CPB Netherlands Bureau for Economic Policy Analysis

The welfare effects of co-payments in long term care

We use a non-parametric nearest-neighbor approach to estimate lifecycle paths of long term care spending for the Dutch older population. The estimated paths are used as inputs in a stochastic lifecycle decision model for singles at the retirement age. With the model, we evaluate the effects of the Dutch income- and wealth-dependent co-payment system. We compare the current system to a co-payment that only depends on income and a flat-rate co-payment, independent of financial means.

The Dutch system offers substantial protection against high costs for middle income groups, compared to a flat-rate co-payment. Only the group with the highest financial means would benefit from the introduction of a flat-rate co-payment.

CPB Discussion Paper

Bram Wouterse, Arjen Hussem, Albert Wong

April 2019

The welfare effects of co-payments in long term care.*

Bram Wouterse †[1,2,5], Arjen Hussem[1,3,5], and Albert Wong[4,5]

[1] *CPB Netherlands Bureau for Economic Policy Analysis, The Hague, The Netherlands*
[2] *Erasmus School of Health Policy & Management, Erasmus University Rotterdam, Rotterdam, The Netherlands*
[3] *PGGM, Zeist, The Netherlands*
[4] *National Institute for Public Health and the Environment, Bilthoven, The Netherlands*
[5] *Network for Studies on Pensions, Ageing and Retirement, Tilburg, The Netherlands*

Abstract

Insight in the lifecycle dynamics of long term care costs is important to understand the effect of policy changes, such as the design of co-payments, on the costs and welfare across income and wealth groups. Modeling long term care expenditures over the lifecycle is challenging because of their very uneven distribution.

We use a flexible non-parametric nearest-neighbor approach to estimate lifecycle paths of long term care spending. We apply this approach to an extensive administrative data set for the entire Dutch elderly population. The estimated paths are used as inputs in a stochastic lifecycle decision model for singles at the retirement age.

We use the model to analyze the Dutch co-payment system. In this system, co-payments are income- and wealth-dependent. To analyze the effects on the distribution of LTC payments and welfare across income and wealth groups, we

*We thank Neha Bairoliya, Casper van Ewijk, Max Groneck, Rosella Levaggi, Jakob Everding, Joost Wammes, and Rob Aalbers for comments on earlier versions of the paper. We also thank the participants of the Netspar Pension Day, the Netspar Pension Workshop, ASHEcon, EUHEA, the Italian Health Econometrics Workshop and the European Workshop on Health Econometrics.

†Corresponding author. E-mail: wouterse@eshpm.eur.nl

perform two counter-factual analyses. We replace the current system by either a co-payment that only depends on income, or a flat-rate co-payment, independent of financial means.

We find that the low and middle income and wealth groups use substantially more long term care over their life than the high income and wealth groups. The Dutch system of income- and wealth-dependent co-payments offers substantial protection against high costs for these groups, especially compared to a flat-rate co-payment. The middle groups benefit the most from the current system: as they do not qualify for income support, a flat-rate co-payment system would mainly burden them. Only the group with the highest financial means would benefit from the introduction of a flat-rate co-payment. The main findings are robust to a number of sensitivity tests, such as excluding a bequest motive and including health-state dependent utility.

1 Introduction

Knowledge of the lifetime distribution of Long Term Care (LTC) costs is important. Confronted with an aging population, policy makers are seeking to provide adequate care for the elderly, while at the same time keep the system financially sustainable (Colombo and Mercier, 2012). For countries with an extensive social LTC insurance, such as the Netherlands, this might entail changes in the amount and design of co-payments. These do not only affect the distribution of *average* payments across income and wealth groups, but also the risk (of very high costs) these groups face.

In this paper, we focus on two issues that are relevant for the analysis of LTC financing reforms. First, we aim to improve the analysis of the lifecycle dynamics in LTC use by applying a very flexible, non-parametric, estimation method. Second, we use the estimated lifecycle paths in a lifecycle decision model that allows us to go beyond a descriptive analysis of average costs, and include the effects of co-payments on the financial risk faced by different groups. We use our approach to assess how the Dutch co-payment system, that depends on income and wealth, affects the welfare of the elderly across income and wealth groups.

The modeling of the lifecycle distribution of LTC costs is a first important issue. Generally, complete data on an individual's LTC costs over the whole lifecycle is not available. Lifecycle dynamics thus have to be modeled using (short) panel data for different individuals. As the distribution of lifetime LTC costs is skewed and exhibits extensive heterogeneity, this can be difficult to do using parametric approaches. Existing parametric approaches use autoregressive models (De Nardi et al., 2010; French and Jones, 2004) or Markov models (Ameriks et al., 2011; Jones et al., 2018) to estimate time dynamics in LTC costs. However, these models require a variety of assumptions that cannot be justified on the basis of the data alone (Wong et al., 2016).

Non-parametric estimation of LTC costs might be a more suitable alternative. A recent study by Hurd et al. (2017) for out-of-pocket LTC spending in the U.S. shows the relevance of such an approach. They compare their non-parametric method, based on matching, to a more standard parametric Markov model. They find that "the risk (the chances of extreme use or costs) as estimated non parametrically is substantially greater than the risk as estimated by the parametric model". The need for non- or semi-paremetric approaches to model rich lifecycle dynamics is not limited to LTC expenditures. De Nardi et al. (2018) and Arellano et al. (2017) have for instance applied a non-parametric approach to model dynamics in earnings.

A second important issue is using the lifecycle estimates to quantify the welfare effects of different policy alternatives, including the effects on risk and (saving) behavior. Protection against financial risk is an important part of the value of public health insurance, especially for low income groups (McClellan and Skinner, 2006). The insurance value of public health insurance is specifically important in LTC, where buying insurance on the private market is difficult or not possible at all (Brown and Finkelstein, 2007). The inclusion of (saving) behavior is needed because the elderly are able to partly self-insure against high co-payments through precautionary savings. A large number of studies, mainly for the U.S., find that out-of-pocket payments for LTC indeed induce precautionary savings, and can (partly) explain why the elderly not fully annuitize their pension wealth (De Nardi et al., 2010; Ameriks et al., 2011; Peijnenburg et al., 2017; Kopecky and Koreshkova, 2014).

To quantify these behavioral effects and perform evaluations of different policies, a descriptive analysis does not suffice. Instead a structural lifecycle decision model can be used. See, for instance, the recent lifecycle studies on the (value of) income transfers and insurance in Medicare (Khwaja, 2010) and Medicaid (De Nardi et al., 2016) for the U.S. The desire to use the lifecycle data in a structural model creates an additional challenge for the empirical estimation. The empirical model should be sophisticated enough to capture the complex dynamics in health, while at the same time parsimonious enough so that its use in a structural lifecycle model is computationally manageable (De Nardi et al., 2017).

The first contribution of this paper is the way we estimate the dynamics in LTC over the lifecycle. We use a, non-parametric, nearest neighbor algorithm (Wong et al., 2016; Hussem et al., 2016) to estimate the lifetime distribution of LTC costs in the Netherlands. The main advantages of our approach are its flexibility and the ability to use it on short periods of panel data. It enables the modeling of the complex dynamics in LTC costs, together with dynamics in income, wealth, and other relevant variables. We apply the nearest neighbor algorithm to estimate 20,000 synthetic lifecycle paths using a rich administrative dataset that includes information on LTC spending, household status, income, and wealth for the whole single Dutch elderly population starting at the age of 70.

The second contribution is that we demonstrate how to use the lifecycle data in the analysis of policy measures. Our estimated lifecycle paths can be seen as draws from a stochastic process. We use them as input in a stochastic lifecycle decision model for singles at the retirement age. This model determines optimal consumption and saving behavior of elderly for different levels of initial wealth and pensions at retirement, taking into account the distribution of LTC costs and mortality. We use a simulation based algorithm developed by Koijen et al. (2010), which allows us to include the dynamics from the lifecycle paths and still solve the model in a computationally tractable way.

We apply the lifecycle model to the case of the Dutch co-payment system. In this system, the maximum amount of annual co-payments depends on an individual's income and wealth. This is different from means-testing or flat-rate co-payment systems that are used in most countries. Even compared to means-based co-payment systems in other countries (see Colombo and Mercier (2012) for an overview), the Dutch system enables quite specific fine-tuning of the financial impact of co-payments across income and wealth groups. To assess the impact of the income- and wealth- dependency of co-payments on payments, risk, and savings across income and wealth groups, we compare the current system to two alternatives: a flat-rate co-payment, independent of an individual's financial means, and a co-payment that depends on income but not on financial wealth.

We find that elderly with low income and wealth use substantially more LTC than elderly with high income and wealth. As a result, compared to the current system, the two alternative co-payment systems shift *average* payments from the higher to the lower income and wealth groups. We also find that the welfare losses, due to additional risk, for the low and especially middle groups, are much more substantial than suggested by the change in average payments alone. We conclude that, compared to alternative co-payment systems, the Dutch system protects the low and middle income and wealth groups well against the risk of high LTC costs.

This paper is organized as follows. In Section 2, we describe the Dutch LTC system and the role of co-payments. In Section 3, we discuss the application of the nearest neighbor algorithm on Dutch LTC data, and we describe the estimated lifecycle paths. In Section 4, we introduce a lifecycle model for consumption and saving of retirees in case of LTC co-payments. We also explain the numerical approach that allows us to use the estimate lifecycle paths in this model. In Section 5 we show our results, and in Section 6 we discuss the implications of our findings and the main limitations of our approach. Section 7 concludes.

2 The Dutch Long Term Care system

The Netherlands has one of the most extensive collective LTC arrangements in the world (Colombo and Mercier, 2012). In the period we investigate (before 2015), a social insurance, called the exceptional medical expenses act (AWBZ), covered a broad range of home care services (social support, personal care, nursing) and institutional care (nursing homes and residential care). The income-dependent premium for the AWBZ was collected through the income tax including pension income in the first and second income brackets.

Users of long term care pay a co-payment. This co-payment functions as a means-dependent deductible: users pay the full costs of LTC, up to a maximum amount. This maximum amount depends on the financial means of the individual, and differs according to the type of care (home care or institutional care) and living situation. The financial means are defined as net income and a fixed percentage of financial wealth, not including wealth of the house someone lives in. In 2013, the share of wealth included in the measure of financial means was increased from 4 to 12 percent. Co-payments for home care are lower than for institutional care: for home care, users pay a maximum amount that equals 15 percent of their means, while users of institutional care have to contribute up to 75 percent of their means. The details of the co-payment system are explained in Section 4.3.

In 2015, the long term care system has been reformed. Nursing home care is still covered by a national social insurance (called WLZ), but the provision of home care is now mainly the responsibility of municipalities. They receive a financial contribution out of the national government's budget. Although there are now differences in the level of co-payments for home care across municipalities, the financing of long term care has remained fairly stable: it is still largely based on income-dependent premiums or taxes, and users of care, in general, still pay a contribution with a maximum based on income and financial wealth.[1]

3 Long term care spending over the lifecycle

3.1 Source data

We use administrative data on LTC use from the Dutch Central Administrative Office (CAK). These data cover the period 2008-2013. The data include information on all publicly financed formal LTC use in the Netherlands. The data contain information on the type of care (institutional care, nursing home care, personal home care, and support) and the amount of care used (in days for institutional care, and in hours for home care). We derive costs of LTC from use in hours/days in the CAK database and the tariffs provided by the Dutch Health Authority (NZA) for extramural care and derived from the CAK and Dutch Health Care Institute (CVZ) annual reports for intramural care. We do not have information on use of privately financed LTC, which seems to be limited in the Netherlands (Van Ooijen et al., 2018) due to the extensive public system.

The LTC data is linked to other datasets using a unique personal identification number. The Dutch Municipal Register provides basic information on everyone enlisted in a Dutch municipality. From this register, we obtain date of death, age, sex and marital status. We use data from the tax services to obtain gross income, net financial wealth, and net housing wealth.[2]

We select individuals who are alive at least up to January 1 2013, who are 67 or

[1] As of January 2019, the income- and wealth-dependent co-payments for home care have been replaced by fixed monthly rate.

[2] Under certain conditions, these microdata are accessible for statistical and scientific research. For further information: microdata@cbs.nl.

older in 2013, and who are single over the whole observation period. We impose these restrictions to keep the lifecycle model, that we will apply later, tractable. We purge the data from period effects (see Appendix A for the details).

3.2 The nearest neighbor algorithm

We estimate lifecycle paths of LTC use with a nearest neighbor resampling (NNR) algorithm. Some of the first implementations of NNR in a time series or panel context are by Farmer and Sidorowich (1987) and Hsieh (1991). We extend the approach developed by Wong et al. (2016) who have implemented a NNR algorithm to estimate lifecycle paths of curative care costs.

The NNR algorithm allows us to simulate N individual lifecycle realizations of LTC spending. Each simulated lifecycle will consist of an age series $Z_i = \{Z^i_{a=67}, Z^i_{a=68}, ..., Z^i_{a=A_i}\}$. Z^i_a is a vector containing LTC spending and other variables of interest (e.g. income, wealth) of individual i at age a. $a = 0$ denotes the starting age and A_i is the age of death. Our data is a set of relatively short panels containing observed values of the variables of interest $Y^j_{a,t}$ for individuals $j = 1, .., J$ over time periods $t = 1, .., T$.

The algorithm has a Markovian nature and can be described as follows. Suppose we already have a simulated lifecycle path for an individual up to age a : $Z^i = \{Z^i_0, Z^i_1, .., Z^i_a\}$. To extend this lifecycle path to age $a + 1$ we consider all individuals in our data who have age $a + 1$ in period T. We pick an individual whose life history over the last p age years $Y^j = \{Y^j_{a-p+1,T-p}, ..., Y^j_{a,T-1}\}$ is similar to $\{Z^i_{a-p+1}, ..., Z^i_a\}$; a so-called nearest neighbor. Note that, because we want to extend the lifecycle by one period, and the time length of the panel is T, we can use a maximum age lag p of $T - 1$ years.[3] When we have picked an individual j, we use $Y^J_{a+1,T}$ as our simulated realization of Z^i_{a+1}. Then, to obtain a realization for age $a + 2$ we can repeat the procedure using all individuals in the data with age $a + 2$ at time T, matching on the life history over ages $a - p + 2$ to $a + 1$. This procedure is repeated until i is matched to an individual who dies in period T; this also marks the end of the lifecycle of i.

Our lifecycles start at age $a = 67$. To initialize the algorithm, we sample from all individuals with age $a = 67$ at time T. For these individuals we have data on Y over $p - 1$ ages before the starting age $a = 67$. We include the information on the last $p - 1$ ages in the simulated lifecycle path to make simulation of the next age year ($a = 68$) possible, so we start with $Z^i = \{Z^i_{67-p+1}, ..., Z^i_{67}\}$.

In our case, the vector Z^i_a contains the numeric variables income, financial wealth, conditional housing wealth, and conditional LTC expenditures. To further distinguish between individuals that have housing wealth, home care costs or nursing home care respectively and individuals that do not, we include a categorical variable for each of them. For housing wealth and home care costs these are coded as indicator variables

[3] The time periods $t = 1, .., T$ and the number of lags p will generally depend on the data at hand. When the available panel data is long enough, the number of lags can be determined by comparing model performance across different choices of p. In our case $T = 5$ and $p \in \{1, 2\}$.

(1 if $>$ than zero; 0 otherwise). For nursing home care we define three categories (0 if zero costs, 2 if costs are associated with a stay in a nursing home during the entire year and are therefore at maximum, and 1 otherwise).

To find an observation from the data that is similar to a simulated lifecycle path we use a two-step matching process. In the first step, we use exact matching on the categorical variables. This implies selecting those observations of $Y = \{Y^1, ..., Y^J\}$ that fall into the same categories as those for the simulated lifecycle. In the second step, we use k-nearest neighbor matching on the selected observations. We measure the distance between two p-long blocks $\mathbf{Z^i}$ and $\mathbf{Y^j}$ using a Mahalanobis distance measure $d(\mathbf{Z^i}, \mathbf{Y^j})$. This distance corrects for the correlation between the observations of $Y = \{Y^1, ..., Y^J\}$ and differences in scale between variables, and is defined as

$$d(\mathbf{Z^i}, \mathbf{Y^j}) = \sqrt{(\mathbf{Y^j} - \mathbf{Z^i})^T \Sigma^{-1} (\mathbf{Y^j} - \mathbf{Z^i})}, \tag{1}$$

where Σ is an estimate of the covariance matrix of Y. Because the Mahalanobis distance works best with multivariate normal distributed data, and our numerical variables are all strongly right skewed, we first take the log-transform of the numerical variables prior to computing the measure. After computing the measure, we take the k nearest neighbors that have the smallest distance, and randomly draw one of them. [4]

The lifecycles are simulated separately by gender. We simulate 10,000 paths for women and 10,000 for men.

3.3 Parameter setting and assessment of fit

To choose the number of neighbors k and the number of lags p used in the algorithm, we perform an assessment study where we compare the model fit across different parameter settings (similar to Wong et al. (2016)). For a group of individuals with gender g and age a in 2009, we simulate the next four years of the life cycles (2010,..., 2013). The first observations of the lifecycles are obtained by drawing randomly from all the individuals with gender g and age a in 2009. The lifecycles are then extended using the nearest neighbor algorithm. However, we make one modification that is particular to this assessment study. After each time a lifecycle is extended one age year with an observation, we exclude that observation from any future pool of neighbors for that particular lifecycle. This ensures that we never use an observation from the data more than once in a simulated lifecycle, which is more in line with an actual application of the nearest neighbor algorithm. Because the simulated life cycles generated for the assessment fall within the period covered by the data, we can assess the fit of the algorithm by comparing the distribution of the simulated data to the actual data.[5] We

[4] In some cases it is not possible to find k nearest neighbors, if there are too few observations left after matching on the categorical variables. In that case, we relax the exact matching on categorical variables by allowing for observations that come from similar but not identical categories (e.g. observations from the stratum 0 for housing wealth / 1 for home care / 1 for nursing home care, when the stratum requested is 0 / 1/ 2). This scarcity rarely occurs, however.

[5] This also means that we do not need to remove period effects from the data for this exercise.

use the Anderson-Darling statistic (Pettitt, 1976) to assess the similarity between the two distributions (see Appendix B). Lower statistic values imply a higher degree of similarity.

Many outcomes are available to compare to the actual data: financial wealth, housing wealth, income, home care costs, and nursing home costs, for each age and gender. In practice, there is not one setting that performs the best across all these outcomes. We aim to choose a setting that performs reasonably well across all outcomes. We therefore perform the assessment study for men and women at three different initial ages (67, 75, 85). Table 1 shows the average and median values of the Anderson-Darling statistic over all outcomes and all these age- and gender-groups. Based on this, we choose the setting with 10 neighbors ($k = 10$) and 1 lag for both the categorical and continuous variables ($p = 1$). The appendix shows some additional statistics on the model fit, that confirm that this setting performs well across all outcomes. Based on this assessment, we conclude that the algorithm provides a sufficiently credible reproduction of real life cycles of health care costs, income and wealth to study the effects of co-payments for LTC.

Table 1: Fit of the NN-algorithm: average and median Anderson-Darling statistic across outcomes for each specification.

k	p cat.	p cont.	av. A-D	med. A-D
1	1	1	1.14	0.74
2	1	1	1	0.69
3	1	1	1.06	0.81
4	1	1	0.95	0.7
5	1	1	1.07	0.75
10	1	1	0.95	0.68
20	1	1	0.97	0.67
1	2	2	5.24	3.94
2	2	2	4.74	3.8
3	2	2	4.51	4.02
4	2	2	4.11	3.57
5	2	2	4.18	3.69
10	2	2	4.17	3.9
20	2	2	3.91	3.65

k is the number of neighbors, p cat. the number of lags for the categorical variables, p cont the number of lags for the continuous variables.

3.4 Estimation results

The lifetime distribution of LTC costs

Table 2 shows statistics of the estimated lifetime LTC costs. On average, a 70-year old single uses almost 31,000 euros of home care and 45,000 euros of nursing home care over the rest of his or her life. The costs are distributed very unevenly: 19 percent of the elderly does not use any home care, while 5 percent of the elderly uses more than 138,000 euros of home care. Almost half of the elderly (48%) do not use any nursing home care, while the top 5 percent use 254,000 euros of nursing home care or more. 13 percent of the elderly uses neither home care nor nursing home care, while the 5 percent of the elderly that use the most LTC overall, have total LTC costs of 320,000 euros or higher.

Figure 1 shows the age pattern of LTC use. The top part shows the average spending by age. Until the age of 80, this amount is limited to 2,500 euros annually for home care and roughly the same amount for nursing home care. For home care, the average costs rise gradually to 5,000 euros for the age of 95. The increase for nursing home care is much steeper, and average cost go up to about 17,000 euros at the highest ages. The bottom figure shows the composition of the population by age in five groups: no costs, low costs ($< 4,956$), medium costs ($4,956 - 22,400$), high costs ($> 22,400$), and deceased. The rising age pattern is explained by both an increase in the percentage of people using LTC (among the survivors) and an increase of the average costs per user (the relative size of the high cost group increases with age).

Distribution of LTC use across pension wealth groups

Our estimates contain individual income and financial wealth for each lifecycle path. To simplify both the analysis and the interpretation, we group all individuals in financial wealth deciles and income quintiles. We assign each individual with a fixed income stream (y), equal to average net income[6] at age 70 within his income group, and initial financial wealth at age 70, equal to average financial wealth at 70 within his wealth group. This means every individual has initial financial wealth equal to one of the ten wealth amounts at age 70 and an income at every age equal to one of the five income levels defined.

In our presentation of the results, we focus on the distribution of LTC costs across pension wealth groups. Pension wealth is the total lifetime wealth an older person has at his disposable, so both his financial wealth and his fixed pension income. We define pension wealth as the sum of the expected[7] present value of the net income stream over the rest of life and initial financial wealth at age 70. We group individuals in

[6]The Dutch tax rates are progressive. For 2013, the average tax rate is 19% for an income under 19,645 euros going up to 52% for the part of the income above 55,992 euros. We transform the gross income in our data into net income using the average tax burden by income bracket for older single households in 2013. These are taken from the tax model used by CPB, see Koot et al. (2016).

[7]The expectations are equal to the average per income and gender group.

five pension wealth quintiles and show average results for each group. In Appendix D, we also show results for specific combinations of fixed pension income and initial financial wealth.

The top part of Figure 2 shows lifetime income and initial financial wealth across pension wealth quintiles. The figure shows that higher pension wealth quintiles have, naturally, both more remaining lifetime income and higher initial financial wealth at the age of 70. For most elderly, financial wealth at age 70 is quite low.[8]

The bottom part of Figure 2 shows the life expectancy, and expected number of years with use of home care and nursing home care, for each pension wealth group. Despite a lower life expectancy, the elderly with the least financial means spend more lifeyears, on average, in need of home care and nursing home care, and presumably, more lifeyears in poor health. This also results in the highest expected LTC costs for these groups. The statistics of the estimated lifetime LTC costs across total wealth groups can also be found in Table 2. The total LTC costs for the quintile with the lowest total wealth are 95,000 euros on average. For the highest quintile, this is 61,000 euros. Groups with low financial wealth do not have a higher probability of using any LTC. The difference in costs is thus driven by the intensity of use[9]: within the lowest wealth quintile, the 5 percent users with the highest cost spend 378,000 euros of LTC or more. For the highest wealth quintile, this is 263,000 euros or more.

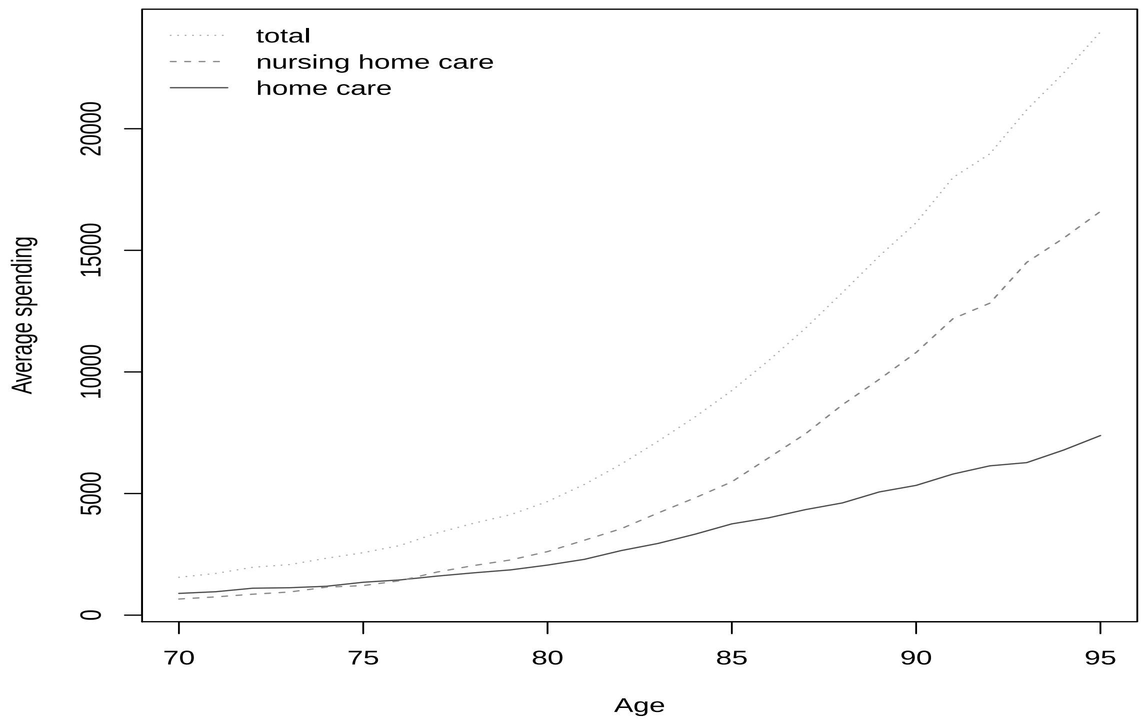
[8]One reasons for this is that we only look at singles. Elderly couples tend to have more wealth than singles. See Hussem et al. (2017) and statline.cbs.nl.

[9]Differences in average discounted costs across income groups are also partly explained by differences in timing. High total wealth groups live longer, and thus, on average, use LTC at higher ages than low groups. Differences in timing explain about 10% of the total difference in discounted costs: with discounting with 1.5% the lowest wealth group has average costs that are 40% higher than for the highest wealth group, without discounting this is 37%.

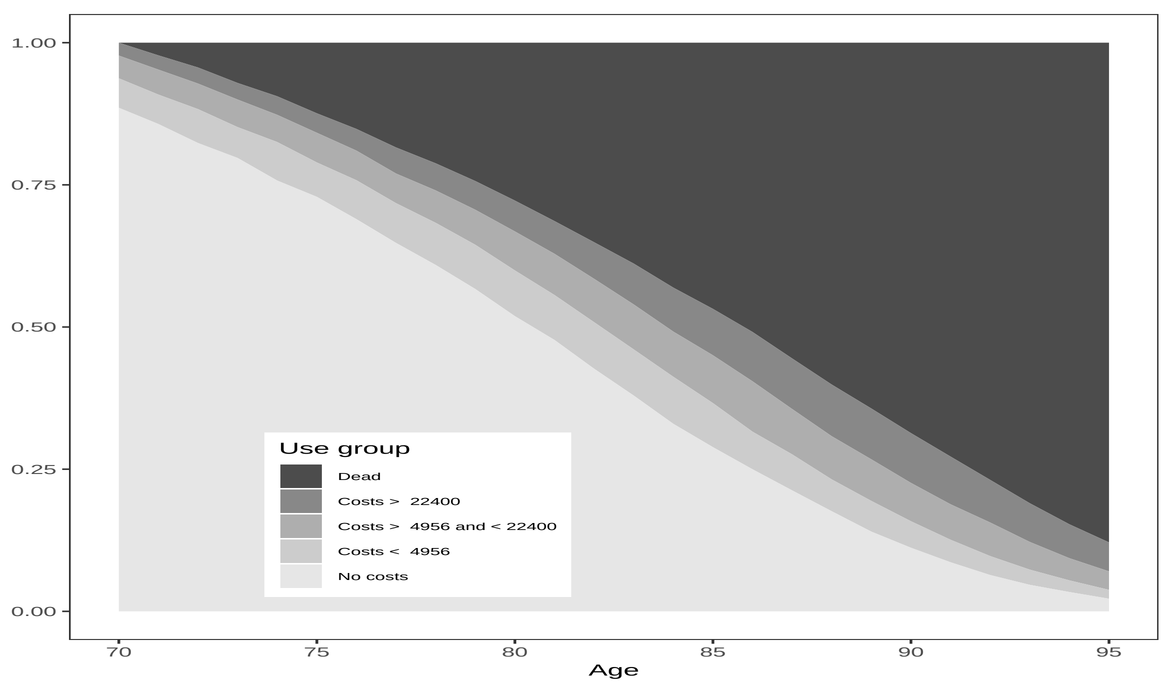
Table 2: Descriptive statistics for lifetime LTC costs at age 70, for the whole population and by pension wealth group 1 (lowest wealth) to 5 (highest).

group		mean	std	% no use	p25	p50	p75	p95
all	Home care	30,828	54,443	19	725	8,336	36,487	137,710
	Nursing home	44,773	96,847	48	0	520	34,564	253,662
	Total	75,601	115,108	13	2,815	24,197	100,691	320,102
1	Home care	41,666	68,518	19	631	11,914	52,097	184,312
	Nursing home	53,470	107,055	45	0	1,647	50,741	282,133
	Total	95,136	131,260	13	3,667	39,399	134,608	378,229
2	Home care	36,128	62,571	20	609	9,409	45,665	156,545
	Nursing home	50,329	106,662	48	0	904	40,772	276,758
	Total	86,457	127,007	14	3,065	31,038	118,524	350,258
3	Home care	28,151	48,228	19	772	7,924	34,437	125,686
	Nursing home	47,533	101,113	47	0	994	38,608	261,889
	Total	75,685	115,777	13	3,017	23,133	97,968	321,145
4	Home care	22,966	40,352	19	723	6,678	26,458	104,716
	Nursing home	35,685	81,948	51	0	0	22,370	216,135
	Total	58,651	94,347	14	2,170	16,609	74,110	258,735
5	Home care	24,422	43,268	18	929	7,845	28,541	108,673
	Nursing home	35,972	81,358	51	0	0	25,914	216,918
	Total	60,394	95,849	13	2,587	18,909	76,217	263,390

Pension wealth groups are quintiles of total lifetime wealth (initial wealth and present value of pension income), see Section 3.4. All amounts are discounted using a discount factor of 1.5% (see Table 4).

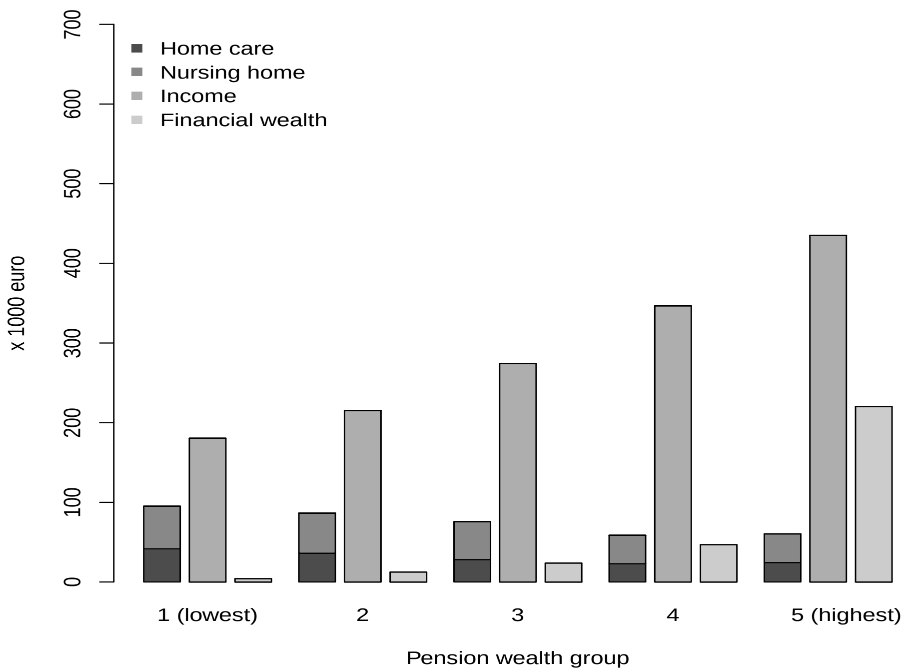


(a) Average costs by age

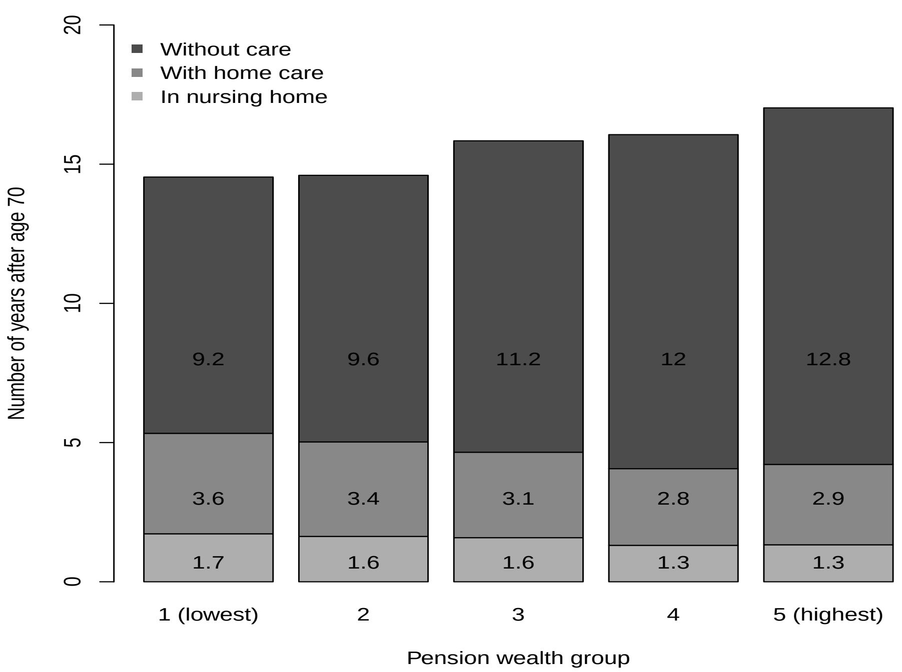


(b) Proportion of people in a LTC use category, by age

Figure 1: LTC costs by age.



(a) Expected LTC costs, expected lifetime income, initial financial wealth



(b) Expected lifeyears (with LTC use)

Figure 2: Descriptive statistics for each pension wealth group, at age 70.
Pension wealth groups are quintiles of total lifetime wealth (initial wealth and present value of pension income), see Section 3.4. All amounts are discounted using a discount factor of 1.5% (see Table 4).

4 A model of lifecycle consumption after retirement

4.1 The model

We implement a standard lifecycle model with forward looking individuals to model consumption and saving behavior under uncertainty about mortality and LTC use. Consumption and saving, conditional on initial wealth and pension income taken from the lifecycle paths, are determined by the model. LTC use and mortality are taken directly from the lifecycle paths, and are exogenous. They do differ across individuals, and individuals do form expectations on them (based on their current and past realizations) but they are not affected by the behavior of the individuals.

The estimated lifecycle paths provide a non-parametric distribution function of LTC costs and mortality: all paths for individuals with the same initial characteristics at 70 are random draws from the same stochastic process. This means that we can use a simulation-based technique to calculate the expected values that individuals need to maximize their expected lifetime utility. We further explain this technique in Section 4.2. First, we discuss the setup of the lifecycle model.

The basic model

We model consumption and savings decisions of an individual i after retirement. We start with a relatively simple model, and add several extensions (bequests, health-state dependent utility of consumption, pension income) in the next section. The individual starts at the pension age, $t = 0$, with initial wealth $W_{i,0}$. He uses this wealth to finance consumption over the remaining time periods $t \in 1, ..., T$. The individual faces uncertainty about the duration of remaining life and the amount of LTC co-payments. We assume that the individual only derives utility from consumption. The individual wants to maximize his expected utility over his remaining lifetime. With a time-separable utility function, the value function (V) an individual maximizes is:

$$V_{i,0} = \mathrm{E}\left[\sum_{t=0}^{T}\left(\beta^t u(c_{i,t})\prod_{s=0}^{t} p_{i,s}\right)\right], \tag{2}$$

with $p_{i,s}$ the probability of surviving period s, and β the discount factor.

Each period, the individual has to choose the amount of his wealth $W_{i,t}$ he wants to consume now ($c_{i,t}$), and the amount he wants to save for later ($m_{i,t}$). The individual is also faced with co-payments for LTC costs $h_{i,t}$. He faces the following annual budget constraint:

$$c_{i,t} + m_{i,t} + h_{i,t} = W_{i,t}. \tag{3}$$

We impose the borrowing constraint $W_{i,t} \geq 0$.The timing is such that first $h_{i,t}$ has to be paid, and then the individual decides how to divide his remaining wealth between $c_{i,t}$ and $m_{i,t}$. We treat the level of private LTC spending, $h_{i,t}$, as given: the individual does not weight utility gained from $h_{i,t}$ against utility from $c_{i,t}$, but instead $h_{i,t}$ is an exogenous shock.

The utility function is defined as a standard CRRA function:

$$u(c_{i,t}) = \frac{c_{i,t}^{1-\gamma}}{1-\gamma}. \tag{4}$$

This implies that individuals want to smooth consumption evenly over the lifecycle. Wealth growths with the risk free interest rate $r-1$, so that

$$W_{i,t+1} = m_{i,t} r. \tag{5}$$

We impose a consumption floor, so that annual consumption cannot drop below 10,000 euros.

Extensions

We extend the model in four ways. First, we allow for a fixed pension income stream y (state pension and/or annuity). We do not endogenize the annuitization decision, but take the amount of initial wealth that is annuitized as given (see Section 4.3)[10]. The budget constraint with a fixed annual income becomes

$$c_{i,t} + m_{i,t} + h_{i,t} = W_{i,t} + y_i. \tag{6}$$

Second, we allow the level of co-payments to depend on wealth and pension income. Let $H_{i,t}$ be the total LTC spending the individual needs in period t. This spending is exogenous. Private LTC spending, $h_{i,t}$, is not necessarily equal to $H_{i,t}$, but depends on the co-payment rules set by the government. We use the following general co-payment rule:

$$h_{i,t} = \min[\tau H_{i,t}, \max(\nu_y y_i + \nu_w W_{i,t} - \delta, 0), \mu]. \tag{7}$$

This general rule allows us to emulate the Dutch co-payment system, but also to include other variants, such as a flat-rate co-payment independent of spending power. The government sets the parameters τ, ν_y, ν_w, δ, and μ. The parameter τ determines what share of total health care spending has to be paid by the individual himself. The parameters ν_y and ν_w are the maximum shares of income and wealth that have to be spent on co-payments. The parameter δ can be seen as a deductible: a fixed amount of income that is exempted from the co-payments. The government can also set an overall maximum μ on annual co-payments on top of the income- and wealth-dependent maximum.

The way the government sets the co-payment rules affects the optimization problem of the individuals. When $\nu_w > 0$, co-payments are no longer fully exogenous since they depend on the annual savings chosen by the individual.

[10]The model can easily be extended to include endogenous annuitziation of initial wealth, see Peijnenburg et al. (2017)

Third, we include a bequest motive. We assume that the individual derives utility from the level of wealth $W_{i,death}$ he leaves at time of death. Following Kopczuk and Lupton (2007) we use a linear specification for the utility function in case of death:

$$u(W_{i,t}|t = t_{death}) = \theta W_{i,t}. \tag{8}$$

As noted by Kopczuk and Lupton (2007), this specification gives an intuitive notion of bequests as a luxury good: as wealth increases, the marginal utility from bequests increases relative to the marginal utility of consumption. At the same time, less wealthy individuals also derive (some) utility from leaving wealth at the moment of premature death.

Fourth, we allow for health state-dependent utility. The utility an individual derives from non-health care consumption could depend on his health status (disability). Finkelstein et al. (2013) find that an increase in the number of chronic diseases has a significant negative impact on the marginal utility of consumption. A priori, however, the effect of poor health could go both ways: individuals might derive less utility from things like eating out or recreation, but at the same time demand for things like cleaning help, wheelchairs, and stair lifts might increase (Meyer and Mok, 2009). Indeed, as pointed out by Peijnenburg et al. (2017), there is no consensus in the empirical literature on the size and even the sign of the effect.

As we do not observe health directly, we use the fact that someone uses nursing home care as a proxy. We only consider the use of nursing home care as an indicator of severe disability and not the use of home care. A negative effect on the marginal utility of consumption is more likely for nursing home care users, as this type of care is relatively comprehensive and encompasses most additional consumption needs related to disability such as housing and cleaning.

To include state-dependent utility, we use the following commonly used adaptation of the utility function in Equation (4) (Palumbo, 1999; De Nardi et al., 2010; Peijnenburg et al., 2017):

$$u(c_{i,t}) = (1 - \kappa\Delta_{i,t})\frac{(c_{i,t} + \xi\Delta_{i,t})^{1-\gamma}}{1-\gamma}. \tag{9}$$

The variable $\Delta_{i,t}$ is a dummy indicator for poor health, which we define as an individual having any nursing home care in period t. The parameter κ determines the relative change in the marginal utility of consumption in poor health ($\Delta_{i,t} = 1$) compared to good health ($\Delta_{i,t} = 0$). When $\kappa < 0$, marginal utility is lower in poor health. When $\kappa = 0$, marginal utility is equal in both health states. The parameter ξ determines the curvature of the utility function in poor health. At the same time, ξ can be given a practical interpretation in the Dutch context. Nursing homes also cover part of the basic costs of living of their inhabitants (e.g. meals). The parameter can thus be used to model the level of basic living costs that is provided by the nursing home.

Outcome

The main outcome measure we use to present the welfare effects of different co-payment schemes across groups is the certainty equivalent consumption (CEC). Based on their characteristics at age 70, individuals expect a particular level of consumption over the rest of their life, but this expectation is surrounded by uncertainty because of LTC payments. The CEC is the minimum level of *certain* annual consumption individuals would be willing to accept instead of their *uncertain* expected consumption. The CEC is lower than the expected consumption, as the individuals are risk-averse and willing to pay a premium to insure this riks. Formally,

$$CEC = u^{-1}\left(\frac{V_{i,0}}{\sum_{t=0}^{T}\beta^t\left(\prod_{s=0}^{t}p_{i,s}\right)}\right) \tag{10}$$

More specifically, we will show the averages of this measure $CEC_{g,v}$ for each pension wealth quintile $g = 1, .., 5$ across policy variants v.

4.2 Numerical approach

The individual's maximization problem can be solved using dynamic programming. The lifecycle optimization problem is divided into smaller yearly optimization problems. The algorithm starts at the last time period T, and is then solved backwards recursively. We set T at age 95. We solve this problem using the approach developed by Koijen et al. (2010), that has been applied to LTC financing in the U.S. by Peijnenburg et al. (2017). The approach combines the method of endogenous gridpoints (Carroll, 2006) with a simulation based approximation of the expected values (Brandt et al., 2005). This makes it well suited to use in combination with the non-parametric estimation of the lifecycle paths. Most approaches approximate the stochastic processes (mortality, LTC costs) by a limited number of discrete states. De Nardi et al. (2018), for instance, first use a non-parametric model to estimate earning dynamics, but then discretize the outcomes (although in a quite flexible way) to use them in their behavioral lifecycle model. Instead, the method of Koijen et al. (2010) allows us to directly use the lifecycle paths as inputs.

Specifically, solving the maximization problem involves the estimation of decision rules (the optimal amount of consumption in period t given initial wealth $W_{i,t}$ *at the beginning* of t) over a grid of values for $W_{i,t}$. In the endogenous gridpoints method, these decision rules are determined by finding the optimal consumption $c^*_{i,t}$ for a grid of values for wealth $m_{i,t}$ *at the end* of period t (after consumption and health care costs). Given that we already have the optimal consumption rules for period $t+1$, optimal consumption in t given $m_{i,t}$ is determined by the Euler condition:

$$c^*_{i,t}|m_{i,t} = (\mathrm{E}(\beta c^{*-\gamma}_{i,t+1} r|m_{i,t}))^{-\frac{1}{\gamma}}. \tag{11}$$

The most relevant part of the method of Koijen et al. (2010), in our context, is that $\mathrm{E}(\beta c^{*-\gamma}_{i,t+1} r|m_{i,t})$ is estimated using a simulation approach. The lifecycle paths provide a large number of random draws ($i = 1, .., N$) from the stochastic process determining mortality and LTC spending. Because of the Markov properties of the matching procedure, this expectation only depends on the value of the state variables (LTC spending and background characteristics) at time t. We can thus approximate $\mathrm{E}(\beta c_{i,t}^{*-\gamma} r | m_{i,t})$ by regressing the realizations of $c_{i,t+1}^{*} | m_{i,t}$ for all individuals on a polynomial expansion of their state variables at time t. Appendix C provides a more detailed overview of the numerical procedure.

4.3 Implementation

We use the lifecycle paths and the lifecycle model to assess the average payments and the welfare effects of the Dutch income- and wealth-dependent co-payment system across income and wealth groups. In order to do so, we compare the current system to two alternatives.

Policy variants

In the Dutch system, co-payments depend on both income and wealth. A stylized example is given in Figure 3: LTC users pay the full costs out-of-pocket until they reach an income- and wealth-dependent annual maximum. We emulate the Dutch co-payment scheme in 2015 using the formula in Equation (7). In this scheme, 75% of income and 9% of financial wealth[11] is included in the co-payment for nursing home care and 15% of income and 2% of financial wealth for home care. There is a deductible of 4,500 euros for nursing home care and 16,600 euros for home care. A maximum co-payment applies of 27,000 euros regardless of income and wealth.

To assess how the Dutch system affects costs and risk across groups, we introduce two alternative co-payment schemes for the counterfactual analysis. To make a fair comparison, we set the parameters of these alternatives in such a way that they raise an equal amount of aggregated revenues as the current system. The first alternative is an income-dependent co-payment: maximum co-payments are a share ν_y of income, but do not depend on an individual's wealth. As the total revenues of the system are set to be the same, ν_y is higher than in the current system. As a result, care users with a relatively high income compared to their financial wealth will pay more, while care users with a relatively low income and high wealth will pay less than they currently do. This variant resembles the co-payment scheme in place before 2013. During the 2017 Dutch election campaign, some Dutch political parties proposed to return to a co-payment system only depending on income (CPB, 2017).

The second alternative is a flat-rate co-payment: co-payments are a fixed percentage τ of an individual's annual LTC costs, independent of his income and wealth. Figure 3 also shows a stylized version of this system. The flat-rate is smaller than

[11] 12% of financial wealth is added to the income definition used to calculate the co-payment. As 75% of this income definition is included, this means that 0.12*0.75 = 9% of financial wealth is included.

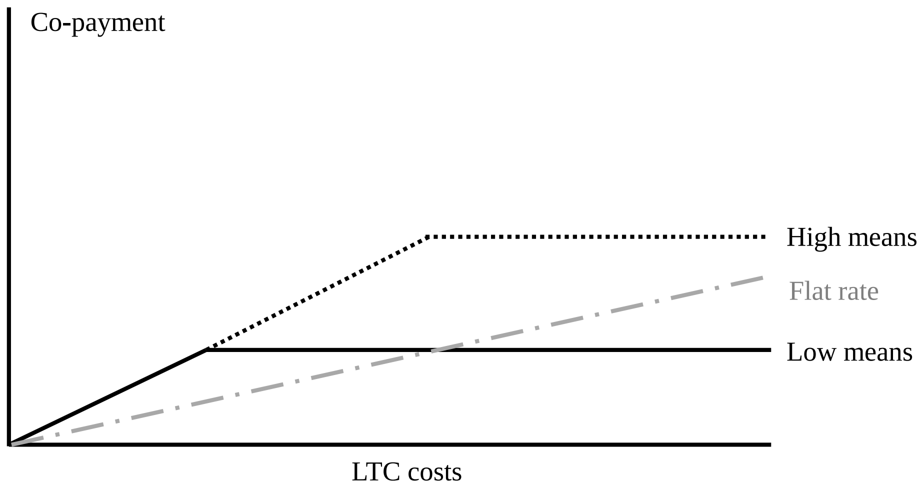


Figure 3: The design of the co-payment. The relationship between total annual LTC costs and annual co-payments for individuals with low and high financial means in the current income- and wealth-dependent system, and in the alternative flat-rate system (independent of financial means).

one, which means that at a low amount of LTC use, co-payments are lower than in the current system. However, as there is no income- and wealth-dependent maximum, at higher amounts of LTC use, the co-payments are higher than in the current system. As shown in the figure, the flat-rate will increase co-payments for the most of intensive LTC users with low financial means.

The policy parameters for the current system and the two alternatives are shown in Table 3.[12] In the two alternative systems, we retain the current maximum co-payment level of 27,000 euros. In all cases, co-payments do no exceed the actual LTC costs. The consumption floor, set at 10,000 euros, also restricts the annual co-payments.

Other parameters

The other parameters are set in line with the literature. See Table 4. In the main specification we include a bequest motive by setting $\theta^{-1/\gamma} = 50.000$. This number is in line with the range of values estimated by Kopczuk and Lupton (2007), and means that above 50.000 euros the marginal utility of leaving a bequest is higher than the marginal utility of consumption. We set the risk aversion parameter γ to 3. In the main specification, the utility from consumption does not depend on health.

[12]For home care, co-payments are not based on costs (tariffs) but on a (lower) fixed hourly amount. We only observe total annual costs in the lifecycle data. Therefore, we set the share of costs paid by the user (τ) to 26 percent for the current system and the income-dependent co-payment variant. This 26 percent is the fixed hourly amount divided by the average hourly tariff.

Table 3: Policy parameters in each variant, for the main specification. The co-payment rule (Equation 7) is : $h_t = \min[\tau H_t, \nu_y y + \nu_w W_t - \delta, \mu]$

Variant		τ	ν_y	ν_w	δ	μ
1 Inc and wealth dep.	nursing home	1	0.75	0.09	4,500	27,000
1 Inc and wealth dep.	home care	0.26	0.15	0.02	16,500	27,000
2 Inc dep.	nursing home	1	0.88	0	4,500	27,000
2 Inc dep.	home care	0.26	0.18	0	16,500	27,000
3 Flat-rate	nursing home	0.37	0	0	4,500	27,000
3 Flat-rate	home care	0.16	0	0	16,500	27,000

We perform six sensitivity analyses. In the first, we do not include a bequest motive. In the second, we set $\theta^{-1/\gamma} = 40.000$, which means that the bequest motive becomes important also at lower levels of wealth. In the third and fourth, we set a higher ($\gamma = 5$), respectively lower ($\gamma = 2$) risk aversion. In the fifth, we introduce health state-dependent utility of consumption. We set $\kappa = 0.2$ which means that the marginal utility of consumption is 20 percent lower for individuals living in a nursing home than for others. De Nardi et al. (2010) choose a similar value for κ and it seems to be at the more extreme side of the range of values found by Finkelstein et al. (2013). In the last analysis, we set $\xi = 5,000$. This means that individuals in a nursing home gain annually 5,000 euros of consumption.

Table 4: Values of parameters in different specifications

	r	β	γ	$\theta^{-1/\gamma}$	ξ	κ
Main specification	1.015	0.985	3	50,000	0	0
No bequests	1.015	0.985	3	.	0	0
Lower bequest level	1.015	0.985	3	40,000	0	0
Higher risk aversion	1.015	0.985	5	50,000	0	0
Lower risk aversion	1.015	0.985	2	50,000	0	0
State dep. utility	1.015	0.985	3	50,000	0	-0.2
Lower costs in a nursing home	1.015	0.985	3	50,000	5,000	0

4.4 Match between the lifecycle wealth data and the model

As we are interested in the effects of LTC co-payments across different wealth groups, the ability of the lifecycle model to match the distribution of wealth in the actual population is of particular interest. The non-parametric method we use to estimate the source data for the model has an additional advantage here. We have included financial wealth as one of the matching variables in the nearest neighbor algorithm. This means that we can compare the distribution of wealth across life generated by the lifecycle model to the wealth data in our lifecycle paths. Normally, researchers do not have this data, and need to rely on comparison to a cross-sectional age pattern of wealth (possibly plagued by cohort effects) or age patterns based on short panel data.

In Figure 4 we show the cumulative distribution of financial wealth, in the lifecycle data and as generated by the model in the main specification, across all ages. Each age for each individual (if alive) is one observation here, so we basically treat our lifecycle data as one cross-section. The lifecycle model seems to fit this overall distribution of wealth in the data quite well. The model slightly undersamples the levels of wealth between 50,000 and 100,000 euros. It slightly oversamples observations in the range between 100,000 and 150,000 euros.

As a second assessment, we consider how well the lifecycle model is able to match the age profiles of wealth for different subgroups. Figure 5 shows median financial wealth by age for individuals belonging to a particular group (based on their initial wealth at age 70 and their annual income). As we have in total 50 combinations (5 income quintiles and 10 wealth deciles), we only show a selected number of them, others are available upon request.

The model seems to match the lifecycle profiles of wealth quite well for most groups. One notable exception are individuals with a low income (and a low or moderate level of wealth). In the lifecycle model, these individuals dissave: their financial means are so limited that saving apparently does not protect them against shocks in LTC costs. If they are hit by any substantial shock, their consumption drops below the consumption floor anyway such that their income is supplemented to guarantee 10,000 euros of consumption. In the lifecycle data, low income groups do save or at least not dissave. One reason for this might be that they face different, relatively small, financial shocks (e.g. repair of durables) that are not taken into account in our model.

The match between the model and the data for groups with low income and wealth could be improved, for instance by increasing the risk aversion or by strengthening the bequest motive. However, this would come at substantial costs in terms of the fit for the other groups, especially the groups with high financial wealth. We do not expect the mismatch for the low income groups to have substantial effect on our results, because the savings of these groups in the data are still very low. We do run a number of sensitivity tests using other parameter settings including lower risk aversion and a stronger bequest motive.

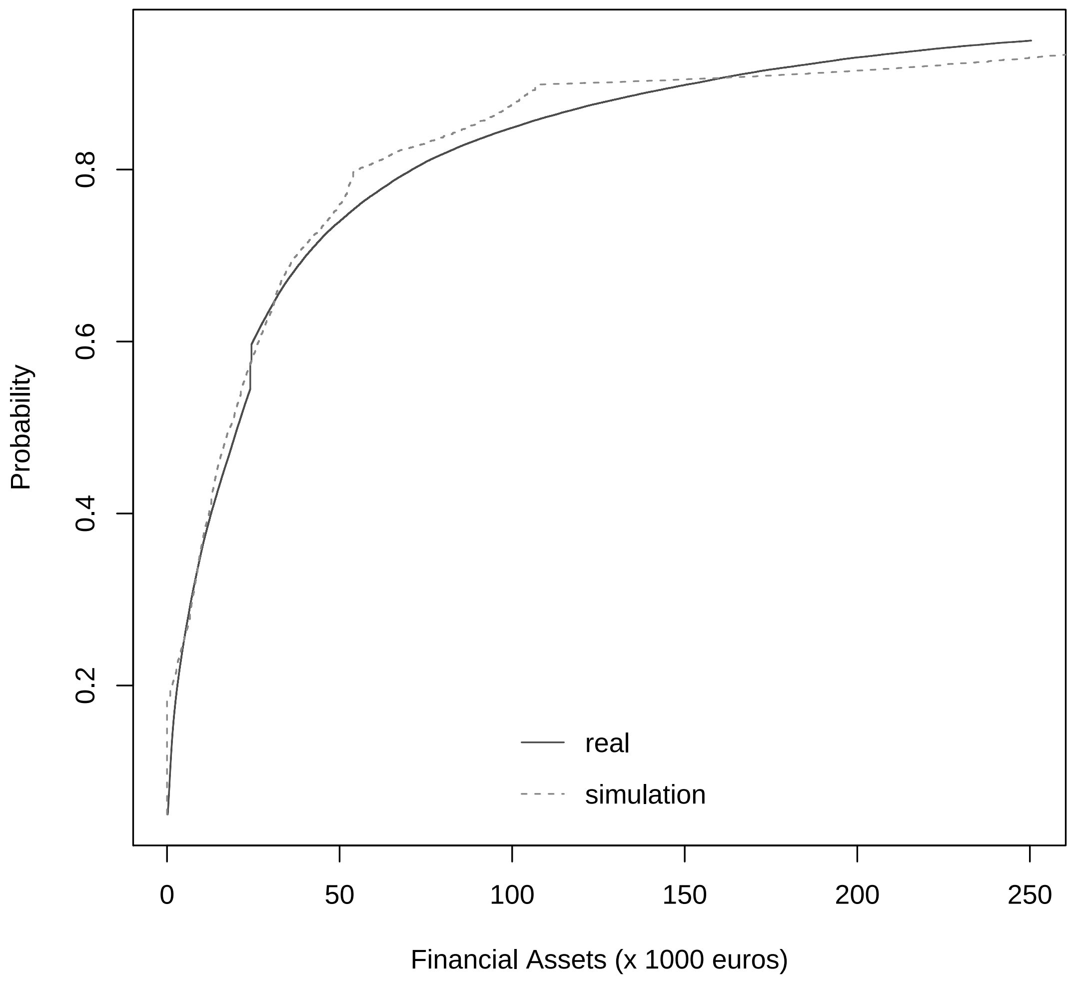


Figure 4: Cumulative distribution of financial wealth: lifecycle data versus model

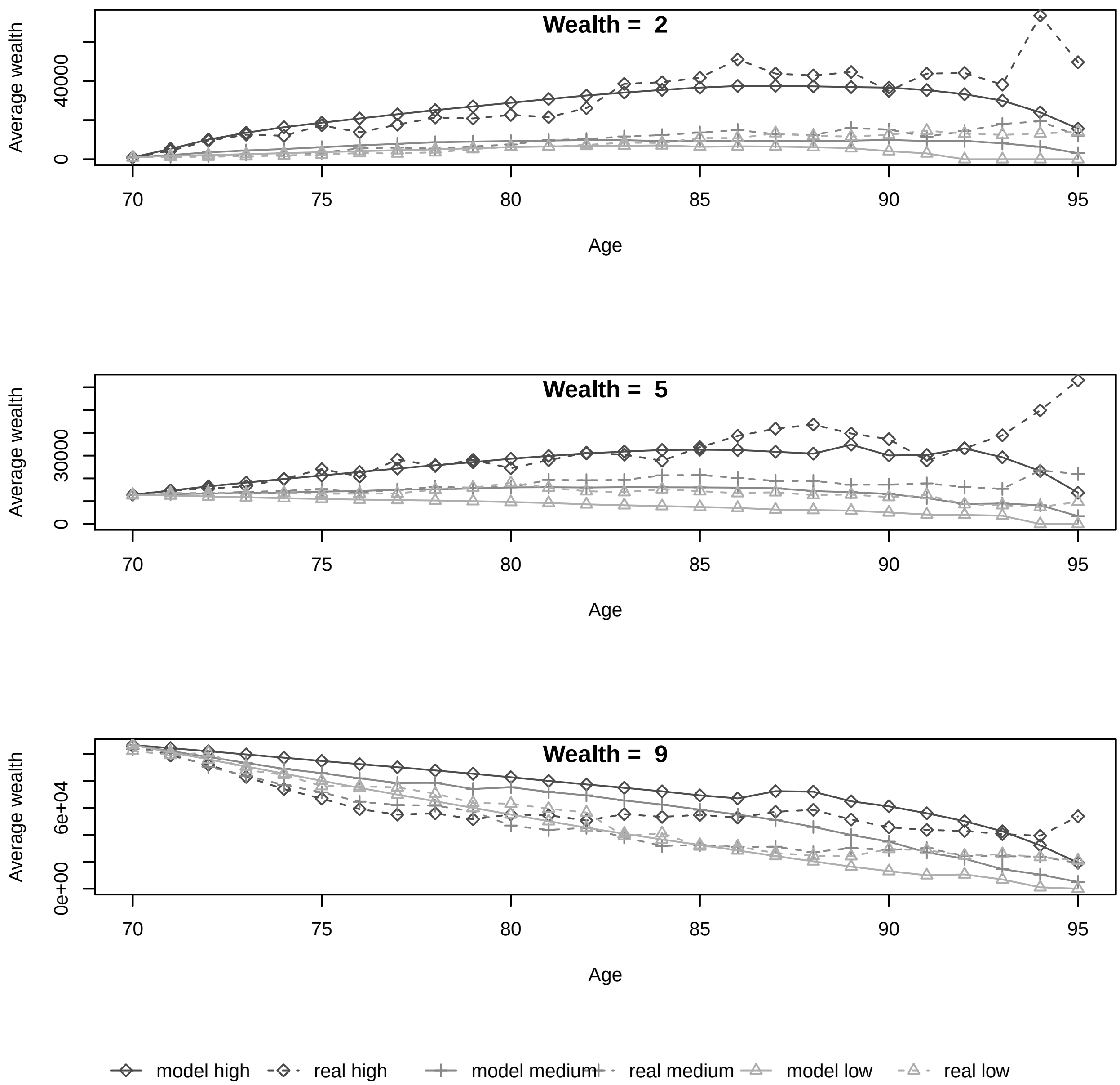


Figure 5: Median financial wealth: lifecycle data versus model. For different combinations of initial wealth at age 70 (2nd, 5th, 9th decile) and income (2nd, 3rd, 5th quintile)

5 Results

5.1 Results for the main specification

Table 5 shows the certainty equivalent consumption (CEC) in the current co-payment system. The table also shows to what degree lifetime wealth is spent on average annual consumption, LTC payments, and annualized bequests (the amount of lifetime wealth at death). The results are shown for each pension wealth group, based on the total lifetime wealth someone has at his disposal (see Section 3.4). There are considerable differences in CEC across pension wealth groups. The group with the lowest financial means has a CEC of 13,368 euros, while the highest group has 40,240 euros. LTC payments also vary considerably across pension wealth groups. The current co-payment system leads to a significant redistribution of income from high to low groups: although the highest pension wealth group uses 30 percent less LTC than the lowest group (see Table 2), its average payments are 2.5 times as high (1,606 vs 617 euros).

Table 5: Certainty equivalent and average annual consumption, annual LTC payments and annualized bequests by pension wealth group (1-5). In the current system (1) and in the two alternatives.

	1	2	3	4	5
1 Inc and wealth dep., in levels					
CEC	13,368	15,551	18,698	24,286	40,240
$Consumption$	13,648	16,062	19,438	25,093	37,538
LTC	617	1,001	1,200	1,263	1,606
$Bequest$	27	244	833	1,751	6,399
2 Inc dep., change compared to 1					
CEC	-45	-205	-309	-352	50
$Consumption$	-47	-231	-402	-446	-227
LTC	25	62	46	5	-142
$Bequest$	12	244	491	567	470
3 Flat-rate, change compared to 1					
CEC	-310	-565	-784	-412	131
$Consumption$	-249	-587	-885	-546	-517
LTC	220	224	134	-94	-437
$Bequest$	14	469	865	635	1,000

Pension wealth groups (1 is lowest, 5 is highest) are quintiles of total lifetime wealth (initial wealth and present value of pension income), see Section 3.4.

To assess the effect of the current co-payment system on the CEC across pension wealth groups, we compare it to the two alternatives: a co-payment based solely on income, and a flat-rate co-payment independent of financial means. Table 5 shows how going from the current system ($v = 1$) to one of the two alternatives ($v = 2, 3$) affects the CEC of each group g: ($CEC_{g,v} - CEC_{g,1}$). In Figure 6, the change in CEC is expressed as a percentage of current welfare: $\frac{CEC_{g,v} - CEC_{g,1}}{CEC_{g,1}}$. The figure shows the change in average payments, and the total change in CEC. The total change encompasses the effect of the average payments, but also includes the effects of risk and the allocation of pension wealth across lifeyears.

That the current system redistributes relatively strongly from high to low pension wealth groups becomes clear when we consider the average payments in the other two alternatives. The two alternatives raise the same overall revenue, which means that the change in average payments is purely a redistribution of the burden across the groups (the change in payments across groups adds up to zero[13]). An income-dependent co-payment would lead to a decrease in average payments for the highest pension wealth group, and an increase for the others, especially the second and third group. A flat-rate co-payment would lead to a decrease in average payments for both the highest and second highest pension wealth group.

Compared to the two alternatives, the current co-payment system offers more protection against risk for low and middle pension wealth groups. Table 6 shows the distribution of discounted lifetime co-payments in the three variants, for the lowest, the middle, and the highest pension wealth group. For both the lowest and the middle group, going to a an income-dependent or flat-rate co-payment would increase payments, especially for individuals using a lot of care (the right-hand tail of the distribution). The increases in payments for heavy users of LTC is most substantial in case of the flat-rate. In contrast to the low and middle group, heavy users of LTC in the highest pension wealth group would actually be confronted with lower payments. This indicates that the current system puts a relatively strong burden on the intensive users of care with high financial means.

The effects on risk are reflected by the welfare effects. Although the two alternatives raise the same overall revenue, all pension wealth groups, with the exception of the highest, are better of in the current system. Especially the welfare loss associated with going from the current system to a flat-rate is substantial. Groups lose between 2.2 tot 4 percent of their current CEC (Figure 6). Interestingly, it is not the lowest pension wealth group that would be most affected by the introduction of a flat-rate, but the middle groups (quintiles 2, 3, and 4). The income of members of quintile 1 is relatively close to the consumption floor. This means that even if the co-payment does not depend in income and wealth, the additional net payments that heavy LTC users in this group are faced with are relatively limited. The middle groups hardly benefit from the consumption floor and do face the risk of having to pay the high flat-rate co-payments.

The protection offered by the current system comes at the costs of the highest pension wealth group: they would have a higher CEC in an income-dependent or a

[13]The numbers in the table do not exactly add up to zero because of the numerical approximation.

Table 6: Distribution of lifetime co-payments, by pension wealth group (1,3,5). In the current system (1) and the two alternatives.

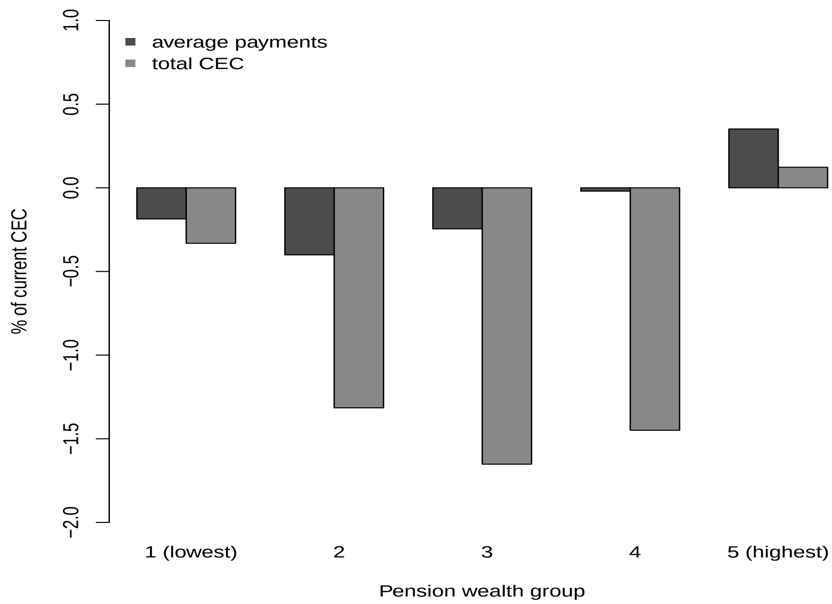
group	variant	p25	p50	p75	p95
1	1 Inc and wealth dep.	872	4,474	11,064	28,586
	2 Inc dep.	880	4,746	11,622	29,577
	3 Flat-rate	723	6,287	16,489	36,942
3	1 Inc and wealth dep.	915	7,386	23,161	66,287
	2 Inc dep.	915	7,221	23,387	70,003
	3 Flat-rate	552	4,926	24,980	81,470
5	1 Inc and wealth dep.	776	6,496	28,787	106,823
	2 Inc dep.	767	6,159	26,017	96,322
	3 Flat-rate	472	3,938	18,377	86,222

Pension wealth groups (1 is lowest, 5 is highest) are quintiles of total lifetime wealth (initial wealth and present value of pension income), see Section 3.4. All amounts are discounted to age 70.

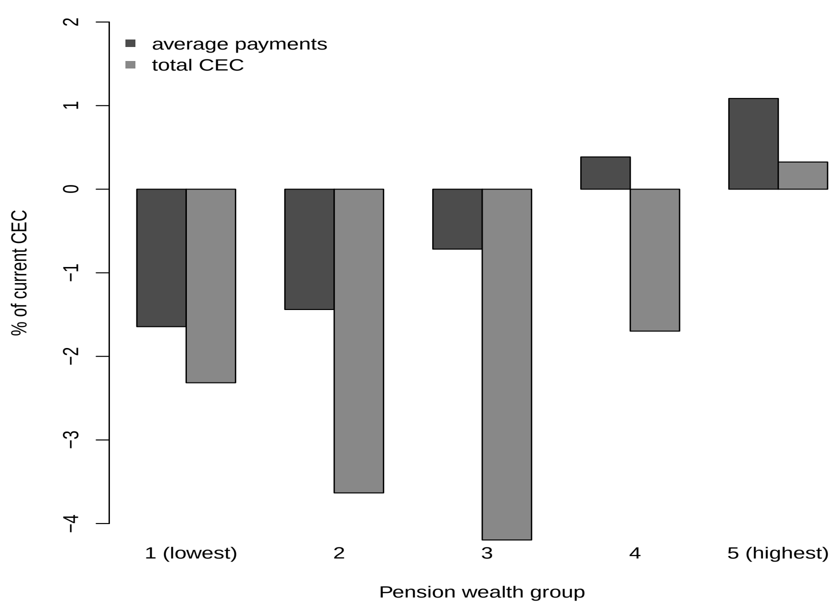
flat-rate system than in the current system. Average payments for this groups are substantially lower in the alternatives. Also, the heavy LTC users from this group already have relatively high co-payments in the current system (close to the overall annual maximum of 27,000 euros in place in all variants), so that the additional risk they would face when going to a flat-rate co-payment is limited. There is substantial heterogeneity behind the welfare effect for the highest pension wealth group as a whole. Individuals with high financial wealth and a relatively low income benefit from a solely income-dependent co-payment, but individuals with a high income and relatively low financial wealth do not (Appendix D, Figure 9). Individuals with a high income benefit from a flat-rate co-payment, but individuals with high financial wealth (and not a high income) do not (Appendix D, Figure 10).

Extending the analysis from average consumption to the welfare effects, makes a big difference. As Figure 6 shows, the effect of a co-payment variant on CEC can differ considerably from the effect on *average* payments. Compare, for instance, the difference between the flat-rate co-payment and the current system for pension wealth group 3: the average annual payments increase by 134 euros, while the total loss in CEC is 784 euros.

Including the effects on saving behavior is relevant as well. This can be seen by comparing the bequests across policy variants (Table 5). The amounts shown here are the (discounted) annualized averages. By comparing this to the annual consumption and payments, we can see what share of lifetime pension wealth is, on average, left at death. The co-payment system affects the bequests in three ways: First, when an individual pays a co-payment this lowers his financial wealth directly. Second, in response to a higher risk of co-payments, individuals increase their savings, which increases average wealth at death. Third, when wealth is taxed (as in the current system) this has a negative effect on savings. In the income-dependent system and especially the flat-rate co-payment, bequests increase for all groups.



(a) Income-dependent co-payment



(b) Flat-rate co-payment

Figure 6: The change in average payments and total welfare, resulting from going from the current co-payment system to one of the alternatives. For each pension wealth group (1 is lowest, 5 is highest).

Pension wealth groups are quintiles of total lifetime wealth (initial wealth and present value of pension income), see Section 3.4. The change in welfare in going from the current system ($v = 1$) to alternative system v, for group g is measured as: $(CEC_{g,v} - CEC_{g,1})/CEC_{g,1}$.

5.2 Sensitivity analysis

As described in Section 4.3, we run six sensitivity tests using different parameterizations. When we change the parameters of the utility function, this also affects the revenues raised in the current co-payment system. In the absence of a bequest motive, for instance, individuals will save less, which reduces the revenues raised through the wealth-dependent part of the co-payment. To make a fair comparison across the co-payment systems within each sensitivity analysis, we keep the policy parameters of the current system fixed (at the level in Table 3), but we adjust the policy parameters of the alternatives so that they raise an equal amount of revenue as the current system in each case.

Our main interest here is to see whether our main conclusion, that the current system leads to a higher welfare for the low and middle pension wealth groups than the two alternatives, is sensitive to our choice of policy parameters. Table 7 shows the relative change in certainty equivalent consumption, $\frac{CEC_{g,v}-CEC_{g,1}}{CEC_{g,1}}$, when going from the current system to an income-dependent or flat-rate co-payment by pension wealth group for the main specification and for the sensitivity analyses (this is equal to what is shown in Figure 6 for the main specification).

In general, the results for all pension wealth groups, except the highest, are quite similar across different parameter settings. Going from the current system to one of the two alternatives leads to a welfare loss. This loss is largest for the middle income groups, and is most substantial in case of the flat-rate alternative. There are some differences in the magnitude of the effects compared to the main specification though. As the different parameterizations also affect the outcomes in the current system, identifying the mechanisms underlying these differences in magnitude is not always straightforward. The exclusion of the bequest motive does not seem to affect the outcomes of the low and middle groups very strongly. A higher risk aversion leads to higher losses in welfare, especially when going to a flat-rate co-payment, and a lower risk aversion to lower losses. The effects of health state dependent utility and lower costs of living in a nursing home are quite heterogeneous, but they seem to lead to less welfare loss for the middle groups when going from the current to a solely income-dependent system.

For the highest pension wealth group, results vary somewhat more. In the main specification, the highest pension wealth group would gain from going from the current system to a solely income-dependent or flat-rate co-payment. In the other parameter settings (no bequest motive, higher risk-aversion), this is not always the case. When we set the level at which bequests outweigh the marginal utility of consumption at 40,000 instead of 50,000, going from the current to a flat-rate co-payment would lead to a more substantial increase in welfare for the highest group.

We conclude that our main results are quite robust: compared to the two alternatives, the current system protects the individuals with low and moderate financial means against high payments for LTC. Only for individuals with very high financial means, the reduction in average payments in the two other variant, due to less redistribution, can outweigh the costs of the additional risk.

Table 7: The change in welfare from going from the current system to one of the two alternatives, by pension wealth group. For different parameter specifications.

Main specification					
2 Inc dep.	-0.33	-1.32	-1.65	-1.45	0.12
3 Flat-rate	-2.32	-3.63	-4.2	-1.7	0.33
No bequest motive					
2 Inc dep.	-0.31	-1.25	-1.56	-1.47	-0.21
3 Flat-rate	-2.25	-3.51	-4.14	-1.62	0
Lower bequest level					
2 Inc dep.	-0.35	-1.37	-1.7	-1.44	0.67
3 Flat-rate	-2.37	-3.74	-4.23	-1.75	2.32
Higher risk aversion					
2 Inc dep.	-0.91	-3.05	-3.3	-3.14	-0.29
3 Flat-rate	-3.7	-5.88	-6.2	-2.44	0.16
Lower risk aversion					
2 Inc dep.	-0.21	-0.62	-0.7	-0.86	0.13
3 Flat-rate	-2.16	-1.63	-2.38	-1.39	0.11
State dep. utility					
2 Inc dep.	-0.25	-0.92	-1.32	-1.35	0.09
3 Flat-rate	-2.42	-2.55	-3.81	-1.75	0.15
Lower costs of living in a nursing home					
2 Inc dep.	-0.28	-0.82	-0.88	-1.03	0.12
3 Flat-rate	-2.65	-4.11	-4.18	-1.67	0.55

Pension wealth groups (1 is lowest, 5 is highest) are quintiles of total lifetime wealth (initial wealth and present value of pension income), see Section 3.4. The change in welfare in going from the current system ($v = 1$) to alternative system v, for group g is measured as: $(CEC_{g,v} - CEC_{g,1})/CEC_{g,1}$. The parameter values for each specification can be found in Table 4.

6 Discussion

We have simulated the longitudinal dynamics of LTC costs in the Netherlands, using the non-parametric nearest-neighbor approach. This approach has advantages compared to parametric approaches, especially its flexibility and the possibility to easily include the relationship between dynamics in LTC costs and other variables of interest. We have also shown that this flexible approach can be applied in the context of a structural lifecycle model using the simulation based numerical optimization procedure developed by Koijen et al. (2010).

We have evaluated the Dutch LTC financing system, in which co-payments are based on a fixed share of income and wealth. We have found that there is a strong income- and wealth-gradient in the lifetime use of long term care. Compared to a flat-rate or a solely income-dependent co-payment raising the same revenue, the Dutch system redistributes the costs of co-payments from the elderly with the lowest financial means, who on average use the most care, to the elderly with the highest means, who use the least care.

The lifecycle model allows us to take the welfare effects of risk into account. Our analysis underlines the point of McClellan and Skinner (2006) that including risk in the effects of care systems is important. It turns out that the income- and wealth-dependency especially protects the elderly in the middle groups against financial risks: the certainty equivalent consumption is considerably higher in the current system than in case of a flat-rate co-payment for these groups. Thus, conditional on the existence of a safety net for the poorest, the protection against risk offered by social LTC insurance is most important for the individuals with substantial income and wealth, as they have most to lose. This finding is quite similar to what De Nardi et al. (2016) have found for Medicaid. In our specific case, the richest group would benefit from a flat-rate system, since they already pay relatively substantial payments in the current system and have sufficient financial means to cope with risk.

Our results show that the Dutch system might be a relatively good way to use co-payments in LTC while still offering substantial income protection. In this system, the financial means of LTC users are taken into account, but they do not have to deplete all their resources before gaining access to the public insurance. This means that the system protects the elderly with some income and wealth better against costs than a fully means-tested system (e.g. Brown and Finkelstein (2007)) that is used in many other countries. Although we think that this general message holds in other settings, our specific results do depend on the setting of the Dutch system and the alternative systems that we have presented. For instance, we have not changed the absolute limit of 27,000 euros of co-payments per year in all variants, and we have kept the overall share of spending financed by out-of-pocket payments constant.

There are three choices in our approach that are important for the interpretation of ours results. First, we have focused on the distributional effects of co-payments during the retirement phase, starting at age 70. Not modeling the working phase of life helps to keep the model tractable and computationally manageable. This has enabled us to include a relatively large amount of detail, both in the dynamics in LTC costs and the policy variants. The costs of not modeling the working life phase is that we might overestimate the welfare losses due to co-payments, as individuals might increase savings before retirement as a precaution.

Second, we have restricted the analysis to singles to keep the lifecycle model tractable. The effects for couples can be expected to differ, as they can rely more on informal care and are able to share financial shocks. One of the advantages of the nearest neighbor approach is that the inclusion of additional variables, such as household status, is very straightforward (see Hussem et al. (2016) for an example). An extension of the model to multi-person households would thus be an interesting exercise for further research.

Third, we have treated LTC costs as exogenous shocks. In theory, co-payments reduce inefficient use of care (moral hazard) as they increase the marginal costs of care use for the patient. An issue in modeling LTC use as an endogenous decision is that the empirical literature on the effects of co-payments (or prices) on LTC use is very limited (Konetzka et al., 2014), and inconclusive (e.g. Grabowski and Gruber (2007); Li and Jensen (2011); Konetzka et al. (2014)). These studies provide no insight in two things that would be crucial in our setting: the effect of the marginal price at different levels of LTC use and the income elasticity of LTC demand.

The insights on these two issues are inconclusive. Theoretical findings on the trade-off between insurance and moral hazard at different levels of care need suggest that co-insurance rates should be high in good health states, in which elasticity of demand is high, and low or zero in poor health states, in which elasticity of demand is low (Drèze and Schokkaert, 2013; Blomqvist, 1997). This seems to be in favor of the current Dutch system, in which the marginal annual co-payment rate is a 100 percent at low levels of care, and zero at high levels of care due to the income- and wealth-dependent maximum. In contrast, a flat-rate might be more optimal as it puts relatively high co-payments on the groups with low financial means, who in standard models (e.g. De Nardi et al. (2010, 2016)) are more price sensitive. In the case of public insurance, however, high income groups might be more price sensitive for public LTC, as they have more possibilities to substitute with private care. In 2013, the Dutch government increased the wealth-dependent co-payment. This might offer another opportunity for future research (for work on this for home care see Non (2017)).

7 Conclusion

Income- and wealth-dependent co-payments provide more value of insurance than flat-rate co-payments, that do not depend on the financial means of the LTC user. This insurance is particularly important for elderly in the middle groups. Elderly with little financial means benefit from an income- and wealth-dependent co-payment, compared to a flat-rate co-payment, both because their LTC payments are lower on average and because they are exposed to less financial risk. Elderly with higher financial means have to pay more on average, but only for the twenty percent of the elderly with the highest means this outweighs the costs of the additional risk that comes with the flat-rate co-payment. Unless one expects that a flat-rate co-payment leads to substantially less distortions during working life, or substantially decreases moral hazard, the welfare case for an income- and wealth-dependent co-payment seems strong.

References

Ameriks, J., Caplin, A., Laufer, S., and Van Nieuwerburgh, S. (2011). The joy of giving or assisted living? Using strategic surveys to separate public care aversion from bequest motives. *The Journal of Finance*, 66(2):519–561.

Arellano, M., Blundell, R., and Bonhomme, S. (2017). Earnings and consumption dynamics: a nonlinear panel data framework. *Econometrica*, 85(3):693–734.

Blomqvist, Å. (1997). Optimal non-linear health insurance. *Journal of Health Economics*, 16(3):303–321.

Brandt, M. W., Goyal, A., Santa-Clara, P., and Stroud, J. R. (2005). A simulation approach to dynamic portfolio choice with an application to learning about return predictability. *Review of Financial Studies*, 18(3):831–873.

Brown, J. R. and Finkelstein, A. (2007). Why is the market for long-term care insurance so small? *Journal of Public Economics*, 91(10):1967–1991.

Carroll, C. D. (2006). The method of endogenous gridpoints for solving dynamic stochastic optimization problems. *Economics Letters*, 91(3):312–320.

Colombo, F. and Mercier, J. (2012). Help wanted? Fair and sustainable financing of long-term care services. *OECD Health Policy Studies*.

CPB (2017). *Keuzes in kaart 2018-2021*. CPB, The Hague.

De Nardi, M., Fella, G., and Pardo, G. P. (2018). Nonlinear household earnings dynamics, self-insurance, and welfare. Working Paper 24326, National Bureau of Economic Research.

De Nardi, M., French, E., and Jones, J. B. (2010). Why do the elderly save? The role of medical expenses. *Journal of Political Economy*, 118(1):39–75.

De Nardi, M., French, E., and Jones, J. B. (2016). Medicaid insurance in old age. *The American Economic Review*, 106(11):3480–3520.

De Nardi, M., Pashchenko, S., and Porapakkarm, P. (2017). The lifetime costs of bad health. Working Paper 23963, National Bureau of Economic Research.

Drèze, J. H. and Schokkaert, E. (2013). Arrows theorem of the deductible: moral hazard and stop-loss in health insurance. *Journal of Risk and Uncertainty*, 47(2):147–163.

Farmer, J. D. and Sidorowich, J. J. (1987). Predicting chaotic time series. *Physical review letters*, 59(8):845.

Finkelstein, A., Luttmer, E. F., and Notowidigdo, M. J. (2013). What good is wealth without health? The effect of health on the marginal utility of consumption. *Journal of the European Economic Association*, 11(suppl_1):221–258.

French, E. and Jones, J. B. (2004). On the distribution and dynamics of health care costs. *Journal of Applied Econometrics*, 19(6):705–721.

Grabowski, D. C. and Gruber, J. (2007). Moral hazard in nursing home use. *Journal of Health Economics*, 26(3):560–577.

Hsieh, D. A. (1991). Chaos and nonlinear dynamics: application to financial markets. *The journal of finance*, 46(5):1839–1877.

Hurd, M. D., Michaud, P. C., and Rohwedder, S. (2017). Distribution of lifetime nursing home use and of out of pocket spending. *PNAS*, 114(37):9838–9842.

Hussem, A., Ter Rele, H., and Wouterse, B. (2017). Inkomens- en vermogensafhankelijke eigen bijdragen in de langdurige ouderenzorg: een levensloopperspectief. Design Paper 87, Netspar.

Hussem, A., Van Ewijk, C., Ter Rele, H., and Wong, A. (2016). The ability to pay for long-term care in the Netherlands: A life-cycle perspective. *De Economist*, 164(2):1–26.

Jones, J. B., De Nardi, M., French, E., McGee, R., and Kirschner, J. (2018). The lifetime medical spending of retirees. Working Paper 24599, National Bureau of Economic Research.

Khwaja, A. (2010). Estimating willingness to pay for medicare using a dynamic life-cycle model of demand for health insurance. *Journal of Econometrics*, 156(1):130–147.

Koijen, R. S., Nijman, T. E., and Werker, B. J. (2010). When can life cycle investors benefit from time-varying bond risk premia? *Review of Financial Studies*, 23(2):741–780.

Konetzka, R. T., He, D., Guo, J., and Nyman, J. A. (2014). Moral hazard and long-term care insurance. *Health & Healthcare in America: From Economics to Policy. Ashecon*.

Koot, P., Vlekke, M., Berkhout, E., and Euwals, R. (2016). Mimosi: microsimulatiemodel voor belastingen, sociale zekerheid, loonkosten en koopkracht. *CPB Background Document, The Hague*.

Kopczuk, W. and Lupton, J. P. (2007). To leave or not to leave: The distribution of bequest motives. *The Review of Economic Studies*, 74(1):207–235.

Kopecky, K. A. and Koreshkova, T. (2014). The impact of medical and nursing home expenses on savings. *American Economic Journal: Macroeconomics*, 6(3):29–72.

Li, Y. and Jensen, G. A. (2011). The impact of private long-term care insurance on the use of long-term care. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing*, 48(1):34–50.

McClellan, M. and Skinner, J. (2006). The incidence of medicare. *Journal of Public Economics*, 90(1):257–276.

Meyer, B. and Mok, W. K. (2009). Disability, earnings, income and consumption. Working Paper 18869, National Bureau of Economic Research.

Non, M. (2017). Co-payments in long-term home care: do they affect the use of care? CPB Discussion Paper 363, CPB Netherlands Bureau for Economic Policy Analysis.

Palumbo, M. G. (1999). Uncertain medical expenses and precautionary saving near the end of the life cycle. *The Review of Economic Studies*, 66(2):395–421.

Peijnenburg, K., Nijman, T., and Werker, B. J. (2017). Health cost risk: A potential solution to the annuity puzzle. *The Economic Journal*, 127(603):1598–1625.

Pettitt, A. (1976). A two-sample Anderson-Darling rank statistic. *Biometrika*, 63(1):161–168.

Van Ooijen, R., De Bresser, J., and Knoef, M. (2018). Health and household expenditures. Design Paper 103, Netspar.

Wong, A., Boshuizen, H., Polder, J., and Ferreira, J. A. (2016). Assessing the inequality of lifetime healthcare expenditures: a nearest neighbour resampling approach. *Journal of the Royal Statistical Society: Series A*, (180):141–160.

A Removal of period effects from the source data

To remove period effects from the data, we rescale the values of the LTC, income, and wealth variables in earlier years to 2013 levels. As period effects may not only affect the mean, but also the shape of the distribution, we perform the following procedure for each variable. First, we divide the variable in 200 quantiles for each year and spline these quantiles (cubic splines with 10 knots). Then, we regress the variable on these splined quantiles. This gives a smooth estimate of the value of the variable over its entire distribution for each year. Finally, we use differences between the estimated value in the year of the observation and in 2013 to determine a scale factor for each quantile. We scale the original values of the variable using these scale factors.

B Comparison of the lifecycle paths to the source data

In this section we provide some additional information on the assessment study to evaluate the performance of our proposed algorithm.

B.1 Assessment of fit for each outcome

To compare the distribution of a particular outcome variable for some gender g and initial age a, we use the Anderson-Darling statistic. This statistic has the form

$$d(G,F) = \int_{-\infty}^{\infty} w(G-F)^2 dF, \tag{12}$$

with $w = [F(1-F)]^{-1}$, F is the cumulative distribution function of the source data, and G of the simulated data. The statistic can be interpreted as a distance between G and F, with lower distances implying a great similarity between G and F. The Anderson-Darling statistic relatively emphasizes any differences in the tails of the distribution. Figure 7 shows a heatmap of this statistic across outcomes and age and gender, for different algorithm settings.The figure shows clear trade-offs: there is no setting that performs best across all outcomes. The figure also shows that our preferred setting (10 neighbors and 1 lag for continuous and categorical variables) performs relatively well across the board.

B.2 Results from the assessment study

To give some additional impression of the fit, we show Q-Q plots and compare the serial correlation in the simulated to that in the actual data. Shown are the results for 85-year old women in 2009. For household income, wealth and home care costs, the Q-Q plots (Figure 8) generally reveal a reasonable agreement between the simulated and observed lifecycles in terms of the distribution of the sum over the entire period. Exception herein are the costs for nursing home care, in which there is substantial downwards bias for the simulated costs. We found that this was persistent for several choices of our algorithm settings. Upon further inspection, we found that the quality of the nearest neighbors is high (in terms of very small distances between observed and expected lifecycles), so the algorithm essentially works well. We suspect that the large variance and skewness of the nursing home care costs (more so than other variables) are a reason for this. As was documented previously by Wong et al. (2016), the performance might suffer when the actual underlying distribution is heavy tailed. Otherwise, we find that the serial correlations are also reasonably similar, even for the nursing home care costs (see Table 8). The simulated mortality rate also corresponds well with the observed mortality rate (not shown).

Table 8: Serial correlation in nursing home care costs for women of 85 in 2010. In the source data and in the simulated data.

Source data (a)					
	84	85	86	87	88
84	1				
85	0.79	1			
86	0.67	0.78	1		
87	0.60	0.67	0.82	1	
88	0.53	0.58	0.72	0.85	1
Simulated data (b)					
	84	85	86	87	88
84	1				
85	0.84	1			
86	0.73	0.83	1		
87	0.64	0.75	0.86	1	
88	0.61	0.69	0.79	0.88	1
Difference (b-a)					
	84	85	86	87	88
84	0				
85	0.05	0			
86	0.06	0.04	0		
87	0.04	0.08	0.04	0	
88	0.09	0.11	0.07	0.03	0

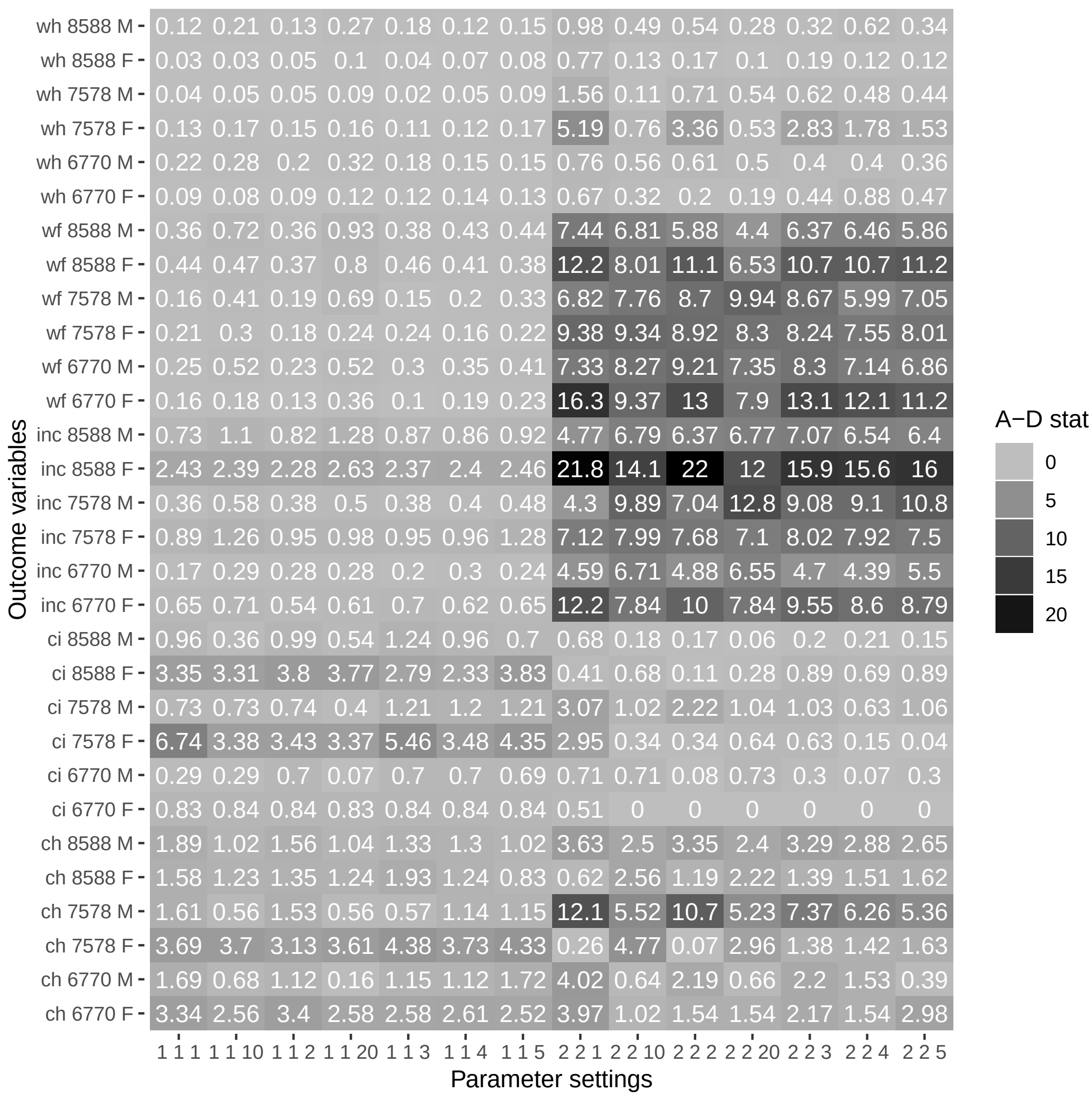
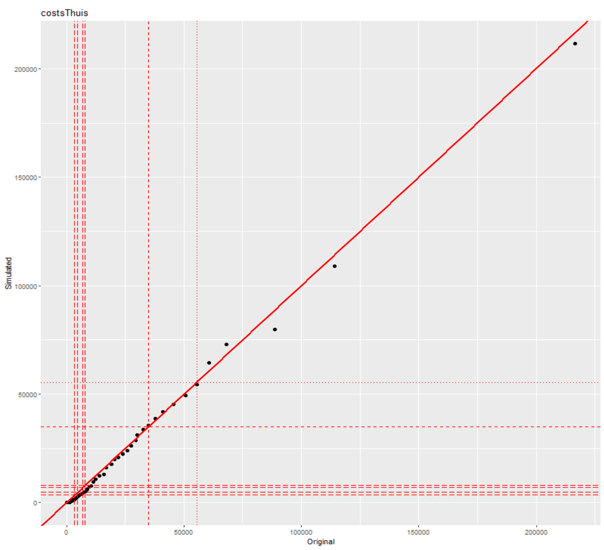
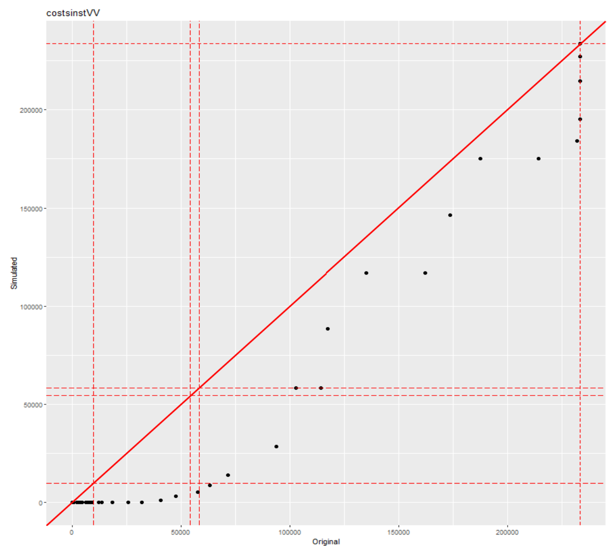


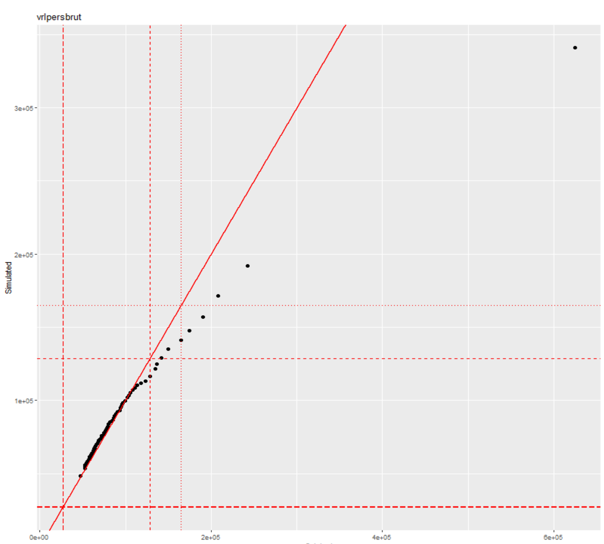
Figure 7: Heatmap of Anderson-Darling values of fit per outcome variable
Outcomes include housing wealth (wh), financial wealth (wf), gross personal income (inc), institutional care (ci), and home care (ch), for different ages and men (M) and women (F). The parameter settings are denoted as follows (lag categorical variables, lag continuous variables, number of neighbors.)



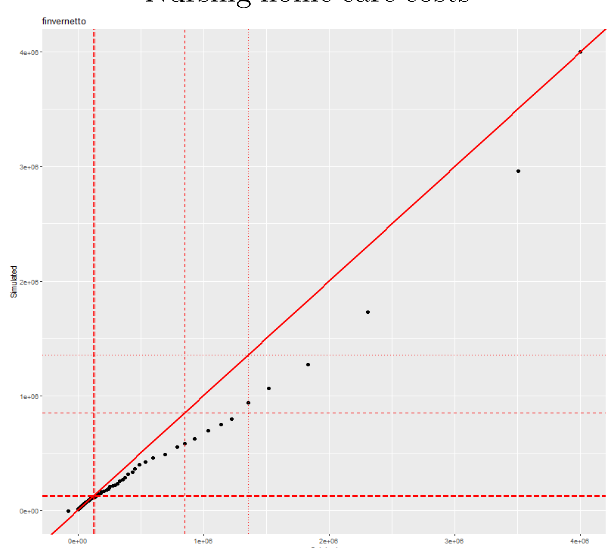
Home care costs



Nursing home care costs



Income



Financial wealth

Figure 8: Q-Q plots of the source data versus the simulated data for women of 85 in 2010.

C Numerical approach

The basic model

We solve the maximization problem using a dynamic programming approach developed by Koijen et al. (2010). The lifecycle optimization problem is divided into smaller yearly optimization problems, using Bellman equations. In each period the optimization problem can be written as

$$\max \left[\mathrm{E}(U_{i,t}) = u(c_{i,t}) + \mathrm{E}_t[V_{i,t+1}(m_{i,t})\right]. \tag{13}$$

The algorithm starts at the last time period T, and is then solved backwards recursively.

To see how the algorithm works, let's start in the final period T. If an individual is still alive at period T, he consumes all his remaining wealth. So optimal consumption is given by:

$$c^*_{i,T} = W_{i,T} - h_{i,T} \tag{14}$$

and $u^*_{i,T} = u(c^*_{i,T})$.

For period $T-1$, we define a fixed grid with $j = 1, .., J$ gridpoints g_j for the level of wealth $m_{i,T-1}$ the individuals wants to leave for period T. If we know the wealth level an individual wants to leave after $T-1$, the level of optimal consumption $c^*_{i,T-1}$ is given by the first order condition:

$$(c^*_{i,T-1} | m_{i,T-1} = g_j) = (\mathrm{E}(\beta c^{*-\gamma}_{i,T} r | m_{i,t-1} = g_j))^{-\frac{1}{\gamma}}. \tag{15}$$

This is the standard Euler condition implying that individuals want to smooth consumption evenly over remaining lifetime.

To determine $\mathrm{E}(\beta c^{*-\gamma}_{i,T} r | m_{i,t-1} = g_j)$ we use a simulation approach. The idea is similar to a Monte-Carlo simulation: the lifecycle paths give us a large number of random draws from the stochastic process determining mortality and LTC spending. The expected value can then be estimated by averaging over these draws. Note that for each individual i the realized consumption in T conditional on $m_{i,T-1}$ is given by the fact that (if still alive) the individual will consume all the wealth he has left: $(W_{i,T} | m_{i,t-1}) = m_{i,t-1} r$ and $(c^*_{i,T} | m_{i,t-1}) = m_{i,t-1} r - h_{i,T}$. To determine the expected value we regress these realizations of consumption at T on (a polynomial expansion) of the state variables (background characteristics and LTC spending) at time $T-1$. This gives

$$\mathrm{E}(\beta c^{*-\gamma}_{i,T} r | m_{i,T-1} = g_j) \simeq \theta f(x_{i,T-1}), \tag{16}$$

with $x_{i,t-1}$ a vector with the state variables in period $t-1$ and $f()$ a polynomial expansion of some order.[14] We estimate this equation using a GLM with log-link, to ensure that the estimated values are strictly positive.

[14]In our application, we include dummies for,wealth group, and income group, and include the levels of current nursing home care and home care use. All variables are interacted with gender.

The expected values are then obtained by using the predictions from the regression model (conditional on the state variables), and this also provides the optimal level of consumption in period $T-1$ given $m_{i,T-1}$. We have to perform this procedure for each gridpoint, and thus have to run a regression for each gridpoint.[15]

Now that we have the optimal consumption levels $c^*_{i,T-1}|m_{i,T-1} = g_j$ for each fixed gridpoint g_j for wealth *at the end* of period $T-1$, we can create a grid with endogenous gridpoints for wealth $W_{i,T-1}|m_{i,T-1} = g_j$ *at the beginning* of period $T-1$. These are given by

$$(W_{i,T-1}|m_{i,T-1} = g_j) = (c^*_{i,T-1}|m_{i,T-1} = g_j) + h_{i,T-1} + g_j. \tag{17}$$

The level of initial wealth at the beginning of $T-1$ is determined by the level of wealth that is saved at $T-2$. So we now have the set-up for the iterative algorithm. Because the endogenous gridpoints $W_{i,T-1}|m_{i,T-1} = g_j$ are not necessarily the same as the fixed gridpoint we use for m_{T-2}, we use linear interpolation to obtain the levels of optimal consumption in $T-1$ belonging to the gridpoints g for wealth saved at the end of period $T-2$ for each individual. This then, allows us to estimate expected optimal consumption at $T-1$ using the same regression as in Equation (16). This gives optimal consumption in $T-2$. And this in turn determines the endogenous gridpoints for $W_{i,T-2}$. We can iteratively perform this algorithm for periods down to $t = 1$. In the end, we have the optimal consumption for a set of endogenous gridpoints, $W_{i,t}|m_{i,t} = g_1, ..., W_{i,t}|m_{i,t} = g_J$, for each period t . These endogenous gridpoints and optimal consumption can be different for each individual (path) i.

Now that we have the consumption rules, we can use these to simulate consumption and saving behavior of the individuals in the lifecycle sample. We do this by assigning an amount of initial wealth at the start of the first period to each individual. We can then simulate forward.

Extensions

The inclusion of a bequest motive and state-dependent utility in the optimization procedure is relatively straightforward. The same is true for including a fixed pension income. The policy variants require an adaptation to the numerical approach. Wealth-dependent co-payments put an implicit tax on savings. Individuals have to include this tax when making decisions on current consumption. Specifically we adapt the Euler equation (15) by including the expected marginal implicit tax on wealth.

[15] As pointed out by Koijen et al. (2010) the endogenous grid method facilitates the use of this regression based approach. The optimal consumption can be derived analytically from the Euler equation (15) once the conditional expectation is known, so we do not need to determine this numerically. Else we would have to run for each gridpoint a (non-linear) regression at each iteration of the numerical optimization process, instead of just once for each gridpoint.

D Additional results

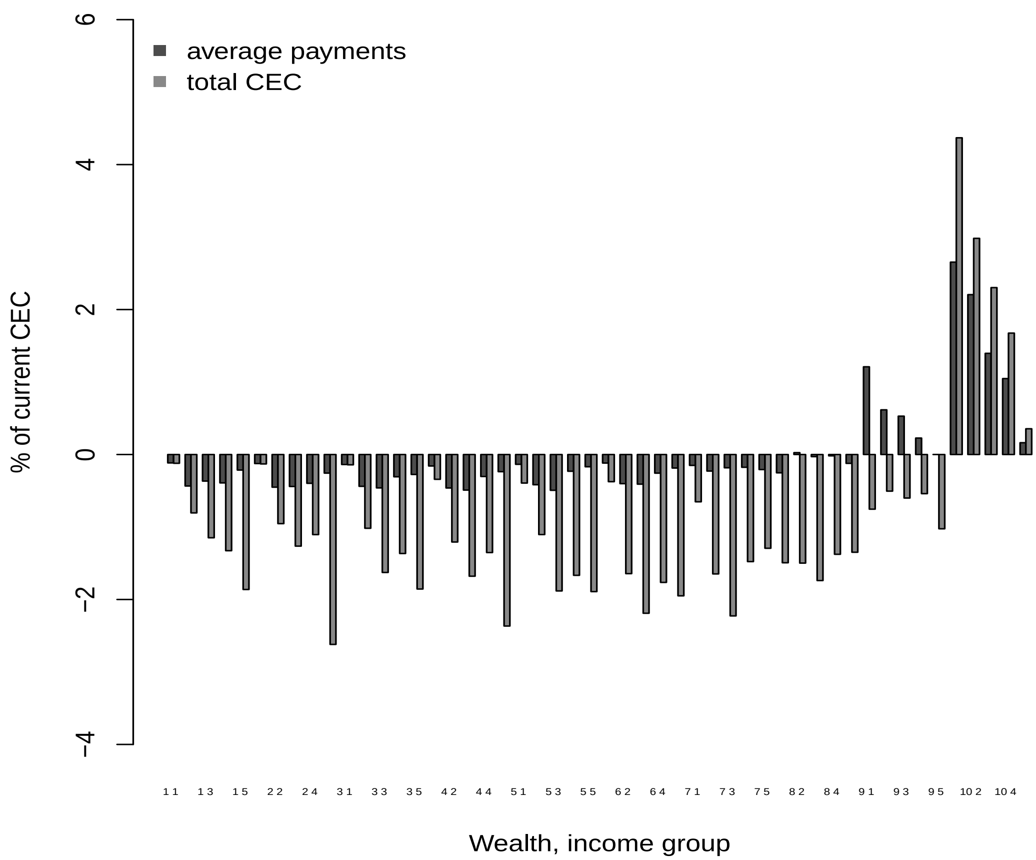


Figure 9: The change in average payments and total welfare, resulting from going from the current co-payment system to a co-payment that only depends on income. For each income and wealth group.
The groups are defined as follows: (wealth decile (1 lowest -10 highest), income quintile (1-5)). Note that not all combinations of income and wealth groups are equally large.

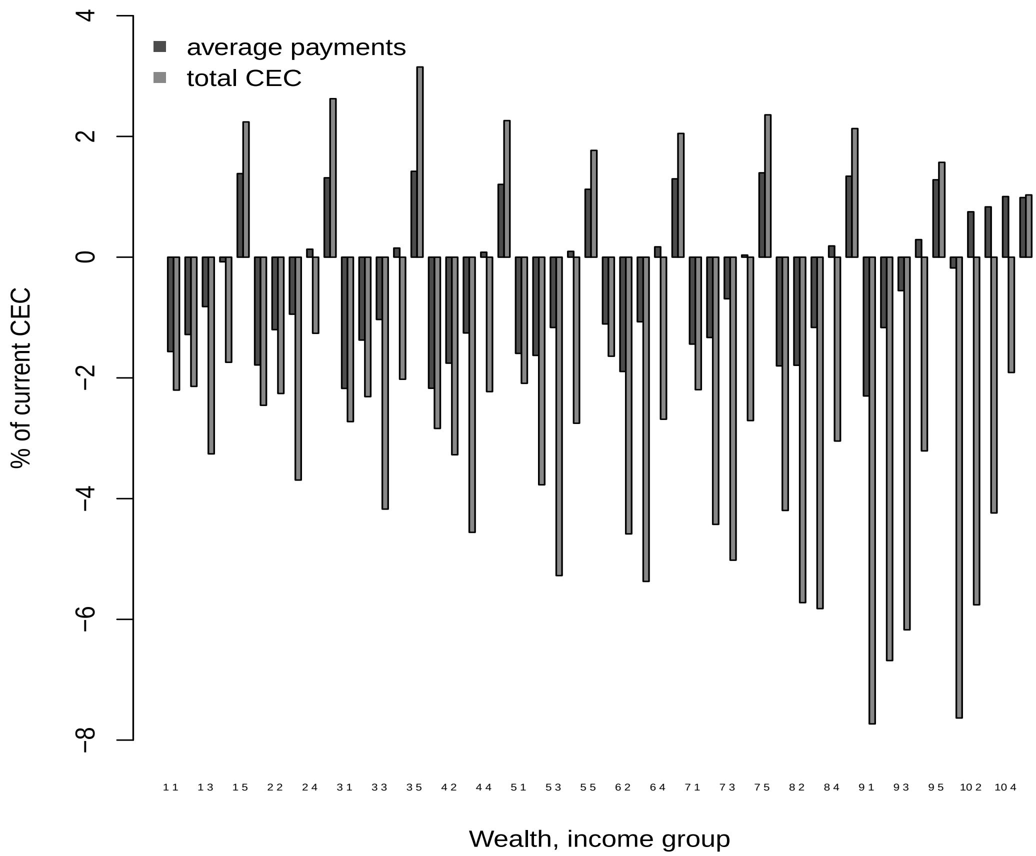


Figure 10: The change in average payments and total welfare, resulting from going from the current co-payment system to a flat-rate co-payment. For each income and wealth group.
The groups are defined as follows: (wealth decile (1 lowest -10 highest), income quintile (1-5)).
Note that not all combinations of income and wealth groups are equally large.