Network for Studies on Pensions, Aging and Retirement

NETSPAR ACADEMIC SERIES

Pension Reforms, Labor supply and Savings

The Importance of Natural Experiments for Structural Estimation

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DP 03/2022-005

Pension Reforms, Labor supply and Savings. The Importance of Natural Experiments for Structural Estimation*

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March 10, 2022

Abstract

We study reforms of the social security system within a life cycle model of savings and discretized labor supply. We extend the standard estimation approach that only relies on data moments o life cycle profiles by exploiting quasi-exogenous variation. We explore the importance of such exogenous variation for the estimated parameters and counterfactual policy analyses. Our estimation relies on administrative data from the Netherlands, which actively taxes wealth. Thus, the data used for estimation has minor measurement errors, especially in wealth.

JEL: D15, D81, H31, J26

Keywords: Structural estimation; identification; dynamic mixed discrete and continuous choice; Retirement; Labor supply; Savings

*The authors wish to thank Jochem de Bresser, Fedor Iskhakov and participants from the NETSPAR International Pension Workshop in 2021 and 2022 for their valuable comments as well as Raun von Oojien and Jeroen van der Vaart for help with the CBS data.

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1 Introduction

The pension systems of most Western countries have become under severe pressure from demographic change.[1] While some reforms of the retirement systems have taken place in various countries, more are likely to be necessary. It is hence of great importance for policy makers to evaluate the impact of potential pension reforms on peoples decision making, their well-being, and government finances. Estimating these impacts presents a challenging task. One possibility is to employ a dynamic structural model of individual behavior and simulate counter-factual policies. Such a model allows to quantify the financial consequences for the government by taking the behavioral consequences of household decisions into account. Moreover, structural modeling allows to compute potentially heterogeneous welfare effects within the population. Yet, the reliability of quantitative structural models depends crucially on the identification of the model parameters that govern the outcome.

In this paper, we evaluate the impact of potential reforms of the pension system by making use of a dynamic life-cycle model of savings with retirement and working hours decisions. We extend the standard estimation procedure that uses data moments on life-cycle profiles to identify the structural parameters that govern the behavior of the individuals in the model. In particular, we make use of a pension reform in the Netherlands in 2006 that altered the financial incentives of early retirement. As the reform only affected cohorts born 1950 or later, it created two almost identical groups of individuals that face different retirement regimes in their future. The cohort born in 1949 has a strong financial incentive to retire before age 65, while the cohort born 1950 has not. Differences in behavior between the two groups in employment and saving behavior provides exogenous variation that we use as an additional identifying source for the structural parameters. We aim to assess how these additional moments improve the precision of the estimation and to quantify how the two estimation methods yield different results when conducting counterfactual analysis to study policy reforms.

[1] Mercer (2019) grades retirement income systems of 37 countries on adequacy, sustainability and integrity. The majority of Western countries receive their lowest score (often by far) on sustainability.

Three components are of special interest in the estimation: First, the manner by which individuals discount their future expected utility – governed by the discount rate. Second, the magnitude by which agents are willing to intertemporally smooth consumption over time – governed by the intertemporal elasticity of substitution (IES).[2] Third, the preferences for labor supply – measured by the disutility of working.

These parameters are key for understanding retirement behavior. The value of the exponential discount factor determines how strongly individuals incorporate future consequences into their current decision making. A shift from pension system with government provided payments towards a system with a more privately focused pension planning relies on forward-looking individuals. The more myopic individuals are, the higher the welfare costs for such a shift. The IES is another important parameter for economic policy. The parameter determines how strongly people are willing to substitute resources over time. For example, the higher the IES, the stronger individuals react to changes of the interest rates. Thus, the optimal level of subsidies on private savings depends strongly on the IES.

Previous literature studying household saving behavior and retirement has aimed at estimating structural parameters by using data moments from a defined steady-state economy.[3] Identification is mostly relying on age profiles of income, wages, and assets.[4] The estimated models are then used to study behavioral and welfare consequences of policy reforms. To this end, parameters of the government systems are changed and the outcomes of the simulated model under the new system is compared with the estimated benchmark economy. Besides the discount factor, elasticities (i.e., the elasticity of intertemporal substitution, and the elasticity of labor supply) are most relevant. In our approach we aim to identify these elasticities from a natural experiment that induced behavioral consequences.

The Netherlands provides an ideal environment for our study for several reasons. Besides the policy reform that aids our identification, the Netherlands are taxing wealth. The wealth tax allows us to use administrative data for assets, an important component

[2]Note that in typically used CRRA utility specification the IES is the inverse of the parameter of relative risk aversion.

[3]See our literature review in Section 2 for a more detailed discussion.

[4]And, since only seldom available in household surveys, on consumption data.

of retirement decisions. Additionally, Mercer (2019) rates the pension system of the Netherlands as the second best overall system among their 37 studied countries, only behind Denmark. An overall system that is already performing well aids the studying of the optimal design of pension systems compared to a system that is far away from being optimal.[5]

The reform, we focus on, creates different expected futures for almost identical groups of individuals. Differences in employment and saving behavior provide the grounds for the identification of the exponential discount factor. Intuitively, the greater the difference in behavior due to different expected futures, the stronger individuals include future consequences into their decisions. In contrast, if there are no differences in behavior, although future consequences differ, individuals have to be myopic.

In a standard dynamic model of consumption and labor supply, the IES is determined by the curvature of the utility function. Our identification of the IES is based on the observation that the pension reform that drastically changed the pension payments for early retirees, and hence, directly affects the (discrete) labor supply choices of individuals while consumption decisions and hence marginal utility of working agents is only indirectly affected. The reform helps to distinguish discounting from the willingness to intertemporally substitute, governed by the IES.

Our study starts by investigating the behavioral responses of individuals to the reform in 2006 in terms of hours worked, early retirement decisions and asset accumulation. We document that households strongly react in the intensive and extensive margin of labor supply. However, there is very little to almost no reaction in private saving behavior.

We then set up a dynamic life cycle model starting at age 50 until the terminal age 100. Our model features continuous consumption choices and discrete choices on labor supply including early retirement. Decisions are subject to uncertainty with respect to income, survival, and health shocks. Health deprivation over age decreases the hourly wage. We model the social insurance system of the Netherlands including social security,

[5] Counter-factual simulations tend to be less reliable the stronger the counter-factual is away from the status quo.

employer pensions depending on working and earning history, unemployment insurance and disability insurance.[6] Early retirement rules mimic the two systems before and after the reform that we study.

We rely on the method of simulated moments (MSM) to estimate the parameters of our model and use two different sets of moments. In the *standard approach* we use the moments that are typically used to estimate these models. We solely rely on average age-profiles of the crucial variables (labor supply, retirement, savings). In the second approach, the *reform approach*, we rely on the behavioral responses following the reform. This approach aims to address the concern that a model estimated via the standard approach might not sufficiently capture elasticities implied by the estimated preference parameters and hence, lead to biased results when conducting counterfactual analysis.

We then compare the two models on three dimensions: First, we assess how precisely the parameters are estimated via the evaluation of standard errors and by comparing the data moments to the model outcome. Second, we compare the outcome of both models with respect to the Dutch reform where we have data on. This allows us to evaluate how well the fit of the standard approach is with respect to the reform compared to the reform approach where the data on the outcome of the reform is actually targeted. Third, we evaluate an ex-ante policy reform for both models, where we replace the lump-sum AOW pension payment and simply allow for a minimum standard of living (welfare payments). The quantitative difference of the results for these two models allows us to draw conclusions about the importance of using quasi-exogenous variation as additional targeting moments for structural estimation.

In Section 2, we summarize the literature regarding the estimation of life-cycle models focusing on the retirement decision. In Section 3, we lay out the Dutch pension reform from 2006. Section 4 describes the data and provides descriptive statistics. Afterward, we lay out the theoretical model and a sketch of how to solve and estimate our model in Section 5. Section 6 explain the two estimation methods that we compare and Section 7

[6] We assume that choosing not to work induces unemployment benefit if the individual is healthy and disability benefits if the individual is sick.

presents estimation results.

2 Literature

In the literature studying saving motives and retirement at older ages the identification of parameters usually stems from age profiles of asset holdings and labor supply or retirement entry. Studies about the entire life-cycle also rely on consumption data.

The seminal paper employing the method of simulating moments in life-cycle models is Gourinchas and Parker (2002). The data they use to match the model moments are the age-profile of consumption, which is hump-shaped and tracks income closely. The authors exploit these profiles to estimate the discount factors and the IES.

Cagetti (2003) estimates the discount factor and risk aversion of a life-cycle model via MSM and matches the age profile of median (and mean) wealth over three education classes. Cagetti (2003) allows for different preferences over education and finds lower discount factors and lower risk aversion parameters for the low educated. However, he struggles to separately identify the discount factor and the intertemporal elasticity of substitution. Both parameters seem to be working in the same direction: being patient and highly risk avers implies relatively high asset holdings.

De Nardi (2015) emphasizes that matching not only the age profile of asset holdings but also its distribution helps identifying the discount factor and the IES separately. In particular, the value for risk aversion is informed by the (skewed) asset distribution. High risk aversion tends to increase savings of everyone and to dampen wealth dispersion which helps identifying the parameter.

De Nardi, French, and Jones (2010) estimate a life-cycle model of saving behavior (without labor supply) to investigate the strength of the bequest motive. They introduce an additional consumption floor which is important to match the distribution of asset profiles in their model (over permanent income profiles). In particular, it is important to be able to match the non-existing savings of low-income households. Low-income households are relatively more protected by the consumption floor and will have lower values of the variance of future consumption growths, and hence weaker precautionary motives. The parameter of relative risk aversion helps the model explain why individuals with high permanent income typically display less asset decumulation. In addition, the bequest parameters are calibrated to match moments of the bequest distribution. Their resulting estimates indicate that bequests are a luxury good - implying that it is mainly important for the rich and induces them to even save more. This, in turn, increases the wealth dispersion.

Most closely related to our paper is French (2005) who estimates the preference parameters of the model by using age-profiles of employment, hours worked, and asset holdings. French (2005) estimates parameters for fixed costs of working by hours worked and employment rates, the IES and the discount factor. Identification of the IES or the parameter of risk aversion, which is its inverse comes from multiple sources: (i) information on hours worked and hourly wages. The fact that hours vary little over the life-cycle but wages do, implies low elasticities, (ii) the observation that wages co-vary little with hours when young but a great deal when old implies a strong precautionary motive, i.e., a high parameter of risk aversion, (iii) risk aversion is identified by the asset profile. High precautionary savings lead to high asset holdings when the relative risk aversion parameter is high. However, most of these profiles are simultaneously informative for the discount factor. For example, according to French (2005), the high working time of young individuals with low wage is also informative for the discount factor. It is equivalent to stating that young people buy relatively little leisure, even though the price of leisure (their wage) is low. In the middle of the life cycle they buy more leisure (work less) although wages rise. Therefore, life cycle labor supply profiles provide evidence that individuals are patient. Thus, these correlations influence both, the discounting and the intertemporal substitution (or risk aversion) in the same manner making it challenging to identify both separately.

The literature exploiting natural experiments for the estimation of structural models has been very small, but is growing lately. DellaVigna, Lindner, Reizer, and Schmieder (2017) are one example using a reform to identify behavioral parameters. They match reactions of a unemployment benefit reform in Hungary to provide evidence that unemployed individuals have reference-dependent preferences. First, they show that a standard job search model has problems fitting the observed responses, but a model including reference-dependent consumption can fit the respective moments well.

An example more closely related to our paper is Best, Cloyne, Ilzetzki, and Kleven (2020). They use discrete jumps, so-called notches, in mortgage interest rates in the UK to estimate the IES. However, they are not able to separably identify the IES and the discount factor, but show that including several extensions does not change their estimate of the IES much.

Low, Meghir, Pistaferri, and Voena (2018) use the behavioral responses in labor supply and divorce from a welfare reform for validating their estimated model. In particular, they estimate their model to the pre-reform economy and validate the model by simulating the policy reform in their model and compare this with their reduced-form estimates. Similarly, De Bresser (2021) validate different variants of a life-cycle model by comparing counterfactual prediction with data on a pension reform in the Netherlands. However, both papers do not use the empirical results for identification of the model parameters.

3 Pension Reforms in the Netherlands

To understand the exogenous variation that helps us to separately recover time preferences and the intertemporal elasticity of substitution, it is important to understand the key features of the Dutch retirement system.

The Dutch pension system consists of three pillars: the first pillar consist of a flat-rate social security benefit (the so-called AOW pension, *Algemene Ouderdomswet uitkering*), which all residents are entitled at the statutory retirement age. The second pillar is earnings-related occupational pensions mainly of the defined-benefit type. The third pillar includes all voluntarily build-up savings supplementary to the occupational pensions and the pubic scheme typically taken as annuities through an insurance company. The reform that this paper focuses on, was implemented in 2006 and abolished early retirement rules (so-called VUT, *Vervroegde Uittreding*) from the second pillar.

The pension payments of the second pillar are fully funded in general. They are negotiated between unions and employer organizations at the sector or firm level. Participation is quasi-mandatory (around 95 percent of the working population is covered) and is organized by special pension funds. Contributions are made by employers and employees. The pension payments depend on the years in the labor market and average life-time earnings.[7]

Before the reform was implemented in 2006, early retirement rules (VUT schemes) for individuals younger than 65 applied in the second pillar. These schemes operated as pay-as-you-go (PAYG) systems implying that the financing of early retirements was made by the current employees.

Early retirement was possible from age 59 onward and benefits retained a replacement rate of 85 percent until the statutory retirement age of 65.[8] Moreover, the years spend in early retirement counted for the accrual of pensions via accumulated years of work experience. At age 65, the early retirement benefit was replaced by the 'regular' occupational pension benefit computed via the pension formula that depends on working years and average annual earnings.

As of January 2006, this two-tied system was unified by applying the benefit formula to all pensioners and adjust early retirement in an actuarial fair manner. Further, late retirees (up to an age of 70) received a higher replacement rate.

This reform, however, was only applied to those born in 1950 or later while the pension rights of those born in 1949 (or earlier) were unaffected. In effect, the pension rights of the

[7] The benefit formula that we use is $0.0175 \times working\,years \times (average\,earnings - 19,131)$. The precise formulas vary slightly over occupations. We implemented the formula that covers the vast majority of individuals.

[8] See Euwals, Van Vuuren, and Wolthoff (2010) for an overview of the rules for different sectors in 2010 where some already offered early retirement at age 55. Grip, Lindeboom, and Montizaan (2012) and Lindeboom and Montizaan (2020) describe the reform for the public sector.

treated cohort were substantially reduced and with these the incentives to retire early. For the public sector, Lindeboom and Montizaan (2020) report a drop in the replacement rate for individuals who want to retire at age 62 by around 6 percentage points. Individuals needed to work an additional 13 months to obtain 70 percent, which was the replacement rate of their slightly older counterparts.

At the same time as the pension reform in 2006, the Dutch government introduced the so-called Life Course Savings Scheme (Levensloopregeling), a tax-facilitated savings program that permits tax-free savings of up to 12% of annual earnings in a fund that could be used to finance periods of non-employment, such as a sabbatical or early retirement. The introduction of the Life Course Savings Scheme thus enables all workers — those treated by the pension reform as well as those who are unaffected by it — to privately save at lower costs.

Various papers have exploited this reform. Most recently, Lindeboom and Montizaan (2020) assess the effect of the reform on the savings and retirement expectations (from a survey) and realizations (from admin data). They show that expectations are in line with realizations. They find that workers in bad health have zero substitution rates between private and public wealth and hence, work longer. On the other hand, there is a group of mostly high-wage workers who participate in the tax-facilitated Life Course Savings Scheme and who increase private savings.

Boot et al. (2019) exploit the impact of this reform on labor market transitions from 2010 (where the 1950/51 cohort is around 60) to 2015/2016 using Kaplan-Meyer survival curves. These two cohorts both have the same AOW pension age (65 and 3 months) and they both have the (same) savings-incentive that was introduced to offset the negative impact of the reform. They find work participation was prolonged until the statutory retirement age for the treated, but also to a larger proportion of unemployment benefits increase.

4 Data and Descriptive Statistics

This section describes our data and presents differences in age profiles between our treatment group, which was affected by the reform, and our control group, which was not affected. We focus on hours worked, asset holdings, retirement, the fraction of individuals in unemployment or on disability. We also disentangle the profiles by education, health status, and wealth quintiles. A detailed definition of these variables is relegated to the appendix.

4.1 Administrative Data in the Netherlands

We make use of various Dutch government administrative data sources which are collected by Statistics Netherlands (CBS) and managed within the System of social statistical data (SSD), a system of interlinked and standardized registers and surveys, cf. Bakker, Van Rooijen, and Van Toor (2014). By removing all individual identity description elements from the data, CBS provides a set of connectable data on the individual or firm level from different government administrations, such as the tax authorities, population registries, or the National Health Care Institute. The connection of different data sets is done with individual specific national identification numbers. In the Netherlands, every resident has a Citizen Service Number known as a *Burgerservicenummer (BSN).* This number is used for almost any official procedure, including housing, work, studies, doctors visits, and taxes. It allows for linking individual level data from many different government institutions. These so-called microdata can be accessed remotely by researchers at Dutch institutions. By connecting different administrative data we can construct a panel data set, which is as rich as household surveys and consist of socio-economic characteristics (age, gender, education), detailed work characteristics (employment, hours worked, labor income), asset holdings (due to a wealth tax in the Netherlands), and even health information from insurances. Yet, the sample size of the data allows for exploiting natural experiments such as the one that we study, which introduced a month-specific cut-off for a specific birth cohort.

4.2 Sample

Starting point is the Municipal Population Register (*Gemeentelijke Basisregistratie*) which consists of the whole Dutch population. It includes basic socio-economic characteristics such as gender and date of birth. We merge this data set with records on income, wealth, education and administrative health records. Details are described further below.

In principal, our sample consists of the entire Dutch population. We are only restricted by the missing values of the variables of our interest. In particular, data on educational attainment is missing for a larger share of the population. Further, asset holdings and health data are not available for all years. Our final data is a panel from 2006-2015. We define all variables to be realized at the end of the year. A detailed description of the sample and the definition of the variables is presented in the Appendix B.

We focus on men only because women's retirement decisions are more complex. We also drop individuals who are self-employed as we are not modeling the choice of self-employment. Since the public sector has different retirement rules as the private sector, we also exclude employees in the public sector. Finally, we focus on individuals that were in the labor force at age 50.

We make use of the full sample to compute the initial conditions of our model using the first available year 2006 for all agents at age 50 (corresponding to the cohort born in 1956). We then create a panel for 2006-2015 to compute the income process, the health transition probabilities and the mortality rates. In addition, we use the panel to compute the age-profiles on wages, and asset holdings.

When analyzing the effect of the pension reform in 2006, we focus on very specific cohorts: we construct a treatment and a control group defined as people born between October and December 1949 (control group) and January and March 1950 (treatment group). We then compare the average profiles for these specific cohorts.

To investigate whether the two cohorts do not differ in observable characteristics, Table

1 presents a selection of variables for the year 2006 where the reform was implemented. The averages do not differ significantly between the two groups.

Although the whole sample size is about $130,000$ observations, the sample size for the control and treatment groups are only a tenth with $13,000$ individuals in 2006. The rather small sample size is due to the fact of missing observations for the education variable especially for older cohorts in the data.

Table 1: Descriptive statistic, control and treatment group 2006

	Control	Treatment	p-val diff.[1)]
Age	56	56	.
High school (fraction)[2)]	0.790	0.797	0.53
Sick (fraction)[3)]	0.301	0.297	0.51
Wages	23.05	23.26	0.48
Net Wealth	196,235	199,218	0.83
Hours Worked	1,824	1,829	0.38
N[4)]	3,255	3,780	

[1)] p-value of t-test about difference in means [2)] Measured as fraction; We distinguish between individuals who have at least a Bachelor's degree and those who have not; [3)] We distinguish between healthy and sick individuals; [4)] No. of observations with non-missing values for socio-economic characteristics (age, education, health).

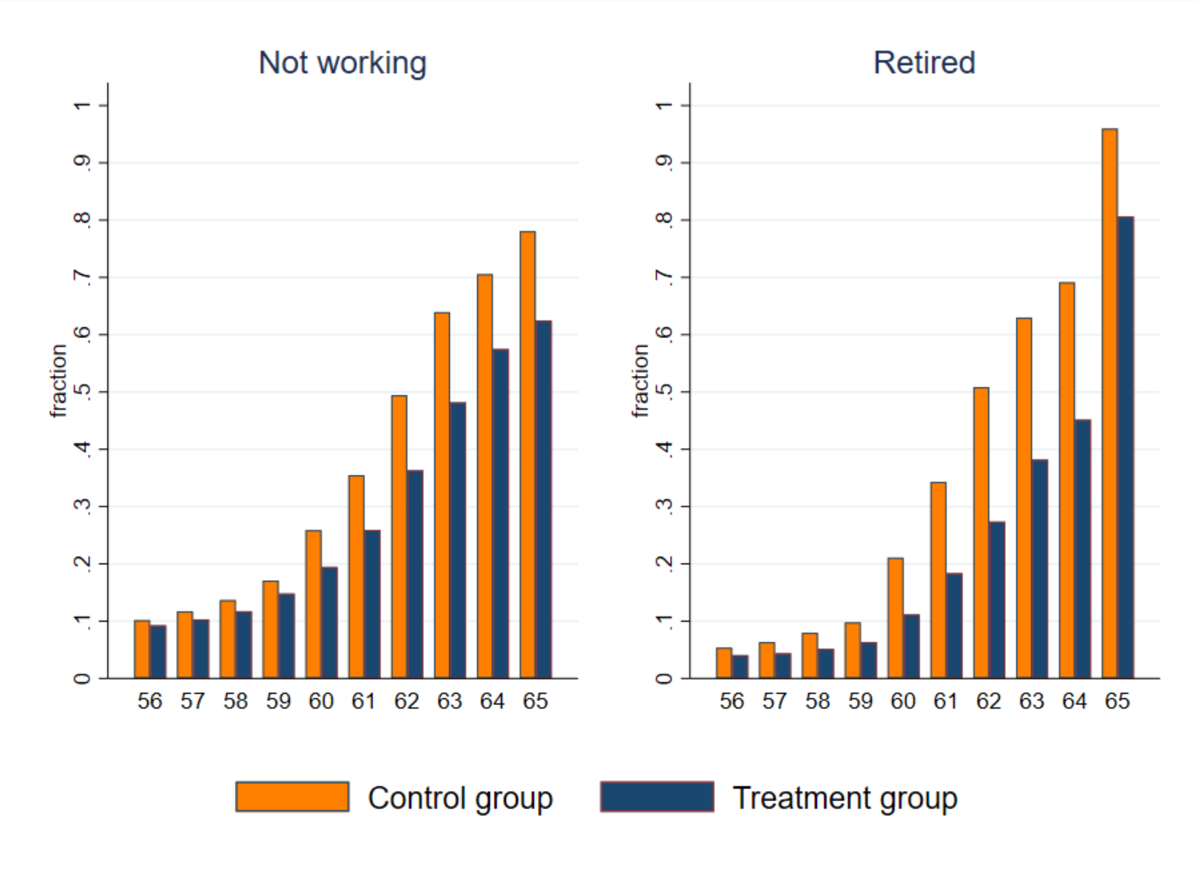
4.3 Employment and Retirement Decision

As our first statistic we present the extensive margin of employment and the retirement decisions of the treatment group affected by the pension reform compared to the control group. Due to the abolition of the early retirement rules we see a very sizable effect for the decision to retire and to stop working.[9]

The right panel of Figure 1 shows that the reform led to a sizable delay in retirement entry. In particular starting at age 60, the difference in the fraction of people who are retired is around 10pp which grows to a difference of 25pp at age 63; hence there is a reduction of people retiring at age 63 and 64 of around one quarter.

[9]Retirement is defined as the state where the individual has retirement income as their main income source, while not-working is defined as working zero hours. The latter includes people on UI and DI, and voluntary staying our of the labor force.

Figure 1: Employment and Retirement Decision

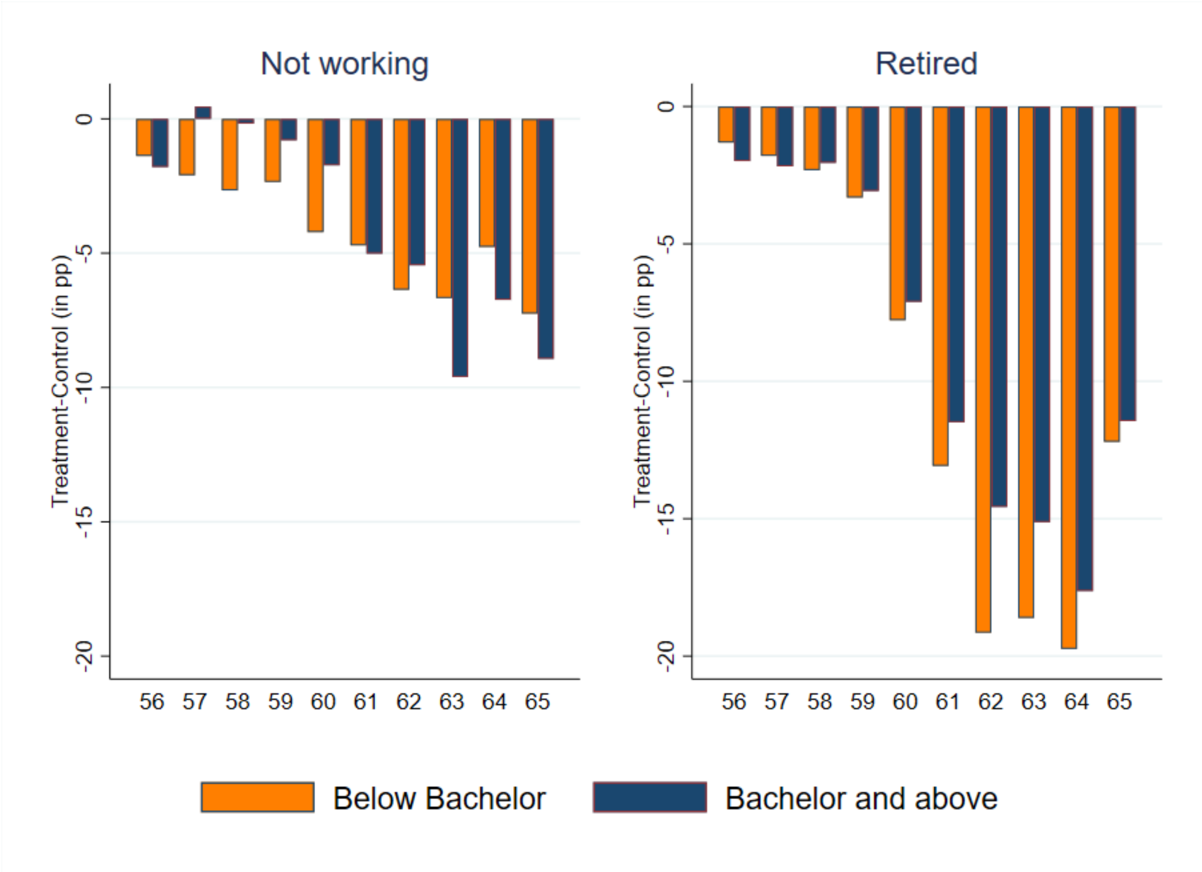


Age-profile of the fraction of men without positive hours working (*not working*) and with retirement income as their main income source (*Retired*).

Figure 2 shows the difference of the treatment and the control group (in percentage points) and disentangles over educational types.[10] We see sizable effects on the extensive margin of labor supply (zero working, retirement) for both educational groups. However, highly educated individuals exhibit a somewhat higher difference (i.e. a larger reaction to the reform) for the decision to stop working, while the retirement entry decision is somewhat larger for the low educated, implying that more low-educated agents postpone retirement due to the reform. The latter is expected due to the fact that high-educated individuals are more wealthy and, hence, might be able to retire earlier and accept the reduction in benefits.

[10]Due to smaller sample sizes the data over education does not fully match with the overall average Figure 1.

Figure 2: Employment and Retirement Decision over Education



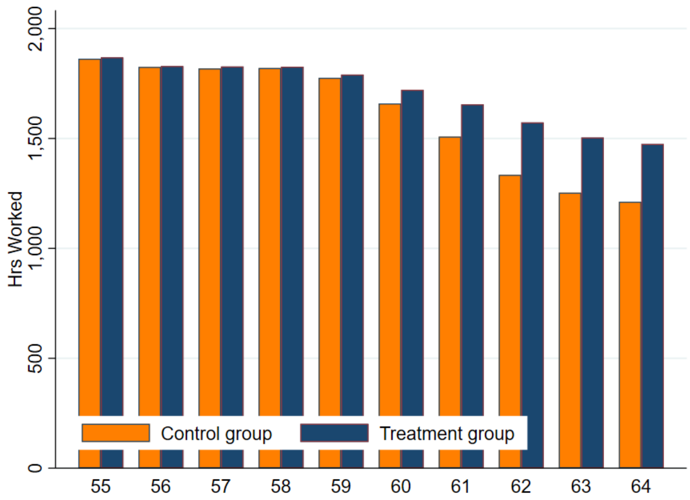
Age-profile of the difference (in percentage points) between the treatment and the control group over educational types (fraction of men with zero hours worked (*not working*) and with retirement income as their main income source (*Retired*).

4.4 Hours worked

We discretize the distribution of hours into four categories (including no work). Our cluster of hours corresponds full-time work, as well as two part-time fractions of roughly 40 and 90 percent of a full-time job, see appendix B for how we determined these numbers.

Figures 3 and 4 plot the total hours (conditional on positive) as well as the fraction in each of the hours clusters for the treatment and control group. At an age of around 60, one can observe that the group that was affected by the pension reform in 2006 adjusted their working hours upwards. This trend is increasing over age, until 65. From age 61 to 65 the reform is associated with an increase of annual hours by around 150, which amounts to roughly seven percent of a full-time job. In addition, the fraction of people not working is significantly lower after the reform indicating that a lower fraction of people go into early retirement. Interestingly, there is hardly any reaction between age 56 to 59 – and even a negative one for high-educated healthy individuals.

Figure 3: Total Hours Worked



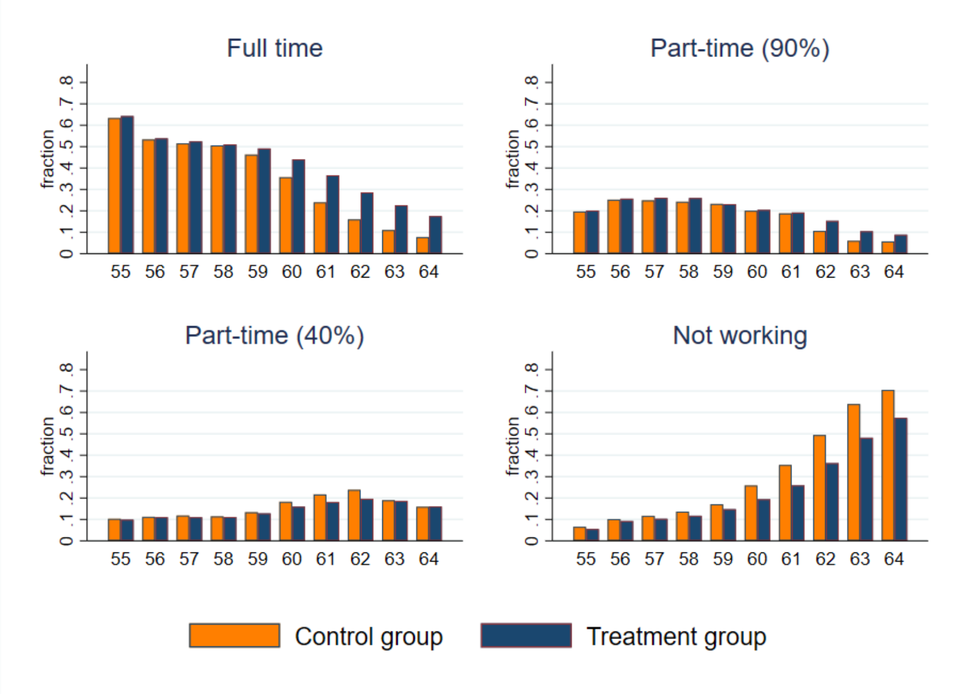
Age-profile of total annual hours worked of treatment and control group.

Figures 5 shows the difference in the fractions of individuals in each of the hours clusters between control- and the treatment group (treatment minus control in percentage points) over education.

The reform was postulated unexpectedly in 2006 where these agents were 56. Age profiles before 2006 reveal that only modest differences in hours worked before the reform was announced.

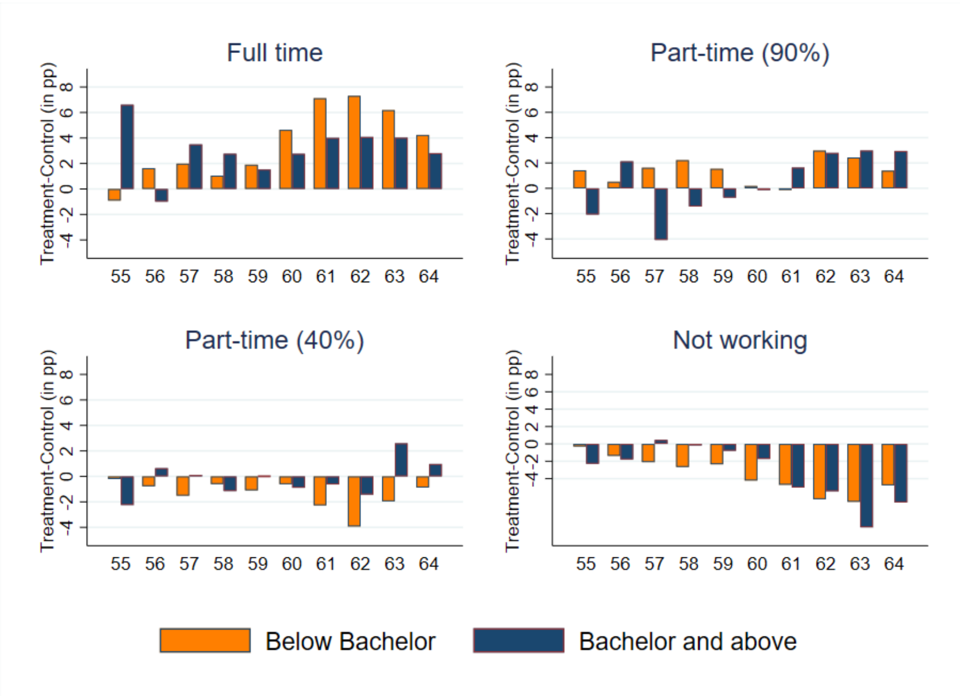
Finally, we present differences in hours worked depending on the asset level in Figure 6. To this end, we construct quintiles of asset holdings at age 55. Here, a hump-shaped pattern emerges over the wealth distribution: there is a low reaction to the reform for individuals in the lowest quintile (with slightly negative assets on average), which is getting stronger until the 3rd quintile and then getting less strong for the very wealthy (for example, in the panel with zero hours worked, the differences are humped shaped; the same pattern is observable for working full-time). For the fractions working 90% part-time, we see a somewhat positive trend in wealth: the richer the household, the more

Figure 4: Fractions Working Full- and Part-time



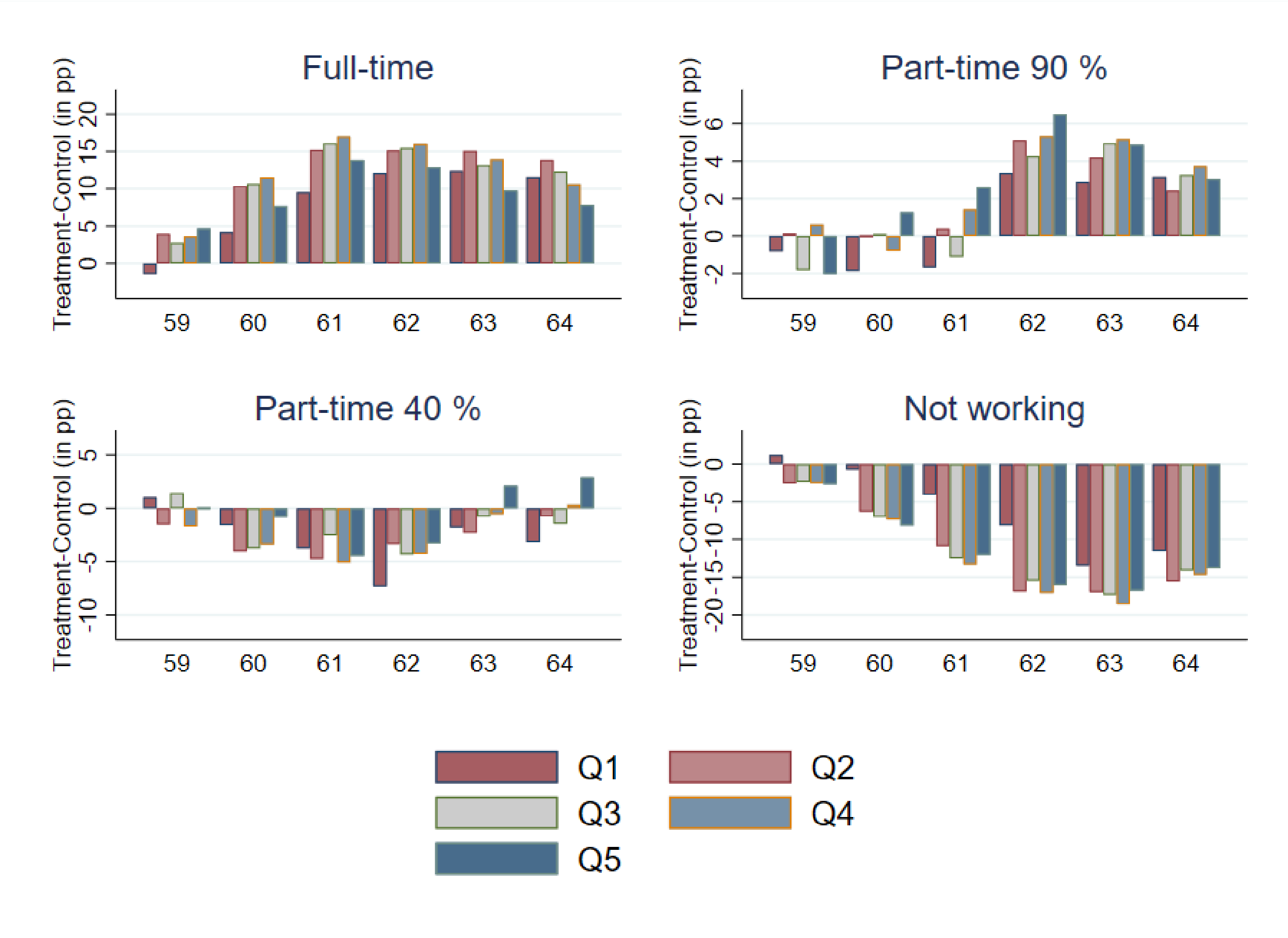
Age-profile of fraction of full-time, part-time (40% and 90%), and no-work work for treatment and control group. Fractions add up to one for every age.

Figure 5: Difference of fractions working full- or part-time between treatment and control groups by educational types.



likely is the reaction to exchange no work to part-time work, rather than full-time work.

Figure 6: Differences in Fraction working Full- and Part-time over Wealth quintiles



Age-profile of the difference of the fraction working full- and part-time between the treatment and the control group. Wealth quintiles determined at age 55 and held constant thereafter.

4.5 Asset Holdings

The registry data allows for the analysis of various asset classes due to the fact that there is a wealth tax in place in the Netherlands. Data is available between 2006 and 2016.

Figure 7 shows the difference in asset holdings between the treatment and the control group. Surprisingly there are almost no reaction to the reform in terms of savings. Differences in asset holdings are small (less than 2% of overall age-specific assets) and without a clear pattern. There seems to be no clear pattern that the treatment group engaged in higher savings due to the pension reform.[11]

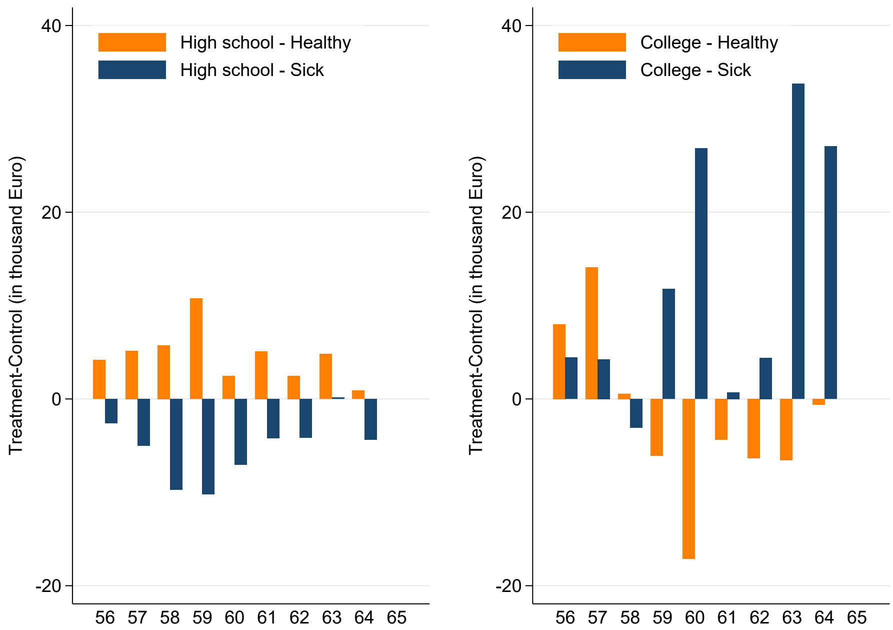
Figure 7: Difference in Wealth over Cohorts

Figure 8 disentangles results over education.

To analyze the wealth distribution further, we compute wealth quartiles of average wealth holdings between age 60-65 for both cohort. Again, we compare the different fractions in each of the quartiles between treatment and control group, cf. figures 7, 9 and

[11]We investigated all available asset classes, such as the value of the main residence, stock holdings, bonds, etc. and could not detect any significant patterns.

Figure 8: Difference in Wealth over Cohorts and Education



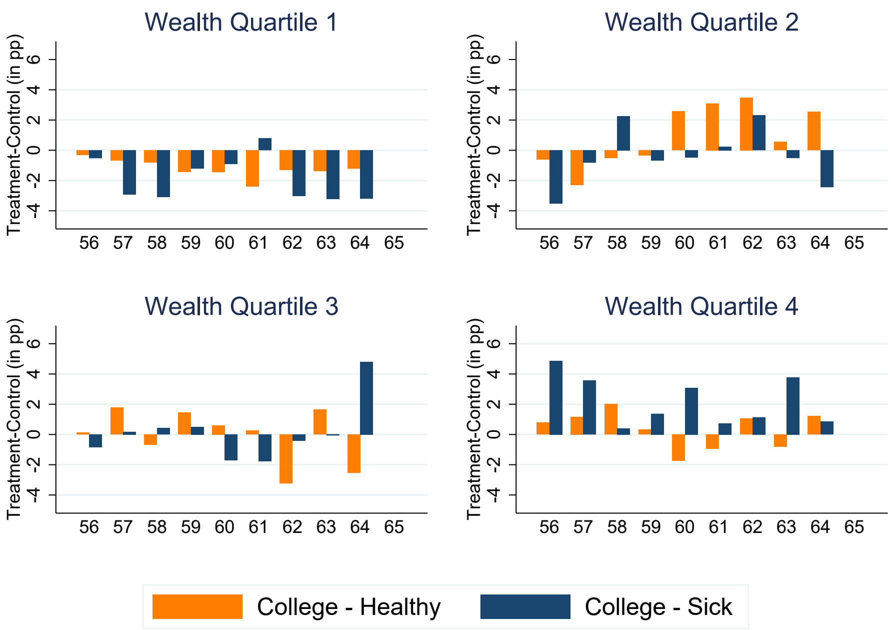
10.[12]

Figure 9: Difference in Wealth Quartiles over Cohorts, High school (in pp)

[12]In future versions of the paper we plan to anayze the wealth distribution by looking at asset holdings depending on permanent income quintiles. Due to the remote environment of the CBS, this was not possible to implement for the current working paper version.

Both figures confirm that the response to asset holdings does not show a clear pattern. Note, that these figures are over different education and health types.

Figure 10: Difference in Wealth Quartiles over Cohorts, College (in pp)

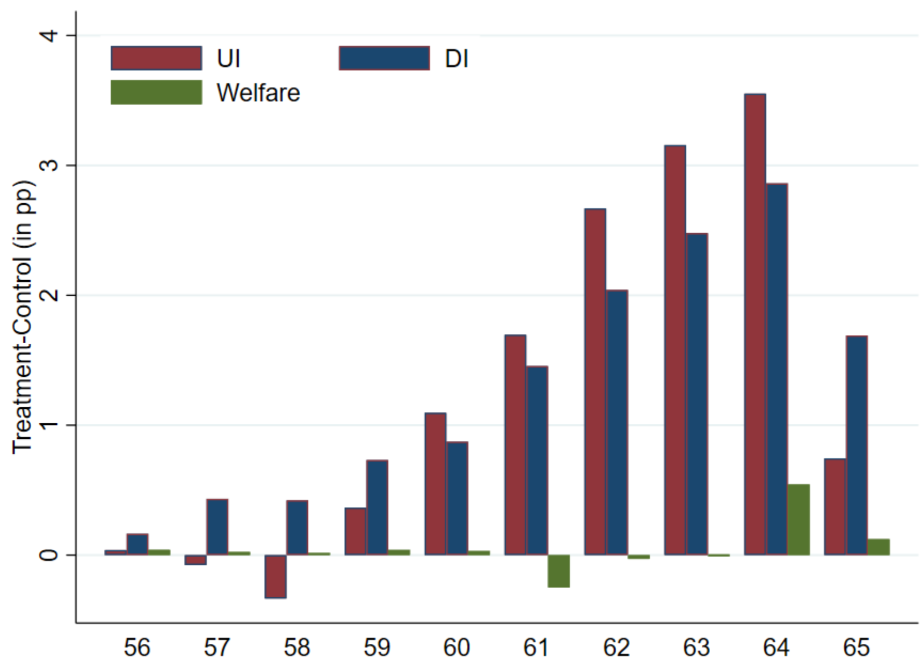


4.6 Social Insurances

To analyze whether the reform has led to a substitution between social insurances we exploit a variable from the admin data indicating the main source of income of the individual.[13] We depict the difference in the fraction of individuals reporting income from unemployment insurance (UI), disability insurance (DI), or general welfare between the treatment and the control group.[14]

We do see a substitution of social insurances by a flow into unemployment insurance and disability. The difference is increasing until the age of 64 and reaches around 3pp. Although an interesting avenue for further research, we do not account for these substitution effects in our structural model.

Figure 11: Difference in Fraction of Social Insurances (in pp)



Age-profile of the difference between the treatment and the control group of the fraction on unemployment insurance (UI), disability insurance (DI), or welfare.

To conclude, the data shows significant behavioral responses in labor supply, both at the extensive and the intensive margin after the pension reform. Individuals worked more

[13]Note that in the current version of our structural model we do not (yet) endogenize decisions on UI and DI.

[14]General welfare is the so-called *bijstandsuitkering* and the *uitkering sociale voorziening overig*.

hours and retire later. However, savings were hardly adjusted after abolishing of the early retirement rules.

5 Model

We start to model decisions when individuals are at age 50. In each year $t \geq 50$ until death, individuals make an employment decision (L_t) and choose current period's consumption c_t. We assume that individuals can reach the maximum age of 100. The decisions are made conditional with respect to the individual's age (t), education (s_t), health (he_t), assets (A_t), working years (wy_t), average life-time earnings (ea_t), possibility of unemployment benefits (ub_t), and the policy environment (pe_t). Additionally, we assume that individuals are of one of either two types of unobserved heterogeneity (ty_t). To ease the notation, we summarize these state variables in $\Omega_t = \{t,\ s_t,\ he_t,\ A_t,\ wy_t,\ ea_t,\ ub_t,\ pe_t,\ ty_t\}$.

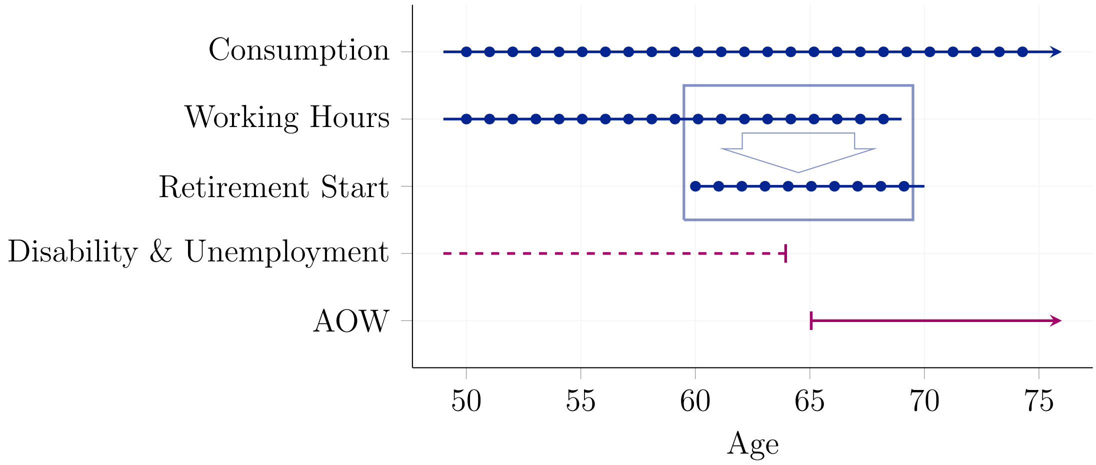
The set of discrete alternatives an individual chooses from is changing over time. Figure 12 provides an overview of the choice sets and potential social security benefits. Without exemption, agents have to choose their current period's consumption in any period until they die. While we do not discretize the consumption choice, we do discretize the labor supply decision. Before entering retirement, individuals can choose between four yearly working hours categories (0, 879, 1872, 2076). When choosing zero working hours, individuals who are in bad health ($he_t = 0$) receive disability insurance benefits. Individuals, who are in good health can receive unemployment benefits if these are still available.[15] A more detailed description of the social insurance system can be found in the appendix A.

Individuals can retire the earliest at age 60 and latest at age 70. We model retirement as an absorbing state, i.e., once retired, individuals can no longer come back to work a positive number of hours. The retirement status determines the payment of the occupational pensions, which only retirees can receive. Independent from the retirement status,

[15] Every ten years of work experience provides an individual with one year of unemployment benefits if unemployed. The maximum is capped at three years.

the public pension (AOW) is payed from age 65 onward. This is also the age from which one onward neither unemployment nor disability insurance benefits are payed out.

Figure 12: Decision sets and availability of social benefits



Note: The working hours decision is discretized into four categories (0, 879, 1872, 2076). The retirement decision is final and must be made between age 60 and 70. Disability insurance and unemployment insurance benefits are only payed until age 65. AOW denotes the public pension benefits which are automatically payed from age 65 onward.

Preferences

Define the choice set[16]

$$\mathcal{D} = \{ret,\ h_0,\ h_1,\ h_2,\ h_3\} \tag{1}$$

$$= \{retired,\ 0,\ 879,\ 1872,\ 2076\}. \tag{2}$$

Given consumption choice c_t and labor supply choice L_t, agents receive instantaneous utility of

$$u(c_t, L_t, \omega_t) = \frac{c_t^{1-\rho} - 1}{1-\rho} - \gamma_{ret} \cdot \mathbb{1}\{L_t = ret\} - \gamma_{h_1} \cdot \mathbb{1}\{L_t = h_1\} - \gamma_{h_2} \cdot \mathbb{1}\{L_t = h_2\} - \gamma_{h_3} \cdot \mathbb{1}\{L_t = h_3\} + \varepsilon_{L_t,t}, \tag{3}$$

[16]Note that the choice set depends on previous made choices and the age of the economic agent.

where $\mathbb{1}\{\cdot\}$ denotes the indicator function about the labor supply decision, and ρ, γ. parameters we estimate. We assume a unique disutility parameter for each labor supply choice in $\mathcal{D}$ besides non-employment. Non-employment is, therefore, the reference category.

The first part of (3) is a standard CRRA utility function in consumption, where ρ denotes the constant degree of relative risk aversion. In our model ρ also determines the elasticity of intertemporal substitution. The second part of the equation describes the disutility of working, for which non-employment is the reference category. The disutility of working varies with the chosen working hours. Finally, $\varepsilon^u_{L_t,t}$ is an hour-specific taste shock. It is independently and identically distributed over all choices with a zero-mean type-I extreme value distribution with a common scale parameter λ ($\varepsilon^u_{L_t,t} \overset{i.i.d.}{\sim} EV(\lambda)$). Let $\boldsymbol{\varepsilon}^u_t$ denote the vector of all five hour specific taste shocks for period t. The parameter λ is estimated along the other parameters.

At the end of life, individuals bequeath their remaining assets. The bequest motive is parameterized with the following utility function

$$B\left(A_t - c_t\right) = \gamma^b_{scale} \frac{\left(A_t - c_t + \gamma^b_{concave}\right)^{1-\rho} - 1}{1-\rho}. \tag{4}$$

This is a common functional form as used in Lockwood (2018) and De Nardi et al. (2010). The parameter $\gamma^b_{concave} \geq 0$ is the threshold consumption level. Under conditions of perfect certainty people do not leave bequests if assets are under $\gamma^b_{concave}$: Higher values of $\gamma^b_{concave}$ implies that bequests increasingly become a luxury good and people are less risk-averse over bequests than over consumption. The parameter γ^b_{scale} measures the weight given to bequests in the overall utility function.

Health and survival probabilities

Health might be an important factor influencing the retirement decision. We distinguish between two states of health: *good* and *bad*. We assume that health evolves according to health shocks, which are independent of the working decision. The probability to be in a bad health state depends on the individual's age and health status of the previous period. The probabilities are education specific and are defined as

$$\Pr\left(he_{i,t+1} = bad \middle| \, \omega_{i,t} \right) = \frac{\exp\left(\mathbf{X}\phi\right)}{1+\exp\left(\mathbf{X}\phi\right)}, \tag{5}$$

where

$$\begin{aligned}\mathbf{X}\phi = \phi_{s,0} + \phi_{s,1}t + \phi_{s,2}t^2 + \phi_{s,3}t^3 + \phi_{s,4}he_{i,t} + \phi_{s,5}he_{i,t} \times t \\ + \phi_{s,6}he_{i,t} \times t^2 + \phi_{s,7}he_{i,t} \times t^3 + \phi_{s,8}C_{1950}.\end{aligned} \tag{6}$$

C_{1950} is the dummy of cohort born in 1950 taken from a set of year-of-birth dummy controls $\mathbf{C}$ included in the logit estimation of the probabilities.

Similarly, the probability of not surviving the current period is given by:

$$\Pr(death|\omega_{i,t}) = \theta(\omega_t) = \frac{\exp\left(\mathbf{X}\varphi\right)}{1+\exp\left(\mathbf{X}\varphi\right)}, \tag{7}$$

where

$$\begin{aligned}\mathbf{X}\varphi = \varphi_{s,0} + \varphi_{s,1}t + \varphi_{s,2}t^2 + \varphi_{s,3}t^3 + \varphi_{s,4}he_{i,t} + \varphi_{s,5}he_{i,t} \times t \\ + \varphi_{s,6}he_{i,t} \times t^2 + \varphi_{s,7}he_{i,t} \times t^3 + \varphi_{s,8}\tilde{C}_{48/50}.\end{aligned} \tag{8}$$

$\tilde{C}_{48/50}$ is the dummy of cohort born between 1949-1950 taken from a set of two-year of birth dummy controls $\tilde{\mathbf{C}}$ included in the logit estimation.[17]

The probability to survive the current period is given by $\theta(\omega_t) = 1 - \Pr(death|\omega_{i,t})$.

[17]We take two-year cohort dummies due to the increase multicollinearity problem between age and year of birth when only taking one-year dummy variables.

Income and budget constraint

We assume hourly wages $w_{i,t}$ to be a function of experience, age, health, education and on the actual hours choice.

Our state variable of experience measures years at the labor market and corresponding data is taken from the accumulated years (*opgebouwde jaren*) as measured by the pension funds. The variable is an indicator for on-the-job human capital accumulation. We also include two dummy variables for part-time work (40 and 90% of full-time) to account for a part-time penalty. Finally, we account for health status following the idea that health impairment is likely to decrease productivity.

For the estimation of wages we implement a two-stage Heckman selection correction procedure. Wages are given by

$$\ln(w_{i,t}) = \mathbf{X}\beta + \eta_{i,t}, \tag{9}$$

where $\mathbf{X}$ includes age, age squared, experience, experience squared, health, as well as two dummies for part-time work. We also include interaction terms of all age, experience, and health variables. In total we use 20 coefficients (including the constant) to predict wages. Finally, $\eta_{i,t} \overset{i.i.d.}{\sim} \mathcal{N}(0, \sigma_w^2)$ denotes a transitory wage shock. We do not model a persistent component to save on the state space. We instead capture (income) heterogeneity in our model by incorporating differences over education and age.

Wages are only observed when working which happens under the following condition:

$$\mathbf{Z}\iota + \nu_{i,t} > 0, \tag{10}$$

In $\mathbf{Z}$ we include $\mathbf{X}$ and a vector of exclusion restrictions that is assumed to explain the extensive margin decision but not the intensive margin. These variables include dummies for the number of children, marital status (single, partnered, married), and years.

Individuals who are not working can receive unemployment benefits (UI_t) and individuals in a bad health state can receive disability benefits (DI_t). Both, UI_t and DI_t pay

70% of the previous earnings and both can only be claimed before the age of 65.

There are two types of pension benefits in our model. The AOW is integrated by an automatic yearly payment of €13,713 for every individual that has reached the age of 65. The integration of the occupational pensions depends on the cohort. Both cohorts can retire between the age of 60 and 70. For cohorts born before 1950, early retirement (before the age of 65) comes with a yearly income replacement rate of 85% of the average yearly life-time earnings. From age 65 onward, they receive the regular occupational pension benefits which pay a fraction of the average annual earnings according to the total years worked. These regular payments are not decreased by the years spent in early retirement. They are also not increased if the individual retires late.

For cohorts born in 1950 or later, benefits are adjusted according to the actual retirement age. For every year an individual retires early, pension benefits are reduced by 6%. In contrast, if an individual worked even after reaching the age of 65, pension benefits were increased by 7% for every year the individual did not retire.

In addition to the pension system, we also integrate the Dutch tax and transfer system, which does not only tax income but also wealth at a rate of 1.2%. For a detailed discussion of the institutional details see the appendix A. The intertemporal budget restriction is defined as[18]

$$\begin{aligned} A_{t+1} = &\left(A_t - c_t\right)\left(1+r\right) \\ &+ TaxTrans\left(L_t \cdot wage_{t+1}, UI_{t+1}, DI_{t+1}, pens^{public}_{t+1}, pens^{occ}_{t+1}\right) \\ &+ \tau^{wealth}\left(A_{t+1} - \alpha\right). \end{aligned} \tag{11}$$

Variable A denotes assets, r the interest rate, $TaxTrans$ is a function applying the tax and transfer rules, $pens^{public}_{age}$ denotes the public pension payments, $pens^{occ}$ the occupational pension payments. The first line of (11) consists of the non-consumed assets of last period and the capital gains. The net income from employment and potential other sources is

[18] That L is indexed by t and not $t+1$ emphasizes that the employment decision is made before the wage error is known. The wage error is integrated out of the budget constraint in our estimation.

given in the second line. The third line represents the Dutch wealth tax where α denotes the tax allowance and τ^{wealth} the tax rate.

We assume that by choosing c_t and L_t, individuals maximize their expected discounted stream of utilities

$$u(c_t, L_t, \omega_t) + \mathbb{E}_t \left[\sum_{\tau=t+1}^{100} \beta^\tau \Theta(\tau, t) \left(\theta_\tau u(c_\tau, L_\tau, \omega_\tau) + (1 - \theta_\tau) B(A_\tau - c_\tau)\right) \middle| c_t, L_t, \omega_\tau \right], \quad (12)$$

where θ_τ denotes the probability to survive period τ conditioned on being alive in period $\tau - 1$. Similarly, $\Theta(\tau, t) = \frac{1}{\theta_t} \Pi_{k=\tau}^{t} \theta_t$ denotes the probability of living to age τ conditional on being alive at age t. Let $V_t(\omega_t)$ denote the highest attainable discounted expected utility over the remaining life cycle, given state ω_t of the decision maker at period t. The intertemporal decision problem can then be expressed in form of the *Bellman equation*:

$$V_t(\omega_t) = \max_{\substack{0 \le c_t \le A_t + a_0 \\ L_t \in \mathcal{D}_t}} \left\{ u(c_t, L_t) + \theta_t \beta \mathbb{E}_t \left[V_{t+1}(\omega_{t+1}) | \omega_t, c_t, L_t \right] + (1 - \theta_t) B(A_t - c_t) \right\}. \quad (13)$$

Note that the expectation operator is over the wage shock and the hour-specific taste shock.

As in Keane and Iskhakov (2020), we assume that individuals choose their labor supply before the current period's wage shock is known. This assumption, in combination with the distributional assumption about $\boldsymbol{\varepsilon}$, allows restating (13) as

$$V_t(\omega_t) = \max_{L_t \in \mathcal{D}} \left\{ W_t(\omega_t, L_t) + \lambda \varepsilon_{L_t, t}^{u} \right\}, \quad (14)$$

where $W_t(\omega_t, L_t)$ denotes the hour-specific value function, and λ a smoothing parameter.

The hour-specific value function is given by:

$$\begin{aligned} W(\omega_t, L_t) &= \max_{0 \le c_t \le A_t + a_0} \Bigg\{ u(c_t, L_t) + (1-\theta_t) B(A_t - c_t) \\ &\qquad + \theta_t \beta \mathbb{E}_t \left[\max_{L_t \in \mathcal{D}} \left\{ W_{t+1}(\omega_{t+1}, L_{t+1}) + \lambda \varepsilon^u_{L_{t+1},t+1} \right\} \middle| \omega_t, c_t, L_t \right] \Bigg\} \\ &= \max_{0 \le c_t \le A_t + a_0} \Bigg\{ u(c_t, L_t) + (1-\theta_t) B(A_t - c_t) \\ &\qquad + \theta_t \beta \sum_{\omega_{t+1} \in \Omega} q(\omega_{t+1} | \omega_t) \, LS_\lambda(\omega_{t+1}) \Bigg\}, \end{aligned} \tag{15}$$

where $LS_\lambda(\omega_{t+1}) = \lambda \ln \left(\sum_{L_{t+1} \in \mathcal{D}} \exp\left(\frac{W_{t+1}(\omega_{t+1}, L_{t+1})}{\lambda} \right) \right)$ is the logsum function. Solving (14)-(15) via backwards solution results in the optimal decision rules for consumption and labor supply

$$\begin{aligned} c_t^\star(\omega_t) &: \omega_t \to [0, A_t + a_0] \\ L_t^\star(\omega_t) &: \omega_t \to (\mathrm{HPr}_t(ret), \ldots, \mathrm{HPr}_t(h_3)), \end{aligned} \tag{16}$$

where $\mathrm{HPr}_t(L)$ with $L \in \mathcal{D}$ denotes the probability of choosing L in period t. There exists a closed form solution for $\mathrm{HPr}_t(L)$ because of the zero-mean type-I extreme value distribution of $\varepsilon^u_{L,t}$:

$$\mathrm{HPr}_t(L) = \frac{\exp\left(\frac{W_t(\omega_t, L)}{\lambda} \right)}{\sum_{j \in \mathcal{D}} \exp\left(\frac{W_t(\omega_t, j)}{\lambda} \right)} \tag{17}$$

5.1 Estimation

5.1.1 Estimations outside of the model

Initial Conditions Since we are working with administrative data on a remote desktop it is not possible to directly copy the initial values of the individuals in our sample and simulate their choices according to our model. Rather, we approximate the empirical distributions by statistical ones. For the initial conditions we focus on working men at age 50 in the first available year 2006/07. This implies that we are looking at the cohort born in 1956.

We compute the initial fractions over the hours clusters (3 states, excluding no work), health (2 states), and education (2 states) implying 12 initial fractions. We then draw the value for experience (rounded to integers) given the empirical distributions conditional on one of the 12 types. Life-time income is approximated as the predicted individual fixed effect from a regression of log-earnings on age-dummies. We then assume lifetime income to be log-normally distributed and draw from that distribution given the mean (defined as the predicted value of a regression of our measure of lifetime income on the initial conditions) and the standard deviation computed from the data (conditional on the initial conditions). Finally, we predict asset holdings in two stages: At the extensive margin, we predict the probability that the agent has low wealth in a regression of a respective indicator variable regressed on the initial conditions. At the intensive margin, we assume a log-normal distribution of the amount of wealth variable and draw from that distribution given the mean (predicted value from a regression of wealth on the initial conditions) and the standard deviation which again, also differs by the initial conditions (i.e., the 12 different types mentioned above). Further details are described in Appendix B.2.

Exogenous processes We estimate equation (9) using a regression that also includes cohort dummies ranging from 1936 to 1989. We estimate the equation separately for both levels of education. For estimating the income process we use the overall panel restricted to the working age population of men at age 25 to 70.

Health transitions are estimated separately for the two education groups using a Logit model.

Mortality is also estimated using a Logit model. Again estimations are carried out separately for the education groups. We include two-year cohort dummies due to problems of separately identifying age and cohort effects from our data when using one-year cohort dummies.

5.1.2 Estimation of the model

Solution of the model We rely on the *endogenous grid method for discrete-continuous dynamic choice models* (DC-EGM) of Iskhakov, Jørgensen, Rust, and Schjerning (2017) to estimate our model. The method relies on the Euler equation as the Euler equation remains a necessary optimality condition even in the presence of a discrete choice (see Clausen & Strub, 2020).

To derive the Euler equation of our model, note that the choice specific value function $W_{t+1}(\omega_{t+1}, L_t)$ might not be differentiable at all points, but Iskhakov et al. (2017) show that the measure of the set of non-differentiable points is zero. Thus, the first order conditions of (15) can be expressed as

$$\begin{aligned} \frac{\partial u(c_t, L_t, \omega_t)}{\partial c_t} \geq (1-\theta_t) & \frac{\partial B(A_t - c_t)}{\partial c_t} \\ & + \theta_t \beta \mathbb{E}_t \left[\sum_{L_{t+1} \in \mathcal{D}} \mathrm{HPr}(L_{t+1}) \frac{\partial u(c_{t+1}, L_{t+1}, \omega_{t+1})}{\partial c_{t+1}} \frac{1+r}{1-\tau^{wealth}} \right] \end{aligned} \tag{18}$$

with equality if the credit constraint is not binding.[19] The DC-EGM algorithm iterates over (18) and uses (15) to evaluate the choice specific value function $W_t(\omega_t, L_t)$. It solves the model by backwards induction. In the last period, the optimal choices c_T and L_T are determined by

$$c_T(\omega_T, L_T) = \underset{0 \leq c_T \leq A_T + a_0}{\arg\max} \{u(c_T, L_T) + B(A_T - c_T)\}, \tag{19}$$

$$W_T(\omega_T, L_T) = u(c_T(\omega_T, L_T), L_T) + B(A_T(\omega_T, L_T) - c_T). \tag{20}$$

The DC-EGM advances in the following way. First, a fixed, strictly increasing grid over savings ($G_t = A_t - c_t$) with 15 grid points is established. We denote the grid by $\{G_1, \ldots, G_J\}$ with $G_0 = 1$ and $G_j < G_{j+1}$. For all periods $t < T$ and all $L_t \in \mathcal{D}$, the below steps are executed. Each step provides an optimal consumption function $c_t(\omega_t, L_t)$ and an hour specific value function $W_t(\omega_t, L_t)$:

[19] To derive (18), we applied the envelope theorem to express $\frac{\partial W_{t+1}(\omega_{t+1}, L_{t+1})}{\partial A_{t+1}}$ as $\frac{\partial u(c_{t+1}, L_{t+1})}{\partial c_{t+1}}$.

1. Compute A_{t+1} for all Grid points G_j using the intertemporal budget constraint (11).

2. Compute the optimal levels of consumption for all $L_t \in \mathcal{D}$ using a three-dimensional interpolation[20] over A_{t+1}, yw_{t+1} and $earn_{t+1}$ to determine the optimal consumption $c_{t+1}(\omega_{t+1}, L_{t+1})$.

3. Compute $W_{t+1}(\omega_{t+1}, L_{t+1})$ for all possible $L_{t+1} \in \mathcal{D}$. Further, compute the right-hand-side of the Euler equation (18).[21]

4. Compute the optimal level of current consumption $c_t(\omega_t, L_t) = \frac{\partial u}{\partial c_t}^{-1}(c_t, L_t, \omega_t)$.

5. Compute $W_t(\omega_t, L_t)$ using the optimal level of current consumption.

6. Build the endogenous hour-specific grid over current wealth levels $\{A_1, \ldots, A_J\}$ using $A_j = G_j + c_t(\omega_t, L_t)$.

   Period t's iteration is completed. Both $c_t(\omega_t, L_t)$ and $W_t(\omega_t, L_t)$ can be computed by interpolation on the endogenous grids $\{A_1, \ldots, A_J\}$.

7. In case the endogenous grid $\{A_1, \ldots, A_J\}$ is not monotone (although $\{G_1, \ldots, G_J\}$ is), use the *upper envelope* subroutine described in Iskhakov et al. (2017).

8. Continue with the next iteration $t-1$ until reaching the initial period t_0.

Method of Simulated Moments We estimate the parameters of our model to best match certain data moments on labor supply (extensive and intensive margin) and asset holdings. We contrast the estimation of two different sets of moments. In one set, we only include moments for the older cohort that is not affected by the pension reform in 2006. In the other set, we additionally include moments for the younger cohort, which was affected by the reform.

[20]Besides wealth, the model includes two more continuous state variables: *years worked* and *average lifetime earnings*. Both are important for the treatment group's determination of the occupational pension benefits. We approximate years worked with an equally spaced 5-point grid, and average lifetime earnings with a 10-point log grid. Note that while these two grids are fix over time, the grid over A is not. We therefore linearly interpolate first over A and then over the other two state variables.

[21]Note that this step requires the computation of an integral. We apply a Gaussian quadrature with 7 points in our estimations.

The model parameter that we estimate are the discount factors that differs by education, β_s, the risk aversion parameter ρ, the disutility parameters γ_L with $L \in \mathcal{D}\backslash\{h_0\}$, the two bequest parameters, γ^b_{scale} and $\gamma^b_{concave}$, and the smoothing parameter λ, summarized via Ψ implying 10 parameters to estimate.

To recover the parameters of our model, we rely on the method of simulated moments. Given the initial conditions and a vector of parameters Ψ, we simulate the life cycles of $10,000$ individuals. We compute the moments for this simulated sample and compare them with the data moments using the objective function

$$f(\Psi) = \left\{ \sum_{k=1}^{K} \left[\left(M_k^d - M_k^s(\Psi) \right)^2 / \, \mathbb{V}\mathrm{ar}\left(M_k^d \right) \right] \right\} \tag{21}$$

where K is the number of moments, M_k^d denotes the k-th data moment, and M_k^s the k-th simulated data moment. Note that equation (21) does not use the asymptotically optimal weighting matrix, because of its poor small sample properties (see, Altonji & Segal, 1996). Instead, we use a diagonal matrix with sample variances of the respective moments as its elements. For the numerical optimization we employ a pattern search method, which is a derivative-free routine. It is implemented using the Dakota toolkit (see, Adams et al., 2013) that allows for parallelization. Standard errors of Θ are estimated following Gourieroux, Monfort, and Renault (1993).

6 Identification and Policy Experiments: Comparing two approaches

In the literature studying pension reforms in dynamic life-cycle models of saving and retirement, it is common to rely on age-profiles as identifying moments for the preference parameters of the disutility of work, the discount factor and the IES, cf. French (2005), for example. A model estimated to these age-profiles is then used for counterfactual policy experiments where the behavioral effects of a change in certain policy parameters are quantified. However, the question arises whether the implied elasticities (e.g. in labor supply) from an estimation using age-profiles only can correctly predict behavioral responses to policy changes.

To get a further understanding of this problem, we estimate two models. In the first model, we take over the standard approach estimating the parameters by solely relying on age-profiles (*standard approach*). In the second model, we make use of our data on the behavioral responses of the pension reform, cf. Section 4, and use those as targeted moments in our estimation to help identify our parameters of interest (*reform approach*).

We then compare the two models in terms of how precisely the parameters are estimated and the moments are matched. We also assess the fit of both models with respect to the pension reform from 2006: the *reform approach* also targets these moments, but the *standard approach* does not. Finally, we evaluate an ex-ante policy reform for both models, where we replace the lump-sum AOW pension payment and simply allow for a minimum standard of living (welfare payments).

6.1 Standard Approach

The common estimation procedure is to use life-cycle profiles for the identification of the structural model parameters. In particular, the disutility of work is heavily guided by the life-cycle employment profile which in our case starts at age 50 and encompasses the early retirement behavior. The disutility of work mainly induces people to work less than full-time and go into early retirement.

Without consumption data the identification of the discount factor and the intertemporal elasticity of substitution stems from the age profile of assets. In the data, the asset profile is commonly hump-shaped over the life-cycle, implying that agents are saving during working age and dissaving in retirement.[22] However, dissaving is lower implying positive assets at the end of life that can be used for bequests. In a life-cycle model, this profile can be generated by assuming a borrowing constraint that prevents young people

[22]Additional variation comes from the distribution of assets. For example, the profiles also differ over socio-economic status with less dissaving for the more affluent

from going in to debt or by generating a 'natural borrowing constraint' when having (uninsured) income shocks in the model that induces households to always keep a buffer-stock of savings to be insured against these shocks. Simultaneously, a social security system with a replacement rate below 100% implies a sudden income drop at retirement where optimizing agents need to save in order to smooth out this income drop at retirement in their age-profile of consumption. Finally, a bequest motive generates positive assets at the end of life. In terms of parameters, the discount factor (in particular relative to the gross interest rate) impacts the asset profile (by guiding how much the future is taking into account). Similarly, the IES guides asset accumulation behavior if there is an income drop at retirement by guiding how strong the agent wants to smooth out the accompanying consumption drop. However, the asset profile does not allow to disentangle the discount factor from the value of the IES.

Hence, a problem of estimating these three kind of parameters simultaneously is that changes in each of the parameters can cause similar changes in the consumption-savings and labor supply patterns. Thus, equally well fitted correlations over the life cycle might be based on a wide range of combinations of the three parameters.

The moments we include in the standard approach are as follows:

1. Age-profile of the fraction of individuals in each of the four hours cluster by education between 50 and 70

2. Age-profile of average net wealth over education between age 50 and 90

The approach to determine these moments and the respective figures to these moments are described in Section 4 and in Appendix B.

6.2 Reform Approach

In the *reform approach* we take a different approach to estimate the structural parameters. Similar to the identification idea in reduced form regressions we rely on exogenous variation from a natural experiment, our pension reform in the Netherlands. Surely, the behavioral responses to the reform for labor supply, retirement and savings do not one-to-one map into the identification of each parameter separately. Rather, in our model, the parameters on the discount factor, risk aversion and the disutility of work simultaneously determine the reaction of household with respect to labor supply and retirement. In ongoing work we further analyze the heterogeneous responses of the reform over assets to get further insights on the identification of the parameters.

In the data, we determine the responses to the pension reform in 2006 in terms of labor supply, retirement and savings, for the treatment group which was affected by the reform and of the control group which was not. In our model, we then mimic the institutional details of the Dutch pension reform in our model assuming a sudden change in policy parameters for agents at age 56 (i.e., in year 2006 for the cohort under study). We then estimate the parameters of the model taking the behavioral consequences of the reform as additional moments into account.[23]

The moments, we match in the *reform approach* are as follows

1. Age-profile of the fraction of individuals in each of the four hours cluster by education between 50 and 70

2. Age-profile of average net wealth over education between age 50 and 90

3. Differences in the fraction in each hours cluster between treatment and control group following the pension reform in 2006 by education between age 56 and 65

4. Differences in wealth between treatment and control group following the pension reform in 2006 by education at ages 56-65.

The approach to determine these moments and the respective figures to these moments are described in Section 4 and in Appendix B.

[23]Due to data availability, we only have data for ages 56 onward when studying the reform.

7 Results

In the following section we present results from an estimation of our model. Note that these are still preliminary and are likely to be updated in future version of the paper.[24]

7.1 Estimated Parameters and Model fit

The estimated parameters of the two models are depicted in Table 2. We set the interest rate exogenously at 5 percent.

Table 2: Estimated Parameters

	Reform Approach	**Standard Approach**
Discount factor		
$\beta_{educ=low}$	0.95703075	0.95709537
$\beta_{educ=high}$	0.97897083	0.98513425
Risk aversion		
ρ	1.21204224	1.13922405
Disutility of Working		
γ_{ret}	-0.24467810	-0.30806091
γ_{h1}	0.32710739	0.24291942
γ_{h2}	0.39428428	0.50183986
γ_{h3}	0.63654309	0.56845808
Bequest parameters		
γ^b_{scale}	2.78799742	2.14927321
$\gamma^b_{concavity}$	10000.00000700	10000.00003200
Smoothing parameter		
λ	0.29533839	0.32475392

Values of disutility of work relative to zero-working decision (which is hence not estimated).

The estimated discount factors do not differ much between the two approaches – except for a somewhat lower discounting value for the high-educated individuals in the

[24]For example, the concavity parameter of the bequest function did not converge in these estimations which still needs to be addressed.

reform approach, implying that the future is stronger taken into account. A difference emerges for the parameter of risk aversion where we see a somewhat larger value of ρ in the reform approach. Since $1/\rho$ can be interpreted as the intertemporal elasticity of substitution, we have a slightly lower substitution elasticity implying a stronger need for consumption smoothing in the reform approach. The intertemporal elasticity guides how strong agents react to the reform and the (non-targeted) responses to the reform in the standard approachare somewhat too strong so that targeting these moments explicitly yields a lower value for ρ. Further, the disutility parameter depending on the (discretized) hours worked change quite substantially when taken the reform-moments into account. To get the model more in line with the additional moments the utility have to change in a non-linear way: lower utility from retiring in the reform approach, but also higher disutility of full-time work. Finally, the bequest scaling parameter changes quite substantially implying a higher weight on bequests. This change in parameter together with the new ρ helps to get less of a strong reaction in savings following the reform.

7.2 Fit of (Non-)Targeted Moments: Do we Match the Reform?

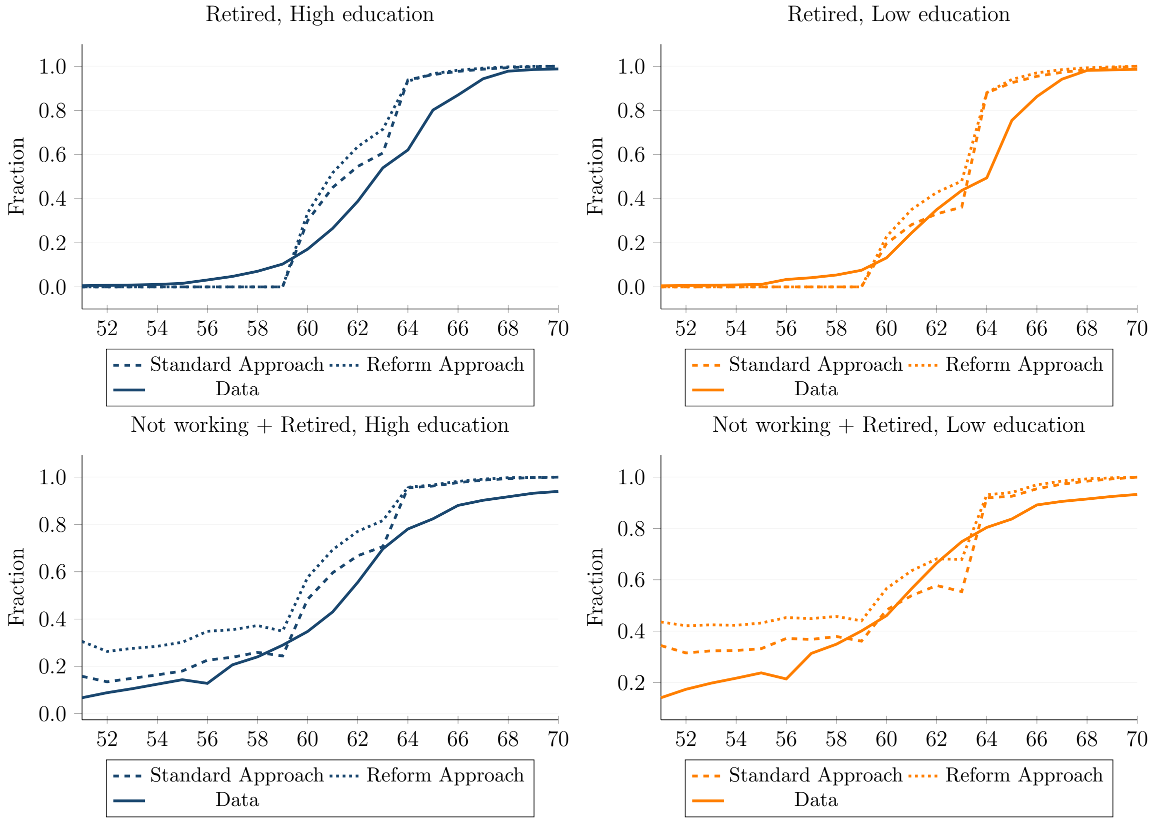
In the following, we present the fit of the two models by comparing its age-profiles with the data. We first focus on the moments that are targeted by both models and then contrast the two models for those moments from the pension reform, which were targeted by the reform approach but not by the standard approach.

7.2.1 Age Profiles: Moments targeted by both models

The extensive margin comprises of retirement entry and zero working, including UI, DI and retirement. The intensive margin comprises of the two part-time options and full-time work.

The figures reveal a decent match of the data with both our models (except for the fulltime work and zero hours work category). The important take away from these figures, however, is that the standard approach actually matches the data better than the reform

Figure 13: Retirement and not working, average Age-Profiles



approach. This is not surprising as the reform approach consists of the same amount of parameters but has to match many more moments and, hence, 'compromises' between the fit of tha age-profiles of the averages and the moments coming from the pension reform.

The age-profile of average asset holdings comparing the two models with the data is given in the following figures.

The comparison of the match of the asset profiles is ambiguous: a better match of the reform approach for the low-educated but a worse match for high-educated individuals.

Figure 14: Intensive Margin of Labor Supply, average Age-Profiles

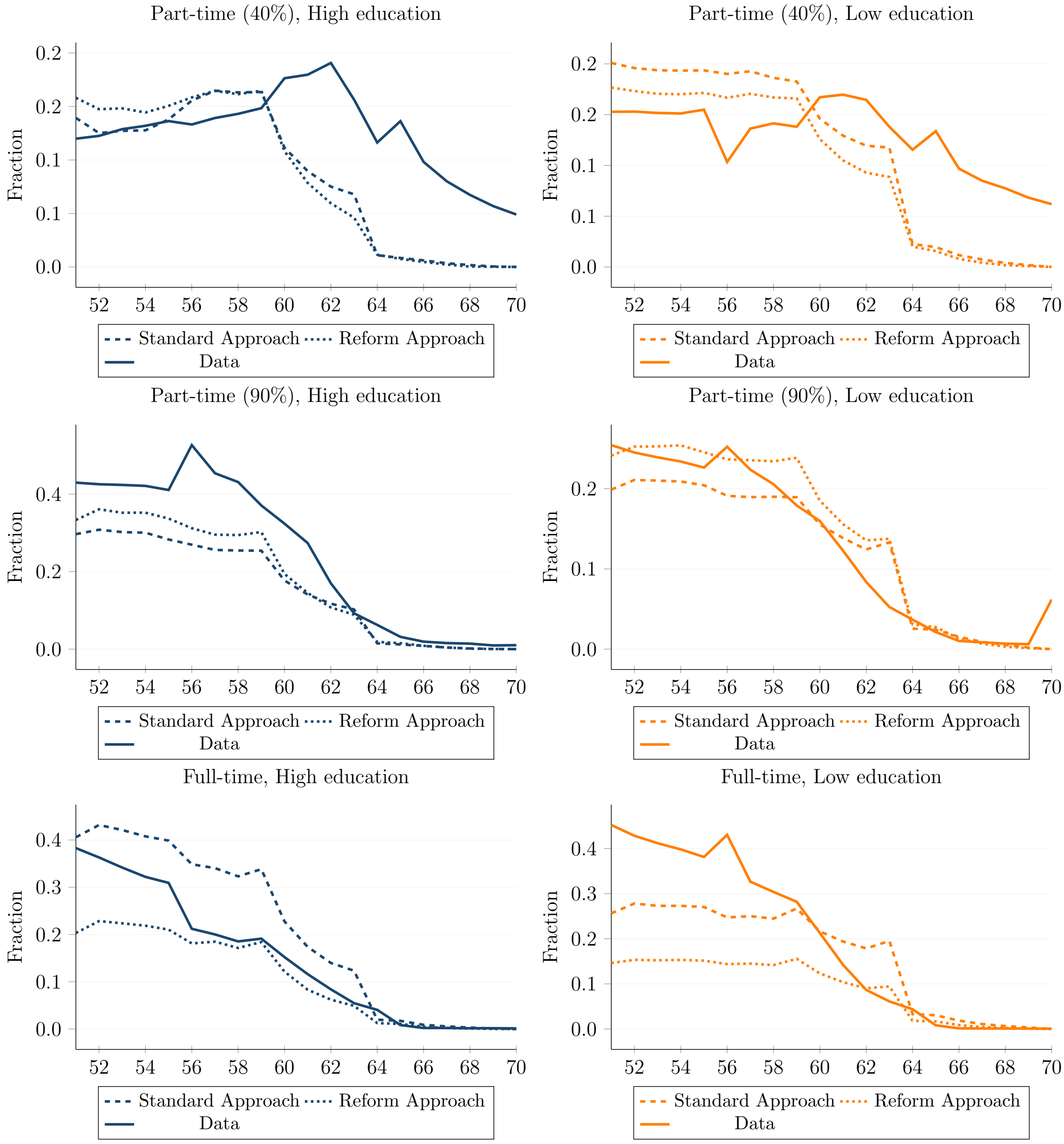
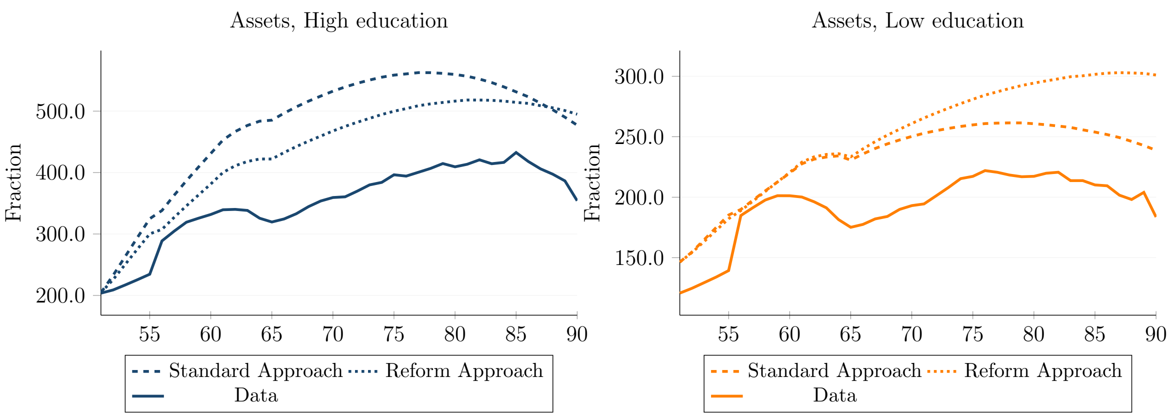


Figure 15: Asset holdings, average Age-Profiles

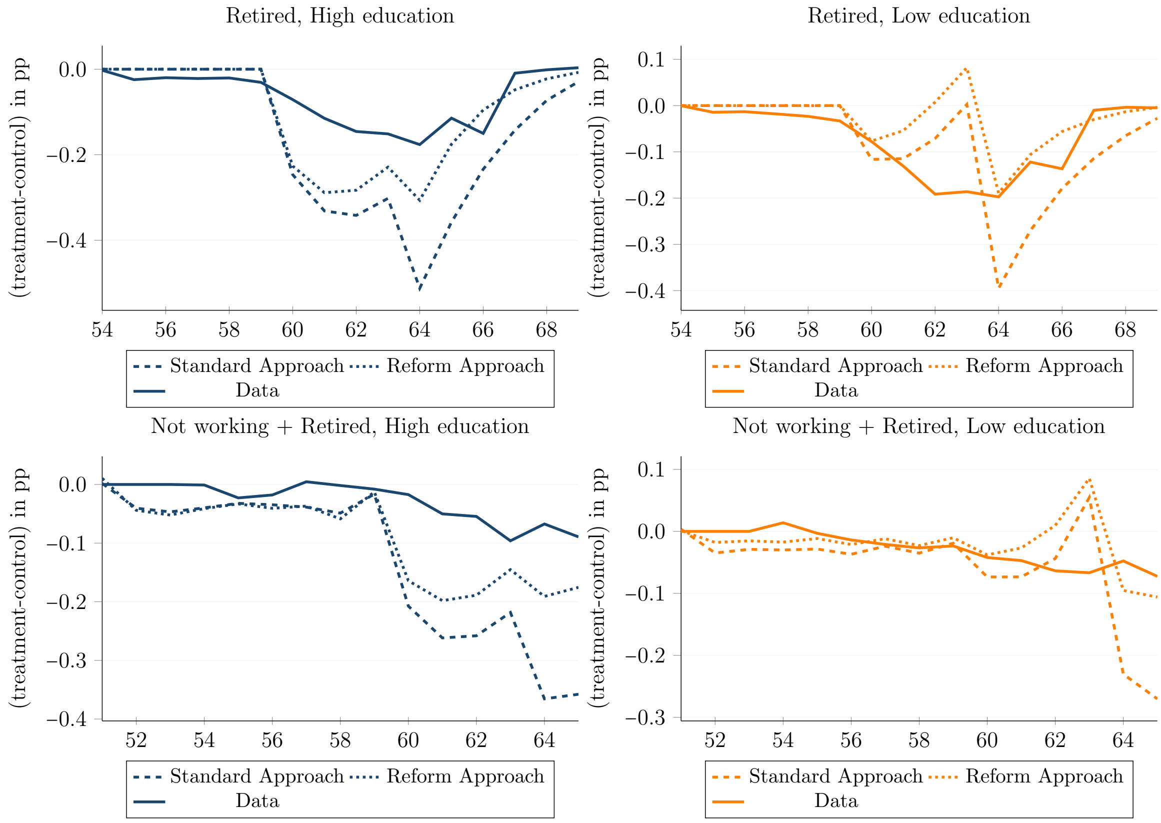


7.2.2 Reform Moments: Targeted versus Non-targeted

In the following, we focus on the moments that shows the percentage point difference between the treatment group, affected by the pension reform in 2006, and the control group which was not facing any changes in policies. The following figures again compare the two models with the data. Different to the figures above, though, we do not target these moments in the *standard approach* while they are explicitly targeted in the *reform approach*.

Figure 16 show results for the difference in retirement entry and zero working, including UI, DI and retirement, between the treatment and the control group.

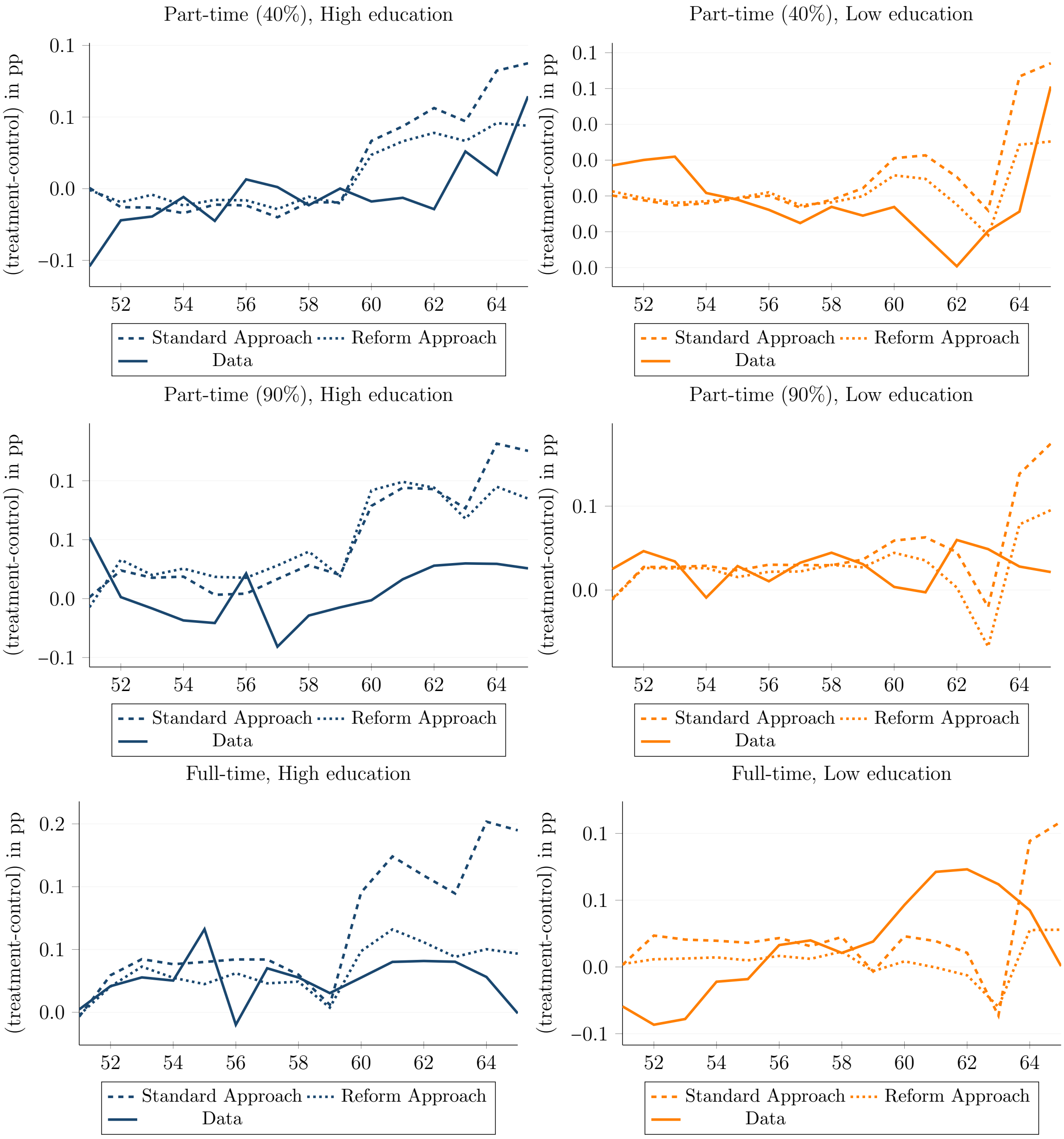
Figure 16: Retirement and not working, Response to Reform



The intensive margin shown in Figure 17 comprises of the two part-time options and full-time work. Again, here, the difference between the treatment and the control group (in percentage points) is shown in the figure.

The difference in the age-profile of average asset holdings comparing the two models

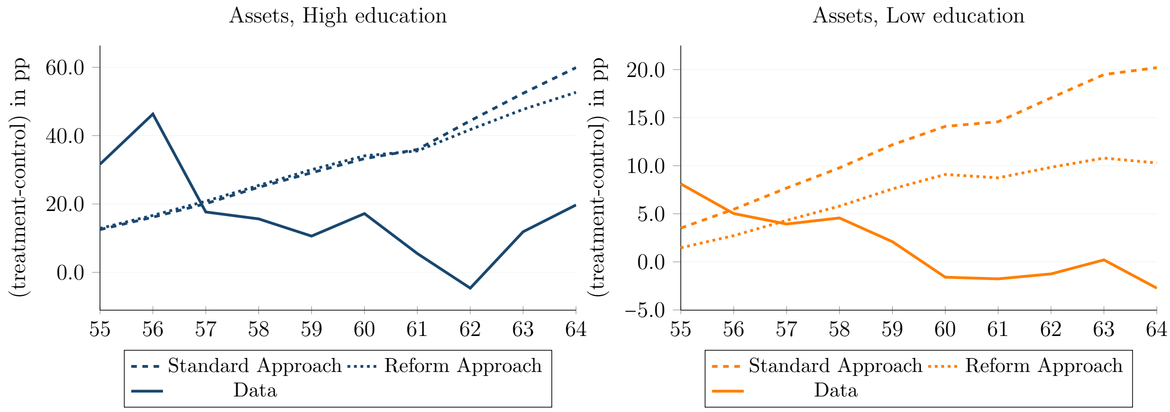
Figure 17: Intensive Margin of Labor Supply, Response to Reform



with the data is given in the following Figure 18.

The general impression from the figures is that the fit of the reform approach is generally better than the standard approach. Again, this is not surprising, as these moments were actually targeted by the former.

Figure 18: Asset holdings, Response to Reform



7.3 A Simple Policy Experiment

Once we have identified and estimated our model, we are interested into simulating policy experiments and analyze their outcomes. We then again contrast the outcomes of the two different models that we estimated to analyze the importance of the estimation method for counterfactual analysis.

As a counterfactual reform, we abandon the lump-sum nature of the AOW, the social security benefit on the Netherlands. Instead of paying the benefit to everyone, our reform only pays out AOW to those who are in need of support. In particular, we top-up retirement payments (coming from private pension payments or working income) for those individuals who would otherwise get less than the standard AOW benefit. Hence, we essentially establish a minimum benefit of annual 13,713 Euro (value from 2012) that individuals will always get as a benefit.

Table 3: Behavioral Responses due to AOW Reform

	Retired at 65	Part-time (40%)	Part-time (90%)	Full-time	Assets
Standard Approach	−2.75	0.15	0.84	1.4	22,585
Reform Approach	−1.57	0.08	0.73	0.60	18,729

Average **Changes** between age 60-64 in percentage points

Table 3 reveals that the different approaches for estimation does matter for the results of counterfactual analzses. In particular, the standard approach yields a more pronounced response in terms of labor supply due to the reform, as well as asset accumulation: the difference in the fraction being retired at age 65 is more than 1pp higher and overall savings are around 4k higher on average. This exercise shows that the results of counterfactual analysis is sensitive to the choice of moments for the estimation of the model.

8 Discussion and Conclusion

We employ two approaches for the estimation of the structural parameters in a life-cycle model of consumption with endogenous labor supply and retirement decision. The approach differs by the set of data moments that we employ to identify the parameters of interest. In a second novel approach, we extend the standard set of moments by making use of a quasi-exogenous variation coming from a large pension reform in the Netherlands. Our aim is that a model that takes behavioral responses into account as moments to target is also more reliable when analyzing the effects of ex-ante policy reforms.

The results in this model are preliminary. In ongoing work we aim to increase the fit of the model by increasing the heterogeneity in preferences. Currently, ten parameters are used to explain twelve age profiles. It seems that the current model is not flexible enough to capture the different patterns precisely enough. We think that an extension into health dependent disutility of work parameters might further aid the fit of the model. But we also want to research how other extensions might influence the fit.

Further work will be on the discussion on how different sets of moments can aid the identification of the important parameters. For example, do moments conditioned on experience aid the identification of the disutility of labor parameters when there is no exogenous variation in the data.

To judge the importance of exogenous variation in estimating structural models, we want also to look into more detail into policy simulations. An estimation solely based on life-cycle profiles might accurately estimate the average effect of a reform, but might fall short in the prediction of distributional effects of it.

The goal is to provide researchers with practical insights what moments they should use to identify different parameters and to understand how crucial exogenous variation is.

Appendix A: Institutions

We implement the tax and transfer system for the year 2012 relying on the OECD publications *Taxing Wages 2013* and *Pensions at a Glance.*

Appendix A.1 Disability and unemployment insurance

Individuals can only claim either disability or unemployment insurance. Disability insurance can only be claimed if the individual is in a bad health status. Both can only be claimed before reaching the age of 65. Each insurance pays benefits of 70% of the last received gross earnings but is capped at €50,064 a year.[25]

The Netherlands guarantees two different minimum incomes. For individuals that receive any social securities, a minimum yearly *net* income of 13,406.60 is guaranteed. For working individuals, who are not receiving any social security benefits, the guaranteed minimum net income is 11,230.00. Thus, individuals whose yearly net earnings are below this threshold are topped up accordingly.

Appendix A.2 Pension Payments

A.2.1 Public Pension (AOW)

The public pension is payed to every citizen aged 65 or older independent of their labor market status. The yearly AOW payment is €13,713.54.

A.2.2 Occupational Pensions

The occupational pension scheme differs between the two cohorts in our model. For individuals born 1949 or before, the occupational pensions had a strong incentive to retire

[25] Technically, unemployed individuals receive 75% of their last earnings in the first two month of their unemployment. Afterwards, the replacement rate is 70%. As we have a yearly model, we abstract from the first two months.

early. If an individual retired before the age of 65, the pension benefit was computed as

$$pens^{occ}_{1949} = \begin{cases} 0 & \text{if } age < 60 \\ 0.85 \times (ea - 19130.76) & \text{if } 60 \leq age < 65 \\ 0.0175 \times wy \times (ea - 19130.76) & \text{if } age \geq 65 \end{cases} \tag{22}$$

Note that besides working years and average lifetime earnings, the payments do not depend on when an individual retires, but only how old the individual is. There are no specific penalties or benefits for retiring early or late. For early retirees, working years increase even when in retirement until the age of 65.

Figure 19: Pension income for cohort born 1949.

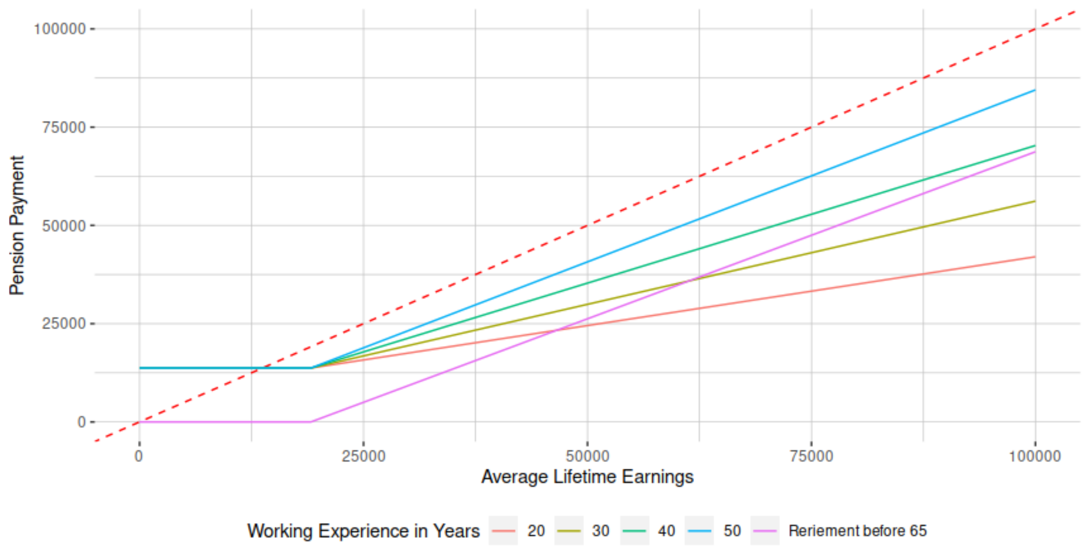


Figure 19 provides an overview of how the pension payments relate to different years of working experiences and average lifetime earnings. The replacement rate of 0.85 for early retirees is equivalent to 48.57 years of working experience for retirees 65 and older. Before the age 65, the public pension (AOW) is not payed out. The high early retirement replacement rate therefore compensates to some degree the missing public pension for early retirees.

For individuals born in 1950, the pension payments depend on the age when entering retirement. They do not change over time.

$$pens^{occ}_{1950} = \begin{cases} 0 & \text{if } age < 60 \\ (1-0.06)^{(65-age^{ret})} \times 0.0175 \times wy \times (ea - 19130.76) & \text{if } 60 \le age < 65 \\ 0.0175 \times wy \times (ea - 19130.76) & \text{if } age = 65 \\ (1+0.07)^{(age^{ret}-65)} \times 0.0175 \times wy \times (ea - 19130.76) & \text{if } 65 \le age \le 70 \end{cases} \tag{23}$$

Figure 20: Pension income for cohort born 1950.

Figure 20 shows how the pension payments relate to the retirement age and average lifetime earnings of individuals born 1950 or earlier. We hold working experience constant at 40 years in this graph. Different years of working experience affect only the income replacement rate. As with figure 19, the public pension payments kick in at age 65.

Appendix A.3 Tax and Transfer System

The tax burden is based on the gross income, which includes the earnings from employment, benefits from disability or unemployment insurances and all pension payments. We denote this as the tax base.

$$taxbase_t = L_t w_t + DI_t + UI_t + pens_t^{public} + pens_t^{occ}.$$

In a first step, social security contributions are computed. They differ with respect to age and gross income. They are computed using the tax base.[26]:

$$s\_contrib_t = \begin{cases} 0.3115 \times taxbase_t & \text{if } taxbase_t < 33,863 \& age < 65 \\ 0.3115 \times 33,863 & \text{if } taxbase_t \geq 33,863 \& age < 65 \\ 0.1325 \times taxbase_t & \text{if } taxbase_t < 33,863 \& age \geq 65 \\ 0.1325 \times 33,863 & \text{if } taxbase_t \geq 33,863 \& age \geq 65 \end{cases} \tag{24}$$

The income tax is also applied to the tax base:

$$inc\_tax_t = \begin{cases} 0.0195 \times taxbase_t & \text{if } taxbase_t < 18,945 \\ 369.43 + 0.108 \times (taxbase_t - 18,945) & \text{if } 18,945 \leq taxbase_t \geq 33,863 \\ 1,980.57 + 0.42 \times (taxbase_t - 33,863) & \text{if } 33,863 \leq taxbase_t \geq 56,491 \\ 11,484.33 + 0.52 \times (taxbase_t - 56,491) & \text{if } taxbase_t \geq 56,491 \end{cases} \tag{25}$$

The Dutch tax system had a general tax credit of 2033. For working tax payers, an additional tax credit is given. With $earnings_t$ denoting the gross earnings from work, the

[26] All monetary values are in 2012 values.

working tax credit is

$$work\_credit_t = \begin{cases} 0.01733 \times earnings_t & \text{if } earnings_t < 9,290.25 \\ 161 & \text{if } 9,290.25 \leq earnings_t \geq 9,295 \\ 161 + 0.1232 \times (earnings_t - 9,295) & \text{if } 9,295 \leq earnings_t \geq 21,064.48 \\ 1611 & \text{if } 21,064.48 \leq earnings_t \geq 45,1780 \\ 1611 - 0.0125 \times (earnings_t - 45,178) & \text{if } 45,178 \leq earnings_t \geq 51,418 \\ 1533 & \text{if } earnings_t \geq 51,418 \end{cases} \tag{26}$$

The total liability to the government is then computed via

$$liabilities_t = \max\{0, s\_contrib_t + inc\_tax_t - 2033 - work\_credit_t\}$$

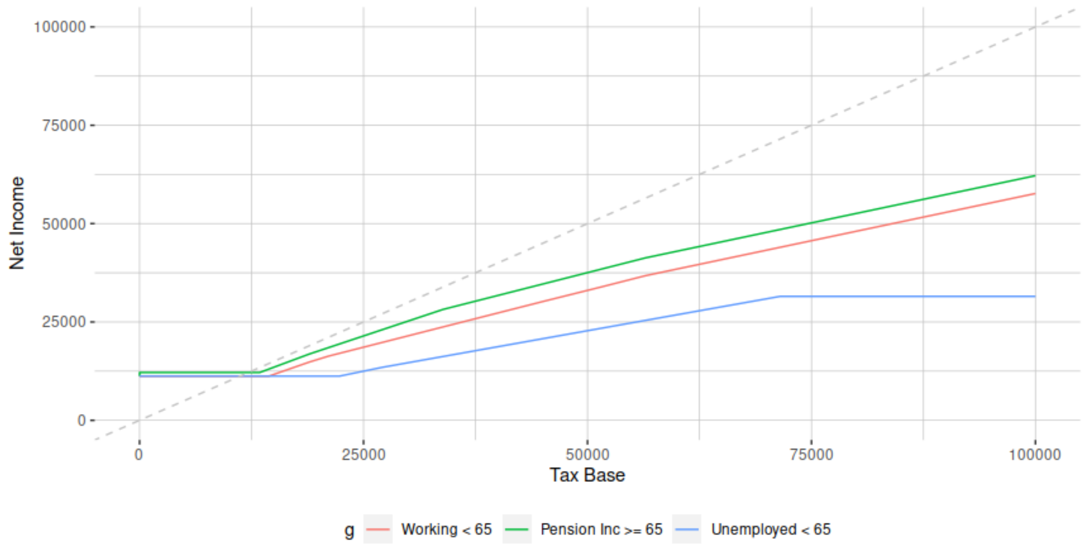
We also include the wealth tax. The wealth tax is applied to income above €21,139. Wealth is was taxed with a tax rate of 1.2%. Finally, we also include a private contribution to a health insurance company of choice that every tax payer has to pay. It is €1253 on average:[27]

$$net\_inc = taxbase_t - liabilities_t - 1253 - \mathbb{1}\{A_t > 21,139\}A_t \times 0.012.$$

Figure 21 illustrates how the tax base translates into net income. Wealth is ignored in this figure. Due to reduced social security payments when aged 65 or older, old individuals have a higher net income than younger individuals given the same tax base. The Netherlands guarantees a minimum net income independent of the employment status. Unemployment benefits are capped at €50,064 a year.

[27] According to the OECD publication *Taxing Wages 2013*, only taxpayers in a marriage or dependent children are available for a refund of their health insurance payment. We therefore abstracts from this here.

Figure 21: Tax and Transfer System



Appendix B: Data Appendix

Appendix B.1 Variables and Data sources

B.1.1 Education

Our education variable comes from a data source compiled by CBS which merges information from different registries and periodic random samples (the so-called *de Enquête Beroeps Bevolking*) to get information on education for the Dutch population. Education is not available for the whole Dutch population but covers around 65 percent of people residing in the Netherlands.

We define two educational bins: Higher educated individuals are defined as those with a Bachelor's degree and above; a fraction of roughly 30 percent of our sample at age 50. The group of lower educated individuals are all other individuals with degrees lower than a Bachelors (or no degree at all).

B.1.2 Health

The data for our health variable comes from the risk equalization files of the National Health Care Institute (*Zorginstituut Nederland*). The file contains data on persons to whom medication were dispensed in the year for which the costs are reimbursed under the statutory basic medical insurance. The data lists the drugs classified by the Anatomical therapeutic chemical (ATC) code. We follow van Ooijen, Alessie, and Knoef (2015) to translate the data on medication prescription into specific chronic health conditions, such as coronary disease, cardiac disease, Respiratory illnesses, etc. Our final health variable is a binary variable defining the sickness-state as having at least two of these chronic conditions. The choice of using two chronic conditions for defining sickness (instead of only one) is due to the fact that one chronic health condition for people age 50+ is widespread and does not seem to affect economic outcomes whereas two chronic condition is associated with (adverse) economic outcomes in our sample.

B.1.3 Mortality

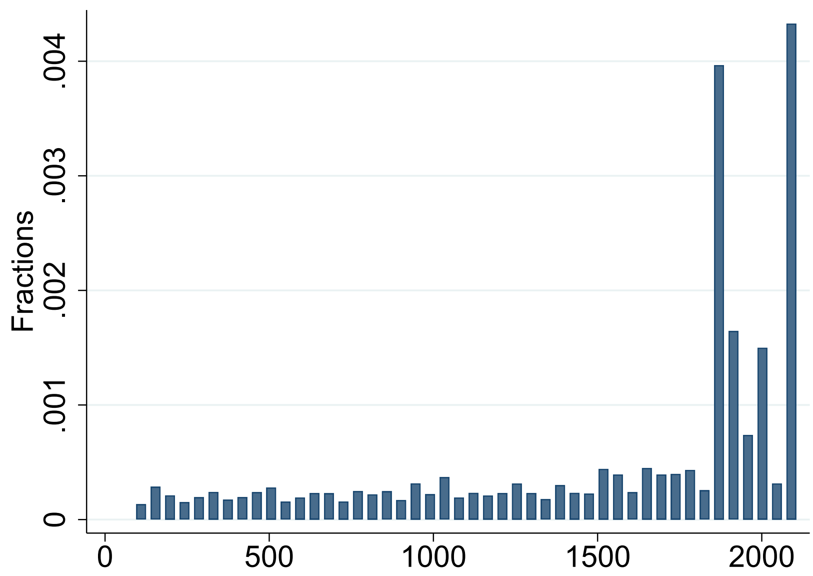
Data on the date of death comes from the Personal Records Database (*Basisregistratie Personen (BRP)*). Since most other variables are missing in the year of death we merge the year of death with the variables from one year lagged, i.e. our variables from t are merged with the relevant year of death $t+1$. Death is defined as an indicator function $d_{i,t+1}$.

B.1.4 Hours worked

The variable on Hours worked comes from a registry for all job files and its characteristics (*Polisadministratie*). It is based on all income taxes from the tax authorities. CBS uses these to construct a variable containing the hours worked relative to a full-time employment in the same sector. For individuals having more than one job, the weighted average is taken.

To construct a measure of hours worked per year, we make use of additional information from the administrative job files. We proceed as follows: First, we multiply the fraction by a variable summarizing the number of days worked per year. Second, we compute the sector specific (median) hours for a full-time employment contract. To this

Figure 22: Distribution of hours, age 60-65 for men



end, we determine the sector that the individual works in.[28] We compute the sector-specific median hours worked for a full-time employment by computing the median of the base-hours per sector for a sample of individuals that worked full-time. This sector specific median is then multiplied with the individual specific fraction of work relative to a full-time employment from above, which yields an approximation of the the amount of hours worked per year.

We define a minimum of 100 hours worked per year, below which we count individuals as being retired (or not working).

To capture the distribution in a way that makes it computationally feasible to work with, we determine four hours categories: no hours (=retired), and three positive hours bins. We refrain from looking at the distribution at age 50 but rather determine those bins by investigating the distribution at ages 60-65 where early retirement decisions are made.

Figure 22 shows the distributions of hours worked at age 60-65 conditional on being positive.

[28]For individuals with more than one job, we approximate this by taking sector from the job where most hours are worked.

There are two spikes that stand out: one at full-time employment (around 2,080 hours per year) and one at around 90 percent of full-time with 1,870 hours per year). In addition, the distribution is rather uniform below these spikes. Conditional on positive hours, we then determine the median for the tertiles of the distribution given in Table 4.

Table 4: Hours Discretization

Hrs. Cluster	Median Hrs. Worked
No work	0
42% of ft	879
90% of ft	1,872
Full time (ft)	2,076

B.1.5 Wealth

The registry data allows for the analysis of various asset classes due to the fact that there is a wealth tax in place in the Netherlands. Data hence comes from the tax authorities and is available between 2006 and 2016. We use the variable on total net wealth including the value of the house net of all liabilities.

B.1.6 Wages

For the estimation of the income process we determine a variable for hourly wages. To this end, we take the ratio of earned labor income and hours worked (described above). Labor income is again a variable retrieved from the tax authorities.

All monetary variables are deflated by the consumer price index.

Appendix B.2 Initial conditions

Since we start our model at age 50 is it of crucial importance to simulate the initial conditions of individuals with respect to education, health, hours worked at age 50, the value of experience (indicating the work history), a measure of life-time earnings at age 50, and asset holdings.

The approach that we take can be summarized as follows:

1. Draw an initial type of individual having a certain education (2 types), health (2 types), and hours distribution (4 types), which is simply taken from the fractions of the 12 different types in the data.

2. Draw value for experience (rounded to integers) given the empirical distributions conditional on one of the 12 types

3. Approximate life-time income as the predicted individual fixed effect from a regression of log-earnings using age-dummies

4. Assume lifetime income to be log-normally distributed, and draw from that distribution given the mean and the sd both conditional on initials.

   To this end, determine the mean of log-lifetime income from the predicted value of a regression on initials and experience, and the standard deviation taken from the data depending on the 12 initials from the approximated life-time income.

5. Predict wealth in two stages

   - Extensive margin: predict probability that the agent has low wealth using equation (30) with the indicator variable
   - Intensive Margin: Assume a log-normal distribution and draw value given mean and standard deviation conditional on initials. Again, run regression with the wealth-amount variable to predict mean wealth value conditional on initials and take the standard deviation from the data.

In the following the approach is described in more detail.

Sample We focus on men at age 50 that are currently working, using data from the years 2006 and 2007. We exclude self-employed and people workin gin the public sector. This gives us 43, 548 observations with non-missing values for education and health information. Note, that we do not match our cohort 1949/50 but rather the cohort 1956/67 - but this is due to data availability - and we get as close as possible to our cohort.

Also note that we have to extend the sample to 2005-2012 when running the fixed effects regression for lifetime earnings to filter out transitory income shocks. We only do this extension to predict lifetime earnings.

Initial Types As before, we first compute the fractions in the population of people being in a certain health state (healthy, sick), education (below bachelor degree, bachelor or above), and hours distribution (full-time, part-time 90% and 40$). This yields $2\times 2\times 3 = 12$ initial types.

Experience For experience, we simply transform the data into integer and directly draw from the empirical distributions for the 12 initial types defined above. We basically have 35 values for each year of experience. We exclude values with zero experience but with positive income for labor earnings. We also cut experience by 35 assuming that the youngest age people start working is at age 15. Due to sample size problems, we increase the age range and use data from men at ages 48-50.

Lifetime Earnings Lifetime earnings are not directly observable and have to be approximated. To this end, we take a panel of households where we have experience data available (this is data from 2005 until 2012) and we focus on the working life from ages 25 until the initial model age 50. We then run the following fixed effects regression (where 25 is the reference year):

$$\ln(earnings) = \gamma + \alpha_i + \mathbf{t}_i \tilde{\beta} + \epsilon_{it} \tag{27}$$

where $\mathbf{t}_i$ are age-dummies. We then predict lifetime income $ltinc$ by

$$\widehat{\ln(ltinc)} = \hat{\gamma} + \hat{\alpha}_i + \hat{\hat{\beta}}_{50} \tag{28}$$

where $\hat{\hat{\beta}}_{50}$ is the estimated coefficient for the indicator of age 50.

This approach basically washes out the transitory income shock component or the earnings equation and focuses on age 50.

We next run the regression giving the association between lifetime income $\ln(ltinc)$, experience dummies and the initial characteristics

$$\hat{\alpha}_i = \delta + \mathbf{exp}_{it}\nu + \beta_1 s_{it} + \beta_2 he_{it} + \beta_3 \mathbf{L}_{it} + \epsilon_{it} \tag{29}$$

where exp is an indicator vector of experience, s is education, he is health and L a vector of indicators representing the discretized hours choice.

We save all coefficients to predict the mean of lifetime income, depending on initial characteristics. Note, that the R-squared here is actually quite high, around 0.44.

Wealth For wealth we want to fit theoretical distributions to the data for each education, health and hours worked-type, i.e., 12 different types. However, we also want different wealth values depending on life-time income and experience. The problem is that the wealth distribution has a shape that cannot be fitted by a theoretical distribution easily.

Our approach is as follows: We first drop all observations with negative wealth, 4% of all observations. We then create a binary variable having zero or low wealth (defines as below 2k) and estimate the probability depending on initial characteristics. The intensive margin of wealth is defined as values above 2k. Now, we run two regressions (1) on the probability to get low wealth, depending on initial characteristics, (2) on the positive wealth value. We use the sample of working men at age 50.

$$Wealth_{it} = \beta_0 + \beta_1 s_{it} + \beta_2 he_{it} + \beta_3 \mathbf{L}^3_{it} + \beta_4 fe_{it} + \beta_5 exp_{it} + \epsilon_{it} \tag{30}$$

where $Wealth_{it}$ is either a binary variable indicating low wealth, or the log of positive wealth measured in 10k.

We predict the means with these equations conditional on draws of the initials. For the positive wealth variable we compute standard deviations over education, health, and hours worked (12 SDs). We then assume a log-normal distribution with the given mean and sd to predict the initial value of wealth.

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