alive. Our policy simulation shows that an increase in retirement ages intensifies time-conflicts and consequently less informal care is provided. As a consequence, the demand for formal care increases. We can show that women with potential for care-demand loose less income and are impacted more negatively in their welfare through the introduction of this reform. As we simulate the introduction of care-leave- the possibility to return to the job after having provided informal care - we see an increase in informal care provision. This reduces the demand for formal care. As we give the opportunity to reduce labor hours to zero while providing informal care, our model predicts a decrease in employment and an increase in unemployment while women provide informal care to a frail parent. This simulation shows that labor market frictions play a role in the decision to provide informal care. Korfhage (2019) and Skira (2015) can show that labor market frictions play an important role in the negative impact of informal care provision on long-term labor market outcomes such as wages and pension benefits. We point to the other side of the equation: Women take labor market frictions into account when deciding whether to provide informal care and reduce labor hours. Further, we point to the fact that pension points that are collected in informal care provision are an important incentive especially for high intensive informal care provision.

Our analysis shows that as retirement ages are increased, the LTCI faces negative consequences as less informal care is provided and more formal care is given. This impacts the LTCI budget negatively. We can also show that reforms that effectively alleviate those negative consequences on care provision and inequality on the individual level can be costly from a fiscal standpoint as they might reduce labor supply. The welfare effects on parents who receive less or more informal care or need to organize more or less formal care due to policy reforms analyzed are beyond the scope of this paper. Hu and Li (2020), Wu and Lu (2017) and Chon et al. (2018) can point to positive effects of an increase of informal care provision on care-dependent elderly individuals.

The results of our paper suggest that changes in female labor force participation and increased retirement ages lead to reduced informal care provision and increased demand for formal care. Our notion is that informal and formal care are no perfect substitutes but rather complement each other dependent on the kind of care dependency. Still, as no informal care is provided due to increased opportunity costs, formal care is in higher demand. Further, our paper suggests that further policy measures like increased pension points collected in informal care times or the introduction of care-leave, similar to child-care leave policy can alleviate the reduction in informal care supply but come with long-term fiscal and individual labor market costs. For a group of women, the increased labor market participation is coupled with provision of informal care which is burdensome for mental and physical health (Schmitz and Stroka, 2013). This comes with long-term health costs for individuals as well as fiscal costs for the public health insurance.

Appendix A

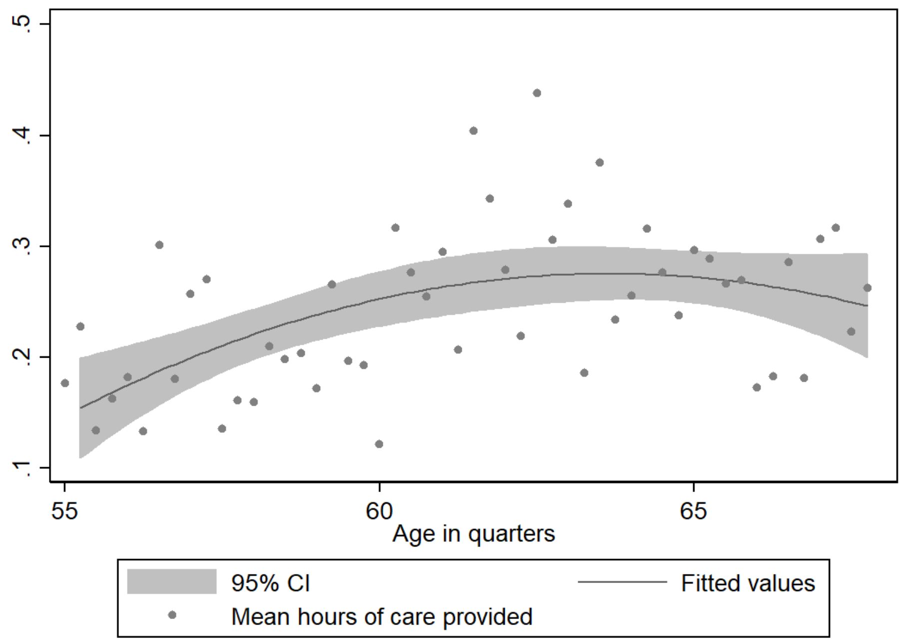
Appendix to Chapter 1

A.1 ERA discontinuity analysis: additional robustness checks

We provide results based on alternative sample selection criteria. We select women retiring from employment by using only pre-determined variables, before women turn 60. Thus, we keep women in the sample that have unemployment spells after crossing their ERA threshold. These women are not yet retired at these ages, but they are part of the control group. Still, they do not face a time conflict according to our interpretation, as they can potentially be unemployed and provide informal care without being retired. We still find an effect of similar magnitude on hours of daily informal care that is, however, less precisely estimated (Table A15). Parameters of the binary care indicators are also smaller and become insignificant.
When standard errors are clustered at a different level, they remain of equal size (Table A16).

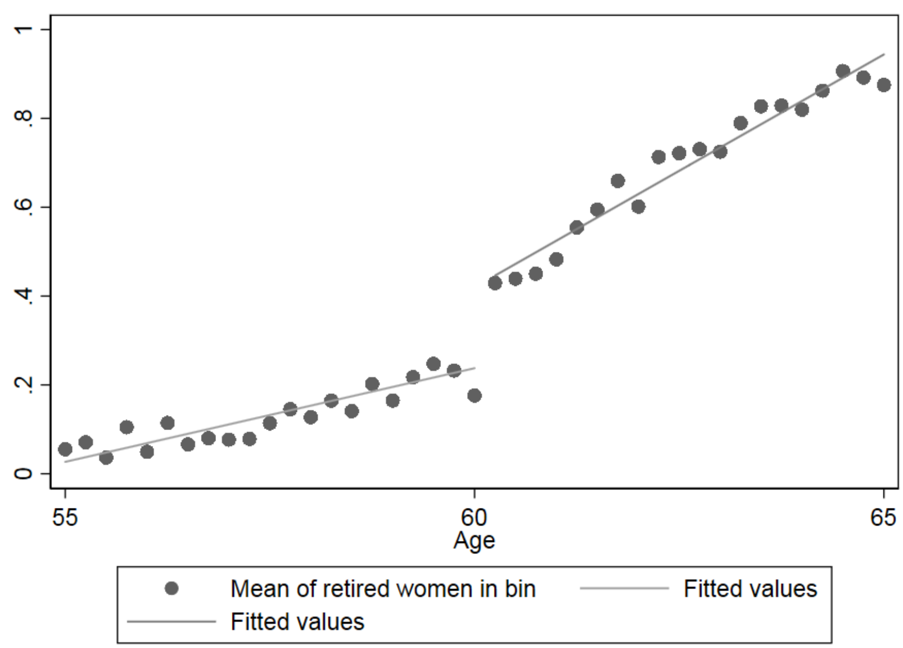
A.2 Additional figures

Figure A1: Mean hours of informal care by age (in bins of quarters of years of age)



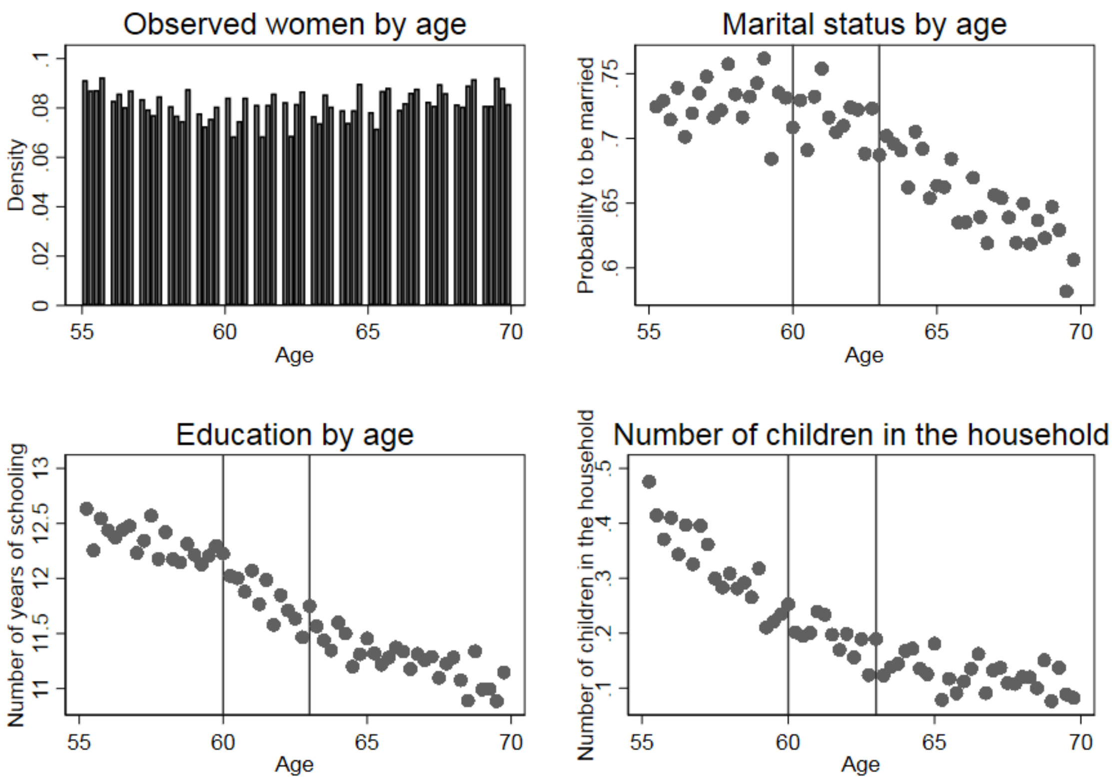
Source: SOEP v33, own calculations.

Figure A2: Retirement behavior by age, 5 year bandwidth.



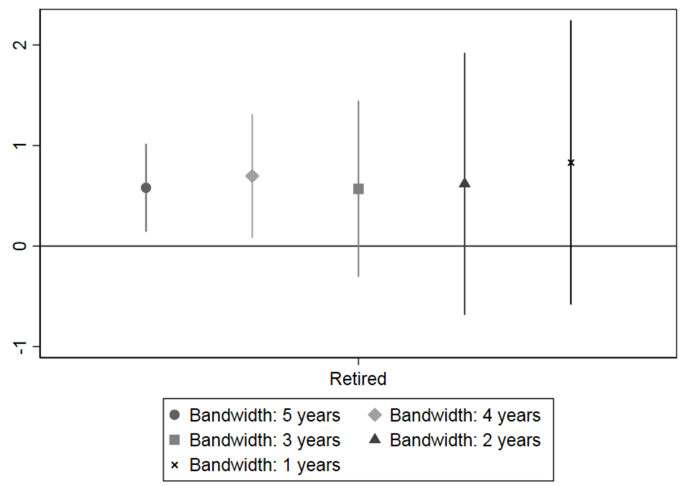
Source: SOEP v33, own calculations.

Figure A3: Distribution of covariates by age around ERA thresholds



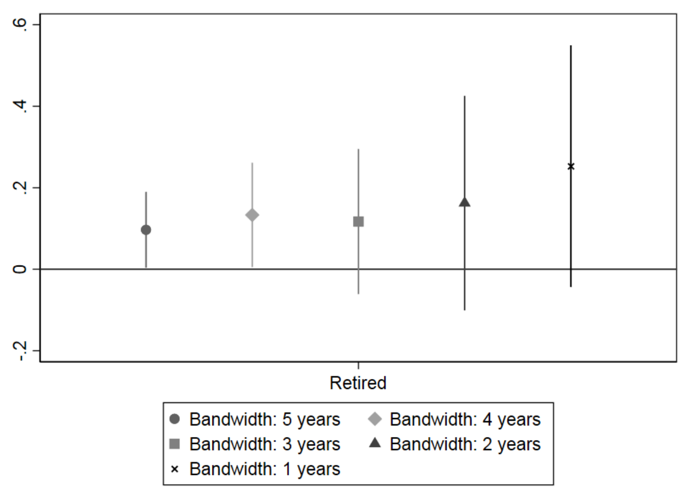
Source: SOEP v33, own calculations.

Figure A4: 2SLS estimates – robustness for bandwidth choice, daily hours of informal care within the household, cohort-specific ERA.



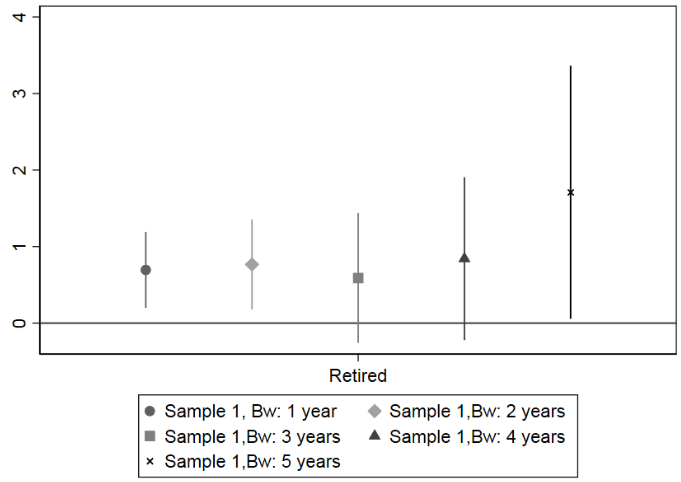
Source: SOEP v33, own calculations.

Figure A5: 2SLS estimates – robustness for bandwidth choice, probability of informal care within the household, cohort-specific ERA.



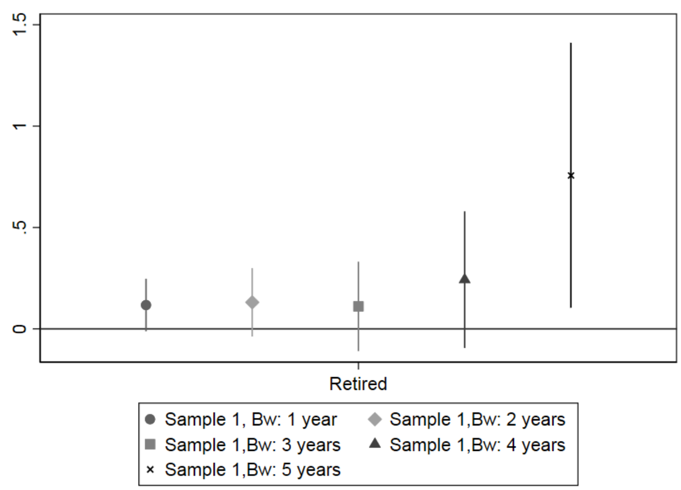
Source: SOEP v33, own calculations.

Figure A6: 2SLS estimates – robustness for bandwidth choice, daily hours of informal care, women with ERA at 60.



Source: SOEP v33, own calculations.

Figure A7: 2SLS estimates – robustness for bandwidth choice, probability of informal care, women with ERA at 60.



Source: SOEP v33, own calculations.

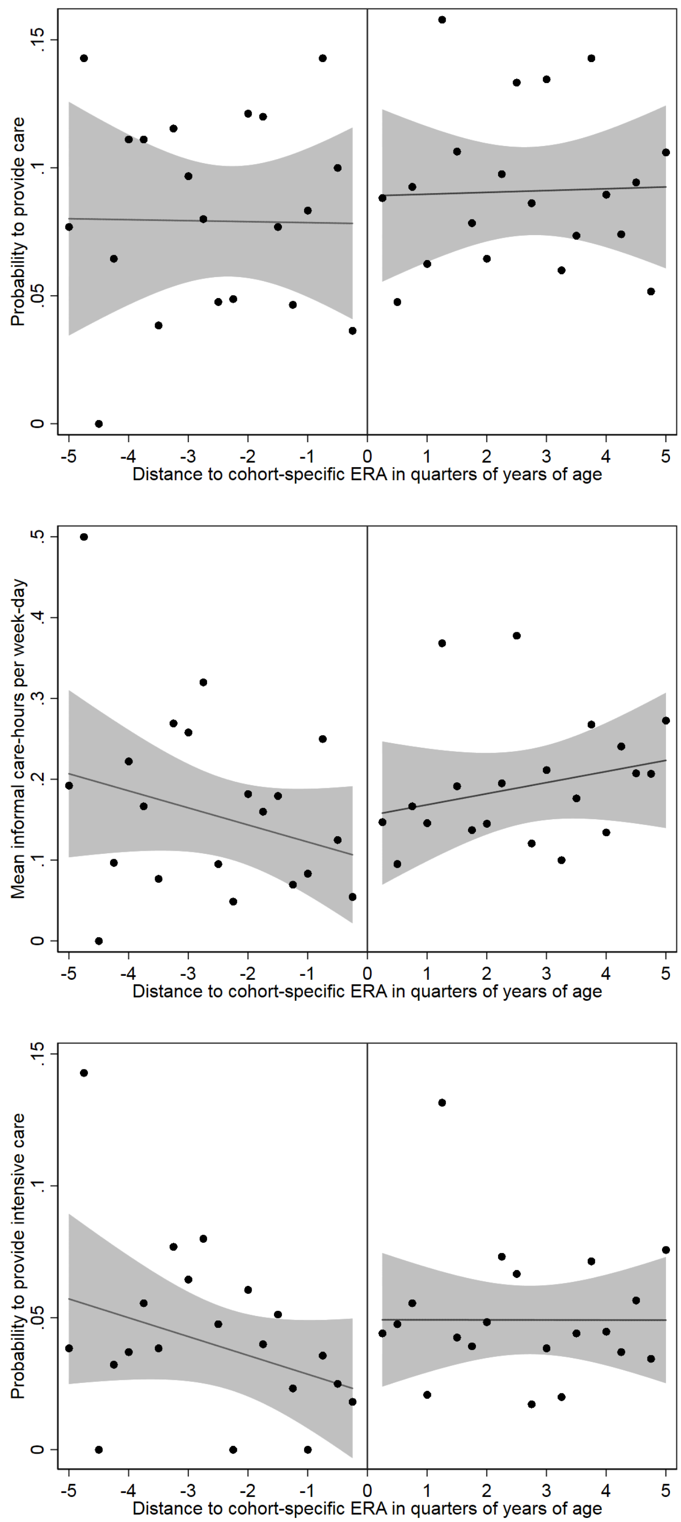


Figure A8: Care provision around the ERA: Women retiring later than their ERA (never-takers)

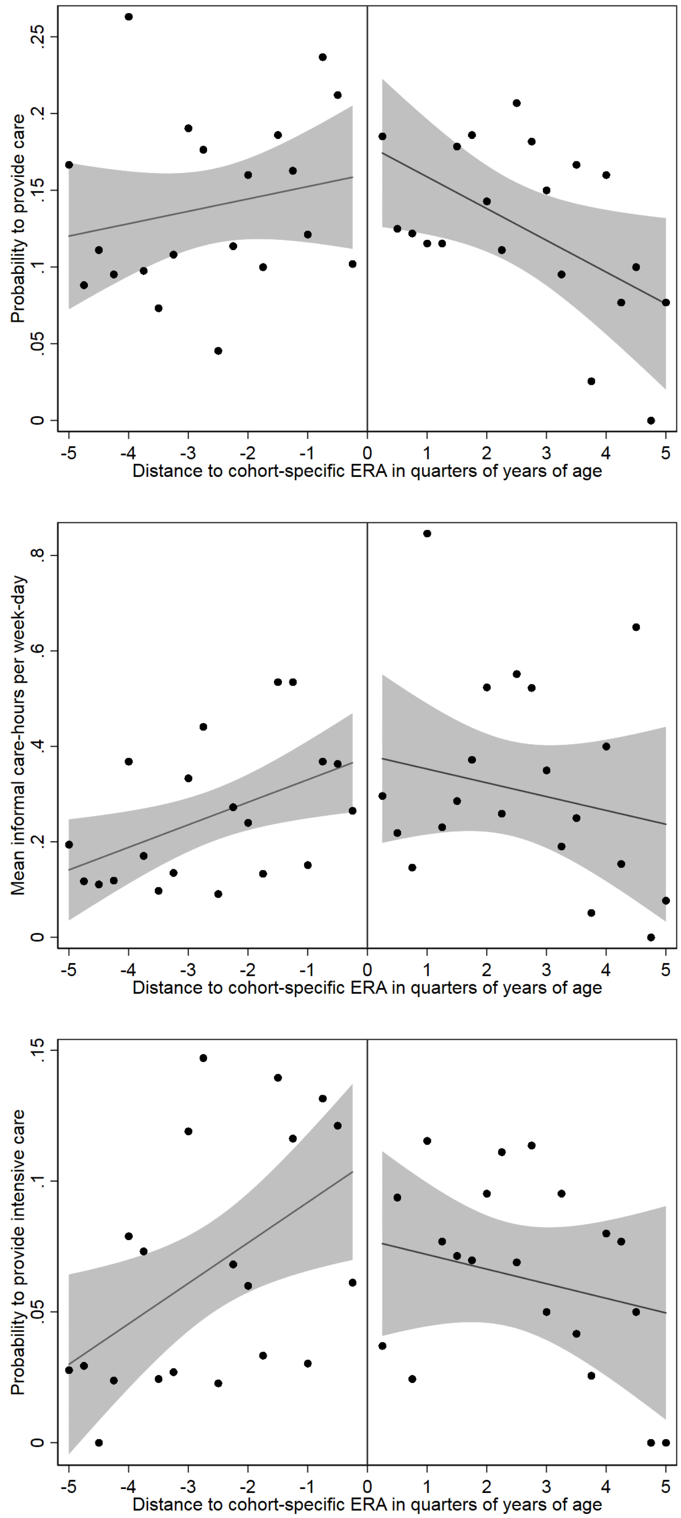


Figure A9: Care provision around the ERA: Women retiring before their ERA (always-takers)

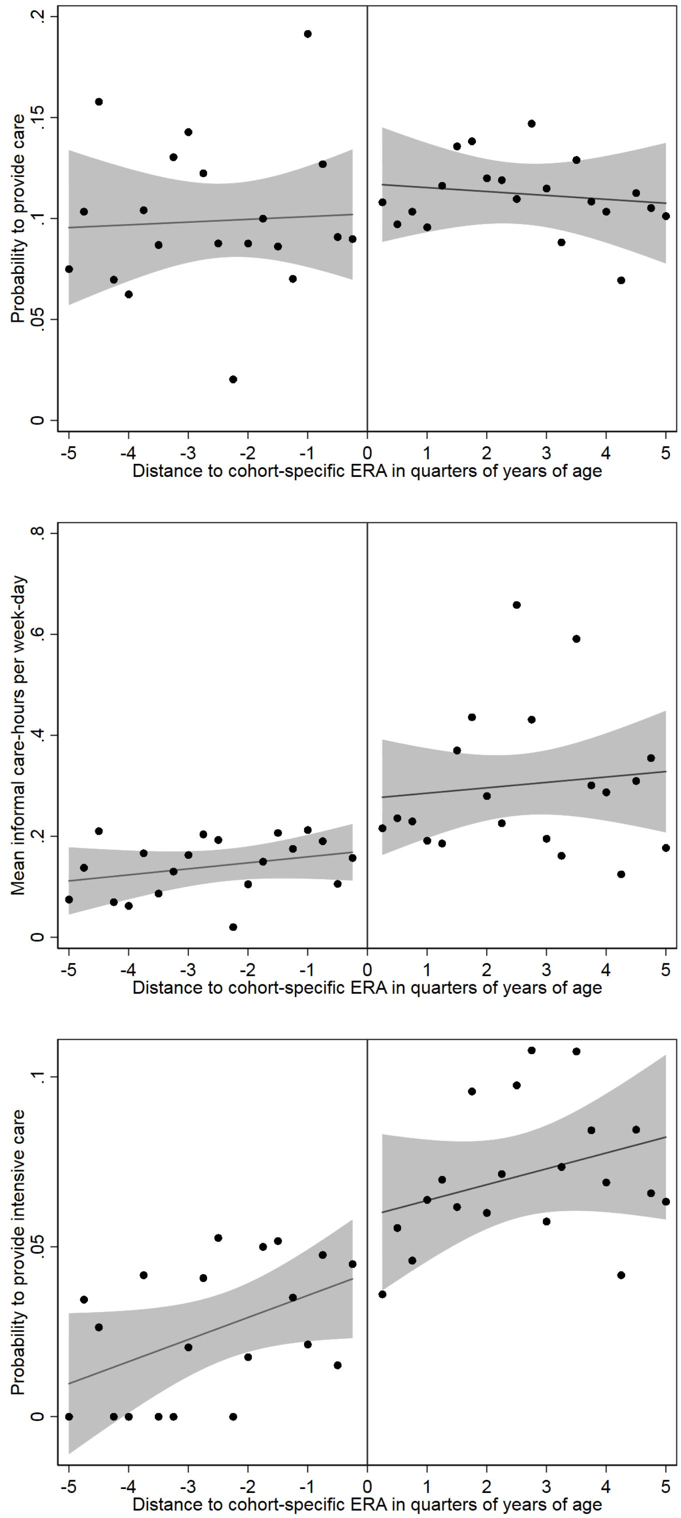


Figure A10: Care provision around the ERA: Women retiring at the ERA

A.3 Additional tables

Table A1: Effects of the ERA threshold on retirement behavior (first stage) for women, several bandwidths.

	(1)	(2)	(3)	(4)	(5)
ERA	0.133**	0.101**	0.121***	0.137***	0.172***
	(0.060)	(0.038)	(0.030)	(0.025)	(0.022)
Observations	1705	3540	5573	7764	10095
Controls	-	-	-	-	-
Bandwidth—years	1	2	3	4	5

Notes: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: SOEP v33, own calculations.

Table A2: Effects of the ERA threshold on retirement behavior (first stage) for women, care only within the household, several bandwidths.

	(1)	(2)	(3)	(4)	(5)
ERA	0.109*	0.098**	0.127***	0.145***	0.178***
	(0.059)	(0.038)	(0.030)	(0.024)	(0.022)
Observations	1570	3265	5122	7139	9303
Controls	-	-	-	-	-
Bandwidth—years	1	2	3	4	5

Notes: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: SOEP v33, own calculations.

Table A3: Effects of the ERA threshold (age 60, women born before 1952) on retirement behavior (first stage), several bandwidths.

	(1)	(2)	(3)	(4)	(5)
Age 60	0.138**	0.115***	0.134***	0.154***	0.187***
	(0.063)	(0.039)	(0.031)	(0.026)	(0.024)
Observations	1592	3236	4923	6649	8379
Controls	-	-	-	-	-
Bandwidth—years	1	2	3	4	5

Notes: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: SOEP v33, own calculations.

Table A4: Effects of the ERA threshold (age 60, women born before 1952) on retirement behavior (first stage), care only within the household, several bandwidths.

	(1)	(2)	(3)	(4)	(5)
Age 60	0.117*	0.109***	0.136***	0.158***	0.191***
	(0.062)	(0.040)	(0.031)	(0.025)	(0.024)
Observations	1467	2988	4534	6131	7750
Controls	-	-	-	-	-
Bandwidth—years	1	2	3	4	5

Notes: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: SOEP v33, own calculations.

Table A5: 2SLS discontinuity analysis: effects of retirement on care provision for married women.

	(1)	(2)	(3)	(4)
Instrument	ERA	ERA	ERA	Age 60
	Hours of care provision			
Retired	0.546***	0.573*	0.583***	0.525***
	(0.192)	(0.322)	(0.200)	(0.186)
Pre-Treatment mean	0.170	0.170	0.170	0.164
Observations	7182	5320	7182	5933
Bandwidth—years	5	3.861	5	5
	Informal care			
Retired	0.156**	0.289*	0.175**	0.141*
	(0.078)	(0.170)	(0.079)	(0.075)
Pre-Treatment mean	0.0970	0.0929	0.0970	0.0897
Observations	7182	4631	7182	5933
Bandwidth—years	5	3.416	5	5
	Intensive care			
Retired	0.098**	0.131	0.105**	0.097**
	(0.048)	(0.083)	(0.050)	(0.047)
Pre-Treatment mean	0.0401	0.0416	0.0401	0.0370
Observations	7182	5533	7182	5933
Bandwidth—years	5	4.003	5	5
Controls	-		YES	-
KL.Paap	52.67		45.77	60.85

Notes: Women retiring from employment, 2001-2015; ERA: cohort-specific early retirement age (all women), Age 60: only age 60 as instrument (women born before 1952); (2): optimally selected bandwidth; Cluster robust (clustered on the month of age level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; YES: controls for year of observation, number of children in the household, and marital status; Kl.Paap: Kleibergen-Paap statistic.
Source: SOEP v33, own calculations.

Table A6: 2SLS discontinuity analysis: effects of retirement on care provision for unmarried women.

	(1)	(2)	(3)	(4)
Instrument	ERA	ERA	ERA	Age 60
	Hours of care provision			
Retired	1.848*	2.511	1.802*	1.407
	(0.980)	(2.070)	(0.995)	(0.906)
Observations	2913	2310	2913	2446
Bandwidth—years	5	4.093	5	5
Pre-Treatment mean	0.126	0.127	0.126	0.116
	Informal care			
Retired	−0.004	−0.061	−0.015	−0.004
	(0.205)	(0.284)	(0.214)	(0.206)
Observations	2913	3319	2913	2446
Bandwidth—years	5	5.566	5	5
Pre-Treatment mean	0.0743	0.0713	0.0743	0.0717
	Intensive care			
Retired	0.088	0.065	0.079	−0.041
	(0.160)	(0.183)	(0.165)	(0.163)
Observations	2913	3706	2913	2446
Bandwidth—years	5	6.046	5	5
Pre-Treatment mean	0.0309	0.0309	0.0309	0.0309
Controls	-		YES	-
KL.Paap	9.696		8.605	11.23

Notes: Women retiring from employment, 2001-2015; ERA: cohort-specific early retirement age (all women), Age 60: only age 60 as instrument (women born before 1952); (2): optimally selected bandwidth; Cluster robust (clustered on the month of age level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; YES: controls for year of observation, number of children in the household, and marital status; Kl.Paap: Kleibergen-Paap statistic.
Source: SOEP v33, own calculations.

Table A7: 2SLS discontinuity analysis: effects of retirement on care provision for women retiring from unemployment.

Instrument	(1) ERA	(2) ERA	(3) ERA	(4) Age 60
	Hours of care provision			
Retired	−0.037	−0.068	−0.017	−0.058
	(0.537)	(0.601)	(0.540)	(0.569)
Observations	8066	9211	8066	7129
Bandwidth—years	5	5.746	5	5
Pre-Treatment mean	0.417	0.413	0.417	0.407
	Probability to provide care			
Retired	−0.104	−0.120	−0.103	−0.101
	(0.087)	(0.094)	(0.086)	(0.087)
Observations	8066	8414	8066	7129
Bandwidth—years	5	5.222	5	5
Pre-Treatment mean	0.129	0.130	0.129	0.125
	Intensive care			
Retired	−0.069	−0.091	−0.067	−0.069
	(0.089)	(0.101)	(0.089)	(0.093)
Observations	8066	8906	8066	7129
Bandwidth—years	5	5.548	5	5
Pre-Treatment mean	0.085	0.087	0.085	0.083
Controls	-	-	YES	-
KL.Paap	55.70		55.55	52.82

Notes: Main effects and robustness checks, women retiring from unemployment, 2001-2015; ERA: cohort-specific early retirement age (all women), Age 60: only age 60 as instrument (women born before 1952); (2): optimally selected bandwidth; Cluster robust (clustered on the month of age level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; YES: controls for year of observation, number of children in the household, and marital status; Kl.Paap: Kleibergen-Paap statistic.
Source: SOEP v33, own calculations.

Table A8: 2SLS discontinuity analysis: effects of retirement on care provision on the weekend.

	(1)	(2)	(3)	(4)
Instrument	ERA	ERA	ERA	Age 60
	Hours of care provision			
Retired	0.316	0.232	0.328	0.317*
	(0.198)	(0.343)	(0.205)	(0.190)
Observations	10095	7179	10095	8379
Bandwidth—years	5	3.756	5	5
Pre-Treatment mean	0.105	0.104	0.105	0.104
KL.Paap	58.75		46.73	63.22
	Probability to provide care			
Retired	−0.320	−0.081	−0.052	0.067
	(0.232)	(0.435)	(0.090)	(0.061)
Observations	10853	8198	10851	8379
Bandwidth—years	5	3.984	5	5
Pre-Treatment mean	0.137	0.130	0.137	0.213
KL.Paap	66.28		45.66	63.22
	Intensive care			
Retired	−0.374	−0.193	−0.104	0.014
	(0.236)	(0.389)	(0.089)	(0.040)
Observations	10853	9450	10851	8379
Bandwidth—years	5	4.456	5	5
Pre-Treatment mean	0.106	0.104	0.106	0.188
KL.Paap	66.28		45.66	63.22
Controls	-		YES	-

Notes: Main effects and robustness checks, women retiring from employment, 2001-2015; ERA: cohort-specific early retirement age (all women), Age 60: only age 60 as instrument (women born before 1952); (2): optimally selected bandwidth; Cluster robust (clustered on the month of age level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; YES: controls for year of observation, number of children in the household, and marital status; Kl.Paap: Kleibergen-Paap statistic.

Table A9: 2SLS discontinuity analysis: effects of retirement on care provision, robustness: local linear estimator.

	(1)	(2)	(3)	(4)
Instrument	ERA	ERA	ERA	ERA
	Hours of care provision			
RD-Estimate	0.816**	1.155	1.485**	0.782**
	(0.356)	(0.733)	(0.715)	(0.336)
Pre-Treatment mean	0.159	0.159	0.159	0.159
	Probability to provide care			
RD-Estimate	0.159	0.364	0.680*	0.139
	(0.114)	(0.254)	(0.356)	(0.105)
Pre-Treatment mean	0.0910	0.0910	0.0910	0.0910
	Intensive care			
RD-Estimate	0.101	0.156	0.207	0.095
	(0.070)	(0.142)	(0.141)	(0.065)
Pre-Treatment mean	0.0377	0.0377	0.0377	0.0377
Observation	10095	10095	10095	10095
Bandwidth—years	5	5	5	5
Local polynomial	1	2	3	1
Kernel	Tri.	Tri.	Tri.	Epa.

Notes: Main effects and robustness checks using a local linear estimator, 5-year bandwidth, women retiring from employment, 2001-2015; ERA: cohort-specific early retirement age (all women); Tri.: triangular, Epa.: epanechnikov; Cluster robust (clustered on the month of age level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: 2SLS discontinuity analysis: effects of retirement on care provision within the own household, robustness: local linear estimator.

	(1)	(2)	(3)	(4)
Instrument	ERA	ERA	ERA	ERA
	Hours of care provision			
RD-Estimate	0.702**	0.846	0.829	0.688**
	(0.343)	(0.832)	(1.055)	(0.314)
Pre-Treatment mean	0.0423	0.0423	0.0423	0.0423
	Probability to provide care			
RD-Estimate	0.142**	0.232	0.266	0.134**
	(0.068)	(0.165)	(0.227)	(0.062)
Pre-Treatment mean	0.0199	0.0199	0.0199	0.0199
	Intensive care			
RD-Estimate	0.138**	0.184	0.181	0.134***
	(0.056)	(0.143)	(0.198)	(0.051)
Pre-Treatment mean	0.0115	0.0115	0.0115	0.0115
Observation	9303	9303	9303	9303
Kernel	Tri.	Tri.	Tri.	Epa.
Bandwidth—years	5	5	5	5
Local polynomial	1	2	3	1

Notes: Main effects and robustness checks using a local linear estimator, 5-year bandwidth, women retiring from employment, 2001-2015; ERA: cohort-specific early retirement age (all women); Tri.: triangular, Epa.: epanechnikov; Cluster robust (clustered on the month of age level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: SOEP v33, own calculations.

Table A11: Reduced-form effects of ERA on care provision for all women retiring from employment that retire later than their cohort-specific ERA (never takers)

	(1)	(2)	(3)
Variable	Hours of care provision	Probability to provide care	Intensive care
ERA	0.052	0.014	0.027*
	(0.048)	(0.023)	(0.016)
Observations	1648	1648	1648

Notes: 5-year bandwidth, Cluster robust (clustered on the quarter age level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: SOEP v33, own calculations.

Table A12: Reduced-form effects of ERA on care provision for all women retiring from employment that retire before their cohort-specific ERA (always takers)

	(1)	(2)	(3)
Variable	Hours of care provision	Probability to provide care	Intensive care
ERA	0.038	0.036	−0.022
	(0.114)	(0.042)	(0.026)
Observations	1359	1359	1359

Notes: 5-year bandwidth, Cluster robust (clustered on the quarter age level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: SOEP v33, own calculations.

Table A13: Reduced-form effects of ERA on care provision for all women retiring from employment.

	(1)	(2)	(3)
Variable	Hours of care provision	Probability to provide care	Intensive care
ERA	0.133***	0.022*	0.017*
	(0.050)	(0.014)	(0.009)
Observations	10095	10095	10095

Notes: 5-year bandwidth, Cluster robust (clustered on the quarter age level) standard errors in parentheses;* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Source: SOEP v33, own calculations.

Table A14: Effects of ERA thresholds on retirement (first stage estimates) on men and women, all cut-offs.

	(1)	(2)	(3)	(4)	(5)	(6)
Gender		Men			Women	
Age 60	0.016			0.187***		
	(0.013)			(0.024)		
Age 63		0.115***			0.040**	
		(0.017)			(0.018)	
Age 65			0.165***			0.033**
			(0.012)			(0.015)
Observations	15347	14805	14736	8379	10829	12262
Controls	-	-	-	-	-	
Bandwidth—years	5	5	5	5	5	5

Notes: Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: SOEP v33, own calculations.

Table A15: 2SLS effects of retirement on care provision, women retiring without unemployment spells before their ERA

	(1)	(2)	(3)	(4)
Instrument	ERA	ERA	ERA	Age 60
	Hours of care provision			
Retired	0.758**	0.065	0.794**	0.597*
	(0.333)	(0.714)	(0.354)	(0.308)
Pre-Treatment mean	0.218	0.209	0.218	0.226
Observations	12.956	6189	12.956	11.124
Bandwidth—years	5	2.642	5	5
	Informal care			
Retired	0.081	0.016	0.097	0.055
	(0.087)	(0.177)	(0.091)	(0.081)
Pre-Treatment mean	0.100	0.098	0.100	0.099
Observations	12.956	7300	12.956	11.124
Bandwidth—years	5	3.063	5	5
	Intensive care			
Retired	0.076	−0.056	0.081	0.042
	(0.070)	(0.138)	(0.074)	(0.067)
Pre-Treatment mean	0.049	0.048	0.049	0.050
Observations	12.956	7540	12.956	11.124
Bandwidth—years	5	3.156	5	5
Controls	-		YES	-
KL.Paap	47.56		41.39	58.35

Notes: Main effects and robustness checks, 2001-2015, linear polynomial, triangular kernel; ERA: cohort-specific early retirement age (all women), Age 60: only age 60 as instrument (women born before 1952); (2): optimally selected bandwidth; Cluster robust (clustered on the month of age level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; YES: controls for year of observation, number of children in the household, and marital status; Kl.Paap: Kleibergen-Paap statistic.

Source: SOEP v33, own calculations.

Table A16: 2SLS effects of retirement on care provision, clustered at personal level.

	(1)	(2)	(3)	(4)
Instrument	ERA	ERA	ERA	Age 60
	Hours of care provision			
Retired	0.772***	0.932	0.813***	0.695***
	(0.274)	(0.576)	(0.287)	(0.253)
Observations	10095	6450	10095	8379
Bandwidth—years	5	3.427	5	5
Pre-Treatment mean	0.159	0.157	0.159	0.151
	Probability to provide care			
Retired	0.131*	0.223	0.146*	0.118*
	(0.071)	(0.163)	(0.075)	(0.066)
Observations	10095	6530	10095	8379
Bandwidth—years	5	3.468	5	5
Pre-Treatment mean	0.0910	0.0882	0.0910	0.0850
	Intensive care			
Retired	0.096*	0.116	0.102*	0.075
	(0.054)	(0.110)	(0.056)	(0.050)
Observations	10095	7268	10095	8379
Pre-Treatment mean	0.0377	0.0385	0.0377	0.0354
Bandwidth—years	5	3.806	5	5
Controls	-		YES	-
KL.Paap	89.87		84.02	106.3

Notes: Main effects and robustness checks, women retiring from employment, 2001-2015, triangular kernel ;ERA: cohort-specific early retirement age (all women), Age 60: only age 60 as instrument (women born before 1952); Standard errors in parentheses (clustered on the individual level); (2): optimally selected bandwidth; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Controls for year of observation, number of children in the household, and marital status; Kl.Paap: Kleibergen-Paap statistic.

Source: SOEP v33, own calculations.

Table A17: 2SLS estimates for women: ERA 63 and NRA 65, 5 year bandwidth.

	(1)	(2)	(3)	(4)	(5)	(6)
Instrument		ERA 63			NRA 65	
	Hours of care	Caring probability	Intensive care	Hours of care	Caring probability	Intensive care
Retired	-2.887	-0.450	-0.197	-2.817	0.004	-0.631
	(2.040)	(0.327)	(0.259)	(5.303)	(0.767)	(1.044)
Observations	10829	10829	10829	12912	12912	12912
Bandwidth-years	5	5	5	5	5	5
Kl.Paap	5.073	5.073	5.073	0.588	0.588	0.588

Notes: ERA: early retirement age; NRA: normal retirement age; standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Columns (1)-(3): women born before 1952, retiring from employment, columns (4)-(6): all women retiring from employment; Kl.Paap: Kleibergen-Paap statistic.

Source: SOEP v33, own calculations.

Table A18: 2SLS estimates for men: ERA 60, 63 and NRA 65, 5 year bandwidth.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Instrument		Age 60			Age 63			Age 65	
	Hours of care	Caring probability	Intensive care	Hours of care	Caring probability	Intensive care	Hours of care	Caring probability	Intensive care
Retired	0.935	0.201	-0.317	-0.184	-0.021	-0.033	-0.112	0.019	0.007
	(1.655)	(0.507)	(0.379)	(0.226)	(0.063)	(0.044)	(0.161)	(0.048)	(0.033)
Observations	15347	15347	15347	14805	14805	14805	14736	14736	14736
Bandwidth-years	5	5	5	5	5	5	5	5	5
Kl.Paap	1.709	1.709	1.709	46.104	46.104	46.104	198.454	198.454	198.454

Notes: ERA: early retirement age; NRA: normal retirement age; standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Kl.Paap: Kleibergen-Paap statistic.
Source: SOEP v33, own calculations.

Appendix B

Appendix to Chapter 2

B.1 Additional tables

Table B1: Observations by birth year and age for SOEP and SARE data.

Birthyear	60	61	62	Total	60	61	62	Total
Data-set	SOEP				SHARE			
1949	167	185	202	554	0	25	16	41
	(30.14)	(33.39)	(36.46)	(100.00)	(0.00)	(60.98)	(39.02)	(100.00)
1950	180	204	184	568	14	22	83	119
	(31.69)	(35.92)	(32.39)	(100.00)	(11.76)	(18.49)	(69.75)	(100.00)
1951	216	205	205	626	22	94	39	155
	(34.50)	(32.75)	(32.75)	(100.00)	(14.19)	(60.65)	(25.16)	(100.00)
1952	195	196	185	576	53	33	31	117
	(33.85)	(34.03)	(32.12)	(100.00)	(45.30)	(28.21)	(26.50)	(100.00)
1953	214	185	193	592	36	62	49	147
	(36.15)	(31.25)	(32.60)	(100.00)	(24.49)	(42.18)	(33.33)	(100.00)
1954	218	215	220	653	48	39	52	139
	(33.38)	(32.92)	(33.69)	(100.00)	(34.53)	(28.06)	(37.41)	(100.00)
Total	1190	1190	1189	3569	173	275	270	718
	(33.34)	(33.34)	(33.31)	(100.00)	(24.09)	(38.30)	(37.60)	(100.00)

Row-percentages in brackets
Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B2: Difference in the probability to be married (women aged 60-62) between women born before and from 1952 onward. Robustness checks.

	(1)	(2)	(3)	(4)	(5)	(6)
OLS	0.134	0.134	0.117*	-0.026	0.144	0.162
	(0.130)	(0.077)	(0.060)	(0.145)	(0.141)	(0.104)
Local polynomial	0.071	0.139*	0.134**	-0.110	0.092	0.139
	(0.116)	(0.085)	(0.064)	(0.090)	(0.121)	(0.101)
Observations	1,234	2,397	3,541	1,234	2,397	3,541
Data	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP
Polynomial	1	1	1	2	2	2
Controls	-	-	-	-	-	-
BW—months	12	24	36	12	24	36
Pre treat. pred.	0.734	0.690	0.715	0.850	0.726	0.677

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy); Pre treat. pred.: Pre treatment prediction
Source: SOEP v34, own calculations

Table B3: Difference in the probability to be married (women aged 55-60) between women born before and from 1952 onward. Robustness checks.

	(1)	(2)	(3)	(4)	(5)	(6)
OLS	0.142	0.120**	0.131***	0.149	0.151	0.132**
	(0.077)	(0.049)	(0.040)	(0.125)	(0.087)	(0.063)
Local polynomial	0.145*	0.133**	0.131***	0.081	0.147*	0.134*
	(0.086)	(0.058)	(0.044)	(0.091)	(0.086)	(0.071)
Observations	1,959	3,919	5,820	1,959	3,919	5,820
Data	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP
Polynomial	1	1	1	2	2	2
Controls	-	-	-	-	-	-
BW—months	12	24	36	12	24	36
Pre treat. pred.	0.750	0.727	0.731	0.746	0.739	0.728

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy); Pre treat. pred.: Pre treatment prediction
Source: SOEP v34, own calculations

Table B4: Difference in the probability of a child living in the household (women aged 60-62) between women born before and from 1952 onward. Robustness checks.

	(1)	(2)	(3)	(4)	(5)	(6)
OLS	-0.019	0.015	0.041**	0.036	-0.003	-0.021
	(0.033)	(0.018)	(0.017)	(0.041)	(0.029)	(0.028)
Local polynomial	0.002	0.008	0.016	0.035	-0.008	-0.003
	(0.030)	(0.017)	(0.014)	(0.044)	(0.033)	(0.022)
Observations	1,245	2,412	3,569	1,245	2,412	3,569
Data	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP
Polynomial	1	1	1	2	2	2
Controls	-	-	-	-	-	-
BW—months	12	24	36	12	24	36
Pre treat. pred.	0.125	0.0845	0.0764	0.0745	0.111	0.108

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy); Pre treat. pred.: Pre treatment prediction
Source: SOEP v34, own calculations

Table B5: Difference in the probability of a child living in the household (women aged 55-60) between women born before and from 1952 onward. Robustness checks.

	(1)	(2)	(3)	(4)	(5)	(6)
OLS	-0.062	-0.002	0.027	-0.090*	-0.064	-0.055
	(0.052)	(0.041)	(0.039)	(0.042)	(0.048)	(0.042)
Local polynomial	-0.081	-0.025	-0.004	-0.122**	-0.081	-0.055
	(0.050)	(0.046)	(0.037)	(0.052)	(0.060)	(0.054)
Observations	1,974	3,940	5,856	1,974	3,940	5,856
Data	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP
Polynomial	1	1	1	2	2	2
Controls	-	-	-	-	-	-
BW—months	12	24	36	12	24	36
Pre treat. pred.	0.252	0.202	0.165	0.190	0.253	0.250

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy); Pre treat. pred.: Pre treatment prediction
Source: SOEP v34, own calculations

Table B6: Difference in the probability to be highly educated (women aged 60-62) between women born before and from 1952 onward. Robustness checks.

	(1)	(2)	(3)	(4)	(5)	(6)
OLS	0.217***	0.083	0.065	0.167*	0.179**	0.133**
	(0.052)	(0.061)	(0.051)	(0.089)	(0.065)	(0.064)
Local polynomial	0.198***	0.125**	0.093*	0.215***	0.220***	0.155***
	(0.052)	(0.056)	(0.049)	(0.058)	(0.051)	(0.059)
Observations	1,245	2,412	3,569	1,245	2,412	3,569
Data	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP
Polynomial	1	1	1	2	2	2
Controls	-	-	-	-	-	-
BW—months	12	24	36	12	24	36
Pre treat. pred.	0.241	0.268	0.297	0.293	0.249	0.243

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy); Pre treat. pred.: Pre treatment prediction
Source: SOEP v34, own calculations

Table B7: Difference in the probability to be highly educated (women aged 55-60) between women born before and from 1952 onward. Robustness checks.

	(1)	(2)	(3)	(4)	(5)	(6)
OLS	0.165***	0.013	-0.005	0.153***	0.160***	0.080*
	(0.032)	(0.051)	(0.044)	(0.033)	(0.041)	(0.044)
Local polynomial	0.163***	0.075*	0.030	0.159***	0.188***	0.110***
	(0.030)	(0.039)	(0.041)	(0.038)	(0.036)	(0.039)
Observations	1,974	3,940	5,856	1,974	3,940	5,856
Data	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP
Polynomial	1	1	1	2	2	2
Controls	-	-	-	-	-	-
BW—months	12	24	36	12	24	36
Pre treat. pred.	0.310	0.369	0.382	0.338	0.298	0.328

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy); Pre treat. pred.: Pre treatment prediction
Source: SOEP v34, own calculations

Table B8: Difference in the probability that a care dependent person lives in the household (women aged 60-62) between women born before and from 1952 onward. Robustness checks.

	(1)	(2)	(3)	(4)	(5)	(6)
OLS	0.041	0.029*	0.031*	-0.000	0.052**	0.037**
	(0.026)	(0.016)	(0.016)	(0.053)	(0.023)	(0.017)
Local polynomial	0.026	0.039**	0.035**	0.023	0.035	0.036
	(0.030)	(0.018)	(0.014)	(0.046)	(0.031)	(0.022)
Observations	1,245	2,412	3,569	1,245	2,412	3,569
Data	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP
Polynomial	1	1	1	2	2	2
Controls	-	-	-	-	-	-
BW—months	12	24	36	12	24	36
Pre treat. pred.	0.0173	0.0282	0.0261	0.0562	0.0237	0.0318

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy); Pre treat. pred.: Pre treatment prediction
Source: SOEP v34, own calculations

Table B9: Reform effects on care provision, 12-months BW.

	(1)	(2)	(3)	(4)
	Hours of care provision			
OLS	-0.094	-0.082	-0.260	-0.259
	(0.130)	(0.156)	(0.267)	(0.289)
Local polynomial	-0.150	-0.140	-0.192	-0.153
	(0.140)	(0.163)	(0.260)	(0.278)
Pre treat. pred.	0.356	0.356	0.592	0.592
	Probability to provide care			
OLS	-0.057*	-0.052	-0.111***	-0.114***
	(0.029)	(0.036)	(0.030)	(0.033)
Local polynomial	-0.075***	-0.075***	-0.090***	-0.085***
	(0.023)	(0.026)	(0.016)	(0.016)
Pre treat. pred.	0.173	0.173	0.256	0.256
	Intensive care			
OLS	-0.031	-0.026	-0.066	-0.065
	(0.020)	(0.026)	(0.039)	(0.045)
Local polynomial	-0.044**	-0.042*	-0.056*	-0.049
	(0.020)	(0.025)	(0.034)	(0.038)
Pre treat. pred.	0.105	0.105	0.137	0.137
Observations	1,245	1,234	1,245	1,234
Data	SOEP	SOEP	SOEP	SOEP
Polynomial	1	1	2	2
Controls	YES	YES+	YES	YES+
BW—months	12	12	12	12

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy).
Source: SOEP v34, own calculations

Table B10: Reform effects on care provision, 36-month BW.

	(1)	(2)	(3)	(4)
	Hours of care provision			
OLS	-0.102	-0.109	-0.056	-0.056
	(0.077)	(0.073)	(0.128)	(0.126)
Local polynomial	-0.085	-0.088	-0.100	-0.103
	(0.080)	(0.081)	(0.123)	(0.123)
Pre treat. pred.	0.366	0.366	0.314	0.314
	Probability to provide care			
OLS	-0.051**	-0.053**	-0.067***	-0.066***
	(0.023)	(0.024)	(0.021)	(0.022)
Local polynomial	-0.056**	-0.056**	-0.072***	-0.071**
	(0.024)	(0.025)	(0.027)	(0.029)
Pre treat. pred.	0.163	0.163	0.181	0.181
	Intensive care			
OLS	-0.020	-0.020	-0.032	-0.030
	(0.015)	(0.016)	(0.022)	(0.024)
Local polynomial	-0.025	-0.023	-0.033*	-0.032
	(0.015)	(0.016)	(0.020)	(0.022)
Pre treat. pred.	0.0870	0.0870	0.0959	0.0959
Observations	3,569	3,541	3,569	3,541
Data	SOEP	SOEP	SOEP	SOEP
Polynomial	1	1	2	2
Controls	YES	YES+	YES	YES+
BW—months	36	36	36	36

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy).
Source: SOEP v34, own calculations

Table B11: Reform effects on care provision. Heterogeneity, 12-months BW.

	(1)	(2)	(3)	(4)	(5)	(6)
Subgroup	All	High Educ.	Low Educ.	Ret. from empl.	With unempl.	Eligible
			Hours of care provision			
OLS	-0.094	-0.533**	0.130	-0.228	0.583	-0.139
	(0.130)	(0.171)	(0.158)	(0.130)	(0.385)	(0.185)
Local polynomial	-0.150	-0.562***	0.094	-0.303*	0.698	-0.199
	(0.140)	(0.158)	(0.158)	(0.168)	(0.514)	(0.215)
Pre treat. pred.	0.356	0.520	0.294	0.457	-0.202	0.463
			Probability to provide care			
OLS	-0.057*	-0.195**	0.012	-0.096***	0.134	-0.060
	(0.029)	(0.071)	(0.039)	(0.028)	(0.112)	(0.037)
Local polynomial	-0.075***	-0.204***	-0.006	-0.117***	0.182	-0.079***
	(0.023)	(0.062)	(0.036)	(0.015)	(0.157)	(0.026)
Pre treat. pred.	0.173	0.254	0.142	0.204	0.00771	0.191
			Intensive care			
OLS	-0.031	-0.194***	0.051	-0.060**	0.124	-0.034
	(0.020)	(0.016)	(0.028)	(0.020)	(0.085)	(0.030)
Local polynomial	-0.044**	-0.209***	0.041	-0.073**	0.130	-0.042
	(0.020)	(0.018)	(0.027)	(0.029)	(0.109)	(0.036)
Pre treat. pred.	0.105	0.196	0.0713	0.135	-0.0507	0.120
Observations	1,245	368	877	1,011	234	976
Data	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP
Polynomial	1	1	1	1	1	1
Controls	YES	YES	YES	YES	YES	YES
BW—months	12	12	12	12	12	12

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Educ.: Education; Ret.: Retirement; empl.: employment; BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire).
Source: SOEP v34, own calculations.

Table B12: Reform effects on care provision. Heterogeneity, 36-month BW.

Subgroup	(1) All	(2) High Educ.	(3) Low Educ.	(4) Ret. from empl.	(5) With unempl.	(6) Eligible
	Hours of care provision					
OLS	-0.102	-0.186	-0.045	-0.118	-0.021	-0.112
	(0.077)	(0.175)	(0.102)	(0.075)	(0.298)	(0.101)
Local polynomial	-0.085	-0.078	-0.058	-0.152*	0.205	-0.092
	(0.080)	(0.173)	(0.102)	(0.085)	(0.305)	(0.111)
Pre treat. pred.	0.366	0.333	0.375	0.367	0.361	0.385
	Probability to provide care					
OLS	-0.051**	-0.122**	-0.017	-0.056*	-0.023	-0.072**
	(0.023)	(0.046)	(0.030)	(0.028)	(0.076)	(0.026)
Local polynomial	-0.056**	-0.121**	-0.023	-0.069***	-0.001	-0.074***
	(0.024)	(0.050)	(0.030)	(0.026)	(0.092)	(0.028)
Pre treat. pred.	0.163	0.177	0.158	0.163	0.167	0.188
	Intensive care					
OLS	-0.020	-0.082**	0.009	-0.028	0.016	-0.034*
	(0.015)	(0.033)	(0.023)	(0.020)	(0.057)	(0.019)
Local polynomial	-0.025	-0.095***	0.012	-0.037*	0.029	-0.034
	(0.015)	(0.033)	(0.021)	(0.020)	(0.061)	(0.021)
Pre treat. pred.	0.0870	0.0997	0.0830	0.0919	0.0680	0.0979
Observations	3,569	1,028	2,541	2,720	849	2,745
Data	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP
Polynomial	1	1	1	1	1	1
Controls	YES	YES	YES	YES	YES	YES
BW—months	36	36	36	36	36	36

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Educ.: Education; Ret.: Retirement; empl.: employment; BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire).
Source: SOEP v34, own calculations.

Table B13: Reform effects on care provision. Heterogeneity, 24-month BW, quadratic trend.

	(1)	(2)	(3)	(4)	(5)	(6)
Subgroup	All	High Educ.	Low Educ.	Ret. from empl.	With unempl.	Eligible
				Hours of care provision		
OLS	-0.107	-0.386	0.082	-0.260*	0.643	-0.213
	(0.151)	(0.276)	(0.175)	(0.147)	(0.502)	(0.221)
Local polynomial	-0.175	-0.744***	0.137	-0.297*	0.478	-0.241
	(0.150)	(0.197)	(0.159)	(0.174)	(0.558)	(0.230)
Pre treat. pred.	0.385	0.352	0.392	0.482	-0.101	0.531
				Probability to provide care		
OLS	-0.069**	-0.165**	-0.016	-0.112***	0.129	-0.094**
	(0.028)	(0.078)	(0.037)	(0.026)	(0.147)	(0.039)
Local polynomial	-0.083***	-0.232***	-0.004	-0.122***	0.126	-0.088**
	(0.031)	(0.070)	(0.044)	(0.023)	(0.162)	(0.035)
Pre treat. pred.	0.184	0.216	0.173	0.210	0.0636	0.220
				Intensive care		
OLS	-0.035	-0.170***	0.039	-0.070**	0.131	-0.064
	(0.023)	(0.038)	(0.034)	(0.025)	(0.101)	(0.040)
Local polynomial	-0.049**	-0.232***	0.046	-0.078**	0.115	-0.052
	(0.023)	(0.020)	(0.029)	(0.033)	(0.113)	(0.039)
Pre treat. pred.	0.112	0.166	0.0925	0.139	-0.0209	0.143
Observations	2412	735	1677	1873	539	1878
Data	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP
Polynomial	2	2	2	2	2	2
Controls	YES	YES	YES	YES	YES	YES
BW—months	24	24	24	24	24	24

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Educ.: Education; Ret.: Retirement; empl.: employment; BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire).
Source: SOEP v34, own calculations.

Table B14: Reform effects on care provision. Heterogeneity, 12-month BW, quadratic trend..

	(1)	(2)	(3)	(4)	(5)	(6)
Subgroup	All	High Educ.	Low Educ.	Ret. from empl.	With unempl.	Eligible
				Hours of care provision		
OLS	-0.260	-0.617*	0.003	-0.422	0.762	-0.311
	(0.267)	(0.269)	(0.295)	(0.272)	(0.511)	(0.383)
Local polynomial	-0.192	-0.479**	0.047	-0.420	1.301***	-0.186
	(0.260)	(0.244)	(0.277)	(0.311)	(0.427)	(0.364)
Pre treat. pred.	0.592	0.630	0.599	0.617	0.193	0.686
				Probability to provide care		
OLS	-0.111***	-0.219**	-0.043	-0.158***	0.213	-0.116**
	(0.030)	(0.092)	(0.039)	(0.031)	(0.126)	(0.043)
Local polynomial	-0.090***	-0.178**	-0.032	-0.154***	0.358**	-0.094***
	(0.016)	(0.074)	(0.039)	(0.021)	(0.171)	(0.020)
Pre treat. pred.	0.256	0.294	0.247	0.279	0.0527	0.278
				Intensive care		
OLS	-0.066	-0.235***	0.025	-0.090**	0.118	-0.056
	(0.039)	(0.032)	(0.049)	(0.034)	(0.127)	(0.057)
Local polynomial	-0.056*	-0.244***	0.038	-0.101**	0.265***	-0.048
	(0.034)	(0.044)	(0.036)	(0.041)	(0.101)	(0.054)
Pre treat. pred.	0.137	0.239	0.106	0.144	0.0283	0.136
Observations	1245	368	877	1011	234	976
Data	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP
Polynomial	2	2	2	2	2	2
Controls	YES	YES	YES	YES	YES	YES
BW—months	12	12	12	12	12	12

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Educ.: Education; Ret.: Retirement; empl.: employment; BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire).
Source: SOEP v34, own calculations.

Table B15: Reform effects on care provision. Heterogeneity, 36-month BW, quadratic trend..

	(1)	(2)	(3)	(4)	(5)	(6)
Subgroup	All	High Educ.	Low Educ.	Ret. from empl.	With unempl.	Eligible
	Hours of care provision					
OLS	-0.056	0.092	-0.073	-0.199	0.542	-0.066
	(0.128)	(0.341)	(0.160)	(0.122)	(0.399)	(0.167)
Local polynomial	-0.100	-0.188	-0.008	-0.257**	0.617	-0.178
	(0.123)	(0.234)	(0.142)	(0.124)	(0.459)	(0.172)
Pre treat. pred.	0.314	0.0622	0.403	0.403	-0.0348	0.389
	Probability to provide care					
OLS	-0.067***	-0.128**	-0.034	-0.091***	0.034	-0.080**
	(0.021)	(0.062)	(0.028)	(0.024)	(0.117)	(0.029)
Local polynomial	-0.072***	-0.158***	-0.026	-0.105***	0.079	-0.087***
	(0.027)	(0.060)	(0.037)	(0.020)	(0.139)	(0.031)
Pre treat. pred.	0.181	0.200	0.174	0.198	0.117	0.212
	Intensive care					
OLS	-0.032	-0.120***	0.015	-0.050*	0.051	-0.036
	(0.022)	(0.038)	(0.032)	(0.027)	(0.082)	(0.030)
Local polynomial	-0.033*	-0.150***	0.028	-0.060**	0.091	-0.051*
	(0.020)	(0.033)	(0.027)	(0.025)	(0.090)	(0.031)
Pre treat. pred.	0.0959	0.131	0.0844	0.110	0.0321	0.111
Observations	3569	1028	2541	2720	849	2745
Data	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP
Polynomial	2	2	2	2	2	2
Controls	YES	YES	YES	YES	YES	YES
BW—months	36	36	36	36	36	36

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Educ.: Education; Ret.: Retirement; empl.: employment; BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire).
Source: SOEP v34, own calculations.

Table B16: Placebo tests on care provision.

	(1) Ages 63-65	(2) Ages 57-59	(3)	(4)
	Hours of care provision			
Reform	0.112***	-0.089		
	(0.038)	(0.078)		
Placebo 1951			0.001	
			(0.147)	
Placebo 1953				-0.003
				(0.091)
Pre treat. pred.	0.329	0.356	0.358	0.291
	Probability to provide care			
Reform	-0.033	-0.016		
	(0.022)	(0.032)		
Placebo 1951			0.049	
			(0.040)	
Placebo 1953				0.032
				(0.037)
Pre treat. pred.	0.192	0.147	0.112	0.0990
	Intensive care			
Reform	0.012	-0.017		
	(0.017)	(0.021)		
Placebo 1951			0.015	
			(0.025)	
Placebo 1953				-0.002
				(0.022)
Pre treat. pred.	0.0968	0.0716	0.0689	0.0675
Observations	1789	2396	2367	2447
Data	SOEP	SOEP	SOEP	SOEP
Controls	YES	YES	YES	YES
BW—months	24	24	24	24

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire).
Source: SOEP v34, own calculations

Table B17: Reform effects on care provision. Robustness checks. (Non-parametric)

	(1)	(2)	(3)	(4)
	Hours of care provision			
Local polynomial	-0.085	-0.151	-0.074	-0.082
	(0.099)	(0.137)	(0.102)	(0.078)
	Probability to provide care			
Local polynomial	-0.075***	-0.073***	-0.059**	-0.055**
	(0.029)	(0.027)	(0.026)	(0.025)
	Intensive care			
Local polynomial	-0.033*	-0.043**	-0.025	-0.024
	(0.017)	(0.020)	(0.019)	(0.015)
Observations	1896	1245	2412	3569
Data	SOEP	SOEP	SOEP	SOEP
Controls	YES	YES	YES	YES
Kernel	Tri.	Epa.	Epa.	Epa.
BW—months	19.79	12	24	36
Polynomial	1	1	1	1

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire); Pre treat. pred.: pre treatment prediction; Tri.: Triangular Kernel, Epa.: Epanechnikov Kernel
Source: SOEP v34, own calculations

Table B18: Reform effects on care provision. Constant trend.

	(1)	(2)	(3)	(4)
	Hours of care provision			
OLS	-0.078	-0.073	-0.076	-0.070
	(0.101)	(0.101)	(0.099)	(0.099)
Pre treat. pred.	0.310	0.310	0.385	0.385
	Probability to provide care			
OLS	-0.056**	-0.054**	-0.057**	-0.054**
	(0.022)	(0.022)	(0.022)	(0.023)
Pre treat. pred.	0.170	0.170	0.184	0.184
	Intensive care			
OLS	-0.024	-0.021	-0.023	-0.020
	(0.017)	(0.019)	(0.017)	(0.020)
Pre treat. pred.	0.0822	0.0822	0.112	0.112
Observations	2412	2397	2412	2397
Data	SOEP	SOEP	SOEP	SOEP
Polynomial	1	1	2	2
Controls	YES	YES+	YES	YES+
BW—months	24	24	24	24

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Control variables: YES (Age of individuals and year of questionnaire); BW: Bandwidth; Pre treat. pred.: pre treatment prediction
Source: SOEP v34, own calculations

Table B19: Reform effects on retirement behavior. (SOEP-data)

	(1)	(2)	(3)	(4)	(5)
Reform	-0.228**	-0.122**	-0.131***		
	(0.092)	(0.044)	(0.035)		
Placebo 1951				-0.047	
				(0.054)	
Placebo 1953					0.004
					(0.033)
Observations	1,245	2,412	3,569	2,367	2,447
Data	SOEP	SOEP	SOEP	SOEP	SOEP
Controls	YES	YES	YES	YES	YES
BW—months	12	24	36	24	24

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Control variables: YES (Age of individuals and year of questionnaire); BW: Bandwidth
Source: SOEP v34, own calculations

Table B20: IV-effects of retirement on care provision. Robustness checks: 12 month BW.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Probability to provide care				Daily hours of care				Probability to provide intensive care			
2SLS	0.251*	0.271	1.003	1.026	0.412	0.431	2.342**	2.323**	0.135*	0.136	0.590*	0.587***
	(0.142)	(0.200)	(0.888)	(0.811)	(0.448)	(0.668)	(0.994)	(1.052)	(0.074)	(0.115)	(0.306)	(0.220)
Local polynomial	0.399*	0.444*	1.338	1.014	0.799*	0.831	2.861	1.822	0.235***	0.248***	0.842	0.587**
	(0.235)	(0.243)	(1.922)	(1.072)	(0.456)	(0.636)	(2.366)	(1.934)	(0.060)	(0.062)	(0.785)	(0.299)
Observations	1,245	1,234	1,245	1,234	1,245	1,234	1,245	1,234	1,245	1,234	1,245	1,234
Data	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP
Polynomial	1	1	2	2	1	1	2	2	1	1	2	2
Controls	YES	YES+	YES	YES+	YES	YES+	YES	YES+	YES	YES+	YES	YES+
BW—months	12	12	12	12	12	12	12	12	12	12	12	12
First stage F-value	6.137	6.148	0.833	0.963	6.137	6.148	0.833	0.963	6.137	6.148	0.833	0.963

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
2SLS: Two stages least squares estimator; BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy).
Source: SOEP v34, own calculations

Table B21: IV-effects of retirement on care provision. Robustness checks: 36 month BW.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Probability to provide care				Daily hours of care				Probability to provide intensive care			
2SLS	0.384**	0.518**	0.515**	0.686*	0.776	1.059	0.432	0.579	0.154	0.198	0.242	0.308
	(0.196)	(0.259)	(0.232)	(0.379)	(0.563)	(0.656)	(0.871)	(1.131)	(0.114)	(0.145)	(0.153)	(0.212)
Local polynomial	0.431*	0.559*	0.419*	0.509*	0.646	0.880	0.585	0.739	0.189	0.231	0.195*	0.229*
	(0.237)	(0.329)	(0.240)	(0.308)	(0.575)	(0.729)	(0.614)	(0.719)	(0.117)	(0.150)	(0.107)	(0.127)
Observations	3,569	3,541	3,569	3,541	3,569	3,541	3,569	3,541	3,569	3,541	3,569	3,541
Data	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP
Polynomial	1	1	2	2	1	1	2	2	1	1	2	2
Controls	YES	YES+	YES	YES+	YES	YES+	YES	YES+	YES	YES+	YES	YES+
BW—months	36	36	36	36	36	36	36	36	36	36	36	36
First stage F-value	14.26	11.63	5.259	3.407	14.26	11.63	5.259	3.407	14.26	11.63	5.259	3.407

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
2SLS: Two stages least squares estimator; BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy).
Source: SOEP v34, own calculations

Table B22: IV-effects of retirement on care provision. Women aged 57 to 62. (First stage: Dif-in-Dif)

	(1)	(2)	(3)	(4)	(5)	(6)
Subgroup		All			Eligible	
	Probability to provide care					
Retired	0.195**	0.156*	0.147*	0.113**	0.199**	0.213**
	(0.087)	(0.088)	(0.085)	(0.055)	(0.088)	(0.087)
	Daily hours of care					
Retired	0.674	0.364	0.451*	0.424*	0.272	0.543*
	(0.437)	(0.255)	(0.263)	(0.249)	(0.296)	(0.280)
	Probability to provide intensive care					
Retired	0.130*	0.047	0.048	0.107*	0.064	0.072
	(0.076)	(0.070)	(0.060)	(0.062)	(0.073)	(0.064)
Observations	2,452	4,808	7,141	1,876	3,726	5,495
Data	SOEP	SOEP	SOEP	SOEP	SOEP	SOEP
Controls	YES	YES	YES	YES	YES	YES
BW—months	12	24	36	12	24	36
F-value	10.84	28.77	36.79	14.66	24.08	36.25

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses;
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; F-value: F-statistic of the first stage estimation; Control variables: YES (Age of individuals and year of questionnaire).
Source: SOEP v34, own calculations

Table B23: IV-effects of retirement on care provision. Robustness checks. (Non-parametric)

	(1)	(2)	(3)	(4)
	Probability to provide care			
Local polynomial	0.446*	0.364*	0.397*	0.439*
	(0.238)	(0.210)	(0.222)	(0.256)
Observations	3217	1245	2412	3569
BW—months	32.56	12	24	36
	Daily hours of care			
Local polynomial	0.537	0.720	0.817*	0.926*
	(0.568)	(0.714)	(0.448)	(0.527)
Observations	2412	2397	2412	2397
BW—months	24	24	24	24
	Probability to provide intensive care			
Local polynomial	0.208***	0.212***	0.165	0.190
	(0.075)	(0.066)	(0.125)	(0.127)
Observations	1697	1245	2412	3569
Data	SOEP	SOEP	SOEP	SOEP
Controls	YES	YES	YES	YES
Kernel	Tri.	Epa.	Epa.	Epa.
Polynomial	1	1	1	1

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire); Tri.: Triangular Kernel, Epa.: Epanechnikov Kernel
Source: SOEP v34, own calculations

B.2 Additional figures

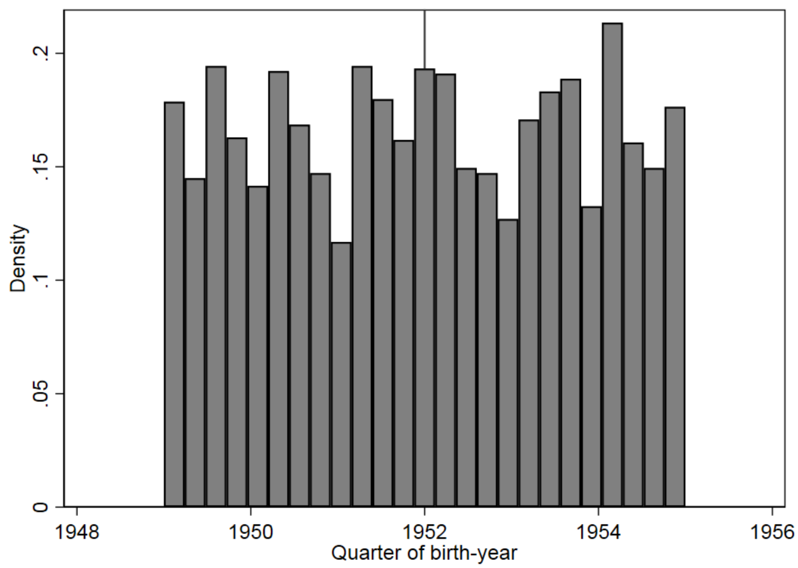


Figure B1: Distribution of women along forcing variable (quarter of year of birth).

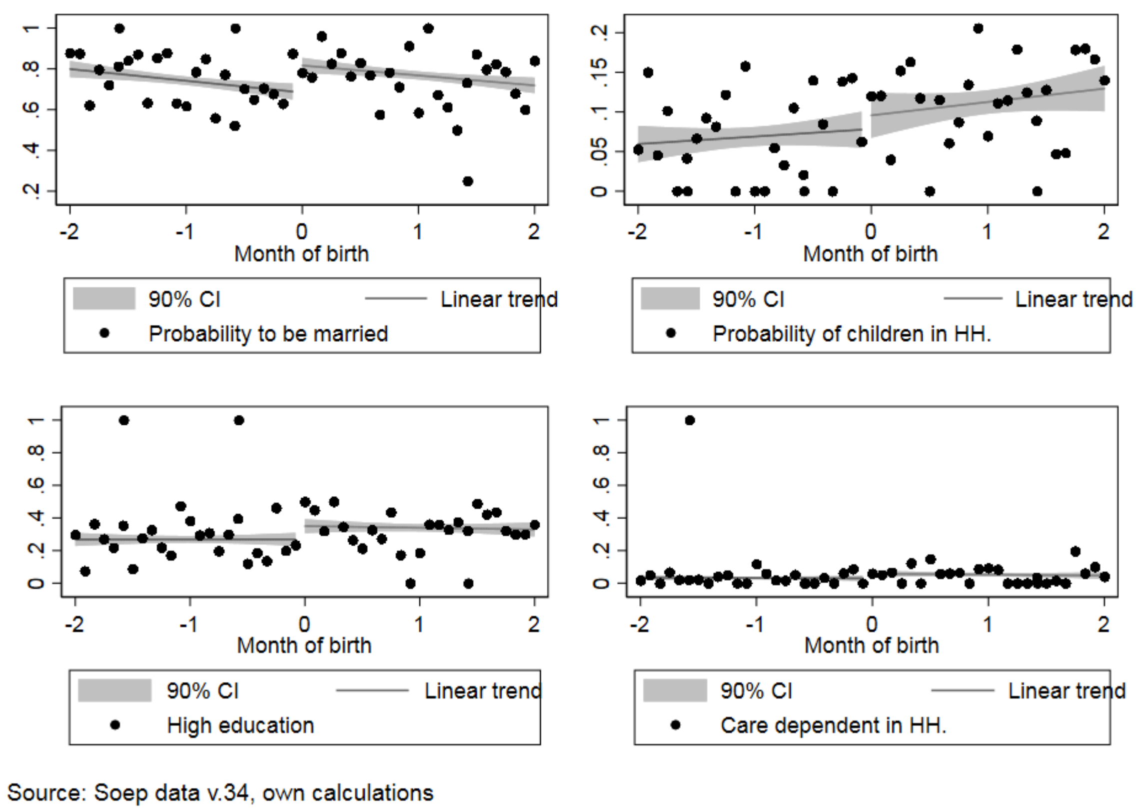


Figure B2: Covariates by birth-date in the group of women aged 60-62 years

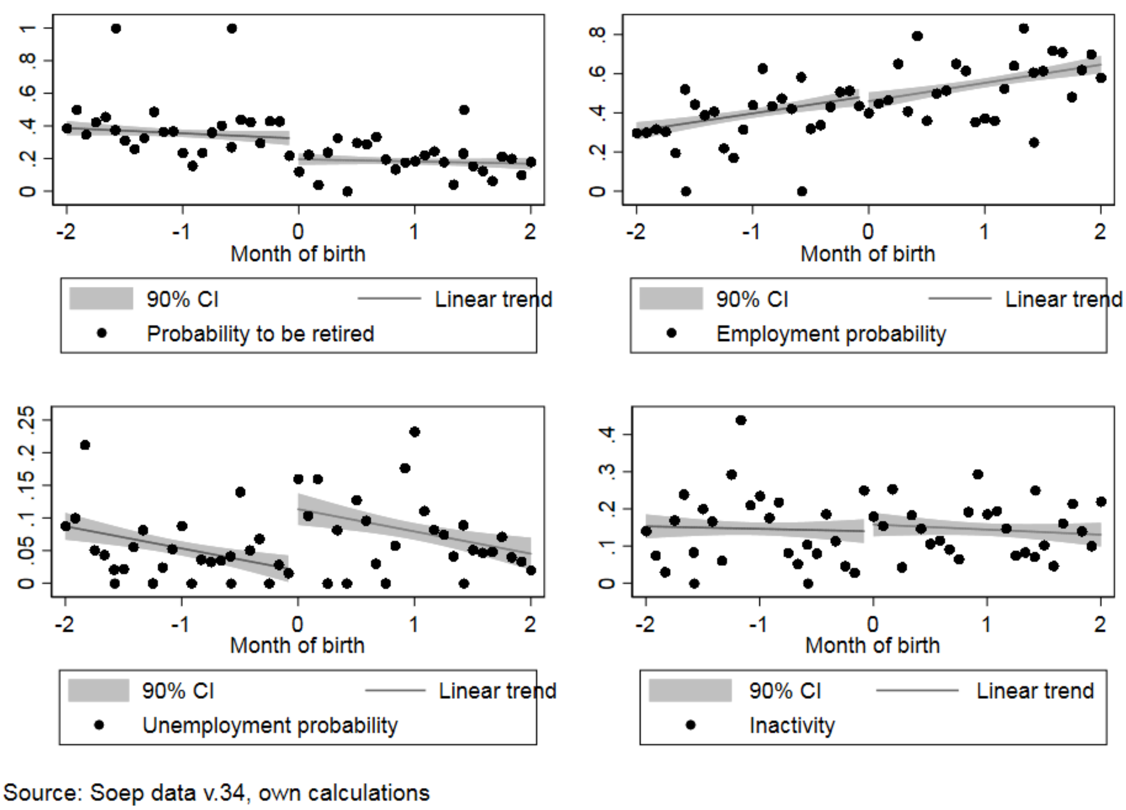


Figure B3: Employment outcomes by treatment.

B.3 Appendix: SHARE data included

To enrich parts of the analysis I add German observations of the Survey of Health, Aging and Retirement in Europe (SHARE). SHARE is a multidisciplinary data set collected in 27 European countries and Israel on micro data concerning health, socio-economic status and social and family networks of more than 120,000 individuals aged 50 or older (more than 297,000 interviews).[129] SHARE was collected in seven waves, six of which (waves 1,2,4,5,6,7) carry individual level data on informal care provision. In Germany, wave 1 was collected in 2004, wave 2 in 2006/2007, wave 4 in 2011/2012 wave 5 in 2013, wave 6 in 2015 and wave 7 in 2017.

B.3.1 Data-set in SHARE

I use the respective German part of SHARE-waves 1, 2, 4, 5, 6 and 7 to construct a sample similar to that from the SOEP. Effectively, as the estimation employs observations aged 60-62 and born from 1949 to 1954 I conduct my analysis only on waves 4, 5, 6 and 7. SHARE has only existed some years and the panel is repeated every 2 years only. Therefore I can not construct those two data sets ensuring attachment to the labor market (no unemployment spells in the ages 55-60 and eligibility for women's pension at age 60) from SHARE.

B.3.2 Varibales

In contrast to SOEP, the SHARE questionnaire does not allow a direct access to individual's provision of informal care. The information is separately asked for help given inside and outside the own household. After asking whether individuals have given some help to people outside the own household [130] people can specify their relationship to that person (mother, father, sibling, child, etc.) and further give information on the kind of help given.[131] The frequency of help is further asked but not compatible to SOEP information.[132] In addition, individuals are asked if they give help to a person living in their own household. For this category, the question states a definition of regularity (daily or nearly daily for at least 3 months) as well as the type of care that is meant ("...personal care, such as washing, getting out of bed, or dressing?"). Further it is asked to whom the care is provided (relationship to this person).

I merge information with regards to care provided within and outside of the household into a binary indicator on care provided. Therefore, a selection on out of household care is done: I take only care given more regularly than on a monthly basis (weekly and daily). Further in both categories I am

[129] For more information on SHARE see Börsch-Supan and Malter (2015); Malter and Börsch-Supan (2017); Börsch-Supan et al. (2013); http://www.share-project.org/

[130] "Now I would like to ask you about the help you have given to others. In the last twelve months, have you personally given personal care or practical household help to a family member living outside your household, a friend or neighbor?"

[131] "Which types of help have you given to this person in the last twelve months? i) Personal care, e.g. dressing, bathing or showering, eating, getting in or out of bed, using the toilet, ii) Practical household help, e.g. with home repairs, gardening, transportation, shopping, household chores, iii) Help with paperwork, such as filling out forms, settling financial or legal matters?"

[132] Four categories of frequency are given:"In the last twelve months, how often altogether have you given such help to this person? Was it...1) almost daily 2) almost every week 3) almost every month 4) less often?" In SHARE waves 1 and 2 respondents give information on how many hours they spend on care in relation to the frequency stated. This information, however, can not be used as individuals from waves 1 and 2 do not fall in the specific age-range of interest in combination with the birth-dates of interest.

interested in care provided to elderly individuals, so I discard help given to children, sons/daughters in law, grandchildren, nieces or nephews. These questions are asked in three cycles, so three independent receivers of care with respective care-type and regularity can be stated. I treat all three similarly. If a respondent states to provide care to a person 1, that falls out of the definition I am using (son/grandchild, ect.) but the second person that this respondent states as care receiving falls into my definition I define the respondent as a care provider. Further insights towards care-activities and the definitions in SHARE can be seen in Riedel and Kraus (2011). From SHARE no variables on the daily hours of informal care provision or intensive care giving is constructed.
I also have information on self-reported labor force status on each observation in SHARE. This information contains the individual's retirement. The same holds for the ISCED_1997 classification.

B.3.3 Summary statistics

Table B24 reports summary statistics on SOEP and SHARE data on some important covariates as well as the outcome variables. The constructed SOEP-sample contains 3569 person year observations on 1390 women. From SHARE I can add 718 person-year observations. Women in the SOEP-data report to provide a mean of 0.25 hours of care per normal weekday and 10% provide care. The mean age in the sample is 61.47 years and 29% of person year observations are reported as retired, 68% as married. In SHARE data I find a significantly higher probability to be a care giver. This appears most probably as the definition for care provision in the question in SOEP is more specific as to the type of care and how regular the care has to be performed. In SHARE, as stated above, the researcher can himself define the care of interest with respect to questions posed. These, however, allow for a refinement of care provision that is a little broader. From SHARE I accept informal care that is carried out on a less regular basis and care that is personal (bathing, helping to dress, medical help, preparation of food) but also care that is concerned with taking care of the household and important paper work.

B.4 Results containing SHARE-data

Table B24: Summary statistic by data set for women born 1949-1954, aged 60-62.

	SOEP			SHARE			Combined		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.
				Outcome variables					
Hours of Care	3569	0.26	1.26	0	.	.	3569	0.26	1.26
Caring Probability	3569	0.10	0.30	718	0.20	0.40	4287	0.13	0.34
Intensive caring Probability	3569	0.06	0.23	0	.	.	3569	0.06	0.23
				Covariates					
Retired	3569	0.29	0.45	718	0.24	0.42	4287	0.27	0.45
Reform	3569	0.49	0.50	718	0.45	0.50	4287	0.48	0.50
Age	3569	61.47	0.87	718	61.51	0.81	4287	61.48	0.85
High education	3569	0.21	0.41	718	0.28	0.45	4287	0.24	0.42
Children in household	3569	0.06	0.23	718	0.06	0.23	4287	0.06	0.23
Care need in the household	3569	0.04	0.19	.	.	.	3569	0.04	0.19
Married	3541	0.69	0.46	718	0.66	0.48	4259	0.68	0.47

Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations
N: Number of observations; Std. Dev.: Standard deviation; Data: Combined (SOEP and SHARE data)

Table B25: Reform effects on retirement behaviour, combined data-set.

	(1)	(2)	(3)	(4)	(5)
Reform	-0.230**	-0.147***	-0.155***		
	(0.072)	(0.038)	(0.029)		
Placebo 1951				-0.030	
				(0.046)	
Placebo 1953					0.009
					(0.027)
Observations	1,547	2,953	4,287	2,829	3,005
Data	BOTH	BOTH	BOTH	BOTH	BOTH
Controls	YES	YES	YES	YES	YES
BW—months	12	24	36	24	24

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Control variables: YES (Age of individuals and year of questionnaire); BW: Bandwidth; Data: Both (SOEP and SHARE data)
Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B26: Reform effects on the probability to provide care, combined data-set. 24-month BW.

	(1)	(2)	(3)	(4)
OLS	-0.050**	-0.050**	-0.070**	-0.070*
	(0.020)	(0.021)	(0.032)	(0.035)
Local polynomial	-0.058***	-0.060**	-0.076***	-0.078**
	(0.022)	(0.024)	(0.027)	(0.030)
Observations	2953	2938	2953	2938
Data	Combined	Combined	Combined	Combined
Polynomial	1	1	2	2
Controls	YES	YES+	YES	YES+
BW—months	24	24	24	24
Pre treat. pred.	0.181	0.181	0.197	0.197

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy); Data: Both (SOEP and SHARE data)
Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B27: Reform effects on the probability to provide care, combined data-set. 12-month BW.

	(1)	(2)	(3)	(4)
OLS	-0.054*	-0.054	-0.085**	-0.090*
	(0.028)	(0.035)	(0.036)	(0.041)
Local polynomial	-0.063***	-0.066**	-0.060***	-0.058**
	(0.022)	(0.028)	(0.019)	(0.025)
Observations	1547	1536	1547	1536
Data	Combined	Combined	Combined	Combined
Polynomial	1	1	2	2
Controls	YES	YES+	YES	YES+
BW—months	12	12	12	12
Pre treat. pred.	0.189	0.189	0.237	0.237

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy); Data: Both (SOEP and SHARE data)
Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B28: Reform effects on the probability to provide care, combined data-set. 36-month BW.

	(1)	(2)	(3)	(4)
OLS	-0.038*	-0.039*	-0.066**	-0.065**
	(0.020)	(0.020)	(0.024)	(0.025)
Local polynomial	-0.050***	-0.050**	-0.068***	-0.069***
	(0.019)	(0.020)	(0.024)	(0.026)
Observations	4287	4259	4287	4259
Data	Combined	Combined	Combined	Combined
Polynomial	1	1	2	2
Controls	YES	YES+	YES	YES+
BW—months	36	36	36	36
Pre treat. pred.	0.176	0.176	0.191	0.191

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy); Data: Both (SOEP and SHARE data)
Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B29: Placebo test on the probability to provide care, combined data-set.

	(1) Ages 63-65	(2) Ages 57-59	(3)	(4)
Reform	-0.018	-0.022		
	(0.021)	(0.031)		
Placebo 1951			0.045	
			(0.032)	
Placebo 1953				0.033
				(0.027)
Observations	2264	2623	2829	3005
Data	Combined	Combined	Combined	Combined
Controls	YES	YES	YES	YES
BW—months	24	24	24	24
Pre treat. pred.	0.247	0.151	0.122	0.128

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy); Data: Both (SOEP and SHARE data)
Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B30: Reform effects on the probability to provide care, combined data-set. Heterogeneity, 24-month BW..

Subgroup	(1) All	(2) High Educ.	(3) Low Educ.	(4) Ret. from empl.	(5) With unempl.	(6) Eligible
OLS	-0.050**	-0.114*	-0.020	-0.069**	-0.012	-0.070**
	(0.020)	(0.055)	(0.025)	(0.027)	(0.096)	(0.028)
Local polynomial	-0.058***	-0.151***	-0.014	-0.086***	0.045	-0.080***
	(0.022)	(0.057)	(0.029)	(0.023)	(0.119)	(0.029)
Observations	2953	876	2077	1873	539	1878
Data	Combined	Combined	Combined	Combined	Combined	Combined
Polynomial	1	1	1	1	1	1
Controls	YES	YES	YES	YES	YES	YES
BW—months	24	24	24	24	24	24
Pre treat. pred.	0.181	0.205	0.172	0.179	0.146	0.201

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Educ.: Education; Ret.: Retirement; empl.: employment; BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire); Data: Combined (SOEP and SHARE data)
Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B31: Reform effects on the probability to provide care, combined data-set. Heterogeneity, 12-month BW.

Subgroup	(1) All	(2) High Educ.	(3) Low Educ.	(4) Ret. from empl.	(5) With unempl.	(6) Eligible
OLS	-0.054*	-0.225**	0.030	-0.096***	0.134	-0.060
	(0.028)	(0.078)	(0.027)	(0.028)	(0.112)	(0.037)
Local polynomial	-0.063***	-0.227***	0.021	-0.117***	0.182	-0.079***
	(0.022)	(0.079)	(0.029)	(0.015)	(0.157)	(0.026)
Observations	1547	472	1075	1011	234	976
Data	Combined	Combined	Combined	Combined	Combined	Combined
Polynomial	1	1	1	1	1	1
Controls	YES	YES	YES	YES	YES	YES
BW—months	12	12	12	12	12	12
Pre treat. pred.	0.189	0.280	0.153	0.204	0.00771	0.191

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Educ.: Education; Ret.: Retirement; empl.: employment; BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire); Data: Combined (SOEP and SHARE data)
Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B32: Reform effects on the probability to provide care, combined data-set. Heterogeneity, 36-month BW.

Subgroup	(1) All	(2) High Educ.	(3) Low Educ.	(4) Ret. from empl.	(5) With unempl.	(6) Eligible
OLS	-0.038*	-0.111**	-0.004	-0.056*	-0.023	-0.072**
	(0.020)	(0.048)	(0.024)	(0.028)	(0.076)	(0.026)
Local polynomial	-0.050***	-0.123**	-0.014	-0.069***	-0.001	-0.074***
	(0.019)	(0.050)	(0.025)	(0.026)	(0.092)	(0.028)
Observations	4287	1218	3069	2720	849	2745
Data	Combined	Combined	Combined	Combined	Combined	Combined
Polynomial	1	1	1	1	1	1
Controls	YES	YES	YES	YES	YES	YES
BW—months	36	36	36	36	36	36
Pre treat. pred.	0.176	0.191	0.171	0.163	0.167	0.188

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Educ.: Education; Ret.: Retirement; empl.: employment; BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire); Data: Combined (SOEP and SHARE data)
Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B33: Reform effects on the probability to provide care, combined data-set. Heterogeneity, 24-month BW, quadratic trend.

	(1)	(2)	(3)	(4)	(5)	(6)
Subgroup	All	High Educ.	Low Educ.	Ret. from empl.	With unempl.	Eligible
OLS	-0.070**	-0.199**	-0.007	-0.112***	0.129	-0.094**
	(0.032)	(0.087)	(0.033)	(0.026)	(0.147)	(0.039)
Local polynomial	-0.076***	-0.261***	0.017	-0.122***	0.126	-0.088**
	(0.027)	(0.087)	(0.032)	(0.023)	(0.162)	(0.035)
Observations	2953	876	2077	1873	539	1878
Data	Combined	Combined	Combined	Combined	Combined	Combined
Polynomial	2	2	2	2	2	2
Controls	YES	YES	YES	YES	YES	YES
BW—months	24	24	24	24	24	24
Pre treat. pred.	0.197	0.260	0.176	0.210	0.0636	0.220

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Educ.: Education; Ret.: Retirement; empl.: employment; BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire); Data: Combined (SOEP and SHARE data)
Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B34: Reform effects on the probability to provide care, combined data-set. Heterogeneity, 12-month BW, quadratic trend.

	(1)	(2)	(3)	(4)	(5)	(6)
Subgroup	All	High Educ.	Low Educ.	Ret. from empl.	With unempl.	Eligible
OLS	-0.085**	-0.235*	-0.003	-0.158***	0.213	-0.116**
	(0.036)	(0.120)	(0.033)	(0.031)	(0.126)	(0.043)
Local polynomial	-0.060***	-0.200	0.015	-0.154***	0.358**	-0.094***
	(0.019)	(0.129)	(0.039)	(0.021)	(0.171)	(0.020)
Observations	1547	472	1075	1011	234	976
Data	Combined	Combined	Combined	Combined	Combined	Combined
Polynomial	2	2	2	2	2	2
Controls	YES	YES	YES	YES	YES	YES
BW—months	12	12	12	12	12	12
Pre treat. pred.	0.237	0.311	0.212	0.279	0.0527	0.278

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Educ.: Education; Ret.: Retirement; empl.: employment; BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire); Data: Combined (SOEP and SHARE data)
Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B35: Reform effects on the probability to provide care, combined data-set. Heterogeneity, 36-month BW, quadratic trend.

Subgroup	(1) All	(2) High Educ.	(3) Low Educ.	(4) Ret. from empl.	(5) With unempl.	(6) Eligible
OLS	-0.066**	-0.145**	-0.028	-0.091***	0.034	-0.080**
	(0.024)	(0.063)	(0.030)	(0.024)	(0.117)	(0.029)
Local polynomial	-0.068***	-0.184***	-0.013	-0.105***	0.079	-0.087***
	(0.024)	(0.064)	(0.033)	(0.020)	(0.139)	(0.031)
Observations	4287	1218	3069	2720	849	2745
Data	Combined	Combined	Combined	Combined	Combined	Combined
Polynomial	2	2	2	2	2	2
Controls	YES	YES	YES	YES	YES	YES
BW—months	36	36	36	36	36	36
Pre treat. pred.	0.191	0.225	0.177	0.198	0.117	0.212

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Educ.: Education; Ret.: Retirement; empl.: employment; BW: Bandwidth; Pre treat. pred.: Pre treatment prediction; Control variables: YES (Age of individuals and year of questionnaire); Data: Combined (SOEP and SHARE data)
Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B36: Reform effects on the probability to provide care, combined data-set. Robustness checks. (Non-parametric)

	(1)	(2)	(3)	(4)
Local polynomial	-0.070***	-0.063**	-0.056**	-0.047**
	(0.023)	(0.025)	(0.022)	(0.020)
Observations	2130	1547	2953	4287
Data	Combined	Combined	Combined	Combined
Controls	YES	YES	YES	YES
Kernel	Tri.	Epa.	Epa.	Epa.
BW—months	17.56	12	24	36
Polynomial	1	1	1	1

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy); Pre treat. pred.: pre treatment prediction; Tri.: Triangular Kernel, Epa.: Epanechnikov Kernel; Data: Combined (SOEP and SHARE data)
Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B37: IV-effects of retirement on the probability to provide care, combined data-set. 24-month BW.

	(1)	(2)	(3)	(4)
2SLS	0.342***	0.387***	0.320***	0.358***
	(0.114)	(0.135)	(0.099)	(0.131)
Local polynomial	0.332***	0.389***	0.344***	0.382***
	(0.115)	(0.140)	(0.112)	(0.128)
Observations	2,953	2,938	2,953	2,938
Data	Combined	Combined	Combined	Combined
Polynomial	1	1	2	2
Controls	YES	YES+	YES	YES+
BW—months	24	24	24	24
First stage F-value	14.79	12.35	8.010	7.606

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
2SLS: Two stages least square estimation; BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy); Data: Combined (SOEP and SHARE data)
Source: Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B38: IV-effects of retirement on the probability to provide care, combined data-set. 12-month BW.

	(1)	(2)	(3)	(4)
2SLS	0.236***	0.266**	0.576***	0.611***
	(0.087)	(0.131)	(0.214)	(0.185)
Local polynomial	0.310***	0.346***	0.749	0.640*
	(0.087)	(0.101)	(0.545)	(0.332)
Observations	1,547	1,536	1,547	1,536
Data	Combined	Combined	Combined	Combined
Polynomial	1	1	2	2
Controls	YES	YES+	YES	YES+
BW—months	12	12	12	12
First stage F-value	10.25	11.21	1.909	2.125

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
2SLS: Two stages least square estimation; BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy); Data: Combined (SOEP and SHARE data)
Source: Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B39: IV-effects of retirement on the probability to provide care, combined data-set. 36-month BW.

	(1)	(2)	(3)	(4)
2SLS	0.245**	0.288**	0.420***	0.487***
	(0.121)	(0.137)	(0.119)	(0.153)
Local polynomial	0.318***	0.368***	0.369***	0.422***
	(0.118)	(0.141)	(0.126)	(0.151)
Observations	4,287	4,259	4,287	4,259
Data	Combined	Combined	Combined	Combined
Polynomial	1	1	2	2
Controls	YES	YES+	YES	YES+
BW—months	36	36	36	36
First stage F-value	28.32	26.19	10.65	8.543

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
2SLS: Two stages least square estimation; BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire), YES+ (Age of individuals and year of questionnaire, marital status, children in the household, high education dummy); Data: Combined (SOEP and SHARE data)
Source: Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B40: IV-effects of retirement on the probability to provide care, combined data-set. Heterogeneity, 24-month BW.

	(1)	(2)	(3)	(4)	(5)	(6)
Soubgroup	All	High Educ.	Low Educ.	Ret. from empl.	With unempl.	Eligible
2SLS	0.342***	0.888***	0.131	1.117*	0.030	0.407***
	(0.114)	(0.299)	(0.157)	(0.658)	(0.224)	(0.130)
Local polynomial	0.332***	0.805***	0.082	0.825**	-0.101	0.391***
	(0.115)	(0.140)	(0.178)	(0.383)	(0.284)	(0.121)
Observations	2,953	876	2,077	1,873	539	1,878
Data	Combined	Combined	Combined	Combined	Combined	Combined
Polynomial	1	1	1	1	1	1
Controls	YES	YES	YES	YES	YES	YES
BW—months	24	24	24	24	24	24
First stage F-value	14.79	2.662	13.98	1.681	7.685	13.98

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
2SLS: Two stages least squares estimator; Educ.: Education; Ret.: Retirement; empl.: employment; BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire); Data: Combined (SOEP and SHARE data)
Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B41: IV-effects of retirement on the probability to provide care, combined data-set. Heterogeneity, 12-month BW.

	(1)	(2)	(3)	(4)	(5)	(6)
Soubgroup	All	High Educ.	Low Educ.	Ret. from empl.	With unempl.	Eligible
2SLS	0.236***	0.957***	-0.136	0.515**	-0.280	0.211*
	(0.087)	(0.128)	(0.118)	(0.204)	(0.308)	(0.111)
Local polynomial	0.310***	0.856***	-0.120	0.636**	-0.953	0.327***
	(0.087)	(0.220)	(0.144)	(0.264)	(0.987)	(0.087)
Observations	1,547	472	1,075	1,011	234	976
Data	Combined	Combined	Combined	Combined	Combined	Combined
Polynomial	1	1	1	1	1	1
Controls	YES	YES	YES	YES	YES	YES
BW—months	12	12	12	12	12	12
First stage F-value	10.25	12.58	6.657	5.203	4.122	8.999

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
2SLS: Two stages least squares estimator; Educ.: Education; Ret.: Retirement; empl.: employment; BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire); Data: Combined (SOEP and SHARE data)
Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B42: IV-effects of retirement on the probability to provide care, combined data-set. Heterogeneity, 36-month BW.

	(1)	(2)	(3)	(4)	(5)	(6)
Soubgroup	All	High Educ.	Low Educ.	Ret. from empl.	With unempl.	Eligible
2SLS	0.245**	0.649***	0.027	0.899*	0.058	0.452***
	(0.121)	(0.240)	(0.160)	(0.526)	(0.181)	(0.166)
Local polynomial	0.318***	0.728***	0.094	1.098	0.002	0.433***
	(0.118)	(0.185)	(0.176)	(0.709)	(0.212)	(0.157)
Observations	4,287	1,218	3,069	2,720	849	2,745
Data	Combined	Combined	Combined	Combined	Combined	Combined
Polynomial	1	1	1	1	1	1
Controls	YES	YES	YES	YES	YES	YES
BW—months	36	36	36	36	36	36
First stage F-value	28.32	7.395	20.96	2.315	12.44	15.91

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
2SLS: Two stages least squares estimator; Educ.: Education; Ret.: Retirement; empl.: employment; BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire); Data: Combined (SOEP and SHARE data)
Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B43: IV-effects of retirement on the probability to provide care, combined data-set. Heterogeneity, 24-month BW, quadratic trend.

	(1)	(2)	(3)	(4)	(5)	(6)
Soubgroup	All	High Educ.	Low Educ.	Ret. from empl.	With unempl.	Eligible
2SLS	0.320***	0.707***	0.038	0.688**	-0.248	0.375***
	(0.099)	(0.198)	(0.161)	(0.306)	(0.345)	(0.122)
Local polynomial	0.344***	0.897***	-0.090	0.612**	-0.355	0.322***
	(0.112)	(0.221)	(0.150)	(0.265)	(0.512)	(0.118)
Observations	2,953	876	2,077	1,873	539	1,878
Data	Combined	Combined	Combined	Combined	Combined	Combined
Polynomial	2	2	2	2	2	2
Controls	YES	YES	YES	YES	YES	YES
BW—months	24	24	24	24	24	24
First stage F-value	8.010	12.45	5.310	3.283	5.038	6.473

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
2SLS: Two stages least squares estimator; Educ.: Education; Ret.: Retirement; empl.: employment; BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire); Data: Combined (SOEP and SHARE data)
Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B44: IV-effects of retirement on the probability to provide care, combined data-set. Heterogeneity, 12-month BW, quadratic trend.

	(1)	(2)	(3)	(4)	(5)	(6)
Soubgroup	All	High Educ.	Low Educ.	Ret. from empl.	With unempl.	Eligible
2SLS	0.576***	0.760**	0.032	0.949	0.909	0.650***
	(0.214)	(0.331)	(0.372)	(0.599)	(0.648)	(0.181)
Local polynomial	0.749	1.359	-0.252	1.180	1.241	0.674**
	(0.545)	(1.842)	(0.442)	(0.864)	(0.993)	(0.340)
Observations	1,547	472	1,075	1,011	234	976
Data	Combined	Combined	Combined	Combined	Combined	Combined
Polynomial	2	2	2	2	2	2
Controls	YES	YES	YES	YES	YES	YES
BW—months	12	12	12	12	12	12
First stage F-value	1.909	8.418	0.523	1.467	5.949	2.806

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
2SLS: Two stages least squares estimator; Educ.: Education; Ret.: Retirement; empl.: employment; BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire); Data: Combined (SOEP and SHARE data)
Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Table B45: IV-effects of retirement on the probability to provide care, combined data-set. Heterogeneity, 36-month BW, quadratic trend.

	(1)	(2)	(3)	(4)	(5)	(6)
Soubgroup	All	High Educ.	Low Educ.	Ret. from empl.	With unempl.	Eligible
2SLS	0.420***	0.811***	0.185	1.438	-0.071	0.429***
	(0.119)	(0.179)	(0.190)	(1.222)	(0.257)	(0.118)
Local polynomial	0.369***	0.879***	0.071	0.794**	-0.185	0.383***
	(0.126)	(0.186)	(0.192)	(0.363)	(0.360)	(0.116)
Observations	4,287	1,218	3,069	2,720	849	2,745
Data	Combined	Combined	Combined	Combined	Combined	Combined
Polynomial	2	2	2	2	2	2
Controls	YES	YES	YES	YES	YES	YES
BW—months	36	36	36	36	36	36
First stage F-value	10.65	5.814	7.875	1.009	6.581	9.829

Cluster robust (clustered on the quarter of year of birth level) standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
2SLS: Two stages least squares estimator; Educ.: Education; Ret.: Retirement; empl.: employment; BW: Bandwidth; Control variables: YES (Age of individuals and year of questionnaire); Data: Combined (SOEP and SHARE data)
Source: SOEP v34, SHARE (German sample, waves 4,5,6 and 7) , own calculations

Appendix C

Appendix to Chapter 3

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)
Industry	10 categories
Education	4 categories (in school, elementary, secondary, tertiary)
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

Notes
a Variable also included for partner
b Extra category for missing values

Table C1: Overview of control variables

Table C2: Effect of unemployment on informal care provision by age group

	(1)	(2)	(3)	(4)	(5)	(6)
Group	Full sample		Men		Women	
	Care provision					
Treatment	0.022*	0.030**	0.008***	0.015	0.045	0.057**
	(0.012)	(0.012)	(0.002)	(0.010)	(0.029)	(0.028)
Treatment &Age group 40-50	0.036*	0.036*	0.008	0.008	0.079**	0.082**
	(0.019)	(0.020)	(0.020)	(0.020)	(0.036)	(0.036)
Treatment &Age group 50-60	0.047**	0.068***	0.068**	0.097***	0.016	0.020
	(0.021)	(0.023)	(0.030)	(0.033)	(0.023)	(0.017)
	Hours of care					
Treatment	0.040*	0.053**	0.009***	0.017	0.090	0.127**
	(0.024)	(0.025)	(0.003)	(0.015)	(0.060)	(0.060)
Treatment &Age group 40-50	0.042	0.037	0.023	0.030	0.075	0.054
	(0.033)	(0.033)	(0.031)	(0.028)	(0.069)	(0.061)
Treatment &Age group 50-60	0.077**	0.111***	0.098**	0.140**	0.048	0.047
	(0.035)	(0.040)	(0.044)	(0.055)	(0.059)	(0.039)
Controls	-	√	-	√	-	√
Weighting	√	√	√	√	√	√
Observations	101,836	101,836	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 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 3.2. Weighting: Estimated applying weights estimated from entropy balancing. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Source: SOEP v35, own calculations.

Table C3: Effect of unemployment on informal care provision (non-clustered standard errors)

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	-	√	-	√
Weighting	-	-	√	√
Observations	129,637	101,836	101,836	101,836

Notes: 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 3.2. Weighting: Estimated applying weights estimated from entropy balancing. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Source: SOEP v35, own calculations.

Table C4: Effect of unemployment on informal care by education (ISCED1997 classification)

	(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	-	√	-	√	-	√
Weighting	√	√	√	√	√	√
Observations	102,497	102,497	58,883	58,883	43,614	43,614

Notes: 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 interacted with low education (ISCED97 Classification). Controls: The set of control variables is reported in Table 3.2. 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
Source: SOEP v35, own calculations.

Table C5: Effect of unemployment on informal care by gender (interaction)

	(1)	(2)	(3)	(4)
		Care provider		
Women	-0.001	0.000	-0.002	0.007
	(0.001)	(0.001)	(0.003)	(0.009)
Treatment	0.024*	0.030**	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	-0.011	0.014
	(0.002)	(0.003)	(0.008)	(0.017)
Treatment	0.041**	0.053**	0.047**	0.044**
	(0.020)	(0.022)	(0.022)	(0.021)
Treatment & Women	-0.004	0.045	0.037	0.066
	(0.049)	(0.035)	(0.035)	(0.041)
Controls	-	√	-	√
Weighting	√	√	√	√
Observations	129,637	101,836	101,836	101,836

Notes: 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 3.2. 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
Source: SOEP v35, own calculations.

Table C6: Effect of unemployment on informal care by treatment definition

	(1)	(2)	(3)	(4)	(5)	(6)
Group	Full sample	Men	Women	Full sample	Men	Women
Treatment		Period t			Period t to $t+2$	
Care provider	0.024	-0.011	0.076***	0.027**	0.029*	0.024*
	(0.015)	(0.015)	(0.022)	(0.012)	(0.016)	(0.013)
Hours of care	0.037	-0.001	0.083**	0.039*	0.051**	0.024
	(0.025)	(0.020)	(0.042)	(0.021)	(0.023)	(0.034)
Controls	√	√	√	√	√	√
Weighting	√	√	√	√	√	√
Observations	101,438	58,250	43,188	101,896	58,519	43,377

Notes: 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 3.2. 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
Source: SOEP v35, own calculations.

Table C7: Summary statistics of covariates (matching variables) in the plain control group, treatment group and weighted treatment group (propensity score weighting)

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 (31294)	26825 (18225)	37122 (28317)	-3192
Tenure[d]	13.40% (9.90)	11.44% (10.79)	11.93% (9.80)	-1.87
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	101462	374	101836	

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.

Appendix D

Appendix to Chapter 4

D.1 Definition of variables in SHARE

Retirement Individuals are considered retired if they respond to be retired in the question on their current job situation. In addition, individuals are considered retired if they respond not to be working and respond to be receiving old age pension benefits.

Working Individuals are considered part-time employed if they respond to be working and provide a number of working hours within the 5th to 50th percentile of the distribution of working hours. This corresponds to 10 to 32 hours per week. Individuals are considered full-time employed if they work more than the median of hours in the distribution of working hours (more than 32 hours per week). In the model we consider the mass-points of the distribution at the 25th percentile (20hours per week) and 75th percentile of the distribution (40 hours per week) for working women as part- and full- time work.

Care provision Individuals in SHARE give information on providing help to family members and close friends outside their own household; they inform about three different individuals they provide care for, state their relationship to them and inform on how regularly they provide care for them. We consider only care to parents (own mother or own father). Care provided almost every day is considered intensive care while care provided less often (every week, every month and less often) is considered non-intensive care. Further, individuals report on personal care they provide for individuals in their own household. If a respondent states to provide personal care to a parent who lives in the same household we consider this as intensive informal care. In order to include information on formal care we use predictions resting on an estimation on elderly respondents in SHARE ($age >= 69$) who have at least one child (see section on estimation).

Years in retirement Individuals give information on the time they have spend in retirement. If the information is missing and individuals are considered retired we use information given in SHARElife to construct retrospectively the year in which the last job ended.

Number of care years Individuals inform on care provided to any person in each wave. We make use of individuals who report to have given care in any former period and produce a variable giving the number of care years. This information cannot be enriched by SHARElife data as care provision is not covered retrospectively.

Parental information Individuals give information on parental age, health and distance individually by parent. We use this information plainly as given. If individuals respond in several waves we impute missing parental information given information in periods around the missing data point. We use the information on parental health and re-code it to reduce the size of the state space: We combine the statements on "very good" and "excellent" health to "good" health; we combine "good" and "fair" to "medium" and "poor" is renamed "bad". On the side of parents we use the information on self-assessed health and proceed the same way. Further, we use information on number of children and construct an indicator whether one child lives close by or not. Individuals further give information on number of siblings which we exploit in the prediction of the probability of formal care provision for parents given the number of children on the side of the parents.

Partner We use marriage information in SHARE to construct an indicator on the existence of a partner living in the same household. We do not distinguish between marriage and registered partnership.

Education We use information in years of education and professional qualification to construct an indicator for high education. If an individual reports at least 15 years of schooling, a practical training with the degree of a master craftsman or any kind of university degree we consider this person as highly educated.

D.2 Description of Parent child data set

We use all observations in SHARE on individuals aged 65 and older and expand it along their children to construct the parent-child data set. Given the rich information elderly respondents give on their children, we construct a data set we use to estimate the care demand and impute formal care usage. Table C1 shows summary statistics on parental and child information in the data set.

D.3 Formal care imputation: estimation

As we do not observe, whether individuals organize formal care for their care dependent parents we must impute the formal care choice. We do this making use of the information in the parent-child data set, separately for men and women. Using individuals aged 70 and older who have as least one child, we regress the binary indicator ($FC_{t,parent}$), indicating whether a person receives formal care on own information (age, number of children, health status) and information on each of the children (age, marriage status, how often they meet their parent, birth date, gender, distance to the parent, labor market status, education and whether they provide informal care fore their parent) in a logit estimation. Many of those variables are introduced as fixed effects in the estimation, e.g. number of children fixed effects (α_{Nchild}).This is done in order not to make linearity assumptions and have better predictions. Parameters from this estimation on men and women (mothers and fathers) separately are then used to predict the probability of formal care usage for each individual parent in the estimation data set. We use the resulting parent specific probability to construct a probability that a parent receives formal care as:

$$\begin{aligned} P(FC_t = 1) = P(FC_{t,mother} = 1) + P(FC_{t,father} = 1) \\ -(P(FC_{t,mother} = 1) * P(FC_{t,father} = 1)) \end{aligned} \tag{D.1}$$

For the final estimation data set we create a binary indicator if an individual organizes formal care for a parent from the smooth probability. We draw a random number from a uniform distribution (between 0 and 1) and compare it to the predicted probability. In this way we can carry the population mean on formal care organization into the model. We estimate the probability that any given parent receives

Table C1: Summary table on the parent-child data set- SHARE

	Male	Female	Total
Parent information			
Age	73.17	73.93	73.56
	(6.041)	(6.682)	(6.391)
Year	2011.3	2011.3	2011.3
	(3.958)	(4.009)	(3.984)
Highly educated	0.114	0.0922	0.103
	(0.318)	(0.289)	(0.304)
Number of children	2.864	2.860	2.862
	(1.397)	(1.324)	(1.360)
Marital status	0.845	0.605	0.721
	(0.362)	(0.489)	(0.449)
Self reported health	3.369	3.511	3.443
	(0.985)	(0.917)	(0.953)
Formal care usage	0.0855	0.139	0.113
	(0.280)	(0.346)	(0.317)
Number of parent observations	1,744	1,838	3,582
Children information			
Age	44.26	47.64	46.01
	(28.51)	(7.779)	(20.65)
Frequency of visit (categorical)	2.920	2.746	2.830
	(1.610)	(1.546)	(1.580)
Birth year	1967.0	1963.7	1965.3
	(28.60)	(8.293)	(20.81)
Female	0.493	0.486	0.490
	(0.500)	(0.500)	(0.500)
Distance to parents (categorical)	5.148	5.000	5.072
	(1.845)	(1.875)	(1.862)
Marital status	1.407	1.369	1.387
	(0.491)	(0.483)	(0.487)
Labor market status (categorical)	2.227	2.218	2.223
	(0.735)	(0.792)	(0.765)
Provide informal care to parent	0.0461	0.105	0.0768
	(0.210)	(0.307)	(0.266)
Number if child observations	9,840	10,123	19,963

Notes: Standard errors in parenthesis.
Source: SHARE, own calculations.

formal care given parental information (age, age squared, number of children, health, marital status) and child information provided by the parents (age, age squared, whether the child gives informal care to the parent ($Icare$), marital status, employment status, gender, educational attainment, birth year ($cohort$), distance to parents and frequency of visits to parents). We introduce all variables, except age as fixed effects into the estimation.

$$\begin{aligned} FC_{t,parent} =& FC_{t,parent}(\delta, age_{parent}, age^2_{parent}, age_{child}, age^2_{child}, Icare_{child},\\ & Nchild_{parent}, Health_{parent}, married_{parent}, married_{child}, empl_{child},\\ & gender_{child} educ_{child}, cohort_{child}, dist_{child}, frequency_{child}) \end{aligned} \tag{D.2}$$

, with $parent \in \{mother, father\}$.
Given the parent-child data set from SHARE (see section D.2) we estimate the probability of any parent using formal care in a probit estimation. The residual categories are always baseline (Number of children:1; Healh of parent: excellent; Non-married parent or/and child; distance to child: in the same building; employment status of child: retired). See Tables C3 and C2 for results.

D.4 Limitations with activities of daily living

In SHARE data, individuals give information on limitations with activities of daily living (ADL) as well as Limitations with instrumental activities of daily living (IADL) they face. We construct a categorcial variable stating whether one faces at least two ADL and at least 1 IADL (category 1), at least 3 ADL and at least 3 IADL (category 2) or at least 5 ADL and at least 5 IADL. The residual category 0 defines less than 2 ADL and no IADL. These categories are close to the definitions of care levels in the German LTCS. Our Category 1 defines care level 2, category 2 defines care level 3 and category 3 defines care level 4. The residual care levels 1 and 5 are very specific and are difficult to define with the data at hand. We use the parent-child data set to estimate the parameters of the multinomial regression given the following specification separately for males and females:

$$B^j_{t,parent} = \omega_1 age + \omega_2 age^2 + \omega_3 health_{good} + \omega_4 health_{medium} + \omega_5 health_{bad} + \omega_6 \tag{D.3}$$

The estimation results are given in Table C4.
We formulate the probability of any of the categories ($ADL_t \in \{1-3\}$) depending on the state vector and Q_t as a multinomial-logit probability. We then calculate the probability that the agent observes any of the discrete ADL categories for the parents facing demand following equation D.4, which includes separate probabilities of either parent facing any of the ALD categories. These are formulated according to equation D.5 for care following the closed form multinomial logit probability.

$$\begin{aligned} P(ADL_t = j) = & P(ADL_{t,mother} = j) + P(ADL_{t,father} = j)\\ & -(P(ADL_{t,mother} = j) * P(ADL_{t,father} = j)) \end{aligned} \tag{D.4}$$

$$P(ADL_{t,parent} = j) = \frac{exp(B^j_{t,parent})}{1 + exp(B^j_{t,parent})} \tag{D.5}$$

Table C2: Regression for imputation of formal care usage for females

	(1)
VARIABLES	Formal care usage
Age	-0.681***
	(0.153)
Age squared	0.00514***
	(0.000989)
Number of children:2	0.147
	(0.161)
3	0.300*
	(0.163)
4	0.280
	(0.180)
5	-0.133
	(0.213)
6	0.0634
	(0.306)
7	0.492
	(0.574)
8	1.821***
	(0.649)
Very good health Health	-2.657***
	(0.562)
Good Health	-0.592*
	(0.329)
Fair Health	0.114
	(0.324)
Poor Health	1.230***
	(0.330)
Age child	0.0941
	(0.105)
Age child squared	-5.34e-05
	(0.00102)
Parent married	-0.391***
	(0.102)
Birth year child	.0513
	(.00679)
Child is female	0.0119
	(0.0930)
Distance to child	
Less than 1 kilometre away	0.180
	(0.316)
Between 1 and 5 kilometres away	0.547*
	(0.304)
Between 5 and 25 kilometres away	0.108
	(0.306)
Between 25 and 100 kilometres away	0.286
	(0.297)
Between 100 and 500 kilometres away	0.372
	(0.305)
More than 500 kilometres away	0.258
	(0.305)
More than 500 kilometres away in another country	-0.0548
	(0.332)
Child married	-0.142
	(0.0980)
Employment status child	
Working	-0.357*
	(0.211)
Unemployed	-0.121
	(0.270)
Disabled or sick	-0.0925
	(0.373)
Homemaker	-0.570**
	(0.277)
Highly educated child	0.0199
	(0.179)
Provide informal care to parent	.3020***
	.0716429
Constant	21.17***
	(5.801)
Observations	5,553

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table C3: Regression for imputation of formal care usage for males

	(1)
VARIABLES	Formal care usage
Age	0.153
	(0.222)
Age squared	-0.000315
	(0.00142)
Number of children:2	0.369
	(0.228)
3	0.267
	(0.234)
4	0.414*
	(0.249)
5	0.544*
	(0.285)
6	1.785***
	(0.341)
7	0.485
	(0.438)
8	0.524
	(0.580)
9	2.518***
	(0.430)
Very good health Health	-0.187
	(0.507)
Good Health	0.0596
	(0.445)
Fair Health	0.851*
	(0.438)
Poor Health	2.470***
	(0.440)
Age child	0.498***
	(0.161)
Age child squared	-0.00360**
	(0.00161)
Parent married	-0.928***
	(0.139)
Birth year child	0.071
	(.00976)
Child is female	0.175
	(0.120)
Distance to child	
Less than 1 kilometre away	-0.186
	(0.479)
Between 1 and 5 kilometres away	0.236
	(0.449)
Between 5 and 25 kilometres away	-0.0803
	(0.446)
Between 25 and 100 kilometres away	0.0163
	(0.439)
Between 100 and 500 kilometres away	0.372
	(0.442)
More than 500 kilometres away	0.352
	(0.440)
More than 500 kilometres away in another country	-0.0713
	(0.473)
Child married	-0.107
	(0.128)
Employment status child	
Working	-0.751**
	(0.335)
Unemployed	-0.269
	(0.397)
Disabled or sick	0.0757
	(0.539)
Homemaker	-1.201***
	(0.441)
Highly educated child	-0.274
	(0.192)
Provide informal care to parent	1.225***
	(0.203)
Constant	-20.37**
	(8.323)
Observations	5,146

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table C4: Probability to have limitations with activities of daily living- multinomial regression

	(1) Female	(2) Male
Limitation Category 1		
Age	-0.185	-0.242
	(0.199)	(0.252)
Age squared	0.002	0.002
	(0.001)	(0.002)
Good health	-2.190***	-1.883***
	(0.723)	(0.705)
Medium health	-0.814	-0.639
	(0.721)	(0.701)
Bad health	0.118	0.464
	(0.727)	(0.708)
Constant	4.264	4.934
	(7.838)	(9.860)
Limitation Category 2		
Age	-0.524*	-0.687*
	(0.270)	(0.357)
Age squared	0.004**	0.005**
	(0.002)	(0.002)
Good health	12.202	-3.359***
	(1508.795)	(0.857)
Medium health	14.205	-1.454*
	(1508.795)	(0.826)
Bad health	16.052	0.894
	(1508.795)	(0.824)
Constant	-1.236	21.584
	(1508.834)	(14.023)
Limitation Category 3		
Age	-0.658**	-0.679**
	(0.274)	(0.341)
Age squared	0.005***	0.005**
	(0.002)	(0.002)
Good health	-3.755***	-2.922***
	(0.774)	(0.871)
Medium health	-2.136***	-1.334
	(0.756)	(0.853)
Bad health	0.241	1.072
	(0.758)	(0.851)
Constant	17.559	19.526
	(11.121)	(13.496)
N	3820	3840

Standard errors in parentheses

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

,with $B^{j}_{t,parent}(\psi, age_{parent}, health_{parent})$ for $parent \in \{father, mother\}$ and $j \in \{1-5\}$.
The predicted ADL, that any given indidivual faces combined for her parents is then used to calculate LTC benefits and costs of formal care usage. Further the separate ADL categories for both parents are used to calculate formal care-demand.

D.5 Care Demand

In order to estimate the care demand paremeters for formal and informal care demand we use SHARE data on individuals aged 69 and older.

D.5.1 Formal care demand

Using the information health, age and marital status we estimate the probability that any given parent uses formal care. The outcome variable is the usage of formal care in the parent household. We estimate the probability that any given household of parents uses formal care give the information separately on single parent households (male and female separately) and households with both parents. Parameters are given in Table C5. In the next step we use predicted probabilities of care demand to find out the impact of existence of siblings and the distance to parents on care provision by children. We do this by estimating the impact of these factors (predicted formal care demand, information on siblings and distance to parents) on the probability that any given child organizes formal care for a parent. These predicted probabilities from the care demand estimation are then carried over to the model and adjusted by these factors according to information on distance to parents and existence of siblings.

D.5.2 Informal care demand

For the estimation of informal care demand we use information on parental health, age and marital status to estimate the probability that a parent household uses informal care (any informal care form outside the household, no informal care from the spouse). The parameters are given in Table C6. As for formal care we then use predicted informal care demand and measure the impact of distance to parents and existence of sibling. To do that we regress the information that any given child provided informal care to a parent on predicted informal care demand and the information on distance to parents and existence of siblings. We use the parameters to predict care demand in the model and adjust them accordingly using the estimated impact of parental distance and existence of siblings.

D.6 SOEP Data

We make use of the German Socio-economic Panel (GSOEP)[133] in order to estimate the parameters of the wage function and health transitions. The following variables are created:

[133] Goebel et al. (2019)

Table C5: Care-demand for formal care- couples and single parents

	(1)	(2)	(3)
	Received informal care		
	Single mothers	Single fathers	Couple
Age of parent	-0.921***	-0.321	
	(-5.73)	(-1.29)	
Age of parent squared	0.00616***	0.00246	
	(6.15)	(1.57)	
Health of parent			
Medium	0.836***	0.499***	
	(9.57)	(4.29)	
Bad	1.715***	0.982***	
	(15.99)	(5.90)	
Parent(s) live close	0.0192	-0.000733	-0.0562
	(0.25)	(-0.01)	(-1.26)
Age of mother			0.0340***
			(6.05)
Age of father			0.0252***
			(3.93)
Health of mother			
Medium			0.277***
			(5.73)
Bad			0.651***
			(9.84)
Health of father			
Medium			0.322***
			(6.50)
Bad			1.169***
			(19.02)
Constant	32.79***	9.012	-5.799***
	(5.10)	(0.91)	(-16.49)
N	1634	760	4860

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C6: Care-demand informal care- couples and single parents

	(1)	(2)	(3)
	Received informal care		
	Single mothers	Single fathers	Couple
Age of parent	0.0358	-0.00244	
	(0.36)	(-0.01)	
Age of parent squared	-0.0000129	0.000386	
	(-0.02)	(0.32)	
Health of parent			
Medium	0.422***	0.272**	
	(7.52)	(2.89)	
Bad	0.724***	0.900***	
	(9.98)	(6.56)	
Age of mother			-0.00432
			(-1.06)
Age of father			0.0427***
			(8.98)
Health of mother			
Medium			0.353***
			(9.81)
Bad			0.515***
			(9.97)
Health of father			
Medium			0.347***
			(9.55)
Bad			0.974***
			(19.95)
Constant	-3.100	-2.744	-3.867***
	(-0.77)	(-0.36)	(-14.90)
N	2586	961	6876

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D.6.1 SOEP Data- Variable definitions

Wage The SOEP data set contains a constructed variable on the yearly wage of the individual from their main job and their secondary job before taxes. In order to create the hourly wage we additionally use a variable containing the annual work hours of the individual.
Experience SOEP data contains constructed information on the years of part-time and full-time employment, which is used to construct an individual experience level.
Education In line with the definition in SHARE individuals are considered to have high education if they either report at least 15 years of schooling, a practical training with the degree of a master craftsman or any kind of university degree.
Region We use SOEP data to construct a variable informing on whether a household lives in parts of Germany formerly belonging to the DDR.
Health SOEP contains information on self reported health status. It is given every period, which we use to construct a lagged health status. In line with SHARE we construct a 3 fold health indicator from the original variable with 5 levels: We combine the statements on "very good" and "good" health to "good" health; "satisfactory" becomes "medium" and "poor" and "bad" is renamed "bad".
Non-labor income Non-labor income is defined as household pre-government income minus own and partner labor income.
Partner income In order to estimate partner income we make use of SOEP's household dimension and use labor income of a spouse living in the same household. We also include other sort of partner specific income (pension etc.).

D.6.2 SOEP data- sample description

In our SOEP data set we end up with 46,249 observations on 5,418 women. Table C7 shows important summary statistics for this data set (women in SOEP observed between 2001 and 2018, aged 55-68. This data set is used to estimate the wage equation as well as non-labor income and partner income. The last 12 rows show mean self-reported health status of men and women aged 69 and older. This data on 64,021 observation on 5,876 individuals is used to estimate health transitions. In German SOEP data we can observe the care level of individuals who live in private households and report their care dependency.[134] We find that of the 4,611 individuals reporting to be care dependent, 56.3% report to be in care level 2, 30.5% in care level 3, 10.9% in care level 3. Only 1.8% are in care level 1 and only 0.34% report to be in care level 5. Discrepancies to the official data are partly due to the fact that SOEP contains very few individuals living in care facilities. Partly, reporting issues arise. Also, as the care levels were reformed in 2017 but data comes from the years 2001-2018, harmonising the reported levels is difficult. Of all individuals reporting a care level, 46% report to be in bad health, and 30% report poor health. With increasing care levels the proportions shift toward worse self-reported health.

[134]SHARE data does not contain information on the care level.

Table C7: Summary table SOEP data

Age	58.99
	(3.124)
Year of observation	2011.6
	(5.688)
Highly educated	0.240
	(0.428)
Married	0.925
	(0.264)
Retired	0.40
	(0.49)
Employed	0.35
	(0.47)
Mean wage (all)	14.24
	(9.445)
Mean wage (employed)	17.55
	(21.62)
Experience	27.08
	(9.641)
Partner income	34314.0
	(33552.5)
Non labor income	4436.9
	(20703.0)
Current Self-Rated Health Status Women	
Good	0.20
	(.40)
Medium	0.41
	(0.49)
Bad	0.37
	(0.48)
Current Self-Rated Health Status Men	
Good	0.26
	(0.43)
Medium	0.43
	(0.49)
Bad	0.28
	(0.45)

Notes: Standard errors in parenthesis.
Source: SOEP v35, own calculations.

D.7 Health transitions

Health transitions of the parents follow a process estimated outside the model on SOEP data.[135] We estimate a simple multinomial logit model on three possible health outcomes of fathers and mothers separately.
The functional form looks as follows:

$$\begin{aligned} health_{t+1} = &\alpha_0 + \alpha_1 age + \alpha_2 age^2 + \alpha_3 \mathbb{1}(health_t = good) + \\ &\alpha_4 \mathbb{1}(health_t = medium) + \alpha_5 \mathbb{1}(health_t = bad) \end{aligned} \tag{D.6}$$

We estimate this on separate data sets of men and women respectively, aged 69 and older. We use the self assessed health status reported in SOEP. Tables C8 and C9 show the parameters of the health

Table C8: Health transitions Women

	(1)	(2)	(3)
Health outcome	Good health	Medium health	Bad health
Age		0.0304***	0.196***
		(0.00321)	(0.0447)
Age squared		-1.31e-05*	-0.000885***
		(7.93e-06)	(0.000282)
Lagged health good		-1.155***	-2.558***
		(0.0486)	(0.0617)
Lagged health medium		0.736***	-0.109**
		(0.0478)	(0.0504)
Lagged health bad		1.434***	2.663***
		(0.0691)	(0.0682)
Constant		-1.550***	-9.220***
		(0.225)	(1.763)
Observations		40,937	
Pseudo R-squared		0.2002	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

transition estimation. The parameters are difficult to interpret. Sign and size have some explanatory power: The probability to be of medium and bad health in some period depends positively on age while higher age increases the probability to be of bad health more. A good health status in the last period reduces the probability of a medium or bad health status now while medium and bad health status in the last period increases this probability now. The estimation takes a good health status as base category and after predicting probabilities for medium and bad health based on the parameters shown in the Table the probability of good health is the residual of the other two.

[135] For details on SOEP see D.6

Table C9: Health transitions Men

Health outcome	(1) Good health	(2) Medium health	(3) Bad health
Age		0.176***	0.260***
		(0.0645)	(0.0757)
Age squared		-0.000968**	-0.00134***
		(0.000414)	(0.000484)
Lagged health good		-1.047***	-2.472***
		(0.0503)	(0.0680)
Lagged health medium		1.016***	0.115**
		(0.0502)	(0.0557)
Lagged health bad		1.743***	3.067***
		(0.0788)	(0.0789)
Constant		-7.374***	-11.89***
		(2.502)	(2.946)
Observations		33,965	
Pseudo R-squared		0.2170	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

D.8 Wage function estimation

The wage function looks as follows:

$$\begin{aligned} ln(wage_t) =& \omega_0 + \omega_1 \mathbb{1}(age_t >= 60) + (\omega_2 + \omega_3 \mathbb{1}(educ = 1))exp_t + \\ & omega_4 + \omega_5 \mathbb{1}(educ = 1))exp_t^2 + \omega_9 \mathbb{1}(educ = 1) + \omega_{year} YEAR \end{aligned} \tag{D.7}$$

As can be seen in equation D.7, wages can increase with experience which is an incentive to work. Also, returns to experience are allowed to vary with education. To incorporate changing macroeconomic conditions, we include a year fixed effect. We use SOEP data to estimate the wage process. Low wages of an individual are estimated dependant on gender, experience, education and the region of habitation. The estimation procedure is conducted on a sample of all employed individuals aged 55 to 69, the ages of interest in the model using a simple linear OLS regression. High education is defined according to the definition used in the SHARE data set: having at least 15 years of education, a finished master training or some university degree. Part time employment is counted as half years of experience. Table C10 shows the parameters from the wage estimation. Females have lower hourly wages. Experience seems to impact the hourly wage deferentially by education, age and sex.

D.9 Non-labor income parameters

On a similar data set we estimate the parameters for non-labor income. Non-labor income is influenced by education, age and the existence of a partner. We use age in linear and quadratic form and on top include a indicator on being older than 64 in order to account for changes on non-labor income in old

Table C10: Wage function

	(1)
Outcome	Wage (logarithmic)
Sex	-0.414***
	(0.0433)
Experience	0.000627
	(0.00259)
Experience squared	0.00770*
	(0.00458)
Experience *High Education	0.0204***
	(0.00307)
Experience squared *High Education	-0.0513***
	(0.00559)
High Education	0.307***
	(0.0415)
Experience *Older than 60 years	-0.000234
	(0.000221)
Experience Females	0.0108***
	(0.00309)
Experience squared Females	-0.0156***
	(0.00564)
Year of observation	0.0128***
	(0.000584)
Constant	-23.12***
	(1.172)
Observations	38,812
R-squared	0.155

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C11: Partner income

	(1)
Outcome	Partner Income
Education	0.358***
	(0.00787)
Age	0.117***
	(0.0427)
Age squared	-0.00129***
	(0.000356)
Age >= 65	-0.00548
	(0.0183)
Year of observation	0.0210***
	(0.000660)
Constant	-35.27***
	(1.865)
Observations	57,130
R-squared	0.133

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C12: Non-labor income

	(1)
Outcome	Non labor income
High Education	0.752***
	(0.0138)
Age	-0.147**
	(0.0738)
Age squared	0.00184***
	(0.000617)
Age >= 65	0.00264
	(0.0320)
Married	0.479***
	(0.0151)
Constant	7.883***
	(2.207)
Observations	110,203
R-squared	0.098

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

age and retirement. Equation D.8 shows the specification.

$$ln(A_t) = \eta_0 + \eta_1 \mathbb{1}(age_t >= 65) + \eta_2 \mathbb{1}(educ = 1) + \eta_3 age_t + \eta_4 age_t^2 \tag{D.8}$$

Parameter estimates are shown in table C11. For the estimation, non-labor income is used in logarithmic form.

D.10 Partner income parameters

We use following regression to estimate spousal income parameters κ :

$$ln(SI_t) = \kappa_0 + \kappa_1 \mathbb{1}(age_t >= 65) + \kappa_2 \mathbb{1}(educ = 1)(\kappa_3 +)age_t + \kappa_4 age_t^2 + \kappa_{year} YEAR \tag{D.9}$$

To include partner income into the model, we estimate the influence of education and age on all women with a partner on logarithmic partner income. Table C12 shows parameters which are then used in the model.

D.11 State space

The state vector s_t determines which options are in the current feasible action space $D(s_t)$, which utility value is given to the feasible choices and what beliefs and expectations about corresponding future states exist. The vector s_t is observed in every period.

$$\begin{aligned} s_t = \{ & H_{t-1}, JO_t, CD_t, expEQ_t, age_t, lrage_t, retyears_t, careyears_t, \\ & mar_t, educ_t, malive_t, falive_t, mage_t, fage_t, fhealth_t, mhealth_t, pdist_t, sibl_t \} \end{aligned} \tag{D.10}$$

H_{t-1} is past choice on work, JO_t and CD_t inform about job offer and care demand probabilities in the current state. Only if these exist, the agent can chose to provide labor and provide some kind of (in)formal care. Further, the state space includes the agent's age age_t, the legal retirement age $lrage_t$, job experience $expEG_t$, time since retirement $retyears_t$, times spend in care provision $careyears_t$, being married mar_t, being highly educated $educ_t$ and information about the parents: If mother and/or father are alive ($malive_t$, $falive_t$), their age ($fage_t$ and $mage_t$) and health ($fhealth_t$, $mhealth_t$) and whether they live close by ($pdist_t$). Further, we track the existence of a sibling $sibl_t$.

D.12 Further information on the ML estimation

We approximate the value function using interpolation as suggested in Keane and Wolpin (1994). We use numerical gradients but utilize the BHHH approximation of the Hessian (Berndt et al., 1974). The estimation of type probability function, the interpolation of the value function, and the numerical maximization procedure are described in detail in the appendices D.13 D.14 and D.15, respectively.

Table C13: Parameter results for unobserved type estimation

Description	Parameter	Coefficient	S.E.
Intercept	λ_1	-1.03	0.26
High education	λ_2	1.13	0.14
Experience at age 55	λ_3	0.04	0.01
Number of children at age 55	λ_4	-0.01	0.06
High education	λ_5	1.00	0.17

D.13 Unobserved type probability

The probability of belonging to type m is modeled conditionally on working experience at age 55[136], on number of children, and whether the women is highly educated.[137] The probability is estimated within the ML estimation.

$$
\begin{aligned}
P(m=1) =& \frac{exp(\alpha M_{T_0})}{1+exp(\alpha M_{T_0})} \\
\alpha M_{T_0} =& \alpha_0 + \alpha_1 age_{T_0} + \alpha_2 expEQ_{T_0} + \alpha_3 children_{T_0}
\end{aligned}
\tag{D.11}
$$

By making the type probability function conditional on state variables in the initial period, we account for non-random initial conditions at the initial period. This approach follows (Wooldridge, 2005). It requires that the initial condition is random conditional on working experience, education and number of children in the previous period.
Table C13 gives the parameters and standard errors estimated inside the maximum likelihood estimation.

D.14 Approximation of the value function

Instead of solving the value function at the entire state space, we approximate the value function using interpolation as suggested in Keane and Wolpin (1994). We follow Korfhage (2019) in this way. That is, starting at the terminal age T, we calculate the value functions at a subset of the state space. This grid includes two values of labor market experience (0, 30), two values of years in retirement (0, 6), years in intensive care (0, 5), father age (70, 90), and mother age (70, 90). Further, it includes states which are not interpolated. I.e., individuals' type (1, 2), father died last period (0, 1), mother died last period (0, 1), father alive (0, 1), mother alive (0, 1), health of father (1, 2, 3), health of mother (1, 2, 3), existence of siblings (0, 1), parents live close by (0, 1) married (0, 1), education (low, high). In contrast to Korfhage (2019) we reduce the number of grid points for experience in order to reduce the size of the overall grid. This results in a total of 229.376 grit points including the 14 ages but excluding the choices. While solving the model recursively, we use a linear interpolation function to predict the value function at values of the state variables that are not included in the grit.

[136] In SHARE data we use the retrospective SHARElife data set to retain this information for those respondents who are not observed at age 55.

[137] We follow (Korfhage, 2019) in estimating the type probabilities. However, we introduce educational attainment into the function. In contrast to (Korfhage, 2019) the type is important only for taste for leisure time and preferences for informal and formal care. We do not estimate differences in wages and non-labor income by type.

D.15 Numerical maximization of the likelihood function

We follow Korfhage (2019). The log-likelihood function takes the form $LL(\theta) = lnL(\theta)$, where $L(\theta)$ is function 4.13. For simplicity, all coefficients are collected in vector θ. After specifying a vector of starting values θ_0 the Newton-based algorithm stepwise approaches the maximum. That is, the algorithm is based on a second order Taylor approximation around θ_τ. The next iteration value is found by maximizing the Taylor approximation with respect to the step to the next iteration value (for an overview of different numerical optimization methods, see for example Train (2009), Ch. 8). It is defined as

$$\theta_{\tau+1} = \theta_\tau + \lambda B_\tau^{-1} g_\tau \tag{D.12}$$

, where $g_\tau = \quad (\frac{\partial LL(\theta)}{\partial \theta})_\tau$ is the gradient vector of first derivatives and B_τ is the approximation of the negative Hessian, the matrix of the second derivatives $H_\tau = \quad (\frac{\partial^2 LL(\theta)}{\partial \theta \partial \theta'})_\tau$. The Newton-based methods hence require gradients and the Hessian matrix. As the gradients are difficult to derive analytically, I use numerical approximations of the scores. For each individual i we calculate the score as

$$s_i(\tau) = \frac{LL_i(\theta_\tau + h) - LL_i(\theta_\tau)}{h} \tag{D.13}$$

, where $h = 10^-6$ and LL_i is the individual contribution to the likelihood. The scores are used to calculate the gradient vector $g_\tau = \sum_i s_i(\tau)/N$ and the BHHH approximation of the Hessian. It is calculated as the average outer product $B_\tau = \sum_i s_i(\tau)s_i(\tau)'/N$ (Berndt et al., 1974).

D.16 Further Tables

Table C14: Retirement ages for German women

Pension pathway	ERA	NRA
Old age pension	-	65 if born pre 1947; increases gradually to 67 for those born in 1964; Criteria: 5 years of waiting period
Old age pension for long term insured	63; Criteria: 35 years of waiting times	65 if born before 1949; gradual increase to 67 if born from 1964; Criteria: 35 years of waiting times
Old age pension for especially long term insured	-	63 Criteria: 45 years of waiting times and born until 1953; gradual increase to age 65 if born from 1964
Women's pension	60; Criteria: born until 1951; 15 years of waiting period, 10 of which have to lay after the age 40	63; Criteria: born until 1951; 15 years of waiting period, 10 of which have to lay after the age 40

Table C15: Care and Working decision

	Caring decision						
	No formal care			Formal care			
Working choice	NIC	LIF	HIC	NIC	LIF	HIC	Total
Unemployed	1,000	39	24	129	30	16	1,238
	80.78	3.15	1.94	10.42	2.42	1.29	100.00
Part-time	856	46	15	105	42	23	1,087
	78.75	4.23	1.38	9.66	3.86	2.12	100.00
Full-Time	692	45	20	124	26	13	920
	75.22	4.89	2.17	13.48	2.83	1.41	100.00
Retired	1,918	40	21	183	29	32	2,223
	86.28	1.80	0.94	8.23	1.30	1.44	100.00
Total	4,466	170	80	541	127	84	5,468
	81.68	3.11	1.46	9.89	2.32	1.54	100.00

Source: SHARE, own calculations.

Table C16: Transitions

	Data	Simulated
% Nonemployed who are nonemployed again next period	95.34	87.29
% Transition from employmend to nonemployment	31.35	47.42
% Transition from nonemployment to employment	4.66	12.71
% Employed who are employed again next period	68.65	52.58
% Informal noncaregiver who are Informal noncaregiver again next period	94.50	93.11
% Transition from informal caregiving to informal noncargiving	71.99	71.63
% Transition from informal noncaregiving to informal cargiving	5.50	6.89
% Informal Caregiver who are informal caregiver again next period	28.01	28.37
% Formal noncaregiver who are formal noncaregiver again next period	92.41	92.13
% Transition from formal caregiving to formal noncargiving	42.06	60.64
% Transition from formal noncaregiving to formal cargiving	7.59	7.87
% Formal caregiver who are formal caregiver again next period	57.94	39.36

The data average was calculated using the estimation sample. The model predictions were calculated using a simulated sample. The simulated sample was constructed using the dynamic model for work, retirement and care-giving and state variables for each individual in the sample. To ensure comparability with the estimation sample, model predictions were only calculated for with simulation outcomes from ages at which a person was also observed in the data. SHARE, own calculations

Table C17: Response in lifetime earnings to increased retirement ages combined with increased collectable pension points

	(1) 1000 Euro	(2) %
	Δ NPV of labor earnings	
total	13.6	14.6
1st quartile	14.8	21.3
2nd quartile	13.7	19.6
3rd quartile	14.3	16.0
4th quartile	11.7	8.21
	Δ NPV of Retirement benefit	
total	-11.5	-24.5
1st quartile	-14.5	-38.4
2nd quartile	-12.3	-27.6
3rd quartile	-10.9	-23.4
4th quartile	-8.6	-14.9
	Δ NPV of total earnings	
total	2.14	1.5
1st quartile	2.6	0.2
2nd quartile	1.4	1.2
3rd quartile	3.3	2.4
4th quartile	3.1	1.5

Notes: NPV: net present values

Source: SHARE, own calculations

Table C18: Response in lifetime earnings (introduction of care-leave combined with increased retirement age)

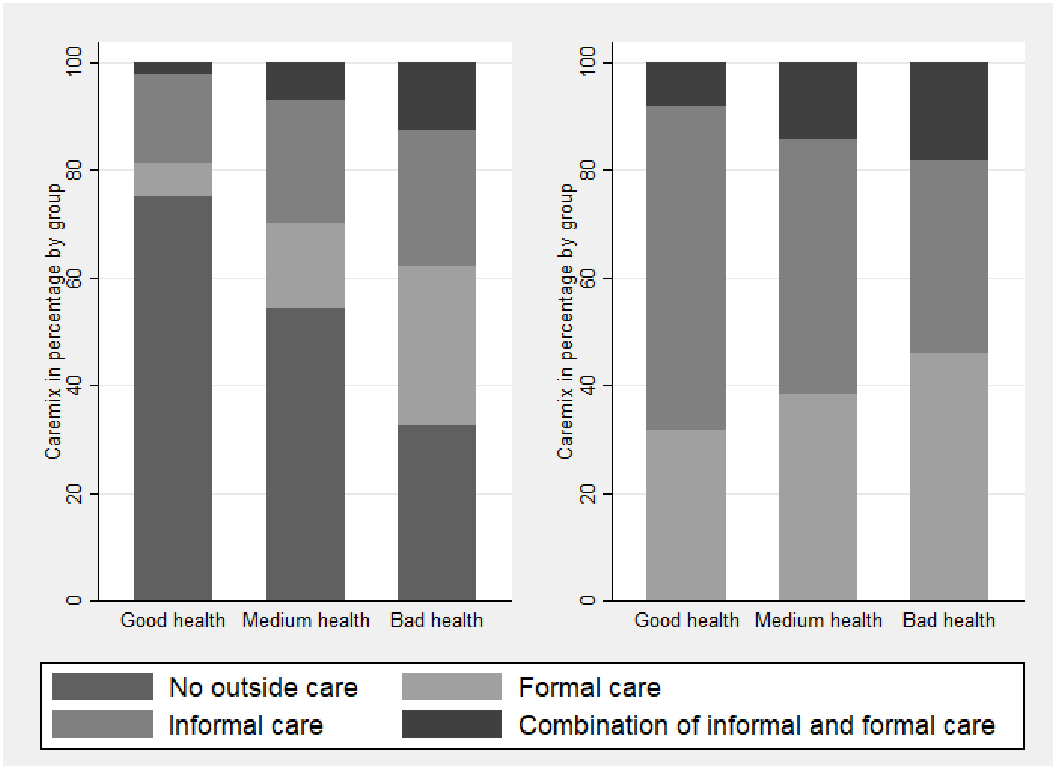
	(1) 1000 Euro (CD)	(2) % (CD)
	Δ NPV of labor earnings	
total	11.5	12.4
1st quartile	15.1	21.7
2nd quartile	13.1	18.8
3rd quartile	11.4	12.8
4th quartile	6.9	4.8
	Δ NPV of Retirement benefit	
total	-12.0	-25.6
1st quartile	-14.9	-39.2
2nd quartile	-12.5	-28.2
3rd quartile	-11.6	-24.8
4th quartile	-9.4	-16.3
	Δ NPV of total earnings	
total	-0.4	-0.3
1st quartile	0.2	0.2
2nd quartile	0.5	0.5
3rd quartile	-0.2	-0.1
4th quartile	-2.4	-1.2

Notes: NPV: net present values; CD: Care-demand

Source, SHARE, own calculations

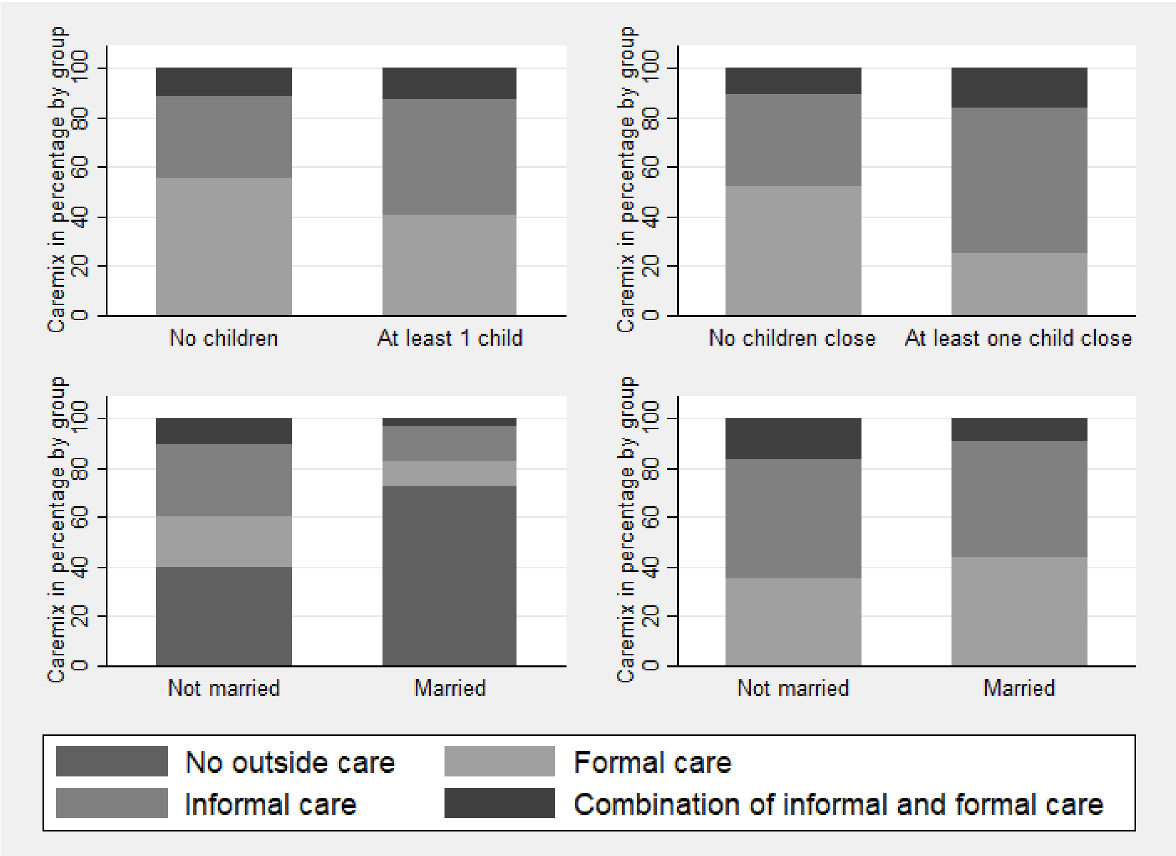
D.17 Further figures

Figure C1: Care mix by health; unconditional left, conditional on outside care received right (SHARE data)



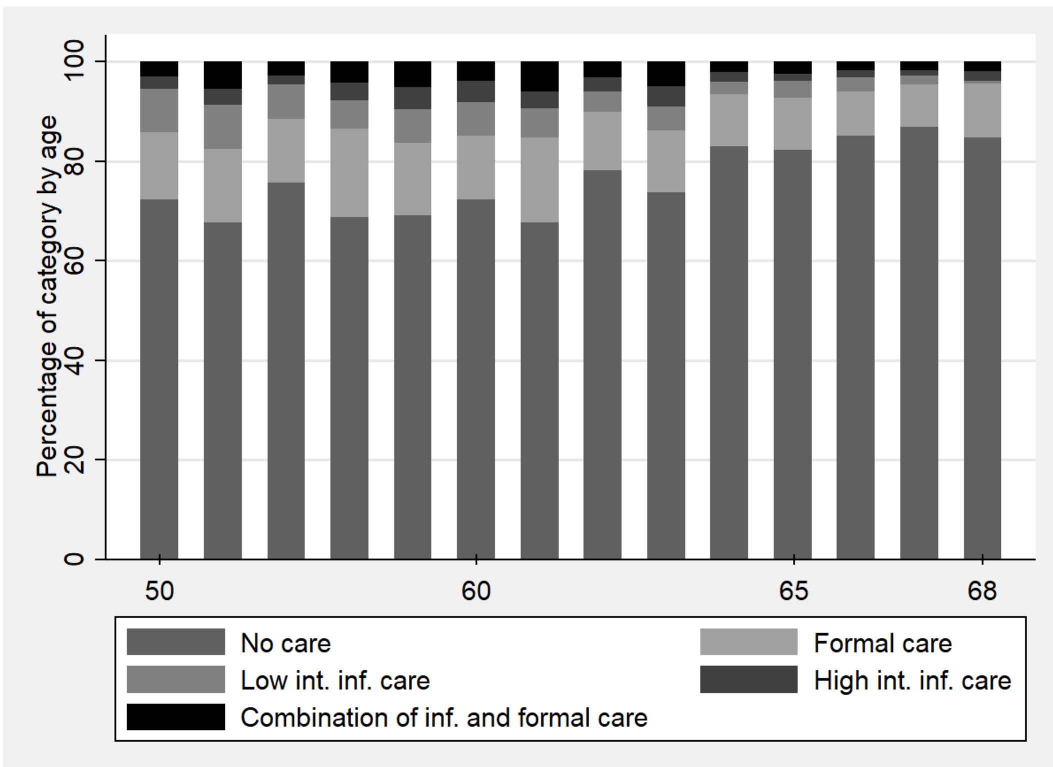
Source: SHARE, own calculations.

Figure C2: Care mix by children, child distance and marriage status (SHARE data)



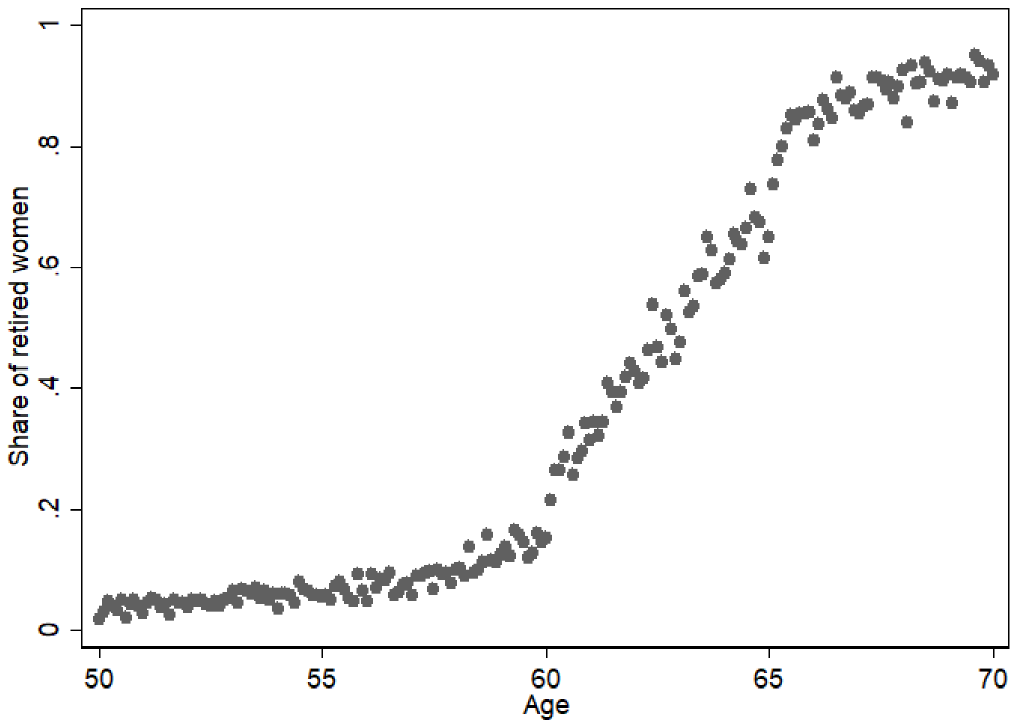
Source: SHARE, own calculations.

Figure C3: Care mix in estimation data by age of agent



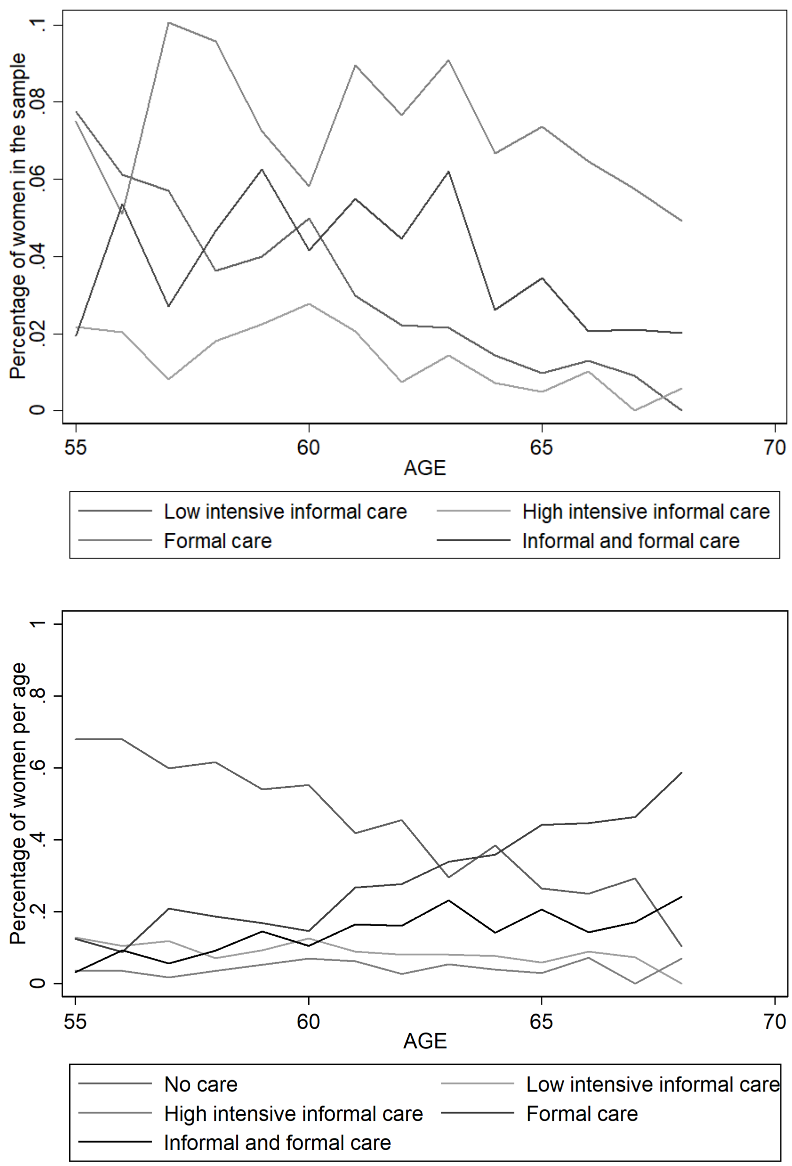
Source: SHARE, own calculations.

Figure C4: Retirement behavior of women in SOEP data by age



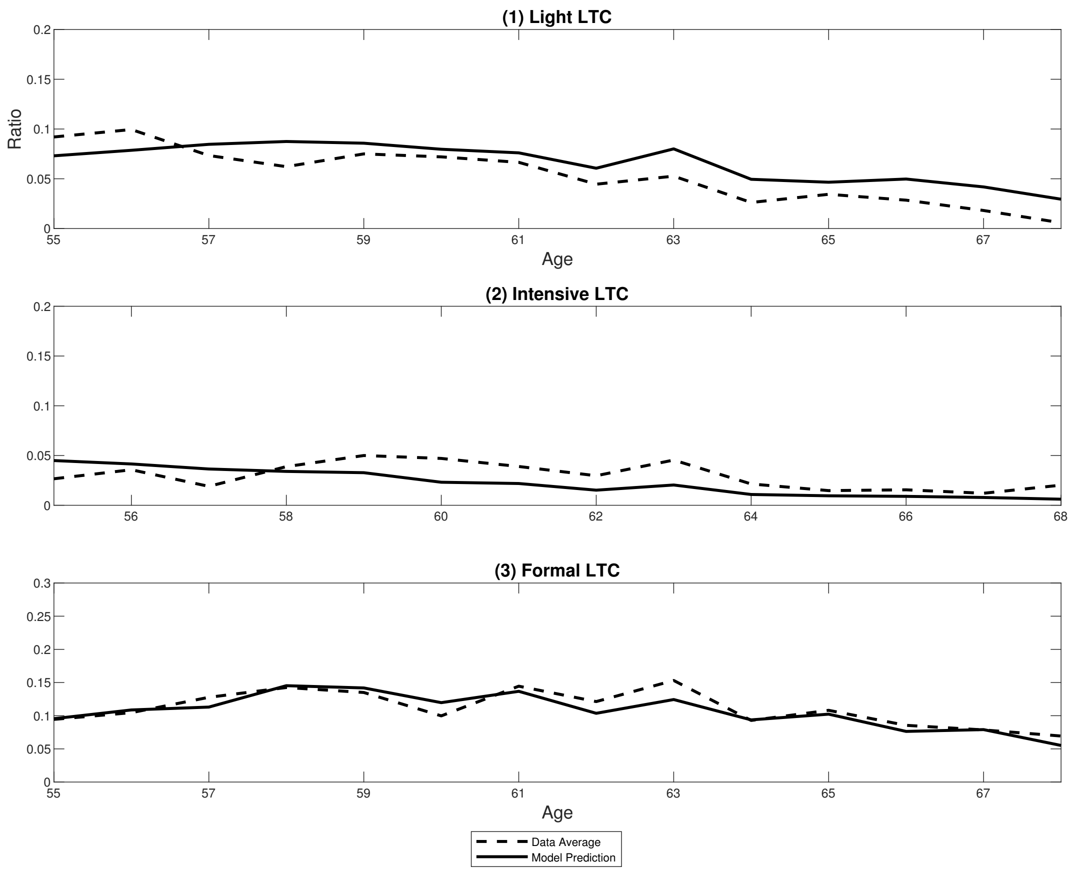
Source: SHARE, own calculations.

Figure C5: Care mix by age, among all (left) and those with at least one parent (right)



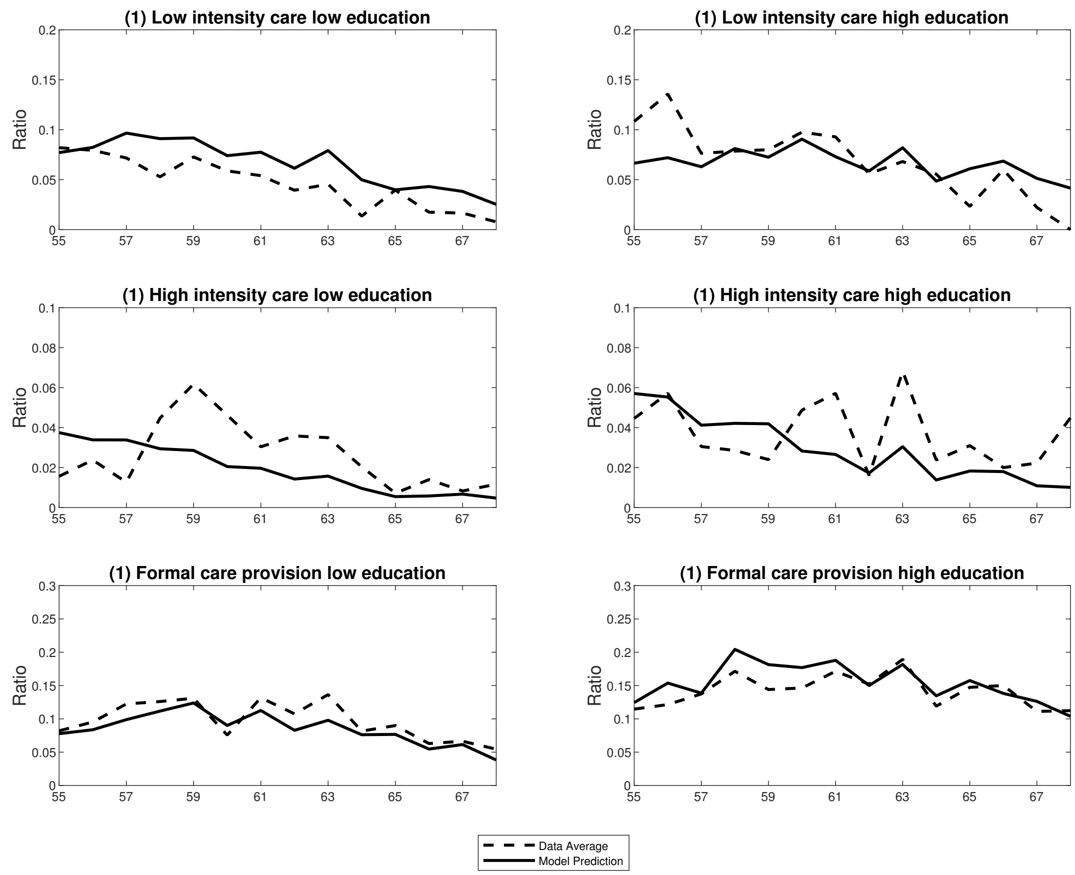
Source: SHARE, own calculations.

Figure C6: Model fit: formal and informal care decisions by age



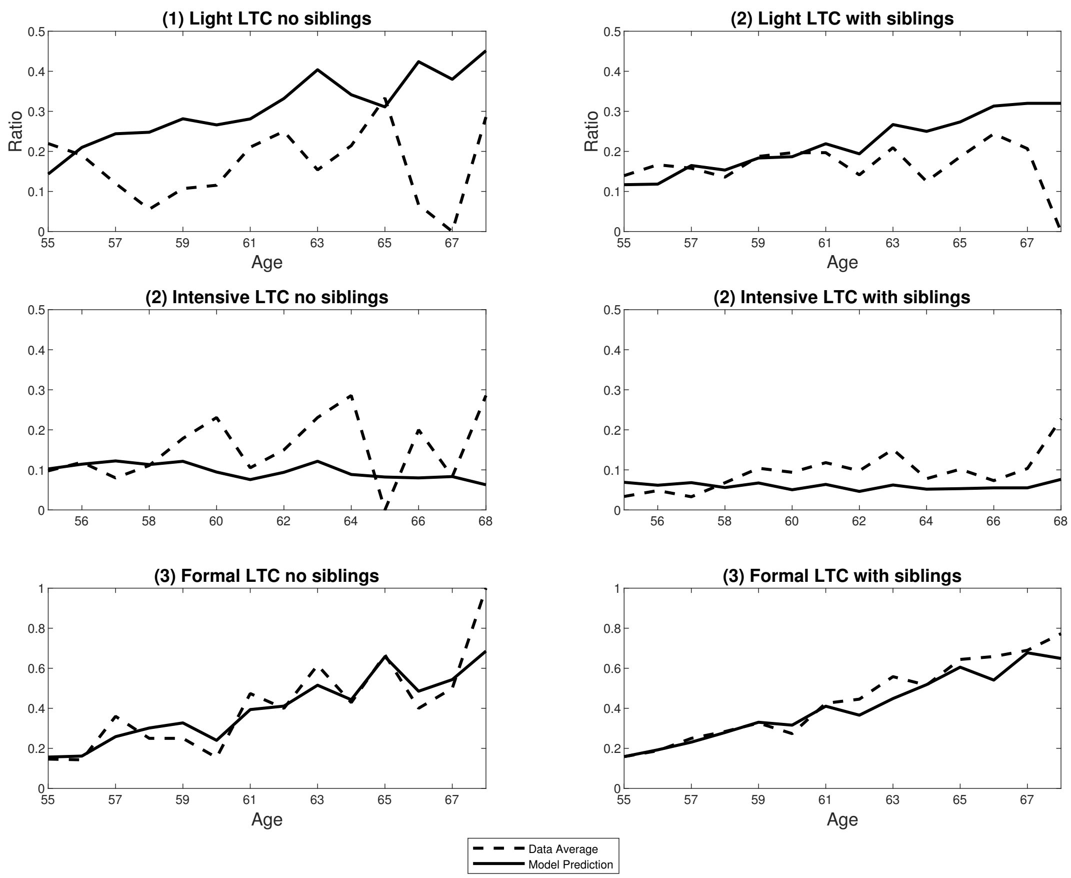
Source: SHARE, own calculations.

Figure C7: Model fit: formal and informal care decisions by age and education



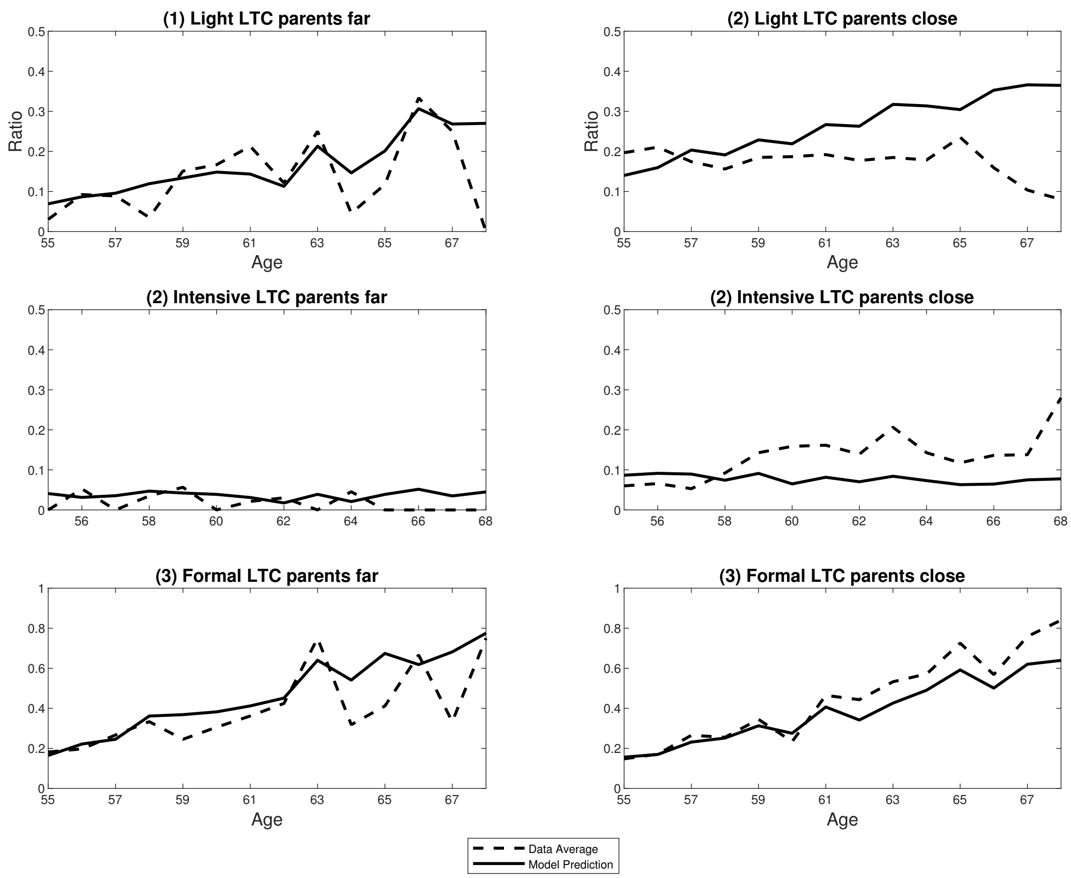
Source: SHARE, own calculations.

Figure C8: Model fit: formal and informal care decisions by age and existence of siblings



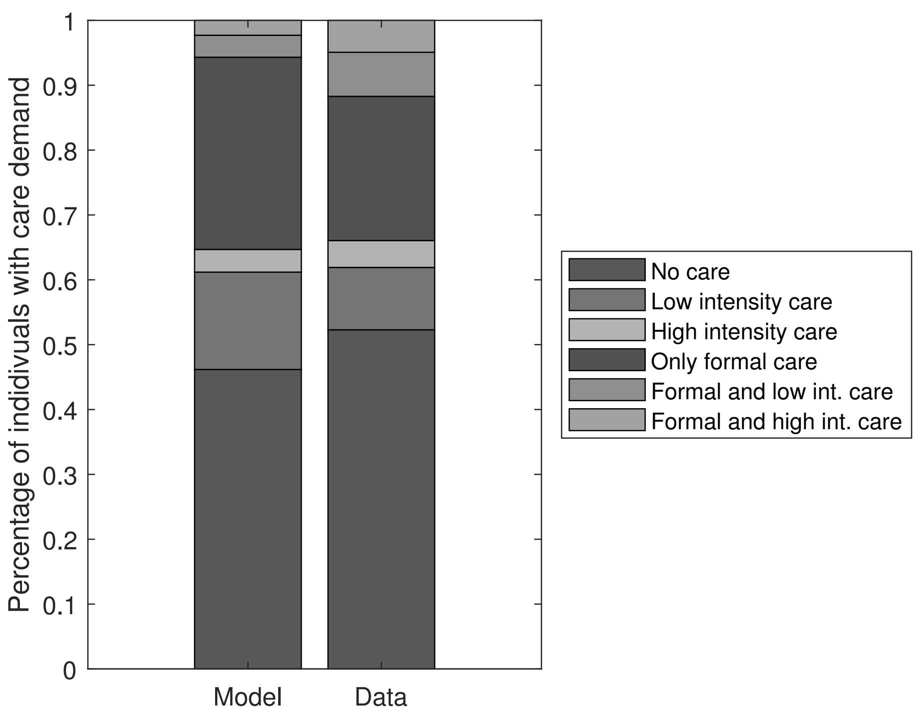
Source: SHARE, own calculations.

Figure C9: Model fit: formal and informal care decisions by age and distance to parents



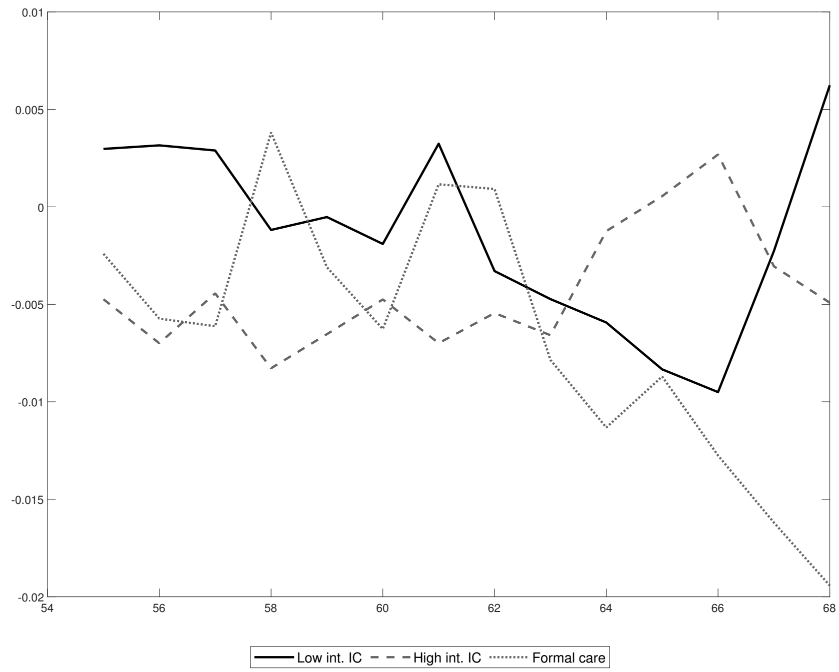
Source: SHARE, own calculations.

Figure C10: Model fit: formal and informal care decisions



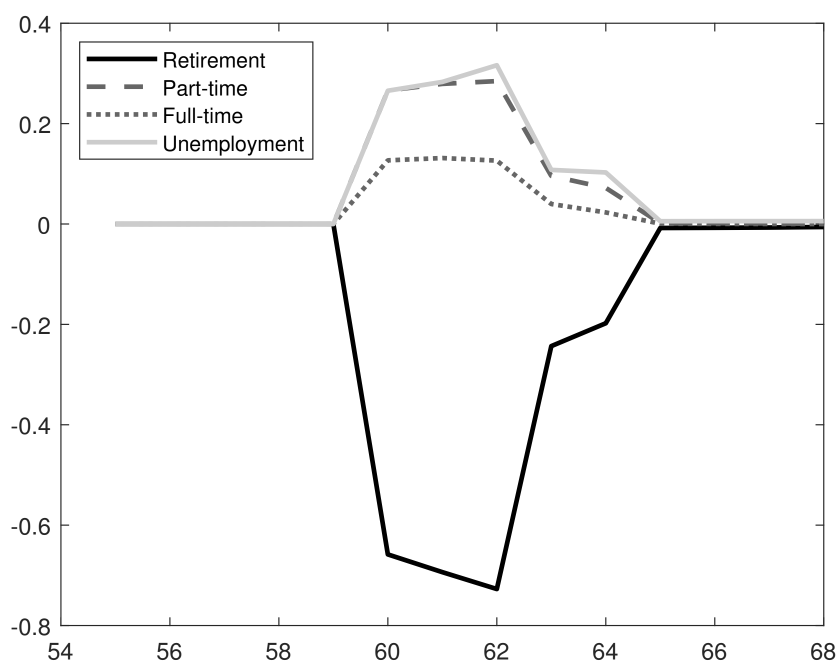
Source: SHARE, own calculations.

Figure C11: Effects of a 10% increase in female labor force participation at age 54 on caring behavior



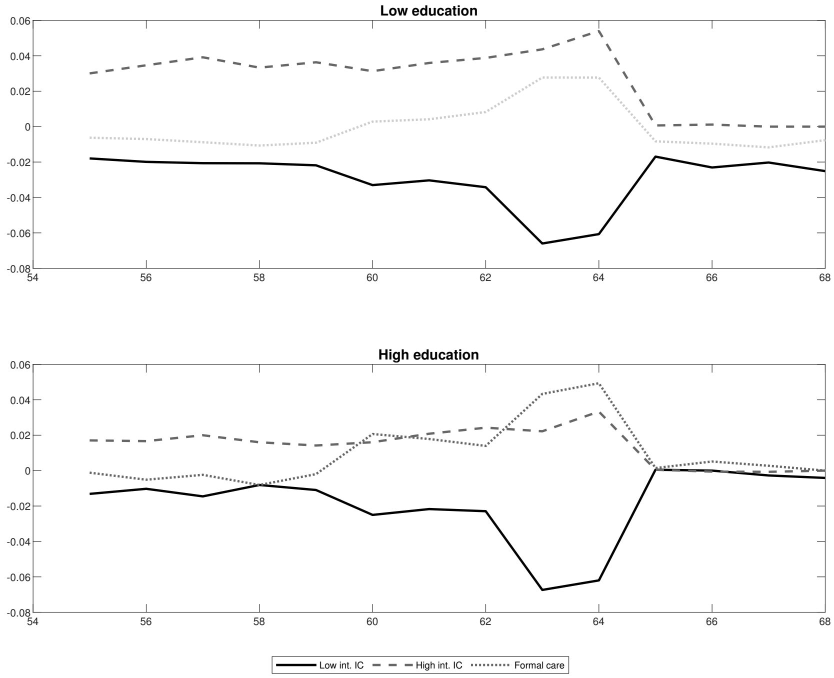
Source: SHARE, own calculations.

Figure C12: Employment effects of abolishing women's pension



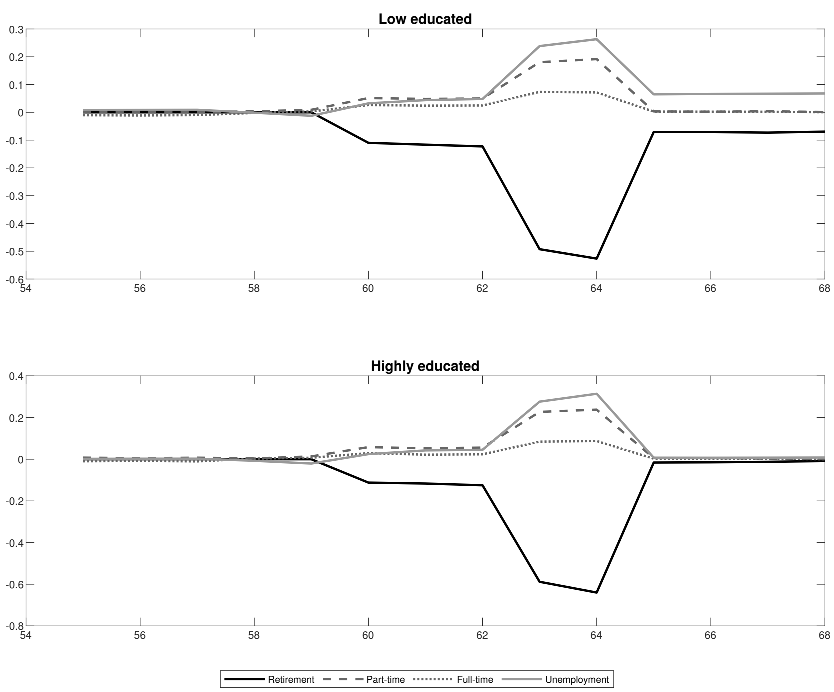
Source: SHARE, own calculations.

Figure C13: Care responses to increased retirement ages combined with increased collectable pension points



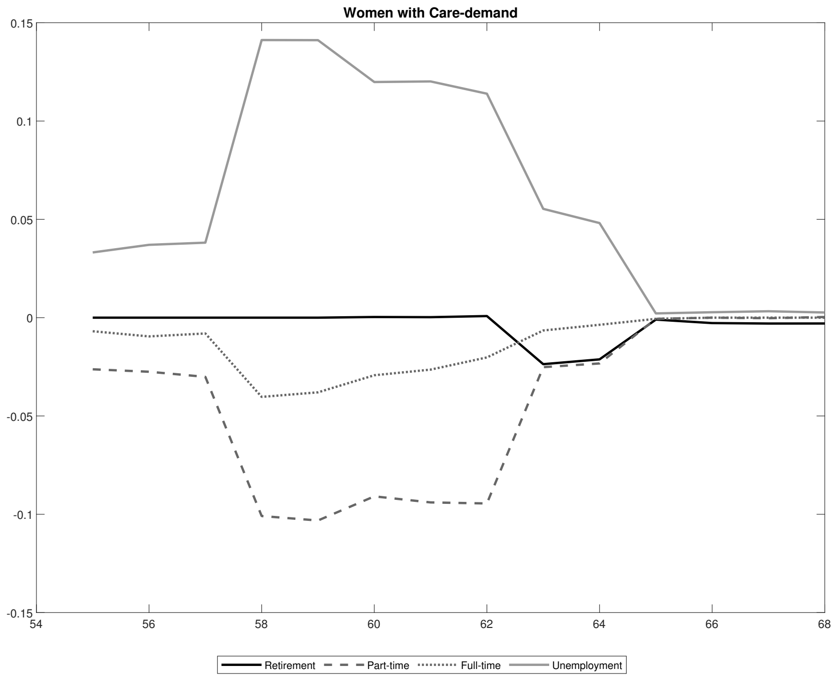
Source: SHARE, own calculations.

Figure C14: Employment responses to increased retirement ages combined with increased collectable pension points



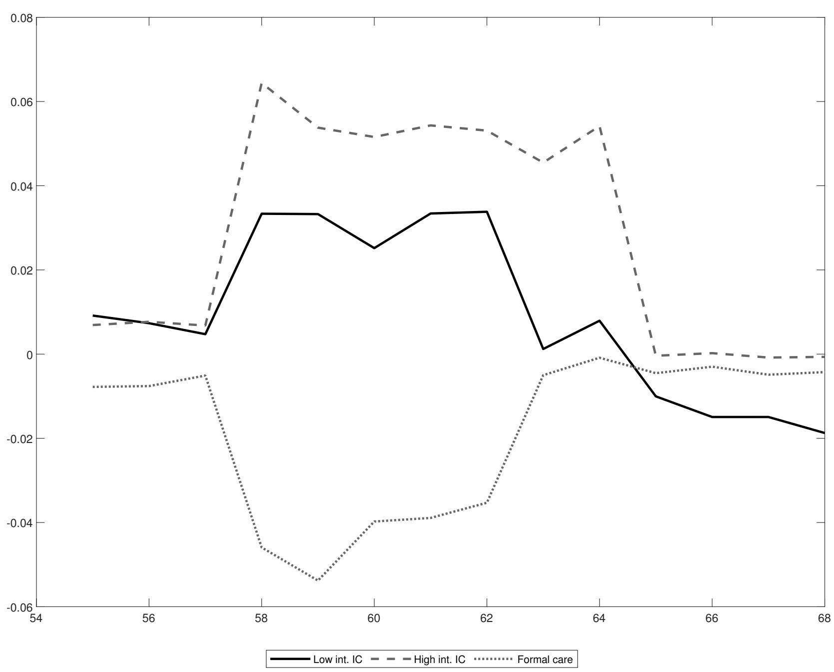
Source: SHARE, own calculations.

Figure C15: Employment responses to the introduction of care-times



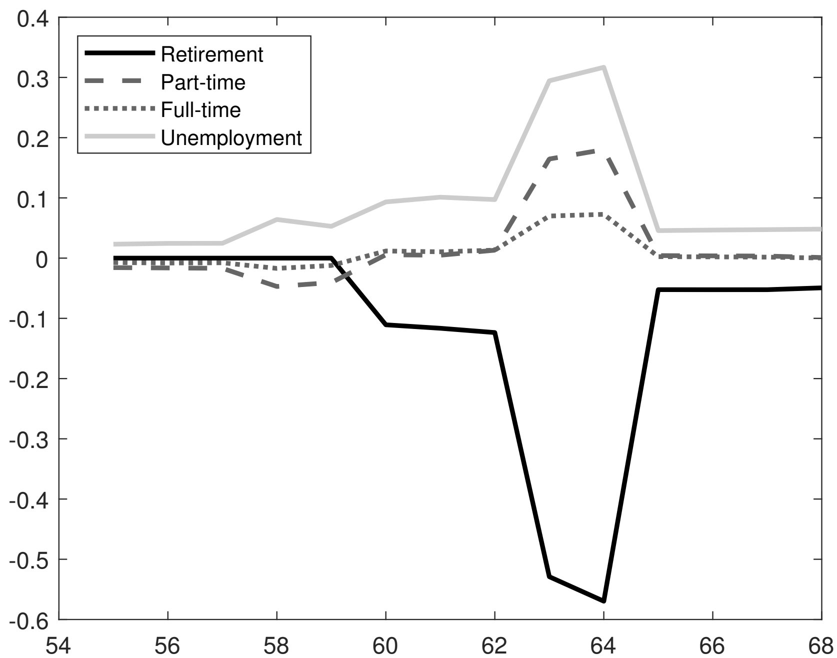
Source: SHARE, own calculations.

Figure C16: Caring responses to increased retirement ages combined with the introduction of care-times



Source: SHARE, own calculations.

Figure C17: Employment responses to increased retirement ages combined with the introduction of care-times



Source: SHARE, own calculations.

Summary

This dissertation studies the relationship of informal elder care and the pension system. The thesis consists of four chapters that apply several micro-econometric methods to survey data sets. The first three chapters use quasi-experimental settings to access important margins in the relationship between informal care giving and retirement and labor market behavior. The fourth chapter builds and estimates a dynamic structural model to simulate effects of future reforms to pension and long-term care policy.

The first chapter analyzes the impact of a reduction in women's labor supply through retirement on their informal care provision. Using data from the German Socio-oeconomic Panel (SOEP) from the years 2001- 2016 the analysis addresses fundamental endogeneity problems by applying a fuzzy regression discontinuity design. We exploit early retirement thresholds for women in the German pension system as instruments for their retirement decision. We find significant positive effects on informal care provided by women retiring from employment at the intensive and extensive margin that are robust to various sensitivity checks. Women retiring from full-time employment, highly educated women and women providing care within the household react slightly stronger. Findings are consistent with previous evidence and underlying behavioral mechanisms. They point to a time-conflict between labor supply and informal care before retirement. Policy implications are far-reaching in light of population aging. Prevalent pension reforms that aim to increase life-cycle labor supply threaten to reduce informal care provision by women and to aggravate the existing excess demand for informal care.

The second chapter examines the effect of an increase in the early retirement age (ERA) for German women on their informal care activity, assessing whether a time conflict between informal care activities and labor supply exist before retirement benefits can be collected. The 1999 pension reform abolished the ERA at age 60 for women born from 1952 onward and therefore supplies quasi-experimental exogenous variation in retirement behavior. I first estimate reform effects on informal care supply applying a regression discontinuity design. Then the reform is used as an instrument for retirement to estimate an elasticity parameter. I apply SOEP data and find that affected women decrease their non-intensive care activity due to the reform and further, my results support the notion that retirement indeed has a causal impact on informal care provision. In a heterogeneity analysis I show that the group of women that is more attached to the labor market reacts more strongly.

In the third chapter we estimate the effect of unemployment on informal care provision. For the identification we use plant closures as a source of exogenous variation and apply a difference-in-differences matching estimation procedure. 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. In the heterogeneity analysis we show that both men and women react with significant increases in care provision and we find the largest effects for women with low education.

In the fourth chapter we develop a comprehensive life-cycle model of elder parent care and work to evaluate options that address pressing conflicts between pension and long-term care (LTC) policies. Many OECD countries react to challenges of demographic change by increasing LTC by family members (informal care) and raising retirement ages. This intensifies conflicts between paid employment and informal care provision. We extend the previous literature, integrating formal and informal care options to point to impacts of institutionalized incentives on the care-mix. We combine endogenous with exogenous processes and improve on earlier models by incorporating important information on parents to model care-demand. We validate the model using a quasi-experimental setting in Germany. Policy simulations show a decrease in informal care supply as retirement ages are increased. Even though formal and informal care are no perfect substitutes in the model, the demand for formal care increases as a consequence. Further, women with potential care-demand suffer higher reductions welfare. Policy simulations suggest that pension points collected in times of informal care supply reduce detrimental effects of changes to pension rules on informal care supply and the care-mix. These policies can also reduce losses in welfare for women with potential care-demand. Labor market frictions matter in the uptake of informal care. Our simulations show that removing these have similar positive effects on the care system while reducing labor supply.

German Summary

Diese Dissertation untersucht den Zusammenhang zwischen der Pflege älterer Personen durch Angehörige und Freunde und dem Rentensystem. Die Arbeit besteht aus vier Kapiteln, in denen jeweils Mikroökonometrische Methoden auf Umfragedatensätze angewandt werden. Die ersten drei Kapitel nutzen Quasi-experimentelle Verfahren, um wichtige Parameter im Zusammenhang zwischen Altenpflege durch Angehörige und Freunde und dem Renten- und Arbeitsverhalten zu schätzen. Im vierten Kapitel wird ein dynamisches Strukturelles Modell gebaut und geschätzt um die Auswirkungen zukünftiger Reformen der Pflege-, und Rentenpolitik zu simulieren.

Das erste Kapitel analysiert den Einfluss eines Rückgangs im Arbeitsangebot von Frauen aufgrund der Verrentung auf ihr Angebot von Pflege für Angehörige und Freunde. Wir nutzen Daten des Socio-Ökonomischen Panels (SOEP) aus den Jahren 2001-2016 und adressieren das zugrunde liegende Endogenitäts-Problem mithilfe eines Instrumenten Verfahrens. Wir nutzen Frühverrentungsaltersgrenzen für Frauen im deutschen Rentensystem als Instrumente für Verrentungsentscheidungen. Wir finden signifikante positive Effekte auf die Pflege für Angehörige und Freunde durch Frauen, die aus einem Anstellungsverhältnis in Rente gehen. Die Effekte zeigen sich in der Aufnahme von Pflegeaktivitäten für Angehörige sowie in den Pflegestunden und sind robust in mehreren Tests. Frauen, die aus Vollzeitbeschäftigung in Rente gehen, hoch gebildete Frauen und Frauen, die in ihrem eigenen Haushalt Pflege leisten reagieren stärker. Die Ergebnisse sind konsistent mit früheren Befunden und dem zugrunde liegenden Mechanismus. Sie zeigen einen Zeitkonflikt zwischen Arbeitsangebot und dem Angebot von Pflege für Angehörige auf, der vor der Verrentung existiert. Die Ergebnisse haben weitreichende Implikationen, wenn man die Alterung der Gesellschaft bedenkt. Diskutierte Reformen des Rentensystems, die auf eine Verlängerung der Erwerbsbiographien abzielen, drohen die Pflege für Angehörige durch Frauen zu reduzieren und den Nachtfrageüberhang nach Pflege zu verschärfen.

Das zweite Kapitel untersucht den Effekt einer effektiven Erhöhung des Frühverrentungsalters für Frauen in Deutschland auf deren Pflege für Angehörige und Freunde. Dadurch wird untersucht, ob ein Zeitkonflikt zwischen der Pflege Angehöriger und Freunde und dem Arbeitsangebot besteht, bevor Frauen in Rente gehen können. Die Rentenreform von 1999 in Deutschland schaffte das Frühverrentungsalter für Frauen zum Alter 60 für nach 1952 geborene Frauen ab. Daher sorgt diese Reform für quasi-experimentelle exogene Variation im Verrentungsverhalten. Zuerst schätze ich den Effekt der Reform auf die Pflege Angehöriger unter Nutzung eines Regressions-Discontinuitätsverfahrens. Daraufhin wird die Reform als Instrument für Verrentung genutzt um einen Elastizitätsparameter zwischen der Pflege Angehöriger und Verrentung zu schätzen. Ich nutze dafür die Daten des SOEP und finde, dass Frauen, die von der Reform betroffen sind ihre nicht-intensive Pflege für Angehörige im Gegensatz zu früher geborenen Frauen reduzieren. Darüber hinaus bestärken meine Ergebnisse die Hypothese, dass die Verrentung die Pflegetätigkeit für Angehörige erhöht. In einer Heterogenitätsanalyse zeige ich, dass am Arbeitsmarkt aktivere Frauen stärker in ihrer Pflegetätigkeit auf die Reform reagieren.

Im dritten Kapitel schätzen wir den Effekt der unfreiwilligen Arbeitslosigkeit auf die Pflege Angehöriger. Zur Identifikation nutzen wir Betriebsschließungen als Quelle exogener Variation und wenden eine Kombination aus einem Difference-in-Difference Schätzer mit einem Matching Verfahren an. Die Analyse basiert auf Daten des SOEP. Wir finden, dass es einen Zeitkonflikt zwischen dem Arbeitsangebot und der Pflege Angehöriger gibt. Die ungewollte Arbeitslosigkeit erhöht die Wahrscheinlichkeit, einen Angehörigen zu pflegen um 2.9 Prozentpunkte. Die täglichen Stunden, die für die Pflege Angehöriger aufgewendet werden steigen um knapp 0.05 Stunden pro Werktag. In der Heterogenitätsanalyse zeigen wir, dass sowohl Männer als auch Frauen signifikant auf die plötzliche Arbeitslosigkeit mit einem Anstieg der Pflege Angehöriger reagieren. Größte Effekte finden wir für Frauen mit niedriger Bildung.

Im vierten Kapitel entwickeln wir ein umfassendes Lebens-Zyklus Model der Entscheidung zur Pflege der Eltern sowie der Arbeitsentscheidung, um Möglichkeiten zu bewerten, die dringlichen Konflikte zwischen den Zielen der Renten-, und Pflegepolitik anzugehen. Viele Länder in der OECD reagieren auf Herausforderungen des demografischen Wandels, indem sie die Pflege durch Angehörige bevorzugt unterstützen und die Regelaltersgrenzen erhöhen. Das intensiviert Konflikte zwischen Arbeit und der Pflege Angehöriger. Wir erweitern die bestehende Literatur, indem wir die Pflege durch Angehörige sowie Pflege durch professionelle Pflegekräfte in einem Modell vereinen. Damit verweisen wir auf die Einflüsse institutioneller Anreize auf den Pflegemix. Wir kombinieren exogene mit endogenen Prozessen und erweitern frühere Modelle außerdem, indem wir wichtige Informationen über potenziell zu pflegenden Eltern in das Modell einbauen. Damit können wir die Nachfrage nach Pflege durch die Eltern besser modellieren. Wir validieren das Modell, indem wir die Simulationsergebnisse mit den Quasi-experimentellen Ergebnissen aus der Literatur vergleichen. Die Simulationen von Politikmaßnahmen zeigen einen Rückgang in der Pflege durch Angehörige auf, wenn die Regelaltersgrenzen erhöht werden. Obwohl die Pflege durch Angehörige und die Pflege durch professionelle Pflegekräfte im Modell keine perfekten Substitute sind, steigt als Konsequenz die Nachfrage nach professioneller Pflege. Wir zeigen auch, dass Frauen, die möglicherweise in Zukunft ihre Eltern pflegen müssen stärker von der Erhöhung der Regelaltersgrenzen betroffen sind. Das zeigt sich besonders in einer Wohlfahrtsanalyse. Weiter zeigen die Simulationen, dass eine Erhöhung der Rentenpunkte, die durch die Pflege Angehöriger gesammelt werden können die negativen Auswirkungen der Maßnahmen der Rentenpolitik auf das Angebot von Pflege durch Angehörige und den Pflegemix auffangen kann. Diese Maßnahme kann auch die höheren Verluste an Wohlfahrt für Frauen, die in Zukunft möglicherweise ihre Eltern pflegen müssen reduzieren. Die Reibungen am Arbeitsmarkt beeinflussen die Entscheidung, Pflege für die eigenen Eltern zu leisten. Unsere Simulationen zeigen, dass Politikmaßnahmen, die diese Reibungen verringern genauso positive Effekte auf die Pflege, den Pflegemix und die entstehende Ungleichheit haben. Jedoch erhöhen diese Maßnahmen teils die Arbeitslosigkeit.

Bibliography

Abadie, A. and Spiess, J. (2021). Robust post-matching inference. *Journal of the American Statistical Association*, pages 1–13.

Adda, J., Dustmann, C., and Stevens, K. (2017). The career costs of children. *Journal of Political Economy*, 125(2):293–337.

Aguirregabiria, V. and Mira, P. (2010). Dynamic discrete choice structural models: A survey. *Journal of Econometrics*, 156(1):38–67.

Al-Janabi, H., Carmichael, F., and Oyebode, J. (2018). Informal care: choice or constraint? *Scandinavian Journal of Caring Sciences*, 32(1):157–167.

Applebaum, R. A., Christianson, J. B., Harrigan, M., and Schore, J. (1988). The evaluation of the national long term care demonstration. 9. the effect of channeling on mortality, functioning, and well-being. *Health Services Research*, 23(1):143.

Barczyk, D. and Kredler, M. (2018). Evaluating long-term-care policy options, taking the family seriously. *The Review of Economic Studies*, 85(2):766–809.

Battistin, E., Brugiavini, A., Rettore, E., and Weber, G. (2009). The retirement consumption puzzle: Evidence from a regression discontinuity approach. *American Economic Review*, 99(5):2209–26.

Bauer, J. M. and Sousa-Poza, A. (2015). Impacts of informal caregiving on caregiver employment, health, and family. *Journal of Population Ageing*, 8(3):113–145.

Becker, G. (1991). A treatise on the family, 1991. *Enlarged Edition (Cambridge, Mass.: Harvard University Print)*.

Bell, D. N., Bowes, A., and Heitmueller, A. (2007). Did the introduction of free personal care in scotland result in a reduction of informal care? Technical Report 2007-3.

Bellman, R. (1957). Dynamic programming, princeton, nj: Princeton univ. *versity Press. BellmanDynamic Programming1957*.

Berecki-Gisolf, J., Lucke, J., Hockey, R., and Dobson, A. (2008). Transitions into informal caregiving and out of paid employment of women in their 50s. *Social Science & Medicine*, 67(1):122–127.

Bergeot, J. and Fontaine, R. (2020). The heterogeneous effect of retirement on informal care behavior. *Health economics*, 29(10):1101–1116.

Berndt, E. R., Hall, B. H., Hall, R. E., and Hausman, J. A. (1974). Estimation and inference in nonlinear structural models. In *Annals of Economic and Social Measurement, Volume 3, number 4*, pages 653–665. NBER.

Blaise, M. (2018). The informal care provision: what are the genuine incentives of children? Working Papers of BETA 2018-12, Bureau d'Economie Théorique et Appliquée, UDS, Strasbourg.

BMAS (2016). Ergänzender Bericht der Bundesregierung zum Rentenversicherungsbericht 2016 gemäss §154 Abs. 2 SGBVI; Alterssicherungsbericht(2016).

BMAS (2017). *Pflege und Beruf vereinbaren.* http://www.bmas.de/DE/Themen/Arbeitsrecht/Vereinbarkeit-Familie-Pflege-Beruf/pflege-und-beruf.html (Accessed 31.07.2017).

BMAS (2021). *Alterseinkommen und zusätzliche Vorsorge.* https://www.bmas.de/DE/Soziales/Rente-und-Altersvorsorge/Fakten-zur-Rente/Alterseinkommen-und-zusaetzliche-Vorsorge/alterseinkommen-und-zusaetzliche-vorsorge.html [Last accessed on 02.08.2021].

BMG (2017). *Zahlen und Fakten zur Pflegeversicherung.* https://www.bundesgesundheitsministerium.de/fileadmin/Dateien/3_Downloads/Statistiken/Pflegeversicherung/Zahlen_und_Fakten/Zahlen_und_Fakten.pdf [Accessed: 31.07.2017].

BMG (2019). *Die Leistungen der Pflegeversicherung im Überblick.* https://www.bundesgesundheitsministerium.de/themen/pflege/online-ratgeber-pflege/leistungen-der-pflegeversicherung/leistungen-im-ueberblick.html [Accessed: 23.01.2019].

BMG (2020). *Zahlen und Fakten zur Pflegeversicherung.* https://www.bundesgesundheitsministerium.de/fileadmin/Dateien/3_Downloads/Statistiken/Pflegeversicherung/Zahlen_und_Fakten/Zahlen_und_Fakten_der_SPV_Juli_2020_bf.pdf [Accessed: 10.02.2022].

BMJ (2008). *Gesetz über die Pflegezeit (Pflegezeitgesetz - PflegeZG).* http://www.gesetze-im-internet.de/pflegezg/PflegeZG.pdf [Accessed 31.07.2017].

BMJ (2011). *Gesetz über die Familienpflegezeit (Familienpflegezeitgesetz -FPfZG).* http://www.gesetze-im-internet.de/fpfzg/FPfZG.pdf [Accessed: 31.07.2017].

Boaz, R. F. (1996). Full-time employment and informal caregiving in the 1980s. *Medical Care*, 34(6):524–536.

Boersch-Supan, A. and Wilke, C. B. (2004). The german public pension system: How it was, how it will be. Working Paper 10525, National Bureau of Economic Research.

Bom, J., Bakx, P., Schut, F., and Van Doorslaer, E. (2019). Health effects of caring for and about parents and spouses. *The Journal of the Economics of Ageing*, 14:100196.

Bonsang, E. (2009). Does informal care from children to their elderly parents substitute for formal care in europe? *Journal of Health Economics*, 28(1):143–154.

Börsch-Supan, A., Brandt, M., Hunkler, C., Kneip, T., Korbmacher, J., Malter, F., Schaan, B., Stuck, S., and Zuber, S. (2013). Data resource profile: the survey of health, ageing and retirement in europe (share). *International journal of epidemiology*, 42(4):992–1001.

Börsch-Supan, A. and Malter, F. (2015). Share wave 5: Innovations & methodology. *Mannheim: MEA*.

Börsch-Supan, A., Rausch, J., and Goll, N. (2020). Social security reforms and the changing retirement behavior in germany. Technical report, National Bureau of Economic Research.

Börsch-Supan, A., Schnabel, R., Kohnz, S., and Mastrobuoni, G. (2004). Micro-modeling of retirement decisions in germany. In *Social security programs and retirement around the world: Micro-estimation*, pages 285–344. University of Chicago Press.

Brauns, H., Scherer, S., and Steinmann, S. (2003). The casmin educational classification in international comparative research. In *Advances in cross-national comparison*, pages 221–244. Springer.

Bremer, P., Cabrera, E., Leino-Kilpi, H., Lethin, C., Saks, K., Sutcliffe, C., Soto, M., Zwakhalen, S. M., Wübker, A., Consortium, R., et al. (2015). Informal dementia care: Consequences for caregivers' health and health care use in 8 european countries. *Health Policy*, 119(11):1459–1471.

Broese van Groenou, M. I. and De Boer, A. (2016). Providing informal care in a changing society. *European Journal of Ageing*, 13(3):271–279.

Bundesamt, S. (2017). *Pflegestatistik 2015 Pflege im Rahmen der Pflegeversicherung Deutschlandergebnisse*. https://www.statistischebibliothek.de/mir/servlets/MCRFileNodeServlet/DEHeft_derivate_00042871/5224001159004.pdf, [Accessed: 10.02.2022].

Bundesamt, S. (2019a). Bevölkerung im wandel. annahmen und ergebnisse der 14. koordinierten bevölkerungsvorausberechnung.

Bundesamt, S. (2019b). Bevölkerung und erwerbstätigkeit. bevölkerungsfortschreibung auf grundlage des zensus 2011.

Bundesamt, S. (2020). *Pflegestatistik. Pflege im Rahmen der Pflegeversicherung. Deutschlandergebnisse*. file:///D:/Temp/pflege-deutschlandergebnisse-5224001199004-1.pdf.

Bundesamt, S. (2021). Ausblick auf die bevölkerungsentwicklung in deutschland und den bundesländern nach dem corona-jahr 2020 – erste mittelfris- tige bevölkerungsvorausberechnung 2021 bis 2035.

Bundestag, D. (2016). Antwort der bundesregierung auf die kleine anfrage der abgeordneten elisabeth scharfenberg, dr. franziska brantner, katja dörner, weiterer abgeordneter und der fraktion bÜndnis 90/die grÜnen. Technical Report Drucksache 18/9111.

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

Calonico, S., Cattaneo, M. D., Farrell, M. H., and Titiunik, R. (2017). rdrobust: Software for regression discontinuity designs. *Stata Journal*, 17(2):372–404.

Calonico, S., Cattaneo, M. D., and Titiunik, R. (2014). Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica*, 82(6):2295–2326.

Card, D., Dobkin, C., and Maestas, N. (2008). The impact of nearly universal insurance coverage on health care utilization: evidence from medicare. *American Economic Review*, 98(5):2242–58.

Carmichael, F. and Charles, S. (1998). The labour market costs of community care. *Journal of Health Economics*, 17(6):747 – 765.

Carmichael, F. and Charles, S. (2003a). Benefit payments, informal care and female labour supply. *Applied Economics Letters*, 10(7):411–415.

Carmichael, F. and Charles, S. (2003b). The opportunity costs of informal care: does gender matter? *Journal of health economics*, 22(5):781–803.

Carmichael, F., Charles, S., and Hulme, C. (2010). Who will care? employment participation and willingness to supply informal care. *Journal of Health Economics*, 29(1):182 – 190.

Carr, E., Murray, E. T., Zaninotto, P., Cadar, D., Head, J., Stansfeld, S., and 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. Technical report, HEDG, c/o Department of Economics, University of York.

Chon, D., Lee, Y., Kim, J., and 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.

Coe, N., Skira, M., and Larson, E. (2018). A comprehensive measure of the costs of caring for a parent: differences according to functional status. *Journal of the American Geriatrics Society*, 66(10):2003–2008.

Coe, N. and Zamarro, G. (2011). Retirement effects on health in europe. *Journal of Health Economics*, 30(1):77–86.

Colombo, F., Llena-Nozal, A., Mercier, J., and Tjadens, F. (2011). Help wanted? providing and paying for long-term care. 2011.

Cooley, T. F. and Prescott, E. C. (2021). 1. economic growth and business cycles. In *Frontiers of business cycle research*, pages 1–38. Princeton University Press.

Costa-Font, J., Karlsson, M., and Øien, H. (2015). Informal Care and the Great Recession. CESifo Working Paper Series 5427, CESifo Group Munich.

Dautzenberg, M. G., Diederiks, J. P., Philipsen, H., Stevens, F. C., Tan, F. E., and Vernooij-Dassen, M. J. (2000). The competing demands of paid work and parent care: Middle-aged daughters providing assistance to elderly parents. *Research on Aging*, 22(2):165–187.

De la Maisonneuve, C. and Martins, J. O. (2013). Public spending on health and long-term care: a new set of projections.

Dentinger, E. and Clarkberg, M. (2002). Informal caregiving and retirement timing among men and women: Gender and caregiving relationships in late midlife. *Journal of Family Issues*, 23(7):857–879.

Destatis (2022). *Pflegestatistik 2019: Pflege im Rahmen der Pflegeversicherung, Deutschlandergebnisse*. https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Gesundheit/Pflege/Publikationen/Downloads-Pflege/pflege-deutschlandergebnisse-5224001199004.pdf?__blob=publicationFile [Accessed: 10.02.2022].

Doty, P., Jackson, M. E., and Crown, W. (1998). The impact of female caregivers' employment status on patterns of formal and informal eldercare. *The Gerontologist*, 38(3):331–341.

Eibich, P. (2015). Understanding the effect of retirement on health: Mechanisms and heterogeneity. *Journal of Health Economics*, 43(C):1–12.

Ettner, S. L. (1995). The impact of "parent care" on female labor supply decisions. *Demography*, 32(1):63–80.

European Commission (2016). Joint report on health care and long-term care systems & fiscal sustainability. Technical report, Commission services (Directorate-General for Economic and Financial Affairs), Economic Policy Committee (Ageing Working Group), European Commission Institutional Papers 37.

Everding, J. and Marcus, J. (2020). The effect of unemployment on the smoking behavior of couples. *Health economics*, 29(2):154–170.

Finkelstein, A. and McKnight, R. (2008). What did medicare do? the initial impact of medicare on mortality and out of pocket medical spending. *Journal of public economics*, 92(7):1644–1668.

Fischer, B. (2017). The impact of retirement decisions on informal care provision. *Master thesis, Freie Universität Berlin*.

Fischer, B. and Geyer, J. (2020). Pflege in corona-zeiten: Gefährdete pflegen besonders gefährdete. *DIW aktuell ; 38*.

Fischer, B. and Müller, K.-U. (2019). Time to care? the effects of retirement on informal care provision. *DIW Berlin Discussion Paper*, No. 1809.

Fischer, B. and Müller, K.-U. (2020). Time to care? the effects of retirement on informal care provision. *Journal of Health Economics*, 73:102350.

French, E. and Jones, J. B. (2011). The Effects of Health Insurance and Self-Insurance on Retirement Behavior. *Econometrica*, 79(3):693–732.

Fujisawa, R. and Colombo, F. (2009). The long-term care workforce: overview and strategies to adapt supply to a growing demand. *OECD Health Working Paper*, no. 44.

Geerts, J. and Willemé, P. (2012). Projections of use and supply of long-term care in europe: Policy implications. *ENEPRI Policy Brief*, No. 12.

Geerts, J., Willem'e, P., and Mot, E. (2012). Long-term care use and supply in europe: Projection models and results for germany, the netherlands, spain and poland. Technical report, European Network of Economic Policy Research Institutes (ENEPRI), ENEPRI Research Report No. 116.

Gelman, A. and Imbens, G. (2018). Why high-order polynomials should not be used in regression discontinuity designs. *Journal of Business & Economic Statistics*, 0(0):1–10.

Geyer, J., Haan, P., Hammerschmid, A., and Peters, M. (2020). Labor market and distributional effects of an increase in the retirement age. *Labour Economics*, 65:101817.

Geyer, J. and Korfhage, T. (2015). Long-term care insurance and carers' labor supply – a structural model. *Health Economics*, 24(9):1178–1191.

Geyer, J. and Korfhage, T. (2018). Labor supply effects of long-term care reform in germany. *Health Economics*, 27(9):1328–1339.

Geyer, J. and Schulz, E. (2014). Who cares? die Bedeutung der informellen Pflege durch Erwerbstätige in Deutschland. *DIW Wochenbericht*, (14):294–301.

Geyer, J. and Welteke, C. (2019). Closing routes to retirement for women: How do they respond? *Journal of Human Resources*.

Goebel, J., Grabka, M. M., Liebig, S., Kroh, M., Richter, D., Schröder, C., and 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*. PhD thesis, University of Michigan.

GRV (2017). *Rentenarten & Leistungen*. http://www.deutsche-rentenversicherung.de/Allgemein/de/Navigation/2_Rente_Reha/01_Rente/01_all-gemeines/03_rentenarten_und_leistungen/00_rentenarten_und_leistungen_node.html (last accessed on 31.07.2017).

Gusmano, M. K. and Okma, K. G. H. (2018). Population aging and the sustainability of the welfare state. *Hastings Center Report*, 48:S57–S61.

Haan, P. and Prowse, V. (2015). Optimal social assistance and unemployment insurance in a life-cycle model of family labor supply and savings. DIW Discussion Papers 1468, Berlin.

Hahn, J., Todd, P., and Van der Klaauw, W. (2001). Identification and estimation of treatment effects with a regression-discontinuity design. *Econometrica*, 69(1):201–209.

Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political analysis*, pages 25–46.

Hainmueller, J. and 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., and König, H.-H. (2018). Langzeitpflegepräferenzen der älteren in deutschland–ergebnisse einer bevölkerungsrepräsentativen umfrage. *Das Gesundheitswesen*, 80(08/09):685–692.

Halla, M., Schmieder, J., and Weber, A. (2020). Job displacement, family dynamics, and spousal labor supply. *American Economic Journal: Applied Economics*, 12(4):253–87.

HCHE (2017). *Präferenz: Zuhause gepflegt werden.* https://www.hche.uni-hamburg.de/ueberuns/presse/haeusliche-pflege.pdf (last accessed on 04.05.2020).

He, D. and McHenry, P. (2016). Does formal employment reduce informal caregiving? *Health Economics*, 25(7):829–843.

Heckman, J. and Singer, B. (1984). A method for minimizing the impact of distributional assumptions in econometric models for duration data. *Econometrica: Journal of the Econometric Society*, pages 271–320.

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.

Heyma, A. (2004). A structural dynamic analysis of retirement behaviour in the Netherlands. *Journal of Applied Econometrics*, 19(6):739–759.

Hiel, L., Beenackers, M. A., Renders, C. M., Robroek, S. J., Burdorf, A., and Croezen, S. (2015). Providing personal informal care to older european adults: Should we care about the caregivers' health? *Preventive Medicine*, 70:64–68.

Hollingsworth, B., Ohinata, A., Picchio, M., and Walker, I. (2017). Labour supply and informal care supply: The impacts of financial support for long-term elderly care. GLO Discussion Paper Series 118, Global Labor Organization (GLO).

Hu, B. and 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.

Insler, M. (2014). The health consequences of retirement. *Journal of Human Resources*, 49(1):195–233.

Iskhakov, F. (2010). Structural dynamic model of retirement with latent health indicator. *The Econometrics Journal*, 13(3):S126–S161.

Jacobs, J. C., Van Houtven, C. H., Laporte, A., and 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.

Jacobs, K., Kuhlmey, A., Greß, S., Klauber, J., and Schwinger, A. (2020). *Pflege-Report 2019: Mehr Personal in der Langzeitpflege-aber woher?* Springer Nature.

Johnson, R. W. and Sasso, A. T. L. (2000). The trade-off between hours of paid employment and time assistance to elderly parents at midlife. Technical report, The Urban Institute, Washington, D.C.

Karlsberg Schaffer, S. (2015). The effect of free personal care for the elderly on informal caregiving. *Health Economics*, 24(S1):104–117.

Keane, M. P. and Wolpin, K. I. (1994). The solution and estimation of discrete choice dynamic programming models by simulation and interpolation: Monte carlo evidence. *the Review of economics and statistics*, pages 648–672.

Keck, W. and Krickl, T. (2013). Vorgezogene Altersrenten – wer geht früher? *RVaktuell*, 11(2013):298–308.

Kolodziej, I. W., Coe, N. B., and Van Houtven, C. H. (2022). The impact of care intensity and work on the mental health of family caregivers: Losses and gains. *The Journals of Gerontology: Series B*.

Korfhage, T. (2019). Long-run consequences of informal elderly care and implications of public long-term care insurance. *SOEPpapers on Multidisciplinary Panel Data Research (No. 1051).*

Lee, D. S. and Card, D. (2008). Regression discontinuity inference with specification error. *Journal of Econometrics*, 142(2):655 – 674.

Lee, D. S. and Lemieux, T. (2010). Regression discontinuity designs in economics. *Journal of Economic Literature*, 48(2):281–355.

Li, H., Rosenzweig, M., and Zhang, J. (2010). Altruism, favoritism, and guilt in the allocation of family resources: Sophie's choice in mao's mass send-down movement. *Journal of Political Economy*, 118(1):1–38.

Lilly, M. B., Laporte, A., and 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., and Xavier, A. (2012). Long-term care: Need, use and expenditure in the eu-27. Technical report, Economic Papers 469, European Commission, Directorate-General for Economic and Financial Affairs, Brussels.

Malter, F. and Börsch-Supan, A. (2017). Share wave 6: Panel innovations and collecting dried blood spots. *Munich: Munich Center for the Economics of Aging (MEA)*.

Manoli, D. S. and Weber, A. (2016). The effects of the early retirement age on retirement decisions. Working Paper 22561, National Bureau of Economic Research.

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.

Mastrobuoni, G. (2009). Labor supply effects of the recent social security benefit cuts: Empirical estimates using cohort discontinuities. *Journal of public Economics*, 93(11-12):1224–1233.

McGrattan, E. R. and Prescott, E. C. (2017). On financing retirement with an aging population. *Quantitative Economics*, 8(1):75–115.

Meng, A. (2012). Informal caregiving and the retirement decision. *German Economic Review*, 13(3):307–330.

Mentzakis, E., McNamee, P., and 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.

Meyer, M. (2006). *Pflegende Angehörige in Deutschland: ein Überblick über den derzeitigen Stand und zukünftige Entwicklungen*. Lit Verlag, Berlin, Münster, Wien, Zürich, London.

Michaud, P.-C., Heitmueller, A., and Nazarov, Z. (2010). A dynamic analysis of informal care and employment in England. *Labour Economics*, 17(3):455 – 465.

Mommaerts, C. (2015). Long-term care insurance and the family. *unpublished, November*.

Mommaerts, C. and Truskinovsky, Y. (2020). The cyclicality of informal care. *Journal of health economics*, 71:102306.

Moreau, N. and Stancanelli, E. (2015). Household consumption at retirement: A regression discontinuity study on french data. *Annals of Economics and Statistics / Annales d'Économie et de Statistique*, (117-118):253–276.

Moscarola, F. C. (2010). Informal caregiving and women's work choices: Lessons from the netherlands. *Labour*, 24(1):93–105.

Müller, T. and Shaikh, M. (2018). Your retirement and my health behavior: Evidence on retirement externalities from a fuzzy regression discontinuity design. *Journal of Health Economics*, 57(C):45–59.

Nguyen, H. T. and 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.

Nielsen, N. F. (2019). Sick of retirement? *Journal of health economics*, 65:133–152.

Niimi, Y. (2017). Does providing informal elderly care hasten retirement? evidence from Japan. Technical Report 730.

Nizalova, O. (2012). The wage elasticity of informal care supply: Evidence from the health and retirement study. *Southern Economic Journal*, 79(2):350–366.

OECD (2017a). *Health at a Glance 2017*.

OECD (2017b). *Pensions at a Glance 2017*. Organisation for Economic Co-operation and Development.

Riedel, M. and Kraus, M. (2011). The organisation of formal long-term care for the elderly. results from the 21 european country studies in the ancien project. *ENEPRI Research Report No. 95*.

Rothgang, H., Müller, R., Unger, R., et al. (2012). Themenreport pflege 2030. *Was ist zu erwarten–was ist zu tun*, 1.

Rouzet, D., Sánchez, A. C., Renault, T., and Roehn, O. (2019). Fiscal challenges and inclusive growth in ageing societies.

Rust, J. (1987). Optimal replacement of gmc bus engines: An empirical model of harold zurcher. *Econometrica: Journal of the Econometric Society*, pages 999–1033.

Rust, J. (1994). Structural estimation of markov decision processes. *Handbook of econometrics*, 4:3081–3143.

Rust, J. and Phelan, C. (1997). How social security and medicare affect retirement behavior in a world of incomplete markets. *Econometrica: Journal of the Econometric Society*, pages 781–831.

Schmitz, H. and Stroka, M. A. (2013). Health and the double burden of full-time work and informal care provision – evidence from administrative data. *Labour Economics*, 24:305–322.

Schmitz, H. and Westphal, M. (2015). Short-and medium-term effects of informal care provision on female caregivers' health. *Journal of Health Economics*, 42:174–185.

Schmitz, H. and Westphal, M. (2017). Informal care and long-term labor market outcomes. *Journal of Health Economics*, 56:1–18.

Schneider, U., Trukeschitz, B., Mühlmann, R., and Ponocny, I. (2013). Do i stay or do i go? job change and labor market exit intentions of employees providing informal care to older adults. *Health Economics*, 22(10):1230–1249.

Skira, M. M. (2015). Dynamic wage and employment effects of elder parent care. *International Economic Review*, 56(1):63–93.

Staubli, S. and Zweimüller, J. (2013). Does raising the early retirement age increase employment of older workers? *Journal of public economics*, 108:17–32.

Stern, S. (1995). Estimating family long-term care decisions in the presence of endogenous child characteristics. *Journal of human Resources*, pages 551–580.

Stöckel, J. and Bom, J. (2022). Revisiting longer-term health effects of informal caregiving: Evidence from the uk. *The Journal of the Economics of Ageing*, 21:100343.

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge university press.

Trochim, W. (1984). *Research design for program evaluation: The regression-discontinuity design*. Sage Publications, Beverly Hills, CA.

van Groenou, M. I. B. and De Boer, A. (2016). Providing informal care in a changing society. *European journal of ageing*, 13(3):271–279.

Van Houtven, C. H., Coe, N., and Skira, M. M. (2013). The effect of informal care on work and wages. *Journal of Health Economics*, 32(1):240–252.

Van Houtven, C. H. and Norton, E. C. (2004). Informal care and health care use of older adults. *Journal of health economics*, 23(6):1159–1180.

Wagner, G. G., Frick, J. R., and Schupp, J. (2007). The german socio-economic panel study (soep)-evolution, scope and enhancements. *SOEPpaper*, No. 1.

Wetzstein, M., Rommel, A., and Lange, C. (2015). Informal caregivers – Germany's largest nursing service. *GBE kompakt. Facts and Trends from Federal Health Reporting*, 6(3):1–11.

Wooldridge, J. M. (2005). Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of applied econometrics*, 20(1):39–54.

Wu, H. and Lu, N. (2017). Informal care and health behaviors among elderly people with chronic diseases. *Journal of Health, Population and Nutrition*, 36(1):40–47.

Declaration

Erklärung gem. §4 Abs. 2 der Promotionsordnung

Hiermit erkläre ich, dass ich mich noch keinem Promotionsverfahren unterzogen oder um Zulassung zu einem solchen beworben habe, und die Dissertation in der gleichen oder einer anderen Fassung bzw. Überarbeitung einer anderen Fakultät, einem Prüfungsausschuss oder einem Fachvertreter an einer anderen Hochschule nicht bereits zur Überprüfung vorgelegen hat.

Berlin, März 2022

Björn Fischer

Erklärung gem. §10 Abs. 3 der Promotionsordnung

Hiermit erkläre ich, dass ich für die Dissertation folgende Hilfsmittel und Hilfen verwendet habe: Stata, Matlab und Microsoft Excel.

Berlin, März 2022

Björn Fischer