HEDG

HEALTH, ECONOMETRICS AND DATA GROUP

THE UNIVERSITY of York

WP 14/14

Long-term care insurance and carers' labor supply – a structural model

Johannes Geyer & Thorben Korfhage

August 2014

york.ac.uk/res/herc/hedgwp

Long-term Care Insurance and Carers' Labor Supply – A Structural Model

Johannes Geyer*, Thorben Korfhage†

– Prelimary version –

Germany introduced a new mandatory insurance scheme for long-term care in 1995. From a budgetary perspective family care is a cost-saving alternative to formal home care and to stationary nursing care. Thus, one of the goals of the insurance is to support informal care provided by family members. However, the opportunity costs resulting from reduced labor supply of the carer are often overlooked. We focus on the labor supply decision of carers and the incentives set by the long-term care insurance. Care recipients can chose between benefits in kind and benefits in cash. We estimate a structural model of labor supply and the choice of benefits of caring spouses. We find that benefits in kind have positive effects on labor supply, while for benefits in cash elasticities are negative but not statistically significant. If both types of benefits are increased proportionately, demand for formal care increases. Labor supply is only adjusted by men but not by women.

Keywords: labor supply, long-term care, long-term care insurance, structural model
JEL Classification: J22, H31, I13

*DIW-Berlin, jgeyer@diw.de
†RWI, thorben.korfhage@rwi-essen.de

1. Introduction

Family care at home is an important pillar of the German long-term care system. From a policy perspective home care provided by informal carers is a cost saving alternative to formal home care and stationary care in nursing homes. However, many family carers are of working age and have to combine care and paid work which is often difficult. Family carers frequently adjust labor supply when they start to provide care (Schneekloth and Wahl, 2005, p.79). Carers work on average fewer hours and are more often not working compared to people who do not provide care on a regular basis. Among the main caregivers, 10% reported to have stopped working and another 11% reported to have reduced their working hours to be able to cope with the extended care burden (Schneekloth and Schmidt, 2011; Institut für Demoskopie Allensbach, 2010). Thus, hidden (public) financial costs of informal care consist of decreased tax revenues as well as fewer social security contributions.[1] From a policy perspective it is important to account for these opportunity costs, since Germany – as many other countries – aims to maintain a high level of family care supply in order to deal with a growing number of older people in the course of demographic change. Germany introduced a long-term care insurance (LTCI) in 1995 which supports people in need of care. While the existing literature on labor supply and long-term care mostly examines the relation between caring responsibilities and working hours in general, in this paper, we give a greater emphasis on the incentives set by the LTCI.

The German LTCI offers different benefit schemes for people in need of care. The main research question of our paper is to analyze empirically how family carers react to the incentives of the LTCI in terms of labor supply and informal care provision. Since its introduction in 1995, the LTCI aimed to support and strengthen family care (BMG, 2007, pp.8f). Family care is given precedence over formal care at home and home care takes precedence over stationary care. The priorization of home care is not only cheaper for the LTCI but also in accordance with preferences of care recipients who most often prefer to stay in their familiar surroundings. The German Care Statistic (*Pflegestatistik*) reports that, of all individuals eligible for LTCI benefits in 2011, 70% received benefits for home based care (Pfaff, 2013, p.5). The German LTCI has different benefit schemes to support home care: the care recipient has the choice between cash benefits, benefits in-kind or a combination of both. Cash benefits can be used to pay for family carers while benefits in kind comprise direct provision of formal home care services. Benefits are not means tested. The LTCI provides benefits for individuals with permanent (at least six months) impairments in at least two activities of daily living (ADL) and one instrumental activity of daily living (IADL). Depending on the level of impairments, three care levels are distinguished (see Schulz, 2010, for more details). Benefits in cash amount to 205 euro (in care level I) up to 665 euro (in care level III) and can be used to pay family carers.

[1] Individual costs of caring exist as well, e.g. forgone earnings and lower wage growth. There is also evidence that caregiving is associated with detrimental health effects (Colombo et al., 2011, ch.3).

If people chose benefits in kind, the care provider is directly reimbursed by the LTCI. In addition to benefits, the insurance includes the possibility for carers to take an unpaid leave of up to six months and emergency leave for medical reasons up to ten days per year. Since 2008, workers in firms with more than 50 employees can request a reduction in working hours (unpaid) for a period of up to six months (renewable once). Moreover, carers receive a small amount of additional pension entitlements.

We focus on a specific care setting which circumvents many econometric problems but is still informative: couples of working age of which one partner is in need of care. In this setting it is innocuous to assume that the partner is the main caregiver.[2] Regarding labor supply, the care need of the partner can have different effects. On the one hand, time and effort spent on informal care may lead to a reduction of working hours (substitution effect). On the other hand, the household has less earnings potential and care related expenses which impacts labor supply positively (income effect). A priori the effect is not unambiguous. At this point, the LTCI sets in. Benefits in cash increase non-labor income and therefore comprise negative labor supply incentives.[3] To the degree that benefits in kind substitute informal care, family carers are able to increase labor supply and leisure. Thus the decision on the type of benefits depends on preferences for own care and labor market opportunities; and on the relative attractiveness of the two different schemes.

We set up a structural behavioral model that explains jointly the partner's decision on the supply of working hours and care hours. The choice of care hours includes the decision about the benefit scheme. We estimate a utility function and assume that households maximize their utility subject to budget and time constraints. Since we estimate structural parameters, we are able to evaluate hypothetical policy reforms of the LTCI. In particular we ask, to what degree households substitute benefits in kind and benefits in cash if their relative attractiveness changes.

We use data from the Socio-Economic Panel Study (SOEP) from 2001 to 2010 to estimate the utility function. We consider only working age individuals whose partners are eligible for LTCI benefits and live in the same household. Thereby we mitigate the problem of endogenous geographic location of other family members since the main care burden is provided within the household. Furthermore, we take into account unobserved individual heterogeneity in the econometric specification.

We find that a 1% increase of benefits provided in kind leads to an increase of average working hours by 0.04%. A 1% increase of benefits in cash is found to decrease working hours by 0.09%, but the effect is not statistically significant. If both types of benefits are

[2] Due to this restriction, we do not model the behavior of children who live with a parent in need of care. Even though their number is declining, they still make up about 25% of all private households that include a person in need for long-term care (Schneekloth and Wahl, 2005, p.69). However, as Himes et al. (2001, p.156) find, the most important care provider in multi-person households remains the spouse of the care recipient. Hence, even with the reduced sample we are able to analyze a relevant group to model the potential opportunity costs of informal long-term care.

[3] Cash benefits are neither earmarked nor is spending monitored. Cash benefits increase family care but it is possible that carers would have provided care in the absence of any financial incentive. However, also in the case if inelastic supply of informal care, an increase in non-labor income reduces labor supply incentives.

increased proportionately, demand for formal care increases significantly. The labor supply effects are mainly driven by male carers. These findings indicate that while the opportunity costs of benefits in cash are ambiguous, benefits in kind seem to yield negative opportunity costs and thus lead to positive effects that are not considered while just looking at the pure expenses for the LTCI.

To the best of our knowledge, the labor supply effects of the German LTCI on carers' labor supply have only been analyzed once in an econometric setting. Geyer and Korfhage (2014) analyze the labor supply effects of the introduction of the LTCI on the labor supply of household members who live with a person in need of care. Using a difference-in-differences approach, they find a negative effect for men and no significant effect for women. Most other studies in this area of research focus on care responsibilities and labor supply. The earlier literature analyzes the relation between caring hours and labor supply of women and is performed in the US context (Lilly et al., 2007, provide a literature review). Depending on the data set or identification strategy, these studies find either no significant effect (e.g. Wolf and Soldo, 1994; Stern, 1995) or a negative impact of caring hours on labor supply (e.g. Ettner, 1995, 1996; Johnson and Lo Sasso, 2000). European studies seem to identify negative effects more often. For example, Carmichael and Charles (1998, 2003) use British data and find negative labor supply responses. They distinguish a direct effect of care provision and an indirect effect resulting from lower wages of carers. Heitmueller (2007) uses also British data and focuses on individual heterogeneity related to the provision of informal care and paid labor. He finds that the link between care provision and employment decisions depends on the care type: While he cannot identify an effect for *extra-residential carers* (who do not live in the same household as the care recipient), he finds a negative relationship for *co-residential carers* (who live in the same household). Spiess and Schneider (2003) use European data which include a variety of European countries. While they cannot identify country specific effects, they find an overall negative relationship between caring hours and labor supply. Viitanen (2005) extends that previous study and accounts for individual heterogeneity, state dependency and country specific effects. Thereby, she finds a negative impact of caregiving on labor supply only for Germany but for none of the other European countries that are analyzed in her study.

Schneider et al. (2001) examine SOEP data from 1985 until 1996. They find that living in a household with someone in need of care increases a woman's propensity to withdraw from the labor market. However, they do not find a significant effect on the reduction of labor supply from full-time to part-time. Using more recent SOEP data (2001–2007) Meng (2013) finds no significant effect of caring on employment, she finds a small negative effect on working hours that is slightly larger for men than for women. In another study, also using SOEP data, Meng (2012) estimates the effect of caring duties on retirement decisions and finds a positive effect on the probability to retire.

This paper is structured as follows: First, we describe the behavioral model in Section 2. Second, we show the econometric methods used for estimation of the structural parameters. In Section 4, we describe the underlying dataset. In Section 5, we present our results.

Section 6 concludes.

2. The Behavioral Model

In order to set up the behavioral model, we follow Johnson and Lo Sasso (2000) and assume a rational utility-maximizing carer who has to allocate her scarce time resources between time spent for caring and time spent on the labor market. As defined in Becker (1991, ch. 8), the carer is altruistic. That is, she not only gains utility from leisure and consumption, but also from the well-being of the handicapped household member. The utility function can be stated as follows:

$$U = u(c, l) + x(\gamma, h_c, h_o) + \varepsilon, \tag{1}$$

where c is real consumption, l is the carer's leisure time and γ describes the care-level of the care recipient. h_c is the number of hours used to care for the household member and h_o is the number of formal care-hours provided by the LTCI. The error-term ε includes all sources of utility that are not captured by the model. Becker (1974) showed that maximizing the carer's personal utility is equivalent to the maximization of an aggregated household welfare function as long as the carer is altruistic. If the carer is altruistic, she takes the utility of all other household members into account and therefore maximizes their utility as well. Hence, even though Equation (1) is thought to be maximized by the caring individual, it also maximizes the households aggregated utility.

2.1. The Budget Constraints

Individuals maximize the utility function subject to constraints describing the available time and income resources. They depend on chosen working categories as well as on the benefits from the LTCI.

We follow Van Soest (1995) and assume a discrete choice set of labor supply and the demand for benefits from the LTCI. With respect to working hours, this approach takes into account the imperfect structure of the labor market that leads to mass points of working hours. It also reduces the computational burden to model the non-linear structure of the budget constraints which result from the non-linear regulations of the tax benefit system.

In our model, the choice set of the carer consists of three working hour categories and two categories of benefits form the LTCI. The working categories include non-working (0 hours), part-time working (19 hours), and full-time working (41 hours). Only very few households choose mixed benefits, therefore we simplify our model by assuming that households can only choose between benefits in cash and benefits in kind. Consequently, households can choose between six sets of choice combinations.

Real consumption depends on labor income (wh_w) as well as on non-labor income (A) and on the tax benefit system $t(\cdot)$ that determines how much of the income is actually available.

$$c = \begin{cases} t(wh_w + A), & \text{if benefits in kind are chosen} \\ t(wh_w + A) + b_c(\lambda), & \text{if benefits in cash are choosen} \end{cases}, \tag{2}$$

where $t(\cdot)$ represents the tax benefit system. Benefits from the LTCI are free from income taxes as long as the benefits are either taken by the care recipient herself or if they are passed on to family members to provide informal care (§3 nr.36 EstG). Furthermore, benefits are not withdrawn and not credited against other transfers, such as social assistance or housing benefits. Therefore, benefits in cash (b_c) can be added to the households net income without further adjustments. According to the LTCI scheme, benefits increase with a higher care-level (λ).

In order to set up constraints describing feasible combinations of leisure as well as formal and informal care hours, we have to make assumptions about supplied working hours and the amount of care needed by the care recipient and the origin of care – meaning the person or institution that provides care.

In our model, two crucial assumptions are made with respect to supplied care: Firstly, we assume that the spouse of the care recipient is always the main caregiver. Secondly, we assume that secondary care can only be provided by the formal care service supplied by the insurance scheme. Hence, we exclude the possibility of caring children, friends or other paid caring services. The first assumption can be motivated with Schneekloth and Wahl (2005, p. 76) who find that of all people who receive home based care, 92% name the closest family member as their main caregiver. It is reasonable to assume that the partner is the main caregiver who takes over the bulk of the informal care load. The second assumption seems more ambitious because the availability of additional carers most likely affects the spouses caring and labor supply decisions. However, as will be further discussed in Section 4, even the simple specification without secondary carers captures the spouse's caring burden well enough to yield information about the relevant tradeoffs they are facing.[4]

We assume that a certain care level is related to a fixed amount of care hours which always has to be provided. We rely on the representative survey study by Schneekloth and Wahl (2005) to obtain average weekly care hours. They find an average provision of care in the first care-level of 29.4 hours per week, in the second care level 42.2 hours per week, in the third level 54.2 hours per week.

We use these averages as total care-time (h_T) which must be provided formally by the care service and/or informally by the caring partner.

$$h_T(\lambda) = h_c + h_o \tag{3}$$

Note that this assumption implies h_c and h_o to be substitutes. We thus assume that at least fundamental care needs can be supplied by any carer and that it is reasonable

[4]We control for household characteristics in the estimation which captures to some extent other potential care sources within the household.

to believe that carers will reduce their caring effort, if the exogenous supply of care is increased *ceteris paribus*.

If households decide to receive benefits in kind, a part of the care load is provided formally. Depending on the care-level households are eligible for different amounts of benefits which are directly paid to a care service. Since benefits in kind ($b_k(\lambda)$) are defined in monetary terms, in order to obtain formal care hours (h_o), they have to be divided by the hourly price of formal care (p_{h_o}).

$$h_o = \begin{cases} b_k(\lambda)/p_{h_o}, & \text{if benefits in kind are choosen} \\ 0, & \text{if benefits in cash are choosen} \end{cases} \tag{4}$$

Unfortunately, the hourly price p_{h_o} of formal care is not observed for our sample. It results from a bargaining process between the LTCI and unions of care suppliers (Büscher et al., 2007, p. 344). Instead of having fixed hourly prices, money is paid for special services, such as washing, feeding somebody or making a bed. In order to derive an hourly price we follow Büscher et al. (2007) who investigate the impact of a revised reimbursement scheme for home care services. They assume an hourly rate of 28.3 euro which they argue is accurate according to the German law (§SGB XI) in 2006. In order to account for inflation, the Consumer Price Index (CPI) is used to adjust prices for all other years.

According to Equation (3) the informal care hours can simply be calculated as the difference between the exogenous total care time (h_t) and formal care time (h_o). Yet, because it can be assumed that even at full-time employment individuals do not work more than five days a week, we assume that all modeled tradeoffs only concern weekdays and that at weekends, care is always provided informally. Hence, only 5/7 of the total care-time must be allocated to formal and informal care time.

$$h_c = (5/7)h_T(\lambda) - h_o \tag{5}$$

It should be noted that the insurance only partly covers the risk of long-term care, meaning that home care is primarily provided by the spouse, no matter what type of benefits is chosen. h_c is thus always positive and larger than h_o.

Leisure (on working days) is calculated as the difference between total time allowance ($T = 80$), time devoted for paid employment (h_w), and for informal care services (h_c).

$$l = 80 - h_w - h_c \tag{6}$$

Substituting Equations (4), (5) and (6) into the utility function (1) yields the carer's maximization problem

$$U = u[t(wh_w + A) + b_c(\lambda), 80 - h_w - h_c] + x[\gamma, h_c, h_t(\lambda) - h_c] + \varepsilon \;\rightarrow \max_{h_c, h_w} \tag{7}$$

subject to non-negativity of the choice variables.

Table 1 shows the values of the choice variable (working and informal care hours) and

Table 1: Summary of Choice Sets in each Care-level

	Working Hours (h_w)	Informal Care Hours (h_c)	Formal Care Hours (h_o)	Pure Leisure (l)	Benefits in Cash (b_c)
Care-level 1					
no work & in cash	0.0	21.0	0.0	59.0	48.2
no work & in kind	0.0	17.8	3.2	62.2	0.0
part time & in cash	19.0	21.0	0.0	40.0	48.2
part time & in kind	19.0	17.8	3.2	43.2	0.0
full time & in cash	41.0	21.0	0.0	18.0	48.2
full time & in kind	41.0	17.8	3.2	21.2	0.0
Care-level 2					
no work & in cash	0.0	30.1	0.0	49.9	96.4
no work & in kind	0.0	22.5	7.6	57.5	0.0
part time & in cash	19.0	30.1	0.0	30.9	96.4
part time & in kind	19.0	22.5	7.6	38.5	0.0
full time & in cash	41.0	30.1	0.0	8.9	96.4
full time & in kind	41.0	22.5	7.6	16.5	0.0
Care-level 3					
no work & in cash	0.0	38.7	0.0	41.3	155.0
no work & in kind	0.0	27.0	11.8	53.0	0.0
part time & in cash	19.0	38.7	0.0	22.3	155.0
part time & in kind	19.0	27.0	11.8	34.0	0.0
full time & in cash	41.0	38.7	0.0	0.3	155.0
full time & in kind	41.0	27.0	11.8	12.0	0.0

Source: Own calculation.

the values of the variables that are given by the constraints (formal care hours, leisure hours, and benefits in cash). All values are expressed as weekly amounts in hours or euro.

3. Econometric Specification

In order to set up the estimation equation, it is more convenient to express utility for different choices as well as for different time periods. The utility U_{ijt} that carer i gains from choice j at time t comprises an observable portion V_{ijt} which is assumed to be linear in parameters and an unobservable portion ε_{ijt}. The carer's utility can therefore be restated as

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt} = X'_{ijt}\beta + \varepsilon_{ijt}. \tag{8}$$

Thereby, β is a vector of coefficients to be estimated. The components of X_{ijt} are disposable household income c, the carer's pure leisure time l, and the number of informal care hours h_c. All of them are included in logs. Furthermore, interactions are included as well as taste shifters to control for observable heterogeneity:

$$X_{ijt} = [\log(l_{ijt}), \log(c_{ijt}), \log(h_{c_{ijt}}), \log(l_{ijt}) \times \log(c_{ijt}), \alpha'_{ijt}]', \tag{9}$$

where the vector α_{ijt} includes interactions of $\log(l_{ijt})$, $\log(c_{ijt})$ and $\log(h_{c_{ijt}})$ with observable characteristics, which will be further discussed in Section 4.

Estimation is based on the comparison of utilities in the different choice sets. It is expected that the carer is making rational decisions, meaning that she will always choose the available alternative that yields the highest utility. For instance, the carer will choose alternative k only if $U_{ikt} > U_{ijt}$ for all $j \neq k$. Consequently, the probability that carer i chooses alternative k at time t can be expressed as

$$\begin{aligned} P_{ikt} &= \text{Prob}(U_{ikt} > U_{ijt}) \quad \forall\, j \neq k \\ &= \text{Prob}(\varepsilon_{ijt} < \varepsilon_{ikt} + V_{ikt} - V_{ijt}) \quad \forall\, j \neq k. \end{aligned} \tag{10}$$

Because ε is unknown further assumptions about its distribution have to be made to be able to estimate choice probabilities. In the following, we describe the conditional logit model which can be used, if ε is expected to be identically and independently distributed (iid) extreme value (type I). We show why the underlying properties associated with the iid assumption might be violated and illustrate how a mixed logit model can be used to relax the assumptions of the conditional logit model.

3.1. Conditional Logit-Model

McFadden (1974) shows that if each ε_{ijt} is iid extreme value (type I), a closed form solution for the logit probability can be derived.[5] According to Equation (10), the probability that individual i chooses k at time t over some other alternative depends on the expression $(\varepsilon_{ikt} + V_{ikt} - V_{ijt})$. If ε_{ikt} was known, this expression would be observable and could simply be substituted into the cumulative extreme value distribution to solve for the probability that U_{ikt} is larger than some other utility U_{ijt}:

$$\text{Prob}(U_{ikt} > U_{ijt})|\varepsilon_{ikt} = e^{-e^{-\left(\varepsilon_{ikt}+V_{ikt}-V_{ijt}\right)}}. \tag{11}$$

The product over all possible pairs of choice probabilities for all $k \neq j$ yields the probability that U_{ikt} is larger than the utilities of all other choices:

$$P_{ikt}\,|\varepsilon_{ikt} = \prod_{j\neq k} e^{-e^{-\left(\varepsilon_{ikt}+V_{ikt}-V_{ijt}\right)}}. \tag{12}$$

However, as ε_{ikt} is unknown, it is necessary to calculate a weighted average over all of its possible outcomes. This is done by an integral in which all outcomes are weighted by the density of ε_{ikt}. Using these arguments, the choice probability can be summarized in the

[5] For the description of the econometric theory in this section we draw from Train (2009, ch. 2,3,6 and 11) and Greene (2011, ch. 18). If other sources are used, they are indicated separately.

following equation:

$$P_{ikt} = \int_{s=-\infty}^{\infty} \left(\prod_{j \neq k} e^{-e^{-\left(s+V_{ikt}-V_{ijt}\right)}} \right) e^{-s} e^{-e^{-s}} \, \mathrm{d}s. \tag{13}$$

If (and only if) ε is distributed iid extreme value, the integral can be solved analytically and the closed form expression of the logit model can be derived.[6]

$$P_{ikt} = \frac{e^{V_{ikt}}}{\sum_j e^{V_{ijt}}}; \qquad k \in J. \tag{14}$$

Resulting from the assumptions about ε, the conditional logit model has some disadvantages. First, the logit model implies proportional substitution across alternatives. This relates to the so called independence from irrelevant alternative (IIA) which implies that the odds ratios of two alternatives, j and k, do not depend on any other alternative. Second, the logit model cannot handle random taste variation. Heterogeneity that relates to observable characteristics, such as gender or household size, can be represented in the model through taste shifters. Even though characteristics cannot be included directly into the model as they would drop out of Equation (14), interactions can be used to capture systematic taste variations between different groups. If, however, individual heterogeneity in taste cannot be observed, it appears in the error $\varepsilon_{ijt} = \mu_i + \tilde{\varepsilon}_{ijt}$. If the unobserved heterogeneity μ_i is correlated with alternatives, the iid assumption is violated and the logit model is likely to yield biased results. Among others, one can think of two reasons that could yield biased estimates in our model. First, access to other informal or formal care providers cannot be observed and most likely correlate with working decisions and the choice of demand from the LTCI. Second, the ability to care informally may vary across individuals and may lead to different preferences relating to the distribution between formal and informal care services.

Because violation of the iid assumption can thus not be ruled out *a priori* we estimate a mixed logit model in which the iid assumption will be relaxed.

3.2. Mixed Logit Model

Because of its similarity to the conditional logit model we are accounting for unobserved heterogeneity using the mixed logit specification with random coefficients. The unobserved individual heterogeneity is modeled by allowing β to vary between individuals. For instance, β_i can be modeled to consist of a fixed part β and a random part μ_i:

$$\beta_i = \beta + \mu_i, \tag{15}$$

where μ_i is assumed to capture all non-observable effects, such as random taste variation. As β_i cannot be observed its distribution has to be estimated. We use a parametric

[6] The proof can be found in McFadden (1974, pp. 106ff) or in Train (2009, pp. 36f and pp. 74f).

specification in which it is assumed that β_i follows a continuous distribution $f(\beta_i)$.

In the conditional logit model, the time dimension of the panel date does not have much relevance because the error term is assumed to be iid over time. In the mixed logit model we expect unobserved heterogeneity to be constant over time, meaning that β_i should be the same in each time period. To capture this assumption, it is more convenient to estimate probabilities of choice sequences. That is, for each individual a sequence is observed which contains all the choices she makes at different points of time: $y_i = \langle y_{i1}, \ldots, y_{iT} \rangle$.

If the error term ε_{ijt} is assumed to be iid extreme value, the conditional probability of choosing a certain sequence can be calculated as the product of the logit probabilities (14) over t:

$$P(y_i|X_i, \beta_i) = \prod_{t=1}^{T} \frac{\exp(X'_{ikt}\beta_i)}{\sum_j \exp(X'_{ijt}\beta_i)}. \tag{16}$$

Because β_i is unknown the unconditional probability must be expressed as a weighted average over all possible outcomes of β_i. In the case of a continuous distribution of β_i this can be done by introducing an integral over its distribution:

$$P(y_i|X_i) = \int_{-\infty}^{\infty} P(y_i|X_i, \beta_i) f(\beta_i) d\beta_i \tag{17}$$

Looking at Equation (17), it can be seen that not only random taste variation can be captured in this specification but also that the mixed logit does not rely on the IIA.

Unfortunately, the integral in Equation (17) cannot be solved analytically and simulation methods have to be used to estimate choice probabilities. Thereby, probabilities are approximated by drawing R values of β_i from its assumed density $f(\beta_i)$. For all R draws the conditional probability (16) is calculated and its mean is derived. The resulting approximation can be stated as:

$$\hat{P}(y_i|X_i) = \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T} \frac{\exp(X'_{ikt}\beta_i^r)}{\sum_j \exp(X'_{ijt}\beta_i^r)}, \tag{18}$$

where R is the number of draws, $\hat{P}$ is the unbiased estimator of P and β_i^r is the rth draw from the distribution $f(\beta_i)$. The simulated log likelihood function of the parametric model takes the following form:

$$\begin{aligned} SLL &= \sum_{i=1}^{n} \ln \hat{P}(y_i|X_i) \\ &= \sum_{i=1}^{n} \ln \left\{ \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T} \prod_{k=1}^{J} \left[\frac{\exp(X'_{ikt}\beta_i^r)}{\sum_j \exp(X'_{ijt}\beta_i^r)} \right]^{d_{ikt}} \right\} \end{aligned} \tag{19}$$

where $d_{ikt} = 1$, if the individual i chooses her observed choice set and *zero* otherwise. The

SLL is maximized to obtain the moments of the distribution $f(\beta_i)$.[7]

Generally, it is possible to allow all explanatory variables in the utility function to have random coefficients. However, as will be described in the following subsection, the number of observations in the dataset is rather small and each random parameter increases the number of coefficients that have to be estimated and thus the needed degrees of freedom. Furthermore, it seems unreasonable to assume random coefficients for interaction terms that are included in the model to capture observable individual heterogeneity. Hence, we only assume random coefficients for disposable household income c and the carer's pure leisure time l. As more than one variable is assumed to have random coefficients, Equation 17 actually consists of multiple integrals – one for each random coefficient. Simulations must thus be performed for each random coefficient. We follow Haan (2006, p. 253) and assume that β_i is normally distributed, $\beta_i \sim \mathrm{N}(\beta, W)$, were the mean β and the variance-covariance matrix W are to be estimated.

Individual-level Parameters

In order to estimate individual specific parameters we use the procedure suggested by Revelt and Train (2000) (see also Train, 2009, ch. 11).

The general idea is to assume that the distribution of preferences among individuals who make a specific choice differs from the distribution over the entire population. While the unconditional taste distribution $f(\beta_i)$ was estimated above, now a distribution shall be derived that is conditional on attributes and choice decision $h(\beta_i|y_i, X_i)$. This can be thought of as the distribution for a sub-group of individuals who face the same alternatives and make the same choices.

To derive $h(\cdot)$ Bayes' rule is used which states that the joint density of β_i and y_i can be expressed as the probability of y_i times the probability of β_i conditional on y_i:

$$h(\beta_i|y_i, X_i)\ P(y_i|X_i) = P(y_i|X_i, \beta_i)\ f(\beta_i) \tag{20}$$

Rearranging yields the expression for the conditional distribution:

$$h(\beta_i|y_i, X_i) = \frac{P(y_i|X_i, \beta_i)\ f(\beta_i)}{P(y_i|X_i)}, \tag{21}$$

which can be used to calculate the expected value of β_i as:

$$E(\beta_i) = \int_{-\infty}^{\infty} \beta_i h(\beta_i|y_i, X_i) d\beta_i \tag{22}$$

Substituting Equations (16), (17) and (21) into (22) yields the complete expression

[7] For estimation, we use the Stata ado `mixlogit` that is described by Hole (2007) and is based on Halton draws. Halton draws are pseudo-random draws and considerably reduce simulation variance in the estimation of mixed logit parameters compared to random draws (see Train, 1999). For the matter of simplicity, we do not allow the random parameters to be correlated.

for $E(\beta_i)$. However, because the integrals can again only be solved by using simulation methods, the formula for the estimations of β_i turns out to have the following shape:

$$\hat{\beta}_i = \frac{\frac{1}{R}\sum_{r=1}^{R}\beta_i^r \prod_{t=1}^{T}\prod_{j=1}^{J}\left[\frac{\exp(X'_{ikt}\beta_i^r)}{\sum_j \exp(X'_{ijt}\beta_i^r)}\right]^{d_{ikt}}}{\frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{T}\prod_{j=1}^{J}\left[\frac{\exp(X'_{ijt}\beta_i^r)}{\sum_j \exp(X'_{ijt}\beta_i^r)}\right]^{d_{ikt}}} \tag{23}$$

Note that the estimated individual coefficients can also be used to estimate individual level specific choice probabilities. We use this concept to calculate individual derivatives and elasticities in Section 5.

4. Description of the Data

4.1. Dataset and Definition of Sample

To estimate the parameters of the utility function we use data of the SOEP from 2001 until 2010. The SOEP is a representative panel study of households and individuals.[8] Questioning started in 1984 and included about 12,000 individuals living in 12,000 households. In 2011 the SOEP contained about 20,000 individuals who lived in almost 10,000 households.

We choose individuals who are able to work and flexible in their labor supply decision. They are between 35 and 65 years old, not retired and their partner in the same household is in need of LTC. The need of care is defined as being eligible for benefits from the LTCI.

Overall, we use 177 observations. Thereby, we observe 67 individuals. 27 are only observed once, 11 are observed in two periods and 27 are observed in three periods or more often.[9]

4.2. Sample Characteristics

In Table 2, the main sample characteristics are presented. The table is divided into characteristics of potential carers, characteristics of care recipients as well as common household characteristics.

Of all carers, 58% are employed and they have an average age of 53 years. The majority of carers are women. As some of them are in higher working age themselves, a relatively large fraction of 53% reports to be in a poor or bad health status which might influence working and caring decisions.

Of all care recipients, 82% receive benefits in cash which is higher compared with official statistics of the LTCI, but not surprising as we look at a special subsample of people living with their spouses. Most of the carers are women and 65% of the care recipients are men. On average they are only about 4 years older than the carer. Since we analyze the

[8] To obtain detailed information about the SOEP, see Wagner et al. (2007).

[9] Panel attrition can bias our estimates, if it is correlated with care related variables. We rely on Meng (2013, p.969) who shows that panel attrition due to caregiving does not bias estimated coefficients systematically.

Table 2: Descriptive Statistics

	Obs.	Mean	St. Dev.
Potential Carer			
employed	177	0.58	0.49
age	177	53.06	7.53
female	177	0.65	0.48
migration background	177	0.22	0.42
number of years of education	175	11.08	1.76
self-rated health status: good–very good	177	0.03	0.18
self-rated health status: satisfactory	177	0.38	0.49
self-rated health status: poor–bad	177	0.53	0.50
Care Recipient			
benefits in cash	177	0.82	0.39
age	177	56.80	10.25
female	177	0.35	0.48
care-level 1	177	0.53	0.50
care-level 2	177	0.30	0.46
care-level 3	177	0.17	0.38
receive care from social service (e.g. church)	177	0.08	0.27
receive care from friends	177	0.12	0.33
receive care from neighbors	177	0.01	0.08
receive care from relatives outside household	177	0.14	0.35
receive care from relatives inside household	177	0.80	0.40
receive formal care[a]	177	0.05	0.21
Household			
east	177	0.31	0.46
number of people inside household	177	2.35	0.68
number of children inside household	177	0.31	0.58
other adults inside household	177	0.04	0.27

[a]other formal care than from long-term care insurance

Source: SOEP, own calculation

effects on partner's labor supply the age structure is not surprising. The older the care recipients are, the higher is the probability that their partner is already retired or not able to provide informal care. Furthermore, with increasing age the probability to turn into nursing homes rises (Himes et al., 2000) as well as the share of home based care provided by children (Schneekloth and Wahl, 2005, p.76). Thus, the focus on caring spouses leads to the relatively young average age of the care recipients.

The SOEP includes a question to obtain information about the source of informal care provision.[10] Because multiple answers are possible, frequencies do not add up to 100%. Of all care recipients, 80% report to receive help from relatives within the household, 14% receive help from relatives outside the household and a surprisingly large fraction of 12% receive care from friends. Note that this variable should be considered endogenous with respect to the spouses labor supply decision. For instance, if the spouse is working full time, it is much more likely that help from other people outside the household needs to be acquired. Hence, the dummies generated from this question cannot simply be included

[10]The exact question is asked as follows: *Does someone in your household need care or assistance on a constant basis due to age, sickness or medical treatment? [...] From whom does this person receive the necessary assistance? Relatives in the household, public or church nurse, social worker, private care service, friends, neighbors and/or relatives not in the household?*

into the model as interactions. Yet, it seems surprising that 20% claim to not receive care from relatives within the household. Their spouses work longer hours. 71% of all partners who live with a full-time working spouse report to receive care from inside the household, this share increases to 77% and 90% for part-time working spouses and spouses who do not work, respectively (not shown in the table). Consequently, our model might overestimate the actual care burden in the highest care alternative.

Households have an average size of 2.35, and a minimum of two. Thereby, the extra individual is either a child (aged younger than 18 years) or an adult. While it can be assumed that extra children decrease the time available for care, extra adults could be grown up children or other relatives who take over some of the care work.

Table 3: Frequencies of actual choosen choices

	All %	Level 1 %	Level 2 %	Level 3 %	Female %	Male %	Kid in HH %	Age mean
no work & in cash	32.7	34.0	28.3	36.7	35.7	27.4	15.9	57.4
no work & in kind	9.0	7.4	15.1	3.3	11.3	4.8	2.3	57.7
part time & in cash	16.4	14.9	26.4	3.3	24.3	1.6	22.7	50.4
part time & in kind	1.1	1.1	0.0	3.3	1.7	0.0	2.3	46.5
full time & in cash	32.8	38.3	26.4	26.7	19.1	58.1	36.4	49.6
full time & in kind	7.9	4.3	3.8	26.7	7.8	8.1	20.5	51.0

Note: Except Age, all values indicated frequencies of chosen choice in percent. For instance, of all women 37% chose not to work and to get benefits in cash. Age is the mean in each choice set.
Source: SOEP, own calculation.

To obtain first insights of the chosen alternatives, in Table 3 presents frequencies of actual chosen choice sets. Except for age, all values indicate frequencies in percent. Overall, the non-working category is chosen as often as the full-time category (both about 41%), the part-time choice set is considerably smaller with 17% of all choices. Furthermore, in all alternatives benefits in cash are preferred over benefits in kind. This remains true for all care-levels. Yet, in care-level III people seem to choose benefits in cash more often when deciding to supply less paid labor and turn to benefits in kind in the full-time working alternative more often than people with other care-levels.

While men work more often full-time than women, the part-time choice sets include almost solely women. If children live in the household, benefits in kind are more attractive. Thus, it is not surprising that especially in the full-time working alternative people with children rely on benefits in kind more often than the average.

4.3. Control variables

We include interactions with variables that might lead to systematic taste variation to control for observable individual heterogeneity. Because living costs are still considerably lower in East-Germany and unemployment rates are higher we include a region dummy into the model interacted with net income. Furthermore, as the available income depends on household size, it is also interacted with net income.

Among others, important sources for systematic variation of utility gained from leisure might be age, gender or migration background. Moreover, household size can have different effects depending on the the additional household member. If extra children are part of the household, leisure is expected to be decreased while further adults might take over care tasks load and increase the time available to the carer.

An important interaction for the utility gained from informal caring seem to be the care levels of the care recipient. Not only does the hourly care burden increase with higher care-levels, the tasks which the carer has to perform regularly are different. Interactions with dummies are included to indicate care-levels 2 and 3. Care-level 1 is the base category.

4.4. Benefits

The SOEP does not include a question that directly asks the household about the type of benefits it is receiving from the LTCI. However, individuals are asked to report the amount of money they are receiving each month from the LTCI. Combined with the knowledge about the care level of the recipient, one can therefore compare the amount of cash the household is eligible for with the amount the household is actually receiving.

We assume that the household chooses benefits in cash whenever the monetary transfers from the insurance are at least 50% of what it is eligible for. Note that we omit the possible choice of combining benefits in kind with benefits in cash to obtain two discrete choice categories. Mixed benefits are a rarely observed. Compared with the German Care Statistic (*Pflegestatistik*) (Pfaff and Rottländer, 2005) and Schneekloth and Wahl (2005), our approximation works relatively well.

4.5. Net Household Income

Net household income is simulated for the choice alternatives on the basis of the microsimulation model STSM.[11] The STSM is a model of the German tax-benefit system and contains the main properties of the German tax and transfer system. In a first step observable sources of labor and non-labor income are used to calculate each household's taxable income. In a second step, taxes and benefits are calculated to obtain net household income. Thereby, taxes and transfers not only depend on the amount of taxable income but also on household composition.

If individuals choose one of the working categories, their labor income is calculated by multiplying the assumed weekly working hours in each choice set by the observed individual wage rate. As for non-working individuals wages cannot be observed, they have to be estimated. In order to account for sample selection, we use the two step-procedure suggested by Heckman (1979). A more detailed description of the wage estimation can be found in Appendix C.

Estimation is based on pooled SOEP-data from the years 1999 until 2010 and is performed separately for women and men as well as for East- and West-Germany. Results are

[11] For detailed information about the STSM, see Steiner et al. (2012).

presented in Tables 10 and 11.

Summary statistics of the simulated net household incomes are presented in Table 12. They also include the benefits provided in cash and are calculated as weekly amounts. As expected, net household income increases with working hours and if benefits in cash are chosen.

5. Results

In this section, we first present estimation results for conditional logit and mixed logit models with random coefficients and motivate why the random coefficient specification is used for the further analysis. Secondly, we derive elasticities for a 1% change of gross wages, benefits in cash and benefits in kind. Thirdly, we simulate a potential reform of the LTCI scheme which increases all benefits by 10%.

5.1. Estimation Results and Model Selection

The coefficients of the estimated models are shown in Table 4. The first model is a conditional logit model, while model (2) is a mixed logit models with random coefficients.

First of all, it should be noted that the estimated standard deviations in the mixed logit model with random coefficients are highly statistical significant at the 1% level for leisure and net income. That is, the assumption of unobserved individual heterogeneity in these variables cannot be rejected. Also, the Akaike Information Criterion (AIC) is lower with random coefficients suggesting a better relative quality of the mixed logit specification.[12] Thus, in the following analysis all further results are based on the mixed logit model.

In Table 5, the in-sample predictions of the conditional logit and the mixed logit model are compared with the observed frequencies in the data. It can be seen that the random coefficients model fits the data quite well with no systematic over- or underestimation of any working category or the chosen benefits from the LTCI.

Generally, the estimated coefficients in Table 4 can be interpreted as effects on the carer's utility but because of the interaction terms, which are included into the utility function, it is more convenient to calculate differentials to identify direct effects of the key variables on the carer's utility. Thereby, derivatives are calculated on the individual level using Equation (23) with 500 draws from the estimated distribution for each of the random coefficients.

The first derivative of the utility function, with respect to income is positive for 88% of all individuals. Due to the log specification the second derivative is consequently negative for the same 88% of all individuals. Thus, the generally made assumption of increasing and diminishing marginal returns is fulfilled for nearly all individuals. The reason for the partly negative first derivatives is the specification of the random coefficient for net income

[12] We also performed Hausman tests of the IIA. At the 1% level the *Null* must be rejected for all except two choices. This is another hint that the conditional logit model is miss-specified and yields biased estimates.

Table 4: Estimation results for conditional logit and random coefficient model

	(1) Conditional Logit	(2) Random Coefficients[a]
Estimated Means		
log (leisure)	21.254*	20.366
	(8.537)	(21.021)
log (net income)	5.568**	11.929†
	(2.014)	(6.943)
log (informal)	10.735**	10.080**
	(1.885)	(2.518)
log (leisure) × log (net income)	−0.877*	−0.023
	(0.420)	(1.250)
log (net income) × east	−2.034*	−9.078†
	(0.790)	(4.824)
log (net income) × (household size > 2)	2.693†	2.675
	(1.602)	(5.390)
log (leisure) × age	−0.700*	−0.890
	(0.327)	(0.831)
log (leisure) × ($age^2/100$)	0.750*	1.011
	(0.321)	(0.870)
log (leisure) × female	0.736*	3.339*
	(0.304)	(1.557)
log (leisure) × children in household	0.558	−0.317
	(0.410)	(1.942)
log (leisure) × adults in household	0.090	1.135
	(1.246)	(3.696)
log (leisure) × migration background	0.917*	1.382
	(0.389)	(2.004)
log (informal) × care-level 2	−0.229**	−0.088
	(0.085)	(0.116)
log (informal) × care-level 3	−0.322**	−0.426**
	(0.068)	(0.102)
Estimated Standard Deviations		
log (leisure)		5.188**
		(1.752)
log (net income)		10.895**
		(3.315)
log likelihood	-238.94	-192.38
Akaike's Information Criterion (AIC)[b]	505.88	416.76
Observations	1062	1062

Note: Values denote estimated coefficients. Standard errors are reported in parentheses.
[a] The random coefficients model is estimated using simulation methods. Simulation was performed using 500 pseudo-random Halton draws for each household.
[b] The AIC is calculated as $-2(\log - \text{likelihood}) + 2p$ where p is the number of parameters of the model.
Significance levels: † p <0.10, ∗ p <0.05, ∗∗ p <0.01
Source: SOEP, STSM, own calculation

and the calculation of individual level parameters. If derivatives are calculated at means – as it is done in the conditional logit model – derivatives are positive for all individuals.

The first derivative of the utility function with respect to leisure is positive for 77% of

Table 5: Insample model-fit

	Data	Conditional Logit	Random Coefficient
no work & in cash	32.8	27.4	29.8
no work & in kind	9.0	6.9	14.4
part time & in cash	16.4	25.0	17.4
part time & in kind	1.1	5.8	2.9
full time & in cash	32.8	29.6	31.9
full time & in kind	7.9	5.3	3.5

Note: For the estimation of the individual specific random coefficients simulation methods are used. On the basis of 500 draws form the estimated distribution, for each household, β_i is chosen conditional on attributes and on choice patterns. Values are given in percent. As values are rounded, sums can differ from 100%.

Source: SOEP, STSM own calculation.

all individuals. It can be assumed that a part of the positive effect of leisure on utility is captured by informal care hours. First derivatives with respect to informal care hours are positive for 100% of all individuals, meaning that they yield positive utility for an extra hour of provided informal care. This corresponds to the preference for LTC that is provided informally by family members (see Schupp and Künemund, 2004, p.292).

While the mean coefficients of informal care hours and net income are significant at the 1% or 10% level, respectively, it is not statistically significant for leisure. Instead, most of the effect of leisure on utility is driven by the highly significant estimate for its standard deviation. Significant coefficients on taste switchers indicate differing utility functions by region and gender. Additionally, people whose spouse has a higher carelevel seem to gain less utility from caring.

5.2. Elasticities

In order to compare results with previous structural labor supply models, we calculate wage elasticities and elasticities of increased benefits in kind or in cash on labor supply. These are calculated by simulating a one percent increase in gross hourly wages, benefits in kind, and in cash.

We obtain confidence intervals for the elasticities using a parametric bootstrap. Because the central limit theorem suggests that the arithmetic mean of a sufficiently large number of iterates of independent random variables is approximately normally distributed (Greene, 2011, pp. 1078ff), we assume that the mean values of the estimated model coefficients follow a multivariate normal distribution. We use the estimated mean and covariance of the estimated coefficients to draw 500 new coefficients.

For each of the 500 draws, choice probabilities are predicted. Individual level estimates for the random coefficients are calculated using Equation (23) with 500 draws form its estimated distribution for each of the random parameters. By comparing the predicted probabilities of the original model with the probabilities predicted after a one percent increase, we can calculate elasticities. 90% confidence intervals are simply obtained from the calculated elasticities that result from the different random draws of coefficients.

Table 6: Estimated Elasticities of a 1% Increase of Wages

	Working Hours (%)	Labor Participation (PP)	Informal Care Hours (%)	Share of Benefits in Cash (PP)
all				
mean	0.3578	0.1422	−0.0151	−0.0548
p5	0.1298	0.0580	−0.0229	−0.0851
p95	0.6170	0.2229	−0.0090	−0.0323
male				
mean	0.2224	0.0966	−0.0178	−0.0616
p5	0.0508	0.0260	−0.0267	−0.0919
p95	0.4206	0.1629	−0.0100	−0.0353
female				
mean	0.4302	0.1665	−0.0136	−0.0511
p5	0.1633	0.0712	−0.0228	−0.0864
p95	0.7461	0.2572	−0.0069	−0.0261
care-level 1				
mean	0.3384	0.1318	−0.0048	−0.0302
p5	0.1201	0.0498	−0.0089	−0.0565
p95	0.5634	0.2110	−0.0020	−0.0129
care-level 2				
mean	0.3566	0.1493	−0.0118	−0.0439
p5	0.1129	0.0618	−0.0248	−0.0920
p95	0.6465	0.2356	−0.0043	−0.0164
care-level 3				
mean	0.4221	0.1624	−0.0543	−0.1535
p5	0.1540	0.0859	−0.0796	−0.2217
p95	0.7427	0.2391	−0.0333	−0.0960

Note: Elasticities are calculated using parametric bootstrap with 500 draws. The estimated means and the variance covariance matrix is used to draw new coefficients, that are used for simulation. p5 and p95 indicate the boundaries of the 10% confidence interval.
Source: SOEP, STSM, own calculation

Results for the wage elasticities are presented in Table 6. The he boundaries of the 90% confidence intervals are indicated by p5 and p95. On average, a 1% increase in gross wages leads to an increase of working hours by 0.36% and an increase of labor participation of 0.14 percentage points (PP). Female labor supply reacts stronger.

These results are in line with other studies estimating labor supply elasticities on the basis of SOEP (e.g., Steiner and Wrohlich, 2004; Haan, 2006; Wrohlich, 2011). For instance, in a parametric random coefficients model, Haan (2006) estimates that men increase working hours by 0.2% and labor participation by 0.13 PP in response to a 1% wage increase. In his model women react also more elastic with a 0.39% increase in working hours and a 0.14 PP increase in labor participation. Wrohlich (2011) estimates labor supply elasticities for mothers who care for children. She finds that if wages increase by 1%, mothers increase working hours by 0.49% and labor participation by 0.13 PP.

As individuals increase labor supply their available time for leisure and informal care decreases. It is thus not surprising that individuals decrease the amount of provided informal care. To close the gap in care hours, more people chose benefits in kind to use formally provided care more often. However, elasticities are considerably smaller than wage elasticities. Overall, a 1% increase in wages only results in a very small reduction of informal care hours of 0.015%, meaning that most of the extra labor supply is provided by reducing personal leisure time. Interestingly, this reduction in leisure is higher for women than for men.

In Table 7, elasticities are presented for a 1% increase of benefits in cash. Overall, the increase leads to higher demand for benefits in cash as it becomes more attractive in relation to benefits in kind. Compared to benefits in kind its share increases by 0.062 PP. Because formal care is thus reduced carers have to increase informal care hours by an average of 0.019%. Again this effect is larger for women than for men and larger in higher care-levels, where a 1% increase results in a larger absolute raise as initial levels are higher. Based on theoretical considerations, one would expect that the increased non-labor income relaxes the budget constraint and consumption possibilities increase. Consequently, the marginal utility of an extra hour of working decreases. The carer thus decreases working hours and uses some of the extra time that becomes available on leisure and some on informal caring. We find negative effects for working hours and labor participation which lead to a 0.093% decrease in working hours and a 0.032 PP reduction in labor participation to back the theory. However, for all of the described effects we estimate large confidence intervals and thus conclude that non of them are statistically significant.

In Table 8, elasticities are presented for a 1% increase of benefits in kind. It can be seen that individuals decrease their supplied informal care hours by an average of 0.045%. The way the model is set up with an exogenous total care time and no other helpers except the formal help provided as benefits in kind, the change in informal care hours can only occur if the share of benefits in cash decreases. Thus, we assume a decrease in benefits in cash, even though this effect cannot be backed up on the 10% level of significance. A fraction of the extra available time resource is used for working (which also compensates for the forgone income from benefits in cash) and working hours increase by 0.041%.

Again, effects are larger for women than for men and larger in higher care-levels. With regard to the care-levels the stronger response probably results from the fact that a 1% increase leads to a higher absolute change of possible formal care services and therefore to a larger impact on the carer's time constraint.

5.3. Simulation

In order to examine a more realistic scenario in which both types of benefits are increased simultaneously, Table 9 shows results for a simulation of a 10% increase of all benefits.

At first sight, the results seem to be puzzling. The attractiveness of the increase in benefits in cash seems to outweigh the increase in benefits in kind in the regard that more households decide to choose the direct financial support over formal help provided by the insurance. On average, the share of benefits in cash increases by 1.24 PP. Consequently, one would expect that informal care hours would increase on average because fewer people choose to use the formally supplied care which has to be substituted by informal care hours

Table 7: Estimated Elasticities of a 1% Increase of Benefits in Cash

	Working Hours (%)	Labor Participation (PP)	Informal Care Hours (%)	Share of Benefits in Cash (PP)
all				
mean	−0.0926	−0.0323	0.0194	0.0622
p5	−0.3154	−0.0916	−0.0013	−0.0174
p95	0.1268	0.0345	0.0402	0.1400
male				
mean	−0.0639	−0.0228	0.0160	0.0498
p5	−0.1602	−0.0421	0.0031	−0.0037
p95	0.0041	−0.0025	0.0287	0.1065
female				
mean	−0.1080	−0.0374	0.0213	0.0689
p5	−0.4886	−0.1382	−0.0068	−0.0296
p95	0.2644	0.0706	0.0487	0.1684
care-level 1				
mean	−0.0401	−0.0169	0.0028	0.0189
p5	−0.0811	−0.0272	−0.0054	−0.0328
p95	−0.0021	−0.0067	0.0124	0.0795
care-level 2				
mean	−0.0910	−0.0304	0.0055	0.0211
p5	−0.7329	−0.2054	−0.0232	−0.0870
p95	0.5359	0.1581	0.0408	0.1516
care-level 3				
mean	−0.2601	−0.0840	0.0961	0.2706
p5	−0.5555	−0.1554	0.0386	0.1103
p95	−0.0134	−0.0122	0.1519	0.4235

Note: Elasticities are calculated using parametric bootstrap with 500 draws. The estimated means and the variance covariance matrix is used to draw new coefficients, that are used for simulation. p5 and p95 indicate the boundaries of the 10% confidence interval.

Source: SOEP, STSM, own calculation

of the household member. Yet, on average, informal care hours decrease by 0.29%. The reason is that formal care hours which can be claimed from the insurance increase. Thus, all people who do not change from benefits in kind to benefits in cash reduce their informal care hours just by staying in that choice category. This effect outweighs the average reduction through changing individuals, and informal care hours decrease on average.

Changes in benefits are larger in the lower carelevels. This is an interesting result as we found a lower elasticity, if only one of the benefits was increased. However, if both benefits are increased simultaneously, carers face a tradeoff between the two benefits. Hence, the result indicates that it is easier to turn away from formal care, if care recipients are in better state of health. An potential reason is that the overall care burden is considerably smaller in lower care-levels.

A look at the response of the labor supply variables *working hours* and *labor participation* supports the view that the incentives given by the different benefits offset each other to a large extend. Yet, a statistically significant reaction can be found for the labor supply of carers in the first carelevel and for caring men. On average they increase their working hours by 0.399% or 0.252%.

Table 8: Estimated Elasticities of a 1% Increase of Benefits in Kind

	Working Hours (%)	Labor Participation (PP)	Informal Care Hours (%)	Share of Benefits in Cash (PP)
all				
mean	0.0410	0.0130	−0.0494	0.0691
p5	0.0130	0.0042	−0.0791	−0.0033
p95	0.0812	0.0234	−0.0244	0.1380
male				
mean	0.0356	0.0112	−0.0411	0.0739
p5	0.0162	0.0051	−0.0677	0.0149
p95	0.0664	0.0171	−0.0184	0.1335
female				
mean	0.0439	0.0140	−0.0539	0.0665
p5	0.0107	0.0039	−0.0893	−0.0203
p95	0.0937	0.0273	−0.0233	0.1436
care-level 1				
mean	−0.0006	−0.0004	−0.0016	0.1401
p5	−0.0047	−0.0020	−0.0201	0.0856
p95	0.0044	0.0017	0.0097	0.1905
care-level 2				
mean	0.0083	0.0016	−0.0195	0.1143
p5	−0.0051	−0.0024	−0.0660	0.0215
p95	0.0328	0.0085	0.0078	0.1862
care-level 3				
mean	0.2292	0.0751	−0.2518	−0.2330
p5	0.0703	0.0254	−0.3555	−0.3987
p95	0.4495	0.1316	−0.1352	−0.0581

Note: Elasticities are calculated using parametric bootstrap with 500 draws. The estimated means and the variance covariance matrix is used to draw new coefficients, that are used for simulation. p5 and p95 indicate the boundaries of the 10% confidence interval.

Source: SOEP, STSM, own calculation

Table 9: Simulation of a 10% Increase of All Benefits

	Working Hours (%)	Labor Participation (PP)	Informal Care Hours (%)	Share of Benefits in Cash (PP)
all				
mean	−0.5076	−0.2047	−0.2878	1.2366
p5	−1.1275	−0.3936	−0.4737	1.0820
p95	0.0088	−0.0256	−0.1084	1.3923
male				
mean	−0.2524	−0.1132	−0.2367	1.1730
p5	−0.5095	−0.2130	−0.4129	1.0176
p95	−0.0403	−0.0181	−0.0741	1.3455
female				
mean	−0.6452	−0.2540	−0.3153	1.2709
p5	−1.4884	−0.4991	−0.5322	1.1012
p95	0.0882	−0.0118	−0.1073	1.4201
care-level 1				
mean	−0.3999	−0.1702	0.0160	1.4789
p5	−0.6263	−0.2686	−0.1083	1.2763
p95	−0.1704	−0.0729	0.0924	1.6212
care-level 2				
mean	−0.8112	−0.3185	−0.1349	1.2602
p5	−1.9366	−0.6452	−0.4350	0.9756
p95	0.2542	0.0009	0.0596	1.5295
care-level 3				
mean	−0.3090	−0.1116	−1.5099	0.4356
p5	−1.6420	−0.4977	−2.2726	−0.1474
p95	0.8046	0.2419	−0.7127	1.0833

Note: Elasticities are calculated using parametric bootstrap with 500 draws. The estimated means and the variance covariance matrix is used to draw new coefficients, that are used for simulation. p5 and p95 indicate the boundaries of the 10% confidence interval.

Source: SOEP, STSM, own calculation

6. Conclusion

Most of the literature on LTC and labor supply focuses on the direct effect of care responsibilities. We add to the literature by taking into account the incentive scheme of the LTCI in Germany. In order to identify how the different benefits affect labor supply and to be able to perform simulations of a potential reform, we set up a structural model in which it is assumed that rational individuals make their decisions on the basis of an individual utility function. Our findings suggest that while each kind of benefit (in kind and cash benefits) seems to have an influence on informal care hours, the effects on labor supply are less clear. Carers seem to increase labor supply if benefits in kind are increased and tend to decrease labor supply if benefits in cash are increased. Yet, the later effect is not significant on the 10% level and a *zero* effect can therefore not be ruled out. Simulations for a 10% increase of all benefits show that the different labor marked effects seem to offset each other and almost no significant effects can be found. Only men and persons who provide care for dependents in the first care-level seem to react to the increased provided formal care and increase their working hours. The finding that male labor supply reacts stronger is interesting as studies by Geyer and Korfhage (2014) and Meng (2013) also find stronger effects for male carers.

Our results indicate that opportunity costs in terms of reduced labor supply of carers due to the LTCI are of minor importance (at least for caring spouses). The considerably more expansive support via benefits in kind has a significantly positive effect on labor supply which can be associated with negative opportunity costs. Thus, their increase has positive effects on tax revenues and social security contributions.

Because to the best of our knowledge, this is the first structural analysis of the effect of the LTCI on carer's labor supply we can only compare results with theoretical considerations. As our sample is rather small and because some of the derivatives of the utility function with respect to key variable only partly fulfill expected algebraic signs, we believe that further research is warranted.

The policy implications depend on the policy goals. If it is the goal to find the most efficient insurance scheme in terms of costs and benefits for LTCI, the implications of our study are not straightforward. Even though benefits in cash seem to be cost saving on first sight, benefits in kind provide incentives to already caring household members to increase labor supply and therefore result in higher public revenue. If it is the goal to strengthen the informal care supply *per se* – e.g. in response to the strong preference within the German population to be cared for by family members in their familiar surroundings – an increase of benefits in cash seems to be the best way to accomplish this goal as they proof to provide incentives for increased informal care hours.

References

Becker, G. S., 1974. A theory of social interactions. *The Journal of Political Economy*, 82(6):1063–1093.

———, 1991. *A Treatise on the Family.* Harvard University Press.

BMG, Bundesminesterium für Gesundheit (German Federal Ministry of Health), 2007. Erster Bericht über die Entwicklung der Pflegeversicherung seit ihrer Einführung am 01. Januar 1995. *Berlin.*

BMG, Bundesminesterium für Gesundheit (German Federal Ministry of Health), 2008. Leistungsempfänger der sozialen Pflegeversicherung am Jahresende nach Pflegestufen. *Berlin.*

Büscher, A., Budroni, H., Hartenstein, A., Holle, B., and Vosseler, B., 2007. Auswirkungen von Vergütungsregelungen in der häuslichen Pflege. *Pflege & Gesellschaft*, 12(4):343–359.

Carmichael, F. and Charles, S., 1998. The labour market costs of community care. *Journal of Health Economics*, 17(6):747–765.

———, 2003. Benefit payments, informal care and female labour supply. *Applied Economics Letters*, 10(7):411–415.

Colombo, F., Llena-Nozal, A., Mercier, J., and Tjadens, F., 2011. *OECD Health Policy Studies Help Wanted?: Providing and Paying for Long-Term Care.* OECD Publishing.

Ettner, S. L., 1995. The impact of "Parent care" on female labor supply decisions. *Demography*, 32(1):63–80.

———, 1996. The opportunity costs of elder care. *The Journal of Human Resources*, 31(1):189–205.

Geyer, J. and Korfhage, T., 2014. Long-term care and the labor supply of household members – A difference-in-differences approach. mimeo.

Götting, U., Haug, K., and Hinrichs, K., 1994. The long road to long-term care insurance in germany. *Journal of Public Policy*, 14:285–285.

Greene, W. H., 2011. *Econometric Analysis, 7/e.* Prentice Hall International.

Haan, P., 2006. Much ado about nothing: Conditional logit vs. random coefficient models for estimating labour supply elasticities. *Applied Economics Letters*, 13(4):251–256.

Heckman, J. J., 1979. Sample selection bias as a specification error. *Econometrica: Journal of the Econometric Society*, 47(1):153–161.

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.

Himes, C. L., Schneider, U., and Wolf, D. A., 2001. The dynamics of long-term care service use in germany. *Vierteljahrshefte zur Wirtschaftsforschung*, 70(1):153–158.

Himes, C. L., Wagner, G. G., Wolf, D. A., Aykan, H., and Dougherty, D. D., 2000. Nursing home entry in germany and the united states. *Journal of Cross-cultural Gerontology*, 15(2):99–118.

Hole, A. R., 2007. Estimating mixed logit models using maximum simulated likelihood. *Stata Journal*, 7(3):388–401.

Institut für Demoskopie Allensbach, 2010. Monitor Familienleben. Einstellungen und Lebensverhältnisse von Familien Ergebnisse einer Repräsentativbefragung – Berichtsband. Technical report.

Johnson, R. W. and Lo Sasso, A. T., 2000. The trade-off between hours of paid employment and time assistance to elderly parents at midlife. *Discussion Paper, The Urban Institute*, pages 1–40.

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. *Milbank Quarterly*, 85(4):641–690.

McFadden, D., 1974. Conditional logit analysis of qualitative choice behavior. *Frontiers in Econometrics. ed. by P. Zarembka, Academic Press.*

Meng, A., 2012. Informal caregiving and the retirement decision. *German Economic Review*, 13(3):307–330.

———, 2013. Informal home care and labor-force participation of household members. *Empirical Economics*, 44(2):959–979.

Pfaff, H., 2013. Pflegestatistik 2011, Pflege im Rahmen der Pflegeversicherung, Deutschlandergebnisse. *Statistisches Bundesamt. Wiesbaden.*

Pfaff, H. and Rottländer, R., 2005. Pflegestatistik 2003, Pflege im Rahmen der Pflegeversicherung, Deutschlandergebnisse. *Statistisches Bundesamt. Wiesbaden.*

Revelt, D. and Train, K., 2000. Customer-specific taste parameters and mixed logit: Households' choice of electricity supplier. *Discussion Paper, Department of Economics, UCB.*

Schneekloth, U. and Schmidt, M., 2011. Abschlussbericht zur Studie "Wirkungen des Pflege-Weiterentwicklungsgesetzes". Technical report, Bundesministerium für Gesundheit.

Schneekloth, U. and Wahl, H. W., 2005. Möglichkeiten und Grenzen selbständiger Lebensführung in privaten Haushalten (MUG III). *Repräsentativbefunde und Vertiefungsstudien zu häuslichen Pflegearrangements, Demenz und professionellen Versorgungsangeboten.*

Integrierter Abschlussbericht im Auftrag des Bundesministeriums für Familie, Senioren, Frauen und Jugend.

Schneider, T., Drobnic, S., and Blossfeld, H.-P., 2001. Pflegebedürftige Personen im Haushalt und das Erwerbsverhalten verheirateter Frauen. *Zeitschrift für Soziologie*, 30(5):362–383.

Schulz, E., 2010. The long-term care system in germany. Discussion Papers of DIW Berlin 1039, DIW Berlin, German Institute for Economic Research.

Schupp, J. and Künemund, H., 2004. Private Versorgung und Betreuung von Pflegebedürftigen in Deutschland. *DIW Wochenbericht*, 71(20):289–294.

Spiess, C. K. and Schneider, A. U., 2003. Interactions between care-giving and paid work hours among european midlife women, 1994 to 1996. *Ageing and Society*, 23(1):41–68.

Steiner, V. and Wrohlich, K., 2004. Household taxation, income splitting and labor supply incentives–a microsimulation study for germany. *CESifo Economic Studies*, 50(3):541–568.

Steiner, V., Wrohlich, K., Haan, P., and Geyer, J., 2012. Documentation of the tax-benefit microsimulation model stsm: Version 2012. *Data Documentation, German Institute for Economic Research, DIW Berlin*, 63.

Stern, S., 1995. Estimating family long-term care decisions in the presence of endogenous child characteristics. *Journal of Human Resources*, pages 551–580.

Train, K., 1999. Halton sequences for mixed logit. *Discussion Paper, Department of Economics, UCB.*

———, 2009. *Discrete choice methods with simulation, 2/e.* Cambridge University Press.

Van Soest, A., 1995. Structural models of family labor supply: a discrete choice approach. *Journal of human Resources*, pages 63–88.

Verbeek, M., 2012. *A guide to modern econometrics, 4/e.* John Wiley & Sons.

Viitanen, T., 2005. Informal elderly care and women's labour force participation across europe. *ENEPRI Research Reports*, 13.

Wagner, G., Frick, J., and Schupp, J., 2007. The german socio-economic panel study (soep)-evolution, scope and enhancements. *Schmoller Jahrbuch*, 127(1):139–170.

Wolf, D. A. and Soldo, B. J., 1994. Married women's allocation of time to employment and care of elderly parents. *Journal of Human Resources*, pages 1259–1276.

Wrohlich, K., 2011. Labor supply and child care choices in a rationed child care market. *Discussion Papers, German Institute for Economic Research, DIW Berlin*, 1169.

A. LTCI in Germany: A short Overview

After 20 years of political discussion, in April 1994, the German *Bundestag* passed a law to extend the existing social system by a compulsory LTCI. Beforehand, individuals had to afford most of their care expenses themselves or depend on family members to support them. Although social assistance schemes provided financial help as a last resort (*Hilfe zur Pflege*), to be eligible for receiving benefits individuals first had to exhaust all their private assets and income resources. Furthermore, close family members were supposed to give financial support, before the social assistance would ship in. Private care insurance had been available since the mid-1980s, but it only played a minor role and failed to reach the majority of the population (Götting et al., 1994, p. 289).

Without regard to age or financial status, home care and nursing home care for people with medically approved needs is provided by the new insurance system. Thereby, the amount of benefits a person is eligible of depends on the disability level and whether care is provided formally or informally. Degrees of need are graduated in three care levels that depend on the amount of help a person needs for his or her daily activities. Once eligible for benefits, individuals can choose between support given for stationary care or home based care. If they decide for home based care, benefits in cash or in kind can be received. Cash is paid to the household and can be used to support family members or other suppliers of informal care. Depending on the care level, the amount that was initially paid to households in 1995 varied between €205 and €665 per month[13] (BMG, 2007, p. 17). Benefits in kind consist of formal care. They are disbursed directly to formal services and initially ranged from €384 up to €1,432 per month (BMG, 2007, p. 16f). Moreover, individuals are allowed to combine the two kinds of benefits. For instance, they can choose to take 50% of benefits in kind and will additionally receive 50% of the amount in cash they are eligible of.

The long-term care expanses are financed by income-related contributions that are split equally between employees and employers. In 1995, the initial contribution rate was at 1%.[14]

The reform was progressively introduced in two steps. First, in January 1995 benefits for home care paid in cash were available, while benefits in kind followed in July 1995. Second, in July 1996, support for nursing come care was added to the existing insurance system (BMG, 2007, p. 9). By the end of 1996, about 1.16 million people received benefits for home care, while about 385,000 received support for nursing home care (BMG, 2008). Thereby, about 69% of all benefits paid for home based care is provided in cash (Pfaff and Rottländer, 2005). That is, even though benefits are considerably smaller in monetary values, not only a strong preference for home based care can be observed but also for care that is formally provided by family members.

[13] Benefits were increased for the first time in 2008 and again in 2010.

[14] To finance further benefits, the contribution rate was raised to 1.7% in 1996 and to 1.95% in 1998.

B. Conditional and Mixed Logit-Model

C. Estimation of Potential Wages

To estimate wages of non-working individuals, one has to account for a sample selection bias because some individuals might be more likely to be part of the labor force than others are. To see how this can result in a biased wage estimate, consider the case were the influence of some variable lowers someone's wage to an extent that she decides to stop working. Her wage is then no longer observable and the effect of this variable is underestimated if sample selection is not controlled for (Verbeek, 2012, p. 228). we use the two step-procedure that is suggested by Heckman (1979).

Consider a linear equation to describe the potential wage (in logs) of person i:[15]

$$\log(w_i^*) = x_{1i}'\beta_1 + \varepsilon_{1i}, \tag{24}$$

where w_i^* is the potential wage that can only be observed for people who are actually working. x_{1i}' is a vector of characteristics and β_1 is to be estimated. Whether a person is working or not is described by the following equation:

$$h_i = x_{2i}'\beta_2 + \varepsilon_{2i}, \tag{25}$$

where h_i is a binary outcome variable that equals *one* if a person is working and *zero* otherwise. x_{2i}' includes characteristics that determine working decisions. If $h_i = 1$ the potential wage w_i^* equals the observable wage w_i and if $h_i = 0$ the potential wage cannot be observed.

Heckman (1979) showed that if the unobserved error terms $(\varepsilon_{1i}, \varepsilon_{2i})$ follow a bivariate normal distribution, wages can consistently be estimated in a two step-procedure. First, Equation (25) is estimated as a standard probit model. Second, the results are used to calculate a scaling factor (mills lambda λ_i) that is included in the wage estimation to account for sample selection.

$$\log(w_i) = x_{1i}'\beta_1 + \sigma_{12}\lambda_i + \eta_i, \tag{26}$$

$$\text{where} \qquad \lambda_i = \frac{\phi(x_{2i}'\beta_2)}{\Phi(x_{2i}'\beta_2)}$$

Thereby, σ_{12} is the covariance between the error terms $(\varepsilon_{1i}, \varepsilon_{2i})$ that accounts for the possibility that working decisions might be influenced by the offered wage rate. $\phi(\cdot)$ and $\Phi(\cdot)$ are the density as well as the cumulative distribution functions of the standard normal distribution. Its values are estimated in the first step probit model. The error term in this model equals $\eta_i = \varepsilon_{1i} - E(\varepsilon_{1i}|x_i, h_i = 1)$ and is uncorrelated with x_{1i} and λ_i by construction. $\hat{w}_i$ is the estimated wage that is conditional on working.

[15] For the description of the wage estimation we heavily draw from Verbeek (2012, ch. 7.5).

For estimation, common independent variables are used that are described by Steiner et al. (2012). Note, however, that unlike Steiner et al. (2012) we include a dummy that indicates if at least one household member is in need for long-term care into the wage equation as well as into the selection equation. The reason is that caring responsibilities might not only influence working decisions but could also limit the job opportunities available to carers by constraining the hours they are able to work (e.g. only at times somebody else can take over caring duties). Therefore, caring individuals might have a weaker bargaining position or less jobs to choose from and might thus earn lower wages (Heitmueller, 2007, p. 538).

Estimation is based on pooled SOEP-data from the years 1999 until 2010 and is performed separately for women and men as well as for East- and West-Germany. Results are presented in Tables 10 and 11. It can be seen that σ_{12} is statistically significant in all models, indicating that sample selection does have an influence on the estimated wages.

D. Tables

Table 10: Wage Estimation for West-Germany

	Females		Males	
Wage Equation				
Household Member in need for Care	−0.011	(0.021)	−0.045**	(0.016)
Age	0.028**	(0.002)	0.011**	(0.002)
Age^2	−0.000**	(0.000)	−0.000	(0.000)
Years of Full Time Work	0.013**	(0.002)		
Years of Full Time Work^2	−0.010	(0.007)		
Years of Part Time Work	0.008*	(0.003)		
Years of Part Time Work^2	−0.020	(0.014)		
Tenure	0.023**	(0.003)	0.020**	(0.002)
Tenure^2	−0.051**	(0.009)	−0.037**	(0.006)
Loss of human capital	−0.009	(0.006)	−0.064**	(0.009)
Degree of Disability	0.002**	(0.001)	0.000	(0.000)
Degree of Disability^2	−0.003**	(0.001)	−0.001†	(0.001)
Years of Education × German	0.011**	(0.001)	0.008**	(0.001)
Years of Full Time Work × German	−0.001	(0.002)		
Years of Full Time Work^2 × German	−0.008	(0.007)		
Years of Part Time Work × German	−0.008*	(0.003)		
Years of Part Time Work^2 × German	0.023	(0.014)		
Tenure × German	−0.010**	(0.003)	−0.009**	(0.002)
Tenure^2 × German	0.036**	(0.009)	0.025**	(0.006)
Loss of human capital × German	−0.022**	(0.007)	−0.077**	(0.009)
Years of Work			0.017**	(0.002)
Years of Work^2			−0.051**	(0.004)
Years of Work × German			−0.003†	(0.002)
Years of Work^2 × German			0.008*	(0.004)
Selection Equation				
Household Member in need for Care	−0.286**	(0.057)	−0.201**	(0.074)
Age	0.055**	(0.005)	0.131**	(0.008)
Age^2	−0.002**	(0.000)	−0.002**	(0.000)
Years of Full Time Work	0.079**	(0.002)		
Years of Full Time Work^2	−0.003	(0.007)		
Years of Part Time Work	0.217**	(0.003)		
Years of Part Time Work^2	−0.467**	(0.012)		
Degree of Disability	0.002	(0.002)	−0.005**	(0.002)
Degree of Disability^2	−0.006**	(0.002)	0.002	(0.002)
Health: Very good (base)				
Health: Good	0.015	(0.023)	−0.002	(0.032)
Health: Satisfactory	−0.051*	(0.024)	−0.185**	(0.033)
Health: Poor	−0.180**	(0.029)	−0.571**	(0.038)
Health: Bad	−0.678**	(0.051)	−1.135**	(0.056)
Married	−0.219**	(0.017)	0.330**	(0.022)
Children in HH = 0 (base)				
Children in HH = 1	−1.714**	(0.029)	−0.110*	(0.046)
Children in HH = 2	−1.124**	(0.028)	−0.113*	(0.047)
Children in HH = 3	−0.668**	(0.018)	−0.129**	(0.025)
Children in HH ≥ 4	−0.256**	(0.025)	−0.103**	(0.032)
Other Income	−0.000**	(0.000)	−0.000**	(0.000)
German	0.224**	(0.021)	0.483**	(0.026)
Years of Work			0.040**	(0.004)
Years of Work^2			0.063**	(0.009)
mills lambda	0.067**	(0.010)	−0.110**	(0.012)
Observations	58305		49788	

Note: Values denote coefficients, standard errors are stated in parenthesis. Wages are gross hourly wages measured in logs. Loss of human capital is a weighted measure of years of unemployment capturing depreciation of human capital. Estimation is based on pooled data for the period 1999-2010. Time and region specific (Bundesland) dummies as well as dummies for occupation, industry sector and firms size and a constant term have been included in the estimation.

Source: SOEP, own calculation

Table 11: Wage Estimation for East-Germany

	Females		Males	
Wage Equation				
Household Member in need for Care	-0.123^{**}	(0.038)	0.038	(0.031)
Age	0.042^{**}	(0.003)	0.015^{**}	(0.004)
Age^2	-0.001^{**}	(0.000)	-0.000	(0.000)
Years of Full Time Work	0.001	(0.002)		
Years of Full Time Work^2	0.006	(0.004)		
Years of Part Time Work	0.006^{*}	(0.002)		
Years of Part Time Work^2	-0.010	(0.008)		
Tenure	0.020^{**}	(0.001)	0.009^{**}	(0.001)
Tenure^2	-0.031^{**}	(0.004)	-0.013^{**}	(0.003)
Loss of human capital	-0.078^{**}	(0.006)	-0.171^{**}	(0.007)
Degree of Disability	-0.001	(0.001)	0.000	(0.001)
Degree of Disability^2	0.001	(0.001)	-0.000	(0.001)
Years of Work			0.011^{**}	(0.002)
Years of Work^2			-0.036^{**}	(0.005)
Selection Equation				
Household Member in need for Care	-0.351^{**}	(0.102)	-0.251^{*}	(0.100)
Age	0.060^{**}	(0.010)	0.126^{**}	(0.013)
Age^2	-0.002^{**}	(0.000)	-0.003^{**}	(0.000)
Years of Full Time Work	0.097^{**}	(0.005)		
Years of Full Time Work^2	0.028^{*}	(0.012)		
Years of Part Time Work	0.181^{**}	(0.006)		
Years of Part Time Work^2	-0.235^{**}	(0.029)		
Degree of Disability	-0.001	(0.003)	-0.018^{**}	(0.003)
Degree of Disability^2	0.006	(0.004)	0.026^{**}	(0.004)
Health: Very good (base)				
Health: Good	0.023	(0.044)	$0.088^{\dagger}$	(0.048)
Health: Satisfactory	-0.129^{**}	(0.046)	-0.035	(0.051)
Health: Poor	-0.365^{**}	(0.054)	-0.418^{**}	(0.061)
Health: Bad	-0.738^{**}	(0.089)	-0.843^{**}	(0.092)
Married	0.193^{**}	(0.027)	0.547^{**}	(0.030)
Children in HH = 0 (base)				
Children in HH = 1	-1.279^{**}	(0.049)	-0.129^{*}	(0.062)
Children in HH = 2	-0.584^{**}	(0.053)	0.037	(0.070)
Children in HH = 3	-0.311^{**}	(0.034)	-0.094^{*}	(0.037)
Children in HH ≥ 4	-0.185^{**}	(0.043)	$-0.082^{\dagger}$	(0.048)
Other Income	-0.000^{**}	(0.000)	-0.000^{**}	(0.000)
Years of Work			0.056^{**}	(0.007)
Years of Work^2			0.130^{**}	(0.016)
mills lambda	0.069^{**}	(0.022)	-0.073^{**}	(0.021)
Observations	18711		17077	

Note: Values denote coefficients, standard errors are stated in parenthesis. Wages are gross hourly wages measured in logs. Loss of human capital is a weighted measure of years of unemployment capturing depreciation of human capital. Estimation is based on pooled data for the period 1999-2010. Time and region specific (Bundesland) dummies as well as dummies for occupation, industry sector and firms size and a constant term have been included in the estimation.

Source: SOEP, own calculation

Table 12: Weekly Net Household Income, STSM Simulation Results

	Base Simulation		1% wage increase	
	Mean	St.Dev	Mean	St.Dev
no work & in cash	448.9	179.2	448.9	179.2
no work & in kind	412.4	225.9	412.4	225.9
part time & in cash	646.4	234.8	647.7	235.1
part time & in kind	398.9	150.8	399.8	150.5
full time & in cash	799.6	180.6	803.0	181.2
full time & in kind	909.1	605.9	911.8	605.8

Note: All amounts are given as weekly amounts.
Source: SOEP, STSM, own calculation.