Disentangling the Roles of Preferences and Shocks in Labor Supply*

Nataliya Gimpelson[†]

Click here for the most recent version

Abstract

Labor supply differs across people, even for the same levels of wages and assets. These differences can be driven by heterogeneity in preferences or by shocks to employment opportunities. Disentangling the two forces is important for policy but difficult to do in practice. I show that retirement decisions and their interactions with assets and labor history help to tell preferences and shocks apart. I document that wealthy people retire later and people with higher prime-age labor supply retire earlier. These facts can be jointly rationalized by the presence of preference heterogeneity and labor market constraints. I quantify the roles of preferences and shocks by calibrating a lifecycle model with endogenous retirement decision to German SOEP data. The model requires significant heterogeneity in bequest motives and allocates a big role to labor market constraints. Labor market shocks explain 50% of total variation in prime-age employment, while preferences explain 10%.

^{*} I am indebted to Mark Bils for his continuous guidance and support. I am grateful to Yan Bai, Lisa Kahn, George Alessandria, Rafael Guntin, Paulo Lins, Marcos Mac Mullen, and to my friends and colleagues from the Department of Economics at University of Rochester for valuable feedback and discussions.

[†] n.gimpelson@gmail.com, Department of Economics, University of Rochester

1 Introduction

Labor supply decisions are at the heart of macroeconomics. They are key for how the economy responds to macroeconomic shocks and policies. Moreover, they play important role in explaining income inequality. However, much of the employment variation remains unexplained after accounting for wages, assets, health and other observable characteristics. This paper revisits the question of what are the forces that drive the differences in labor supply.

The literature discusses two potential drivers of the unexplained variation in hours. One explanation is that people differ in their preferences towards work and in their bequest motives. Individuals who are more hardworking or more passionate about their jobs will work more than someone who is less excited about their career. Similarly, those with stronger bequest motives will also work more to leave a larger inheritance to their kids. Another explanation emphasizes that some employment outcomes are involuntary. People can be laid off or be restricted to working part-time. As a result, they are not able to work as much as they would like to.

In this paper, I contribute to understanding the employment variation by proposing a new strategy to identify the roles of preference heterogeneity and employment constraints. The main idea is to look at retirement decisions and their interactions with assets and work history. First of all, there is a lot of variation in retirement age – many people retire before pension eligibility and many keep working after they start getting pensions. Hence, it reflects information about individual behavior that is lost if we model retirement as an exogenous event. For example, since retirement is an additional margin of labor supply, it captures any permanent preference heterogeneity. Secondly, retirement is largely a voluntary choice and hence it is less likely to be contaminated by exogenous employment shocks compared to prime-age labor supply. All of this means that retirement should be helpful to identify preference heterogeneity.

The two moments that are key to the identification are the correlation between assets and retirement hazard and the correlation between individual labor histories and retirement hazard. I show that the empirical signs of these correlations pin down whether preference heterogeneity and employment constraints are present or not.

To empirically document these moments, I use German Socio-Economic Panel data (SOEP) because it provides a unique opportunity to track retrospective employment histories and to relate them to retirement decisions. I find that wealthier people tend to retire later, while those who work more in their prime-age retire earlier. What does this say about preferences and employment constraints?

In a standard model without preference heterogeneity, we would expect people at the top of the asset distribution to retire earlier due to the wealth effect. To rationalize that in the data wealthier people retire later, there has to be a force that makes some people accumulate more assets and to keep working. I show that preference heterogeneity in bequest motives and in disutility of labor can generate this result. Indeed, people with higher bequest motive would be at the top of asset distribution and at the same time would have incentive to keep working longer to build up their bequest. Disutility of labor generates similar effects: those with lower disutility of work accumulate more assets and retire later. Although the two types of preference heterogeneity are qualitatively similar, my calibration results show that heterogeneity in bequest motives plays a much bigger role than heterogeneity in disutility of labor.

Conditional on having this preference heterogeneity, we should see that those who have higher prime-age labor supply retire later. This is because preferences dictating high labor supply should be manifested by working more at any point in life, both at the prime-age and later in life. The empirical evidence contradicts this hypothesis, meaning that there is an additional force that breaks the correlation between preferences and employment outcomes. This can be explained by labor market constraints that push people off their labor supply curves. For example, those who are hit by unemployment shocks would exhibit low labor supply even if their preferences towards work are different. As a result, preferences do not fully map to employment histories. This highlights the importance of looking at retirement decisions to better understand prime-age labor supply.

To quantify the extent of preference heterogeneity and labor market constraints, I set up a life-cycle model with endogenous retirement and labor supply choice. The model incorporates permanent heterogeneity in both disutility of labor and in bequest motives in order to match the correlation between assets and retirement. I consider two variations of the model: with and without labor market constraints. To mimic the actual data, I augment model-generated data with the measurement errors calculated from merging SOEP and SOEP-RV (novel administrative data which links SOEP respondents to their pension records). This allows me to simulate the data which has similar measurement error structure as the original data.

I start with the model without labor market constraints and calibrate it using simulated method of moments to match key moments of retirement, assets and employment distributions. The first result is that the negative correlation between assets and retirement hazard indeed requires preference heterogeneity in both disutility of labor and bequest motive. Moreover, disutility of labor and bequest motive have to be negatively correlated to qualitatively match the relationship between assets and retirement hazard we observe in the data. As a result, people with low disutility of labor and high bequest motive accumulate more assets and retire later – confounding the standard wealth effect. Given this preference heterogeneity, the model without employment shocks predicts that people with longer work history retire later. This result goes against what I see in the data.

This suggests that, despite the presence of preference heterogeneity, those preferences do not map to earlier working history. Going back to the model, I allow for persistent labor market constraints with the following three realizations: individuals might not be able to get a wage draw at all and hence are forced into non-employment, they might have access to part-time job but not to a full-time job, or they are free to choose any type of employment they prefer. Once I recalibrate the model to allow for exogenous separations, the relationship between hours and retirement hazard becomes positive – in line with the data. This suggests that preferences are indeed muted when it comes to earlier labor supply.

This paper shows that retirement decisions provide important information about earlier labor supply outcomes. By exploring the relationship between assets and retirement I identify the need for strong bequest heterogeneity, while the relationship between work history and retirement pins down the presence of non-trivial labor market constraints. I quantify the relative roles of preference heterogeneity and employment constraints in explaining employment variation. The model suggests that 50% of that variation is explained by the constraints, and only 10% is generated by preferences.

The rest of the paper is organized as follows. Section 2 describes related literature. Section 3 explains the intuition behind the main idea of the paper. Section 4 introduces the datasets I am using in my analysis. Section 5 discusses the empirical results and patterns that emerge from the data. Section 6 introduces the baseline model and discusses how it is calibrated. Section 7 augments the baseline model with exogenous employment shocks and shows that these shocks are important for matching the data. Section 8 discusses how we can use the simulated models to disentangle the roles of preferences and labor market constraints in explaining lifetime employment variation. Section 9 talks about welfare implications of the labor constraints. Section 10 concludes.

2 Related Literature

This paper is related to several strands of literature. First of all, it speaks to research on preference heterogeneity. Chang and Kim (2006) emphasized the importance of stepping away from the representative agent framework to understand why macro estimates of labor supply elasticities are much larger than what microdata suggests. They abstracted from exante heterogeneity, but introduced idiosyncratic wage shocks which generate heterogeneity in asset holdings and spousal earnings.

Since then a number of papers have considered whether ex-ante heterogeneity is also important to explain observed behavior. For example, Mustre-del-Rio (2015) argues that heterogeneity in disutility of labor is required to generate relatively flat relationship between assets and employment, which would be declining otherwise. Moreover, disutility of labor needs to be negatively correlated with market skills. Hence, different dimensions of examte heterogeneity interact to deliver empirically valid results. Heathcote, Storesletten, and Violante (2014) also emphasize the importance of allowing for heterogeneity in disutility of labor to generate the observed distribution over wages, hours, and consumption.

Another important source of preference heterogeneity in my paper is bequest motive. De Nardi (2004) and De Nardi and Yang (2014) emphasize the importance of bequest motive to explain why wealth distribution is more concentrated than labor earnings, and why there is so much heterogeneity in wealth at the time of retirement. These papers introduce bequest

motive as a luxury good in an overlapping generation model, which helps to generate the upper tail of the wealth distribution. These papers abstract from ex-ante heterogeneity and calibrate one value of bequest motive for the whole population. Kopczuk and Lupton (2007) allow for two types of people: with and without bequest motive, and estimate a structural empirical model to recover the strength of the bequest motive and the fraction of each type. Using US data they show that while majority of population have bequest motive, 25% do not.

I also acknowledge the importance of exogenous labor market constraints for explaining observed variation in employment. Krusell et al. (2011) emphasize the importance of persistent shocks to employment (e.g. shocks to market opportunities, shocks to health) to explain persistent movement across employment, unemployment and non-participation. Krusell et al. (2020) extend the model to general equilibrium and show that those shocks are more important to explain transitions across labor market states than TFP shocks. However, these papers emphasize the distinction between non-participation and unemployment which I abstract from in my paper. Low, Meghir, and Pistaferri (2010) also highlight the importance of considering employment shocks separately from productivity fluctuations. These shocks not only directly affect employment outcomes by pushing people into non-employment, but generate uncertainty about future employment opportunities and hence affect precautionary behavior.

The papers mentioned above look at prime age behavior and do not consider retirement decisions in their framework. However, prime age employment is likely affected by both preference heterogeneity and exogenous shocks which makes it difficult to separate the two. I argue that retirement age and its interaction with wages, assets and earlier labor supply is informative about both preference heterogeneity and the existence of exogenous shocks. I build on the literatures described above by bringing endogenous retirement decisions to the life-cycle model with rich preference heterogeneity in both disutility of labor and bequest motives and exogenous employment shocks.

The retirement literature is largely focused on understanding determinants of retirement, and thinking about appropriate policies. French (2005) builds a rich model of retirement decisions with wage and health shocks that realistically captures Social Security system. The

model allows one to analyze how changes in Social Security might affect labor supply over the life-cycle, e.g. changes in retirement age and generosity of Social Security payments. Laun and Wallenius (2016) build on French (2005) to conduct cross-country analysis of different pension and health insurance policies and their effects on labor supply later in life. They allow for preference heterogeneity to match retirement distribution. Fan, Seshadri, and Taber (2005) add human capital accumulation to the endogenous retirement model, while allowing for correlated heterogeneity in disutility of labor and the ability to learn. They look at how changes in Social Security system affect labor supply later in life and as a result how they affect human capital accumulation over the life-cycle.

These papers provide rich frameworks to analyze pension systems and conduct policy experiments. I borrow theoretical foundations from this literature and use retirement decisions as a source of information about earlier behavior rather than an outcome of interest in itself. Rogerson and Wallenius (2013), and later Ameriks et al. (2020), take a similar approach to estimating the intertemporal elasticity of substitution in labor supply, which is usually estimated using prime age employment. They point out that retirement decisions contain important information about intertemporal elasticity of substitution since retirement represents an abrupt change in labor supply.

3 Identification Strategy

I disentangle the roles of preferences and labor constraints in employment variation by using two key moments: the correlation between assets and retirement hazard and the correlation between labor history and retirement hazard.

Why are these moments informative of the roles of preferences and labor market constraints in driving employment variation? In the absence of any preference heterogeneity and constraints, there should be a positive relationship between assets and retirement hazard (through the wealth effect). When it comes to labor history, it should not contain any additional information about retirement decision once assets, wages, and all the demographic characteristics are accounted for.

If there is heterogeneity in disutility of labor and/or in bequest motives, preferences are

now correlated with both assets and retirement hazard. For example, someone with a higher bequest motive will want to accumulate more assets at any age, and at the same time they will want to keep working longer to keep building up the bequest. Furthermore, if bequest motive is negatively correlated with disutility of labor (which I will show to be true) – higher assets would be associated with even lower willingness to retire. Hence, unobservable preferences create omitted variable bias and distort the measured wealth effect. In this case, the relationship between assets and retirement hazard can be negative. This idea is illustrated in Figure 1a. Red and blue lines represent the positive relationships between assets and retirement hazard for the two types. However, since assets are correlated with preferences: lower assets will mostly be held by low bequest type (corresponding to the red line) and high assets will mostly be associated with the high bequest people. Taking into account this correlation, the black line traces the average relationship weighted by the distribution of preference types in each asset quartile.

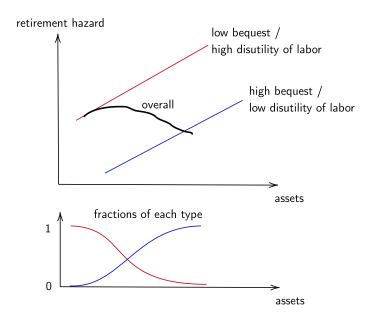
At the same time, preference heterogeneity implies negative relationship between labor history and retirement hazard. Those with higher disutility of labor and/or smaller bequest motive will both work less during working life and will retire earlier. This is illustrated in Figure 1b.

However, in the presence of labor market constraints preference heterogeneity will not be fully reflected in employment because some people will be pushed off their labor supply curves. This means that the relationship between labor history and retirement will be less negative or even positive. The relationship between assets and retirement hazard will remain negative because of the role of preferences.

Therefore, looking jointly at these two moments in the data can help us distinguish between different cases. I summarize the four combinations of the constraints and preference heterogeneity in Table 1: each cell shows the signs of the relationship between work history and retirement hazard and between assets and retirement hazard.

Figure 1: Role of preference heterogeneity

(a) assets and retirement hazard



(b) work history and retirement hazard

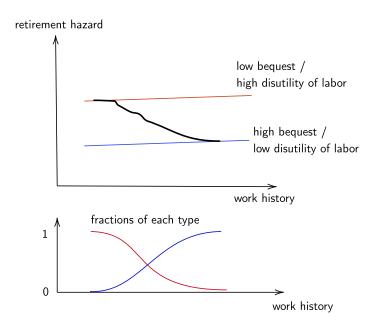


Table 1: Identification strategy

	no emp constraints	emp constraints
no pref heterog	wkhist: ≥ 0 , assets: > 0	wkhist: ≥ 0 , assets: > 0
pref heterog	wkhist: < 0 , assets: < 0	wkhist: ?, assets: < 0

4 Data

In this section, I describe the dataset I use for the empirical analysis and for generating the moments to calibrate the model.

4.1 SOEP

For my empirical analysis I use the German Socio-Economic Panel data (SOEP). This is an extensive annual household panel survey from Germany, which runs starting from 1984 and is updated every year. It contains information on employment, wages, family status, health indicators, assets and other characteristics for more than 10000 households. One of the key variables in my analysis is a measure of labor market history which I define as cumulative labor supply at ages 30-49. That requires information on people from when they were 30 years old. At the same time, I connect these labor histories to retirement decisions which requires observing those same people into the older ages as well.

Most datasets do not track an adequate number of people for that many years. An advantage of the SOEP is that it contains retrospective information on employment for everyone entering the sample, which is crucial for relating retirement to earlier labor supply. Moreover, the SOEP can be linked to a novel administrative dataset SOEP-RV which contains employment and income records from pension insurance system that go back to the beginning of respondents careers. It provides a unique opportunity to quantify the extent of measurement error in both employment history and earnings. I describe the SOEP-RV in more details below.

Next, I define two key variables of my analysis: retirement age and labor market history. The relationship between these variables helps me identify the relative roles of preferences vs labor market constraints in lifetime employment variation.

4.1.1 Retirement age

To identify retired people in the data, I look at those who are older than 50 and apply the following two rules:

• a person stops working and is not seen coming back to the labor force for as long as

they are observed in the survey, if they are observed for at least 3 years after the labor force exit (to avoid counting those who are temporarily non-employed as retired)

• a person reports being retired and at the same time I observe them to be out of the labor force

Note that this definition does not condition on receipt of a retirement pension.

Figure 2 plots the distribution of retirement ages as defined above. We can see that a majority of people retire around 65 when the pension becomes available. However, there is a lot of heterogeneity with some people retiring earlier and some retiring long after they become eligible for pension.

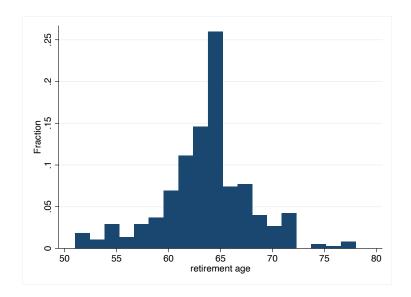


Figure 2: distribution of retirement ages for men, SOEP

4.1.2 Labor market history

The other key variable is labor market history from 30 to 49 years old. Ages 30-49 are chosen to avoid periods of schooling or retirement. To measure work history I use contemporaneous information from the survey whenever possible. However, most individuals will not be sampled back to their 30s. For those ages where I do not see the respondents contemporaneously, I use retrospective data.

For each person entering the survey, at any age, the survey collects information on their prior labor market activity. In particular, respondents are asked whether they were employed full-time, part-time, not employed, studying, etc at each of the previous ages back to age 15. This data does not distinguish between people who worked 60 hours vs 40 hours, but it does capture variation on the extensive margin which was shown to be important (Mukoyama, Shintani, and Teramoto (2021), Elsby, Hobijn, and Sahin (2015)).

To combine retrospective responses on the extensive margin, I use the following strategy: for each of the ages 30-49 I assign 0 hours if the person reported being non-employed, 1000 annual hours – if the person was employed part-time and 2000 annual hours if the person was employed full-time. Then I sum those responses to obtain a total measure of labor supply over ages 30-49. In some ages, people report several different labor force statuses (e.g. a person might report being employed full-time and unemployed in one year). I treat such cases as part-time work.

Below are the distributions of labor supply histories for men and women. We can see that for men the distribution is highly skewed with most men working full-time throughout the 30-49 period. For women it is much more dispersed since women tend to have lower employment rates and are much more likely to be out of the labor force. Even though there is more variation in female employment, I will focus on men in my analysis since female labor supply is affected by raising kids which my theoretical model does not capture.

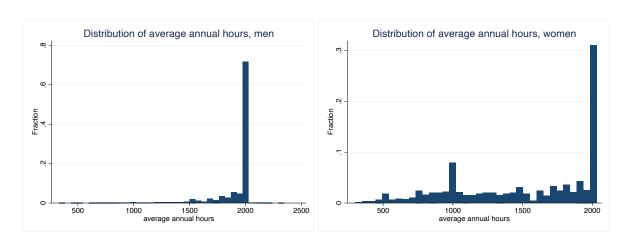


Figure 3: Distributions of cumulative labor history

4.1.3 Additional Variables

A life-cycle model with endogenous retirement predicts that assets and wages should affect retirement through income and substitution effects. For wages I construct the most recent hourly earnings as reported monthly earnings divided by reported weekly hours multiplied by 4.3. Information on assets is available every 5 years; I use that information when assets are available and impute missing values with the lagged assets. In my regression I enter assets as a quartile in the distribution. Health is also collected every 5 years. The respondents are asked to evaluate their health from very bad to very good. I generate a dummy variable, which takes a value of 1 if the person reported bad health and 0 otherwise. I also account for marital status – whether the person is married or not.

4.2 SOEP-RV

Labor history is a key variable in my empirical analysis. However, since it is based on retrospective data it is prone to measurement error. Incomes are also self-reported in the SOEP, which adds another source of measurement error. To account for the role of these measurement errors in the data moments, I utilize the newly available project SOEP-RV. The project is a collaboration between the SOEP and the Research Data Centre of the German Pension Insurance (FDZ-RV), described in details in Lüthen et al. (2021). It allows to merge SOEP respondents, who agreed to share their pension identifier, with their administrative records from FDZ. The SOEP-RV includes monthly employment spells and income histories from age 14 to the most recent SOEP survey. However, it does not contain any information on occupations or assets.

The original FDZ dataset contains information on the whole population. However, not all SOEP respondents agreed to publicly share their pension record identifiers, meaning that only 20% of the SOEP sample can be linked to the administrative records. This makes the SOEP-RV sample too small to be the core data of my analysis. However, it can be used to infer the size of measurement error both for income process and for employment history. In the Appendix I compare descriptive statistics for the SOEP and the SOEP-RV, and show that the SOEP-RV is representative of the larger population.

Employment records in the SOEP-RV reflect entries for the "number of days recorded with compulsory contributions from employment subject to social insurance contributions or self-employment in the respective month". Incomes are recorded as "period earnings based on compulsory contributions from employment subject to social insurance contributions or self-employment in the respective month, rounded to integers."

4.3 Combining SOEP and SOEP-RV

4.3.1 Measurement Error in Employment Spells

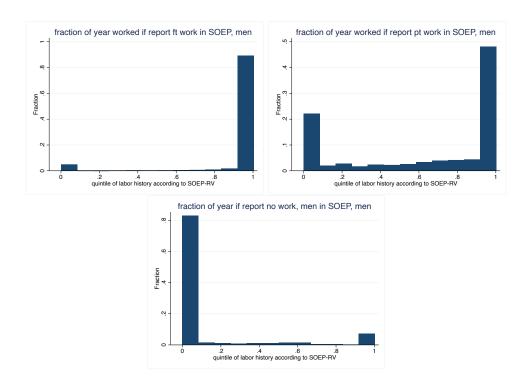
One complication with FDZ is that it records employment only for those occupations that are covered by public pension system. This excludes civil servants who do not make contributions to pension system, and those who are covered by occupation-specific pensions – doctors, lawyers and architects. For these occupations, records show up as missing values. The SOEP does not track occupations retrospectively and FDZ does not record them either. Therefore, it is impossible to determine if the employment record is missing because the person did not work during that month or they worked in an occupation that does not contribute to the public pension system.

To address this issue, I look at the occupations the person had while being observed in the SOEP. In particular, I check which occupation the respondent reported most frequently, what was their first occupation, and which one was reported at their first SOEP survey. For measurement error calculations, I exclude those respondents for whom these occupations included civil servants, doctors, lawyers and architects. I also exclude self-employed who can contribute to the pension system but are not required to.

To infer measurement error in employment from retrospective SOEP data, I compare annual values (aggregated from monthly information) from FDZ to retrospective annual values from the SOEP. I attribute any deviation as measurement error in the SOEP.

Figure 4 shows that 90% of those who report that they worked full-time did work for the full year; and 85% of those who reported not working in that year did not work. The actual employment of those who reported part-time work is much more dispersed. Overall, these figures suggest that retrospective data is highly correlated with the true employment patterns; but some people do misreport their past employment.

Figure 4



To further quantify the measurement error, I split yearly labor supply from FDZ into 5 equal bins, and look at how the SOEP responses are distributed conditional on how much the person actually worked that year. Figure 5 plots the distribution of men and women over different values of labor supply recorded in FDZ. As we would expect, almost 80% of men work for the whole year, while female employment is more spread out.

Figure 5

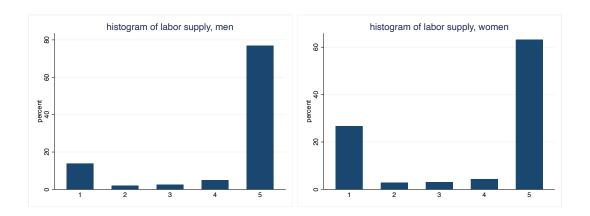
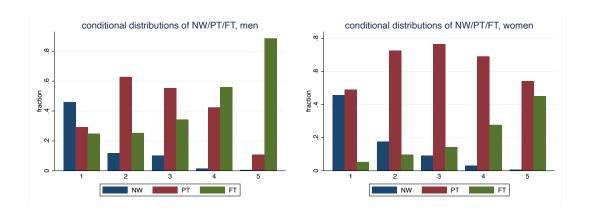


Figure 6 shows how retrospective responses are distributed across different values of FDZ employment records. This distribution implicitly defines the measurement error in employment. We see that probability of reporting "full-time work" (FT) in SOEP increases with the FDZ employment record, while probability of responding "no work" (NW) goes down. These patterns hold for both men and women but, not surprisingly, part-time work (PT) plays a bigger role for women.

In the theoretical model that I discuss in Section 6, I treat labor supply decisions as true employment values corresponding to FDZ records. I then make them comparable with SOEP values by adding measurement error as in Figure 6.

Figure 6



4.3.2 Measurement Error in Income

Income values recorded based on pension insurance contributions will also be much closer to the true income than self-reported SOEP responses. I directly compare the values reported in SOEP and recorded in FDZ, and define the SOEP measurement error as the difference between the two. Since income in SOEP is reported only for the month before the survey and FDZ data is recorded monthly, I use the same month for both datasets. Values above a known year-specific threshold are censored in FDZ but not in SOEP. I calculate measurement error based on uncensored values.

Figure 7 plots a histogram of measurement error, which is defined as the difference between log monthly SOEP income and log monthly SOEP-RV income. I will add this measurement error to the "true" income process when I simulate the theoretical model in Section 6.2.

log(SOEP income) - log(SOEP-RV income), men

Figure 7

5 Empirical Results

In this section I describe the empirical strategy and show the results that will be central to calibrating the theoretical model. As explained earlier in the paper, the key moments that will help me separate the roles of labor market constraints and preferences are the correlation between assets and retirement hazard and the correlation between labor history and retirement hazard.

5.1 Methodology

I am interested in how retirement is related to cumulative labor history (how much people work when they are 30-49) and to assets, conditional on wages, health, and other demographic characteristics.

Figure 3 showed that distribution of labor histories for men is very concentrated: more than 50% of people work full-time every year from 30 to 49. To account for this, I split people in two groups based on how much they work. I define a dummy variable wkhist, where wkhist = 1 for those who on average worked at least 1800 hours a year, and wkhist = 0 otherwise. Assets are split in four quartiles, with each quartile j denoted as $assets^{j}$. Health is another important variable to consider. It is directly related to retirement through lower productivity, and it can be correlated savings through health expenditures (De Nardi, French, and Jones (2010)).

Retirement is a right-censored variable because we do not observe retirement events for those who retire after leaving the survey or after the last wave of the SOEP. To extract as much information as possible from these censored observations, I rely on survival analysis methods and look at retirement hazards rather than retirement ages. For my analysis, I use Cox proportional hazards model with the following specification:.

$$h(t) = h_0(t)exp(\beta_1 wkhist_i + \sum_{j=2}^{4} \beta_j assets_{it}^j + \alpha logwage_{i,t-1} + \gamma X_{it} + \epsilon_{it}),$$

where $h(t) = \frac{\partial S(t)/\partial t}{S(t)}$, S(t) – probability of "survival" (not retiring) until t+1 conditional on surviving to t, $h_0(t)$ – baseline hazard function. X_{it} includes demographic characteristics such as health, education, marital status, and birth year.

The main results in this paper correspond to men, but I show the alternative specifications and the results for women in the Appendix.

5.2 Results

Table 2 presents the results in terms of hazard ratios: a coefficient greater than 1 implies that the corresponding variable increases the retirement hazard (people retire sooner), while a coefficient less than 1 implies a decrease in the retirement hazard. From Column 2 we see, not surprisingly, that bad health is associated with a larger retirement hazard: reporting bad health is associated with 40% increase in the retirement hazard at any age. We also see that more schooling is associated with a lower retirement hazard: 1 extra year of schooling is associated with 7% reduction in the retirement hazard. One explanation is those with more education are more likely to work in occupations that are less physically demanding.

Turning to the main coefficients of interest, we see that those in the 2^{nd} and 3^{rd} quartiles of the asset distribution are almost as likely to retire as those in the 1^{st} quartile. However, those at the 4^{th} quartile are 20% less likely to retire than those with fewer assets. From the discussion earlier in the paper, this suggests that preference heterogeneity might be present. At the same time those who work more than 1800 hrs are 20% more likely to retire at any age relative to those who work less. The coefficient is marginally significant, but what matters is that it is definitely not negative which would be the case if preference heterogeneity was not accompanied by the presence of labor market constraints.

Table 2: Retirement hazard, men

	1	2	3				
more than 1800hrs		1.20+	1.32*				
		(0.11)	(0.10)				
log past wage	1.12*	1.11*	1.03				
	(0.04)	(0.05)	(0.04)				
2nd quart assets	1.12	1.11	1.04				
	(0.09)	(0.09)	(0.09)				
3rd quart assets		1.00	0.91				
	(0.09)	(0.09)	(0.09)				
4th quart assets	0.83 +	0.82*	0.69***				
	(0.09)	(0.09)	(0.09)				
bad health	1.37***	1.38***	1.39***				
	(0.07)	(0.07)	(0.07)				
married	1.10	1.09	1.12				
	(0.07)	(0.07)	(0.07)				
years of schooling	0.93***	0.93***					
	(0.01)	(0.01)					
N	17,710	17,710	17,710				
retirement events	1,366	1,366	1,366				
concordance ratio	0.661	0.662	0.647				
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001							

Model's ability to explain retirement hazard is given by concordance ratio. When we compare the model with and without labor history (Columns 1 and 2), concordance ratios are almost the same. This means that labor history does not bring any new information to the model. Even if there is preference heterogeneity, it does not show up through the labor history – this is consistent with the presence of labor market constraints.

To summarize, from this empirical evidence we find that wealthy people retire later and that those with higher prime-age labor supply retire earlier. In line with the logic described above, this suggests that both preference heterogeneity and employment constraints are present in the data.

6 Model

To quantify the relative roles of preferences and constraints, I set up a life-cycle model with endogenous retirement decisions. To better illustrate the mechanism, I start with the model that allows for preference heterogeneity but does not have exogenous constraints. Once I calibrate it to match retirement and labor history and uncover the extent of preference heterogeneity, I run regressions from Section 5 on model-simulated data and show the model predictions for the relationship between labor supply and retirement. I show that the model cannot match both the relationship between assets and retirement hazard and the relationship between labor history and retirement hazard without allowing for employment constraints. When I bring the constraints into the model, I can match the relationships between retirement hazard and both assets and labor history.

I show that the empirical facts together with a life-cycle model help us identify heterogeneity in disutility of labor and bequest motives and tell us how much of the employment variation is explained by preferences versus employment constraints.

6.1 Setup

I set up an annual life-cycle model with endogenous retirement: individuals maximize their life-time expected utility by choosing savings, labor supply and whether to retire or not. In this section I allow people to have permanent differences in bequest motives and disutility of labor, however there are no labor constraints. The only source of uncertainty in this version of the model is the stochastic income process. Later in the paper I will consider a full model with the stochastic employment constraints – that will add another source of uncertainty.

6.1.1 Preferences

Agent i solves the following problem:

$$\max_{\{a_{i,j+1},h_{ij},R_{ij}\}_{j=t}^{T}} u_i(c_{it},h_{it}) + E_t \left[\sum_{j=t+1}^{T} \beta^j u_i(c_{ij},h_{ij}) + \beta^{T+1} b_i(a_{i,T+1}) \right], \tag{1}$$

where agent's utility depends on consumption c_{it} , hours worked h_{it} , and bequest value $b_i(a_{i,T+1})$. The agent is choosing savings, hours worked and whether to retire or not (if not retired yet). Retirement is an absorbing state: once the agent decides to retire, they cannot go back to work.

Ideally, I would want labor choice to be continuous, but for computational purposes I discretize it. In particular, I allow for 5 discrete values: $h \in \{0; 0.25; 0.5; 0.75; 1\}$. This allows to capture the distribution of actual employment outcomes. To convert these values to nonemployment, part-time and full-time as in the data, I will add the measurement error described in Section 4.3.1.

Consumption consists of two components: market consumption c_t^m and home production c_t^h . Total available time is split between working hours h_t^m , home production hours h_t^h , and leisure l_t , so that $h_t^m + h_t^h + l_t = 1$.

In addition to permanent heterogeneity in disutility of labor, I assume that disutility of labor increases with age starting from \bar{t} . This generates decline in labor force as we see it in the data and reflects decline in health among other things.

Agent i has additively separable CRRA preferences that look as follows:

$$u_i(c_{it}, h_{it}) = \frac{(c_{it}^m + c_{it}^h)^{1-\sigma}}{1-\sigma} - \frac{\phi_i^h}{1+\sigma_h} (h_{it}^m + h_{it}^h + \theta_h \mathbb{1}_{h_{it}^m \ge 0})^{1+\sigma_h} \left[1 + \mathbb{1}_{t \ge \bar{t}} \left(\frac{t-\bar{t}}{\xi_2} \right)^{\xi_1} \right], \quad (2)$$

where $h_{it}^h = h_n(1 - h_{it})$ and $c_{it}^h = c_n h_{it}^h$. I assume that fraction h_n of non-working hours is used in home production, and the consumption from home production is a linear function of hours worked at home. This implies that home production is negatively correlated with hours worked and is in line with the evidence from SOEP (Bonsang and van Soest (2020)). To match the share of part-time employment, I include fixed cost of work θ_h (e.g. commuting cost). Notice, that it affects disutility of labor only if the person is engaged in market work $(h_{it}^m > 0)$.

Disutility of labor is reflected by ϕ_i^h , where higher values are associated with valuing leisure more. Bequest motive follows De Nardi (2004): $b(a_{i,T+1}) = \phi^b(1 + \frac{a_{i,T+1}}{\psi_b})^{1-\sigma_b}$. Higher ϕ_i^b indicates stronger motive for leaving bequests. I allow ϕ_i^h and ϕ_i^b to be different across people. The goal is to calibrate the extent of this heterogeneity and its role in employment

variation. For simplicity I allow for two values in both disutility of labor $\{\phi_1^h, \phi_2^h\}$ and bequest motive $\{\phi_1^b, \phi_2^b\}$. This gives me four types of agents (ϕ_i^h, ϕ_j^b) , where $i, j \in 1, 2$ and each type constitutes a fraction π_{ij} of the population.

6.1.2 Budget constraint

Individual income is the sum of labor income and pension. The budget constraint then looks as following:

$$a_{i,t+1} = a_{it}(1+r) + w_{it}h_{it}^m + P_{it} - c_{it}^m, (3)$$

where P_{it} is a pension benefit and is paid out only if the person is older than 65 years old and retired. Pension is determined based on previous labor history. To capture German pension system in a stylized way, I define it as a function of past average labor income $PAI_{i,t-1}$. At the time the worker becomes eligible for pension, the pension benefit equals: $P_{it} = pPAI_{i,t-1}$, where p is a multiplier which is calibrated to match the average replacement rate.

Wage is stochastic and non-linear with respect to hours. This non-linearity (as in Rogerson and Wallenius (2013)) ensures that part-time workers are getting lower hourly wages than full-time workers. The stochastic process has both transitory and permanent shocks, and initial heterogeneity z_{i0} , which corresponds to age 25.

$$w_{it} = w_0 (h_{it}^m)^{\alpha} exp(y_{it})$$
$$y_{it} = z_{it} + v_{it}$$
$$z_{it} = \rho z_{i,t-1} + \epsilon_{it},$$

where z_{it} – permanent component with $\epsilon \sim N(0, \sigma_{\epsilon})$, $v_{it} \sim N(0, \sigma_{v})$ – temporary shock, and $z_0 \sim N(0, \sigma_{z_0})$.

6.1.3 Recursive problem

The optimization problem can be rewritten in a recursive way. State variables in the problem are: $X_t = (a_t, w_t, PAI_{t-1}, R_{t-1}, t)$, where t is age, a_t and w_t stand for assets and wage shock

at time t, PAI_{t-1} is past average labor income accumulated until t, and R_{t-1} is the lagged retirement status.

At every age a non-retired individual chooses whether to retire or not by comparing the value they will get from staying in the labor force and the value from retiring. Since retirement is an absorbing state and pensions are deterministic conditional on the previous labor history, once the person retires they do not face any further uncertainty.

For t = 1, ..., T - 1 and for a particular preference type:

$$V_{it}(a_{it}, w_{it}, PAI_{i,t-1}, R_{i,t-1} = 0) = \max_{R_{it}} \{V_{w,it}(a_{it}, w_{it}, PAI_{i,t-1}), V_{R,it}(a_t, PAI_{i,t-1})\}$$
(4)

$$V_{it}(a_{it}, w_{it}, PAI_{i,t-1}, R_{i,t-1} = 1) = V_{R,it}(a_{it}, PAI_{i,t-1}),$$
(5)

where $V_{w,it}$ is the value of not retiring and $V_{R,it}$ – value of being retired.

$$V_{w,it}(a_{it}, w_{it}, PAI_{i,t-1}) = \max_{a_{i,t+1}, h_{it}^m} u(c_{it}, h_{it}) + \beta EV_{i,t+1}(a_{i,t+1}, w_{i,t+1}, PAI_{it}|w_{i,t}, PAI_{i,t-1})$$
(6)

$$V_{R,it}(a_{it}, PAI_{i,t-1}) = \max_{a_{i,t+1}} u(c_{it}, 0) + \beta V_{R,i,T+1}(a_{i,t+1}, PAI_{i,t-1})$$
(7)

At time T, the value functions for both retired and non-retired individuals equal to the sum of contemporaneous utility and bequest value:

$$V_{w,iT}(a_{iT}, w_{iT}) = \max_{a_{i,T+1}, h_{iT}^m} u(c_{iT}, h_{iT}) + \beta b(a_{i,T+1})$$
(8)

$$V_{R,it}(a_{it}) = \max_{a_{i,T+1}} u(a_{i,T+1}, 0) + \beta b(a_{i,T+1})$$
(9)

To calculate policy functions, I start from period T and solve the value function backwards.

6.2 Simulation

I simulate the model for 65 periods (equivalent to ages 20-85) for 10000 individuals. The solution is a series of assets, hours and retirement decisions conditional on accumulated

assets, realized wage shocks, preference types, and average past labor history.

While in the model we see the exact age when a person decides to retire, in the data we do not. To make the model and the data comparable to each other, I define retirement age in the model exactly as in the data. Hence, retirement age is the cutoff age after which the person never works. Notice that it can be earlier than the actual retirement decision.

To better align the model-generated data with the SOEP, I add measurement errors both to employment outcomes and to wages as defined in Section 4.3. The model employment outcomes are equivalent to administrative records in that they are considered to be free of measurement error. For each agent, I assign one of the three responses: not-working, part-time or full-time – as a function of the true outcomes according to the conditional distributions from Figure 6.

To augment the model income values with measurement errors, I first look at the relationship between those errors and the actual SOEP-RV income records. I regress the measurement errors described in Section 4.3.2 on the SOEP-RV income values and find a correlation of 0.2. After examining the residuals from this regression, I find that they are normally distributed with zero mean and standard deviation of 0.3. Combining these results, I express measurement error process in logs as: $log(err_{it}) = -0.2log(w_{it}) + \gamma$, where $\gamma \sim N(0, 0.3)$. I add these errors to the model-generated wages according to: $w_{it}^{obs} = w_{it}err_{it}$.

6.3 Calibration: No Labor Constraints

In this section I describe how I calibrate the unknown parameters in the model without labor market constraints.

6.3.1 Estimating income process

For the income process I assume the following specification¹:

$$y_{it} = z_{it} + v_{it}$$

$$z_{it} = \rho z_{i,t-1} + \epsilon_{it}$$

¹ARMA(1,1) process has a similar goodness of fit but is less parsimonious

where y_{it} – residual log income (after accounting for education, age, gender, year), z_{it} – permanent shock with $\epsilon \sim N(0, \sigma_{\epsilon})$, v – temporary shock distributed as $N(0, \sigma_{v})$, and initial heterogeneity z_0 is distributed according to $N(0, \sigma_{z_0})$. All of the innovation terms are orthogonal to each other. Overall, there are four parameters to be calibrated: $\rho, \sigma_{\epsilon}, \sigma_{v}, \sigma_{z_0}$.

Following extensive literature, I estimate permanent and transitory shocks by fitting model-implied autocovariance function to the empirical one which is calculated based on the SOEP-RV income values. A common problem in this literature is that measurement error and transitory shocks are indistinguishable from each other. However, in administrative data, such as the SOEP-RV, measurement errors can be assumed to be zero. This makes it feasible to estimate both permanent and transitory shocks.

Theoretical variance and autocovariances are calculated as follows (j denotes the age, and individual index is omitted to simplify notations):

$$E(y_j, y_j) = E(z_j + v_j, z_j + v_j)$$

= $E(z_j^2) + E(v_j^2)$

$$E(y_j, y_{j+h}) = E(z_j + v_j, z_{j+h} + v_{j+h})$$

$$= E(z_j z_{j+h} + z_j v_{j+h} + v_j z_{j+h} + v_j v_{j+h})$$

$$= E(z_j z_{j+h}) = E(z_j (\rho z_{j+h-1} + \epsilon_{j+h}))$$

$$= \dots = E(\rho^h z_j^2 + \sum_{i=0}^{h-1} z_j \epsilon_{j+h-i}) = \rho^h E(z_j^2),$$

where
$$E(z_{j}^{2}) = \rho^{2j}\sigma_{z_{0}}^{2} + \sum_{k=1}^{j} \rho^{2(j-k)}\sigma_{\epsilon}^{2}$$
.

I calculate the whole set of autocovariances in the SOEP-RV², and pick parameters that minimize the distance between theoretical autocovariances and the empirical ones. I estimate the parameters to be: $\rho = 0.98, \sigma_{z0}^2 = 0.18, \sigma_{\epsilon}^2 = 0.02, \sigma_v^2 = 0.08$. This implies a highly persistent income process with rich initial heterogeneity in wages.

²I calculate both the model-based and empirical autocovariances based on the wages corresponding to full-time jobs.

6.3.2 Parameter values

Table 3 summarizes information on calibrated parameters and their values. Real interest rate is set to 2%, and discount rate is $\beta = \frac{1}{1+r}$. Intertemporal elasticity is $\frac{1}{\sigma_c} = \frac{1}{2}$. Share of non-working hours used in home production is set to 0.25, in line with the evidence from Bonsang and van Soest (2020). Bequest function parameters, exluding the bequest motive, are taken from De Nardi (2004). Pension multiplier is set 0.6 to match average replacement ratio of 60%. Non-convexity parameter α is set to 0.4 as in Aaranson and French (2004). This implies that part-time workers who work 20 hours per week earn 25% less per hour relative to full-time workers who work 40 hours per week.

Table 3: Parameter values

parameters	meaning	value
\overline{r}	interest rate	0.02
eta	discount factor	0.98
$\overline{\rho}$	persistence of income process	0.98
$\sigma^{ ho}_{z_0} \ \sigma^2_{z_0} \ \sigma^2_{\epsilon} \ \sigma^2_{v}$	variance in initial heterogeneity at age 25	0.18
$\sigma^{ec{ ext{2}}}_{\epsilon}$	variance in innovation of permanent shocks	0.02
σ_v^2	variance in innovation of transitory shocks	0.08
α	non-convexity in wage function	0.4
σ_h	labor elasticity	1
σ_c	relative risk aversion	$\overline{2}$
h_n	fraction of non-working hours used in home production	0.25
σ_b	elasticity in bequest function	1.5 (De Nardi 2004)
ψ_b	scaling parameter in bequest function	11.6 (De Nardi)
ξ_1	how disutility increases with age	2
$rac{ ilde{ heta}_h}{ar{t}}$	fixed cost of work	0.2
\overline{t}	age after which disutility of labor starts increasing	50
p	pension multiplier	0.6
ϕ_1^h,ϕ_2^h	values for disutility of labor	SMM
ϕ_1^b,ϕ_2^b	values for bequest motive	SMM
π_{ij}	share of type (ϕ_i^h, ϕ_i^b)	SMM
ξ_2	how disutility increases with age	SMM
c_h	productivity of home production	SMM

I jointly calibrate a vector of parameters $(\phi_1^h, \phi_2^h, \phi_1^b, \phi_2^b, \pi_{11}, \pi_{12}, \pi_{21}, \xi_2, c_h)$ using simulated method of moments (SMM). The moments I am targeting are mean and standard deviation of retirement age, mean and standard deviation of log average hours worked at 30-49, mean and

standard deviation of assets/income, employment rate at age 70, employment rate at ages 30-49, share of part-time workers at 30-49, and the key moments – coefficients in regression of retirement hazard on assets and labor history, along with the relationship between retirement hazard and the most recent wage. For the SMM I use equally-weighted distance function, which compares how far the model-generated moments are from the data-generated ones.

Calibrating this model poses two quantitative challenges: speed and multiplicity of local minima, which make optimization results heavily dependent on the vector of initial guesses. To deal with this, I draw inspiration from Guvenen (2011) in using a global search algorithm. First, I create a Sobol sequence of 1000 parameter vectors that uniformly cover parameter space. I solve the model at each of these points and choose 15 best-fitting initial vectors. Then I use the simplex local search method to solve for the minimum around each of those points. At the end of the procedure, I take the best-fitting local minimum as the solution to the problem.

6.4 Model results: No Labor Constraints

In Table 4, I show the parameter values calibrated by SMM. The model requires a lot of heterogeneity in both disutility of labor and bequest motive to match heterogeneity in employment, retirement, and asset holdings. Notice also, that agents with high disutility of labor and low bequest motive constitute the biggest fraction of the population – 44%. On the other hand, the smallest group is the type with high disutility and strong bequest motive (7%).

REMOVE W/O CONSTRAINTS

Table 4: calibrated parameters, w/o constraints

	ϕ_1^h	ϕ_2^h	ϕ_1^b	ϕ_1^b	p_{11}	p_{21}	p_{12}	p_{22}	ψ_2	c_h
w/o constraints	2.04	4.28	1718.18	2.26	0.25	0.07	0.23	0.44	21.95	0.16

Table 5 lists the non-regression moments used in calibration and shows that that the model fits the data well.

Table 5: targeted moments, w/o constraints

	model w/o constraints	data
mean retirement age	62.93	63.99
std of retirement age	4.91	3.49
mean of assets/income	4.93	5.17
std of assets/income	4.63	5.14
mean cum history	7.54	7.56
std of cum history	0.09	0.11
share of emp at 30-50	0.93	0.95
share of pt at 30-50	0.02	0.06
share of emp at 70	0.12	0.10

As mentioned earlier, the key insights come from how well the model matches correlations between assets and retirement hazard and between labor history and retirement. I run the same survival analysis regression on the model-generated data as on the SOEP in Section 5. Table 6 reproduces the results from the data and compares them to the ones generated by the model.

Table 6: Retirement hazard, targeting wage and asset coefficients

	data (1)	data (2)	model (1)	model(2)	model simul (control for pref)
more than 1800hrs		0.18		-0.87	-0.14
		(0.11)		(0.03)	(0.03)
log past wage	0.11	0.11	0.83	0.76	0.08
	(0.05)	(0.05)	(0.02)	(0.02)	(0.03)
2nd quart assets	0.11	0.10	0.06	0.16	0.37
	(0.09)	(0.09)	(0.03)	(0.04)	(0.04)
3rd quart assets	0.02	0.00	-0.32	-0.04	1.21
	(0.09)	(0.09)	(0.03)	(0.04)	(0.04)
4th quart assets	-0.18	-0.20	-0.76	-0.42	2.56
	(0.09)	(0.09)	(0.04)	(0.04)	(0.06)
N	17,725	17,710	153,542	153,542	153,542
retirement events	1,366	1,366	9,491	9,491	9,491
concordance ratio	0.661	0.662	0.672	0.705	0.831

To fully replicate the empirical exercise from Section 5, for both the data and the model I present two sets of results: with and without labor history. Comparing the regression coefficients with and without past employment tells us whether labor history brings any information to the regression. Table 6 shows that the relationship between assets and retire-

ment hazard in the model is qualitatively similar to the one in the data. The results suggest that those with more assets retire later – this goes against the standard wealth effect. The relationship between assets and retirement exhibits this pattern because of the preference heterogeneity. Indeed, retirement hazard increases monotonically with assets when preferences are controlled for, as shown in the last column of Table 6. This implies that the relationship between assets and retirement is informative of the underlying preference heterogeneity.

Notice also that the correlation between past wage and retirement hazard is opposite to what we would expect in a standard model where substitution effect dominates. In the presence of unobservable preference heterogeneity, if a high wage person has low bequest motive and a low wage person has high bequest motive – they might end up having the same levels of assets. At the same time, low bequest motive will make the high wage person retire earlier, while high bequest motive will make the low wage person retire later. This implies that conditional on assets, the high wage person will retire earlier because of the underlying correlation between the wage and the preference type. As a result, preference heterogeneity confounds not only the relationship between assets and retirement hazard, but also the relationship between recent wage and retirement hazard.

Moving on to the relationship between labor history and retirement hazard, we see that there is a strong negative relationship between early labor supply and retirement hazard. This is because preferences that dictate high labor supply increase employment both in prime-age and at the retirement margin. As a result, there is a negative correlation between past employment and retirement probability. However, this result goes against the data. Another thing to notice is that in the model results concordance ratio increases significantly when labor history is added to the regression model. This is because it contains information about preferences and helps to better explain retirement decisions. In the data, adding work history to the regression does not have any significant effect on the concordance ratio, meaning that past employment does not help to predict retirement.

These results suggest that either preference heterogeneity is overestimated in the model, or the preference heterogeneity does not map to earlier labor supply in the data. Indeed, if workers are facing labor market constraints, their labor choices can be uninformative of their preference types. For example, if a "hardworking" person and a "lazy" person are both hit

with an unemployment shock, their employment outcomes would look the same even though without the constraints one person would work more than the other.

In the next section I explore this idea by adding stochastic labor market constraints to the model described above. I show that including these constraints indeed breaks the tight connection between preferences and labor history.

7 Adding Labor Market Constraints

As mentioned earlier, preference heterogeneity might not map to employment outcomes because people are subject to exogenous labor market constraints that push them off their labor supply curves. For example, people might be fired and unable to find a new job, or they might be employed "part-time for economic reasons". Bureau of Labor Statistics defines such part-time workers as those who would have preferred to work full-time but have to work reduced hours because they are unable to find a full-time job. As a result, people cannot work as much as they would like to due to the employment constraints.

Now consider adding these labor market constraints to the model described in Section 6. The constraints have three realizations: the person might 1) be unemployed, 2) be able to find a part-time job but not a full-time one, or 3) be able to freely choose their hours (same as in the model without employment shocks). In this scenario, preferences should have a smaller role in determining labor market history while still affecting retirement decisions.

The core of the model is the same as before, but now the household problem changes to account for the stochastic labor market constraints. I assume that the constraints follow Markov process, which means that realizations of the employment shocks depend on the lagged realizations. This brings 6 new parameters that need to be calibrated – transition probabilities across different realizations of labor market constraints.

$$\begin{bmatrix} p_{uu} & p_{up} & p_{uf} \\ p_{pu} & p_{pp} & p_{pf} \\ p_{fu} & p_{fp} & p_{ff} \end{bmatrix} = \begin{bmatrix} p_{uu} & p_{up} & 1 - p_{uu} - p_{up} \\ p_{pu} & p_{pp} & 1 - p_{pu} - p_{pp} \\ p_{fu} & p_{fp} & 1 - p_{fu} - p_{fp} \end{bmatrix}$$

If an agent gets "full choice" realization of the employment shock, their choice set is the same as in the model without labor market constraints. Notice, however, that the presence of the employment shocks adds another source of uncertainty, in addition to stochastic incomes. Due to this added uncertainty, the decisions might differ from the ones discussed in Section 6. Stronger precautionary motive can make people work more and save more. If the agent gets a "part-time" realization, they can choose to supply up to 0.5 units of labor. And if they get the unemployment shock, they cannot work at all in current period.

Let $j \in \{f, p, u\}$ stand for full choice, part-time constraint, and unemployment. Then the value functions for each realization of the employment shock are defined as follows:

$$V_{it}^{j}(a_{it}, w_{it}, PAI_{i,t-1}, R_{i,t-1} = 0) = \max_{R_{it}} \{V_{w,it}^{j}(a_{it}, w_{it}, PAI_{i,t-1}), V_{R,it}(a_{it}, PAI_{i,t-1})\}$$
(10)

$$V_{w,it}^{j}(a_{it}, w_{it}, PAI_{i,t-1}) = \max_{a_{i,t+1}, h_{it}^{m}} u(c_{it}, h_{it}) +$$

$$\beta \left[p_{ju} E V_{i,t+1}^{u}(a_{i,t+1}, w_{i,t+1}) + p_{jp} E V_{i,t+1}^{p}(a_{i,t+1}, w_{i,t+1}) + p_{jf} E V_{i,t+1}^{f}(a_{i,t+1}, w_{i,t+1}) \right], \qquad (11)$$

where $V_{w,it}^j$ is the value function of a non-retired individual i at age t who received constraint realization j for this period, $V_{R,it}^j$ – the value function of a person who decides to retire at age t, and $p_{jj'}$ are transition probabilities across different realizations of the employment shock.

If the person has already retired, there is no more uncertainty over wages and future employment shocks. The resulting value function and the solution is the same as in the model without constraints:

$$V_{R,it}(a_{it}, PAI_{i,t-1}) = \max_{a_{i,t+1}} u(c_{it}, 0) + \beta V_{R,i,T+1}(a_{i,t+1}, PAI_{i,t-1}).$$
(12)

7.1 Calibration: Labor Constraints

To calibrate transition probabilities across employment shock realizations, I bring in extra moments to the SMM algorithm— empirical flows between non-employment, part-time employment and full-time employment from the SOEP.

To speak more directly to how many people are constrained, I exploit additional moment: a fraction of nonemployed people whose reservation wage is lower than their recent income. The idea behind this moment is that nonemployed people are more likely to be constrained if their reservation wage is low, which indicates high willingness to work. The information about reservation wages comes directly from the SOEP data, where nonemployed individuals are asked how high should the monthly wage be for them to start working and how many hours they would have to work. I calculate reservation wages for those who report looking for a full-time job, and compare their reservation wages to their incomes from the most recent employment. Similarly, I calculate the reservation wage in the model as the minimum wage at which the person is willing to work full-time. I then compare these reservation wages to the most recent incomes as I do in the data.

With the labor markets constraints included in the model, I can now target the positive relationship between labor history and retirement hazard. This will be the key moment to counteract the effects of preference heterogeneity implied by the relationship between assets and retirement decision.

The calibration strategy is the same as in Section 6.3, except for the additional parameters and moments discussed above. Table 7 shows the comparison between the calibrated parameters for the two models: with and without labor market constraints.

Table 7: calibrated parameters, with and w/o constraints

	ϕ_1^h	ϕ_2^h	ϕ_1^b	ϕ_1^b	p_{11}	p_{21}	p_{12}	p_{22}	ψ_2	c_h
w/o constraints	2.04	4.28	1718.18	2.26	0.25	0.07	0.23	0.44	21.95	0.16
w/ constraints	2.07	2.45	1499.87	2.89	0.28	0.02	0.05	0.65	16.15	0.09

Both models require a lot of heterogeneity in bequest motives to match the relationship between assets and retirement hazard. However, adding the labor market constraints generates significant employment variation, which reduces the role of disutility of labor. As a result, the model with labor market constraints requires a much smaller heterogeneity in disutility of labor. Notice also that in the model with labor market constraints 65% of the population have low bequest motive and higher disutility of labor, while 28% have high bequest motives and lower disutility. Only 7% of agents have the remaining two types.

Since the four preference types are distributed differently in the two models, it is hard to gauge the amount of overall heterogeneity without taking those distributions into account. Moreover, disutility of labor increases after age 50, which means that the mean and the variance of disutility of labor are age-dependent. To better capture the overall heterogeneity in each model, I calculate the mean and the variance of disutility of labor at ages 30 and 60, the mean and the variance of bequest motive (which is independent of age), and the correlation between the two types of heterogeneity.

Table 8: overall heterogeneity

	mean $\phi^{h,30}$	std $\phi^{h,30}$	mean $\phi^{h,60}$	std $\phi^{h,60}$	mean ϕ^b	std ϕ^b	$\operatorname{corr}(\phi^h, \phi^b)$
w/o constraints	3.17	1.12	3.83	1.35	566.62	806.16	-0.40
w/ constraints	2.33	0.18	3.22	0.25	435.67	678.65	-0.85

STOPPED HERE

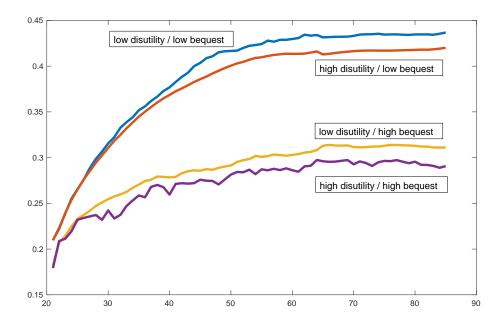
We can see that the model with labor constraints indeed requires much smaller heterogeneity in disutility of labor, and a slightly lower heterogeneity in bequest motives relative to the model without labor constraints. This makes sense since when there are no labor constraints, all the variation in employment needs to be explained by preferences – hence, those preferences need to be much more dispersed. When we introduce labor constraints into the model, these constraints are going to create exogenous variation in employment outcomes reducing the role of preferences (especially disutility of labor). Bequest heterogeneity is still crucial to explain the relationship between assets and retirement hazard and this mechanism cannot be reproduced by constraints, so including the constraints does not eliminate this source of heterogeneity.

Another result we get is that disutility of labor and bequest motive are correlated: those with high bequest motive are more likely to be more hardworking (lower disutility of labor). This means that the two sources of heterogeneity reinforce each other. Those who have large bequest motive want to work more and accumulate more assets. At the same time they have

lower disutility of labor which increases their incentives to work and as a result allows them to save even more.

To get a better sense of how different the "high" and "low" bequest motives are, we can look at the consumption profiles of the two types. Figure 8 shows mean life-cycle paths of consumption for all four types and indicates that people with strong bequest motive consume about 35% less in their 60s and 70s than people with a weak bequest motive.

Figure 8: Mean life-cycle consumption



From the calibrated Markov transition matrix in Table 9, I find that labor market constraints need to be persistent with the following probabilities:

Table 9: calibrated transition matrix

	unemp	partial choice	full choice
unemp	0.69	0.13	0.18
partial choice	0.08	0.69	0.22
full choice	0.01	0.01	0.98

7.2 Model Results: Labor Constraints

Now we can look at how well the model with constraints matches the moments. Most of the non-regression moments from Table 10 are close to the data, however, the model generates too many nonemployed people with reservation wage lower than their past income: 74% instead of 65% as in the data. This suggests that the model might slightly overestimate the role of constraints.

Table 10: targeted moments, with constraints

	model w/ constraints	data
mean retirement age	63.65	63.99
std of retirement age	3.52	3.49
mean of assets/income	5.88	5.17
std of assets/income	4.20	5.14
mean cum history	7.54	7.56
std of cum history	0.10	0.11
share of emp at 30-50	0.94	0.95
share of pt at 30-50	0.06	0.06
share of eu	0.02	0.02
share of ep	0.02	0.02
share of pu	0.09	0.08
share of pp	0.68	0.55
share of uu	0.60	0.48
share of up	0.11	0.09
reserv wage < recent wage	0.54	0.66

In terms of the regression coefficients – the model generates correct pattern between assets and retirement. Moreover, now it also generates slightly positive correlation between labor history and retirement hazard, meaning that working more is now associated with retiring earlier despite preference heterogeneity. Looking at the last column we can again see that controlling for preferences (in this case mainly heterogeneity in bequest motives) restores coefficients on assets in line with standard wealth effect. On the other hand, it almost does

not change coefficient on labor history since labor supply is mainly affected by disutility of labor and not by bequest motives. Hence, removing very small heterogeneity in disutility of labor does not significantly affect this result.

We can also see that adding labor history in the regression does not change concordance ratio. This result is in line with the data, and means that labor history does not carry any additional information about retirement decisions. This is because heterogeneity in disutility of labor is now much smaller compared to the model without constraints, and this heterogeneity is masked by the presence of labor market constraints. This means that hours no longer carry information about the preference types and do not tell us anything that cannot be told by assets.

Table 11: Retirement hazard, model with constraints

	data (1)	data (2)	model (1)	model(2)	model(2): pref
more than 1800hrs		0.18		0.14	0.10
		(0.11)		(0.02)	(0.02)
log past wage	0.11	0.11	0.62	0.63	-0.06
	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)
2nd quart assets	0.11	0.10	0.14	0.14	0.42
	(0.09)	(0.09)	(0.03)	(0.03)	(0.03)
3rd quart assets	0.02	0.00	0.00	-0.01	1.00
	(0.09)	(0.09)	(0.03)	(0.03)	(0.04)
4th quart assets	-0.18	-0.20	-0.33	-0.35	2.04
	(0.09)	(0.09)	(0.03)	(0.03)	(0.04)
N	17,725	17,710	156,457	156,457	156,457
retirement events	1,366	1,366	9,944	9,944	9,944
concordance ratio	0.661	0.662	0.625	0.625	0.802

Overall, these results show that adding constraints into the model is crucial to be able to match both the relationship between assets and retirement and the relationship between labor history and retirement. This suggests that employment constraints play important role in explaining behavior at middle ages and that people are pushed off their labor supply curves.

8 Preferences vs Constraints

In the previous section we saw that the model requires the employment constraints to match the data. Moreover, adding the constraints to the model reduces the heterogeneity in disutility of labor needed to match the moments. Next step is to understand to what extent the lifetime employment variation is explained by those constraints vs preferences.

First of all, we can look at how people make employment decisions conditional on the constraint realization they get. Each cell of Table 12 contains probability of having a particular realization of the constraint and choosing a particular employment outcome. Notice that none of the workers with partial choice are able to get full-time job and none of the unemployed are able to work. Hence, these cells have zero probabilities by construction. The allocation among the remaining cells is informative of the role of remaining factors (preferences, wages, assets) conditional on constraints. We can see that almost all of the workers who got the full choice are choosing full time work (98%), and almost all of the workers with partial choice are choosing part-time work rather than nonemployment. This tells us that majority of employment outcomes are driven by what constraints people are at, rather than other observable and unobservable sources of heterogeneity.

Table 12: On vs Off labor supply curve

	full-time	part-time	not working
full choice	0.8858	0.0012	0.0119
partial choice	0.0000	0.0575	0.0004
unemployed	0.0000	0.0000	0.0432

Another way to get a sense of the relative roles of constraints and preferences is to decompose the employment variation into portions explained by each of the drivers. To do that, I first solve and simulate the model calibrated in Section 7 but set probabilities of getting full choice outcome to 1. This shuts down the constraints while keeping the preference heterogeneity at the level calibrated for the full model. And then in addition to shutting down the constraints, I set disutility of labor and bequest motive to their means from Table 7.

Table 12 summarizes how the employment variation (standard deviation of log of average hours worked at 30-49) changes when removing the constraints and then the preference

heterogeneity. Since in the model I have results for both "true" hours worked and measured hours work (taking measurement error from SOEP into account), I present the decomposition for both outcomes.

Table 13: Decomposition of employment variation

	full model	no constr	no constr and no pref
variation in observed hours	0.10	0.05	0.04
variation in true hours	0.17	0.04	0.01

The variation in the last column comes from the heterogeneity in wage shocks and assets. Hence, we are interested how much of the residual variation is explained by constraints and shocks. The results for both observed and true hours suggest that shocks explain about 83% $(\frac{0.1-0.05}{0.1-0.04})$ of the variation unexplained by wages and assets, while preference heterogeneity explains the remaining 17%.

Table 14 shows the importance of the relationship between work history and retirement and between assets and retirement for identifying preferences and constraints. Columns 1 and 2 repeat the results from the data and the model with constraints and preference heterogeneity. Column 3 shows that shutting down the constraints without removing preference heterogeneity turns the relationship between work history and retirement around. Because of preference heterogeneity, those who have higher bequest motive and lower disutility of labor both work more and retire later. In the model with constraints, this role of preferences is masked by the exogenous restrictions on the labor market. Column 4 corresponds to the model without constraints and without preference heterogeneity, and we see that coefficients on assets turn back to the standard wealth effects: people with more assets are more likely to retire. At the same time, the relationship between hours worked and retirement hazard is no longer negative since there is no preference heterogeneity that makes work history negatively linked to retirement hazard.

Table 14: Retirement hazard, w/ constraints and w/o

	data	model (w/ shocks)	model (w/o shocks)	w/o constr and pref
more than 1800hrs	0.18	0.14	-0.45	0.12
	(0.11)	(0.02)	(0.04)	(0.06)
log past wage	0.11	0.63	0.68	-0.54
	(0.05)	(0.02)	(0.02)	(0.03)
2nd quart assets	0.10	0.14	0.02	0.02
	(0.09)	(0.03)	(0.03)	(0.03)
3rd quart assets	0.00	-0.01	-0.11	0.23
	(0.09)	(0.03)	(0.03)	(0.03)
4th quart assets	-0.20	-0.35	-0.49	1.30
	(0.09)	(0.03)	(0.03)	(0.03)
N	17,710	156,457	158,767	161,630
retirement events	1,366	9,944	9,958	10,000
concordance ratio	0.662	0.625	0.641	0.715

9 Welfare Implications

Now that we have established the importance of employment constraints, it is useful to know how welfare reducing those constraints are. To what extent would welfare change if everyone is on their labor supply curve? To get the answer to this question I compare the results from the full model with the constraints and from the same calibration but with constraints shut down (same as in Section 7) using Hicksian equivalent variation.

Let V_i denote the discounted present value of utility, V_i^c – discounted present value of utility from consumption, V_i^h – discounted present value of disutility from labor, and V_i^{beq} – discounted utility from leaving a bequest. And let V_i' , $V_i^{c'}$, $V_i^{h'}$ and $V_i^{beq'}$ denote corresponding present values for the economy with constraints shut down. To calculate Hicksian equivalent variation, I derive by what percentage should consumption increase each period in the model with constraints to make the welfare equal to the welfare in the economy without constraints.

In other words, I need to find Δ_i such that:

$$\sum_{i=1}^{T} \beta^{j-1} \frac{[c_{it}(1+\Delta_i)]^{1-\sigma}}{1-\sigma} - V_i^h + V_i^{beq} = V_i',$$

which is equivalent to

$$(1 + \Delta_i)^{1 - \sigma} V_i^c - V_i^h + V_i^{beq} = V_i'.$$

From this I derive that

$$\Delta_i = \left(\frac{V_i' + V_i^h - V_i^{beq}}{V_i^c}\right)^{\frac{1}{1-\sigma}} - 1.$$

I calculate Δ_i for each individual, and I find that on average consumption should increase by 13% to compensate for the presence of labor market constraints. For a median individual consumption should increase by 6%. This suggests that being off labor supply curve is significantly reducing welfare. Moreover, the welfare is lower in the model with constraints not only because individuals are forced to work less which reduces their earnings, but also because precautionary motive leads them to increase savings and to backload consumption.

10 Conclusion

Employment variation unexplained by observable characteristics can be driven by preferences (disutility of labor, bequest motive) or exogenous shocks (e.g. labor market constraints). This paper proposes a new way to disentangle these channels by looking at the moments that are not usually discussed in the literature – correlations between retirement hazard and assets and between retirement hazard and work history.

The main idea is that the signs of those two correlations are different depending on the presence of preference heterogeneity and labor market constraints. In a standard model without preference heterogeneity, we would expect people at the top of asset distribution to retire earlier due to the wealth effect. In the presence of preference heterogeneity, those who accumulate more assets might also be less likely to retire (for example, because of a strong bequest motive). Hence, preference heterogeneity can mask the standard wealth effect and turn the relationship between assets and retirement hazard to be negative. However, with such heterogeneity we would also expect negative relationship between earlier labor history and retirement hazard: people who have lower disutility of labor and higher bequest motive will work more earlier in life and will also retire later. If the labor market constraints

are present, correlation between preference types and labor history is weakened. This means that the relationship between labor history and retirement hazard can be negative or positive depending on the strength of the labor market constraints.

To empirically document these moments, I rely on German Socio-Economic Panel (SOEP). This dataset allows me to track employment histories throughout the whole lifecycle, making it suitable for my analysis. I find that the correlation between assets and retirement is negative for higher asset quartiles and the correlation between labor history and retirement is marginally positive. Given the identification strategy described above, this suggests that both preference heterogeneity and labor market constraints are present.

To explore this idea more formally and to quantitatively disentangle the two channels, I set-up a life-cycle model with endogenous retirement decision and calibrate it to match important moments related to retirement and employment. I start with a model without labor market constraints and show that coefficients on asset quartiles help to identify preference heterogeneity. In particular, when targeting those coefficients the model requires strong heterogeneity in both disutility of labor and in bequest motive. Moreover, those sources of heterogeneity need to be strongly correlated: those who have low disutility of labor also have strong bequest motive. With calibrated heterogeneity, the coefficient on labor history is largely negative which leads me to augmenting the model with exogenous separations.

After adding persistent exogenous separation shocks, the model is able to replicate both the negative relationship between retirement and assets and the slightly positive correlation between hours and retirement hazard. With the labor market constraints present, the model no longer requires strong heterogeneity in disutility of labor. However, it still predicts that bequest motives need to differ significantly across the people for the correlation between assets and retirement hazard to be negative. Despite having this preference heterogeneity, the model with labor market constraints can generate slightly positive correlation between labor history and retirement by weakening correlation between preferences and labor history.

After calibrating the model with both preferences and labor market constraints, the remaining question is: how important these two channels are in explaining employment variation. By shutting down labor constraints and then preference heterogeneity, I find that labor market constraints explain 50% of total of employment variation, while preference

heterogeneity explains only 10%. Moreover, welfare analysis suggests that shutting down labor market constraints is equivalent to significant consumption gains – on average it is equivalent to 13% increase in consumption, and for a median individual it is equivalent to 6% increase.

This paper opens more avenues to pursue in the future. Further extensions could include generalizing preference heterogeneity to continuum of types, replicating the analysis for other countries, deriving policy implications.

References

- Aaranson, Daniel and Eric French (2004). "The Effect of Part-Time Work on Wages: Evidence from the Social Security Rules". In: *Journal of Labor Economics*.
- Ameriks, John et al. (2020). "Older Americans Would Work Longer if Jobs Were Flexible". In: American Economic Journal: Macroeconomics.
- Bonsang, Eric and Arthur van Soest (2020). "Time devoted to home production and retirement in couples: A panel data analysis". In: *Labour Economics*.
- Chang, Yongsung and Sun-Bin Kim (2006). "From Individual to Aggregate Labor Supply: a Quantitative Analysis Based on a Heterogeneous Agent Macroeconomy". In: *International Economic Review*.
- De Nardi, Mariacristina (2004). "Wealth Inequality and Intergenerational Links". In: Review of Economic Studies.
- De Nardi, Mariacristina, Eric French, and John B. Jones (2010). "Why Do the Elderly Save? The Role of Medical Expenses". In: *Journal of Political Economy*.
- De Nardi, Mariacristina and Fang Yang (2014). "Bequests and heterogeneity in retirement wealth". In: *European Economic Review*.
- Elsby, Michael W.L., Bart Hobijn, and Aysegul Sahin (2015). "On the Importance of the Participation Margin for Labor Market Fluctuations". In: *Journal of Monetary Economics*.
- Fan, Xiaodong, Ananth Seshadri, and Christopher R. Taber (2005). "Estimation of a Life-Cycle Model with Human Capital, Labor Supply and Retirement". In: *The Review of Economic Studies*.
- French, Eric (2005). "The Effects of Health, Wealth, and Wages on Labour Supply and Retirement Behaviour". In: *The Review of Economic Studies*.

- Guvenen, Fatih (2011). "Macroeconomics with Heterogeneity: A Practical Guide". In: *Economic Quarterly*.
- Heathcote, Jonathan, Kjetil Storesletten, and Giovanni L. Violante (2014). "Consumption and Labor Supply with Partial Insurance: An Analytical Framework". In: American Economic Review.
- Kopczuk, Wojciech and Joseph P. Lupton (2007). "To Leave or Not to Leave: The Distribution of Bequest Motives". In: *The Review of Economic Studies*.
- Krusell, Per et al. (2011). "A Three State Model of Worker Flows in General equilibrium". In: *Journal of Economic Theory*.
- Krusell, Per et al. (2020). "Gross Worker Flows and Fluctuations in the Aggregate Labor Market". In: *Review of Economics Dynamics*.
- Laun, Tobias and Johanna Wallenius (2016). "Social insurance and retirement: A cross-country perspective". In: *Review of Economic Dynamics*.
- Low, Hamish, Costas Meghir, and Luigi Pistaferri (2010). "Wage Risk and Employment Risk over the Life Cycle". In: *American Economic Review*.
- Lüthen, Holger et al. (2021). "SOEP-RV: Linking German Socio-Economic Panel Data to Pension Records". In: Jahrbücher für Nationalökonomie und Statistik.
- Mukoyama, Toshihiko, Mototsugu Shintani, and Kazuhior Teramoto (2021). "Cyclical Part-Time Employment in an Estimated New Keynesian Model with Search Frictions". In: Journal of Money, Credit and Banking.
- Mustre-del-Rio, Jose (2015). "Wealth and Labor Supply Heterogeneity". In: Review of Economics Dynamics.

Rogerson, Richard and Johanna Wallenius (2013). "Nonconvexities, Retirement, and the Elasticity of Labor Supply". In: *The American Economic Review*.

11 Appendix

11.1 SOEP-RV vs SOEP sample

The table 15 shows summary statistics for those who shared their pension identifier (and were included in SOEP-RV) versus those who were not. We can see that the samples look very similar, hence SOEP-RV sample is representative of the larger SOEP sample.

Table 15: Comparison between SOEP and SOEP-RV sample

	not in RV	RV
N (time-ind obs older than 30)	618979	120398
mean wage	16.3	17.3
std wage	16.7	18
mean ret age	62	62.8
std ret age	4.17	4.14
mean hours	38.2	36.5
std hours	13	13.6

11.2 Robustness to other specifications

Table 16: Retirement hazard with two groups in work history, men

	1	2	3	4
1600-1800 hrs			0.83	0.76+
			(0.13)	(0.13)
less than 1600 hrs			0.83	0.74+
			(0.16)	(0.16)
log past wage	1.08 +	1.12*	1.11*	1.03
	(0.04)	(0.05)	(0.05)	(0.04)
2nd quart assets		1.12	1.11	1.04
		(0.09)	(0.09)	(0.09)
3rd quart assets		1.02	1.00	0.91
		(0.09)	(0.09)	(0.09)
4th quart assets		0.83 +	0.82*	0.69***
		(0.09)	(0.09)	(0.09)
bad health	1.39***	1.37***	1.38***	1.39***
	(0.07)	(0.07)	(0.07)	(0.07)
married	1.07	1.10	1.09	1.12
	(0.07)	(0.07)	(0.07)	(0.07)
years of schooling	0.93***	0.93***	0.93***	
	(0.01)	(0.01)	(0.01)	
N	17,710	17,710	17,710	17,710
retirement events	1,366	1,366	1,366	1,366
concordance ratio	0.661	0.661	0.662	0.647

⁺ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 17: Retirement hazard with continuous work history, men $\,$

	1	2	3	4	5
log work history	1.859**	2.537***	2.641***	2.511**	1.733
	(0.250)	(0.347)	(0.362)	(0.362)	(0.359)
log past wage		0.973	1.034	1.032	1.114**
		(0.038)	(0.044)	(0.044)	(0.046)
2nd quart assets			1.052	1.043	1.108
			(0.086)	(0.086)	(0.087)
3rd quart assets			0.930	0.913	1.003
			(0.085)	(0.086)	(0.087)
4th quart assets			0.712***	0.695***	0.817**
			(0.088)	(0.090)	(0.093)
bad health	1.198***	1.517***	1.387***	1.386***	1.377***
	(0.052)	(0.064)	(0.069)	(0.069)	(0.069)
married				1.119	1.091
				(0.073)	(0.073)
years of schooling					0.935***
					(0.010)
N	28,995	20,189	17,783	17,738	17,710
retirement events	2,142	1,500	1,369	1,366	1,366
concordance ratio	0.624	0.657	0.647	0.647	0.662

^{*} p < 0.1, ** p < 0.05, *** p < 0.01

Table 18: Retirement hazard with two groups in work history, women $\,$

	1	2	3	4	5
more than 1800hrs	1.114**	1.036	1.046	1.049	1.091
	(0.053)	(0.067)	(0.071)	(0.071)	(0.072)
log past wage		1.050	1.066	1.080	1.156**
		(0.051)	(0.054)	(0.054)	(0.058)
2nd quart assets			1.102	1.098	1.146
			(0.105)	(0.106)	(0.107)
3rd quart assets			1.105	1.060	1.110
			(0.105)	(0.108)	(0.109)
4th quart assets			1.050	1.000	1.099
			(0.106)	(0.112)	(0.114)
bad health	1.130**	1.334***	1.340***	1.341***	1.323***
	(0.062)	(0.082)	(0.087)	(0.087)	(0.087)
married				1.172**	1.151*
				(0.081)	(0.081)
years of schooling					0.954***
					(0.014)
N	20,446	13,325	11,902	11,831	11,798
retirement events	1,444	932	857	853	850
concordance ratio	0.657	0.696	0.686	0.688	0.693

 $[\]frac{\text{* p < 0.1, ** p < 0.05, *** p < 0.01}}{\text{* p < 0.1, ** p < 0.05, *** p < 0.01}}$