

Disentangling the Roles of Preferences and Shocks in Labor Supply^{*}

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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 life-cycle 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 Bills for his continuous guidance and support. I am very grateful to Yan Bai, Lisa Kahn, George Alessandria, Rafael Guntin, Paulo Lins, Marcos Mac Mullen, and participants at the University of Rochester Student Seminar and 2023 European Summer Meeting of the Econometric Society, for valuable feedback and discussions.

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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 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 ex-ante 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 ex-ante 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.

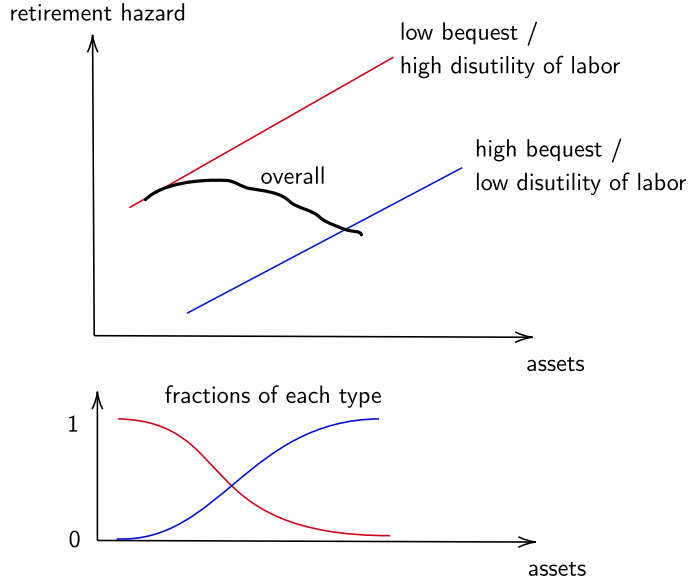
At the same time, preference heterogeneity implies a negative relationship between labor history and retirement hazard. Those with higher disutility of labor and/or smaller bequest motive will both work less during working life and will retire earlier. This is illustrated in Figure 1b.

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

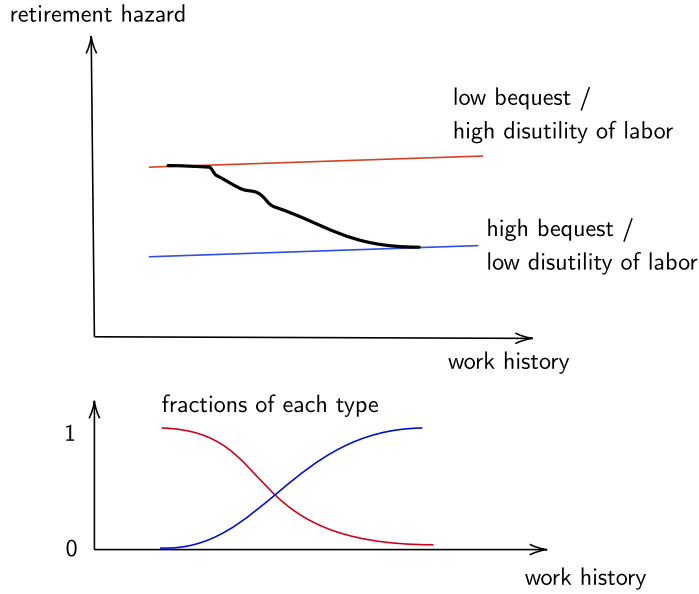


Table 1: Identification strategy

	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

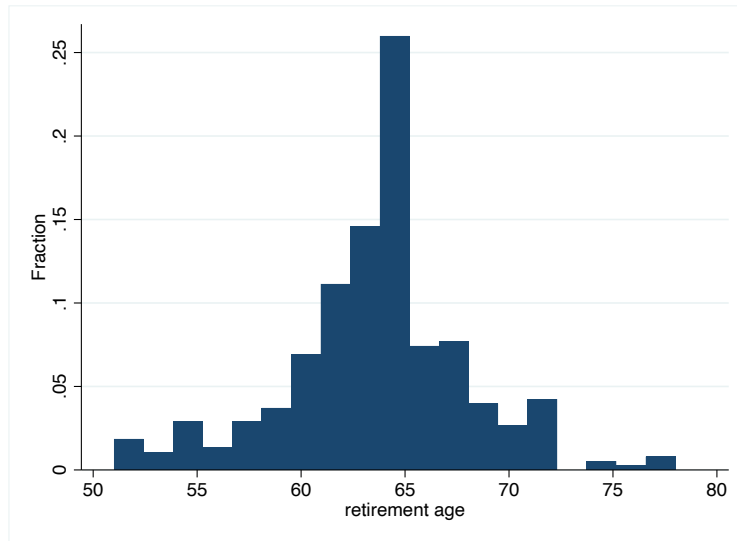
they are observed in the survey, if they are observed for at least 3 years after the labor force exit (to avoid counting those who are temporarily non-employed as retired)

- 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

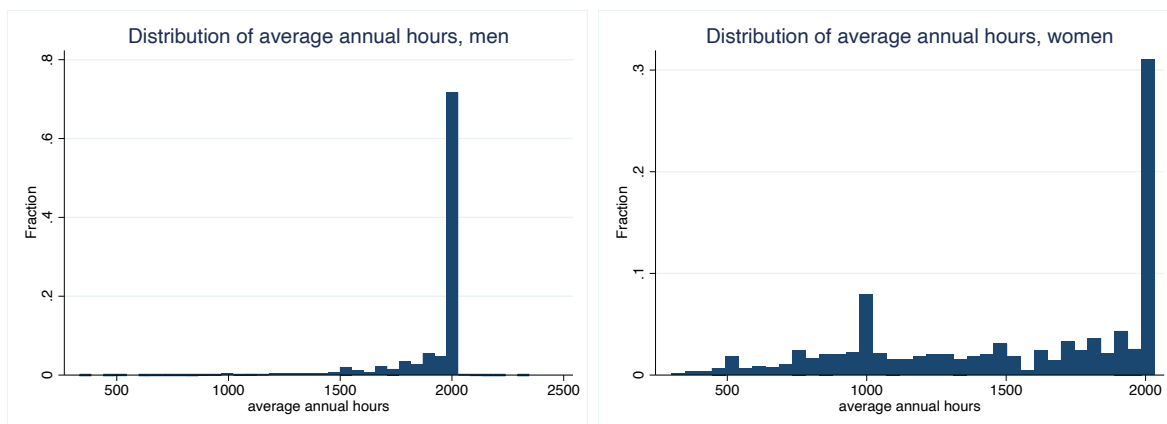
The other key variable is labor market history from 30 to 49 years old. Ages 30-49 are chosen to avoid periods of schooling or retirement. To measure work history I use contemporaneous information from the survey whenever possible. However, most individuals will not be sampled back to their 30s. For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

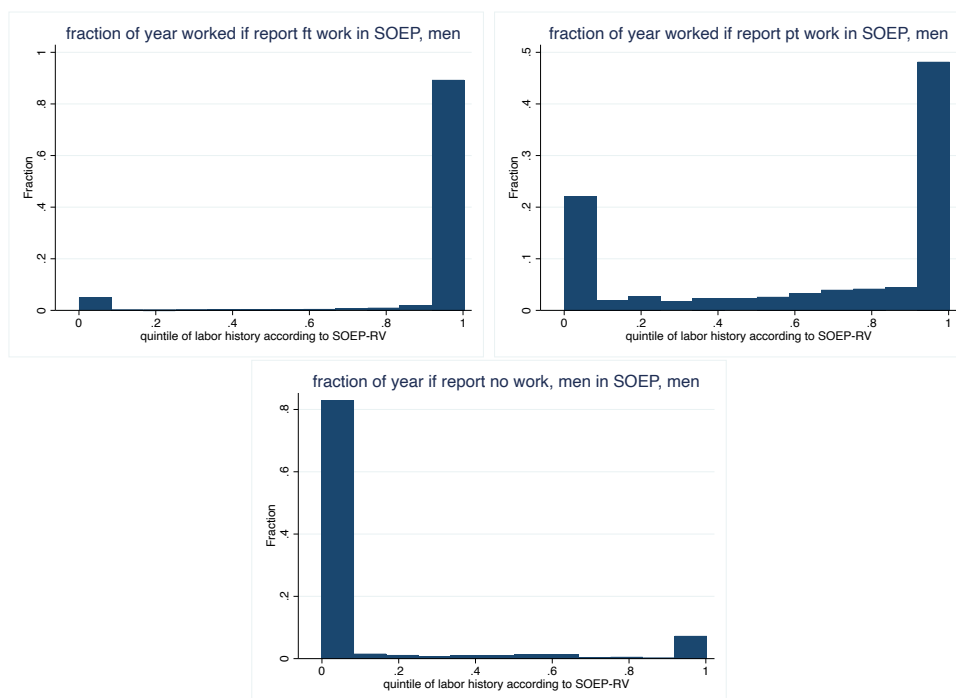
To address this issue, I look at the occupations the person had while observed in the SOEP. I check which occupation the respondent reported most frequently, and which occupation was reported in their first survey. Besides that, the SOEP has a separate question about what was the first occupation in the individual’s career. 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

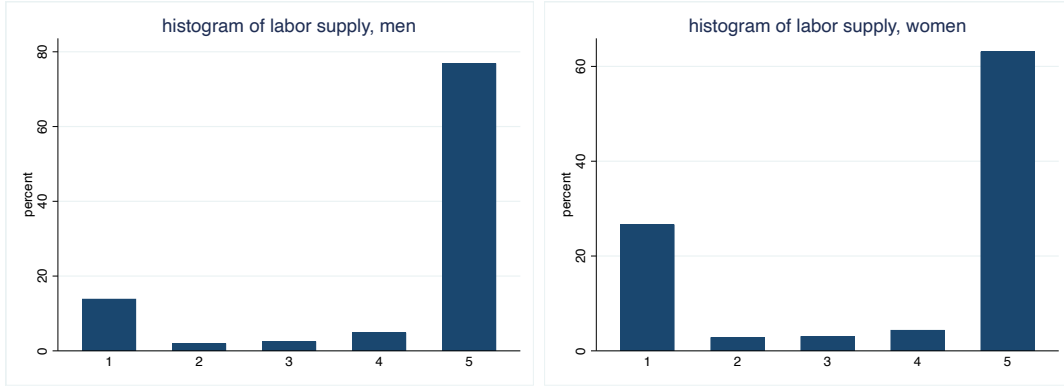
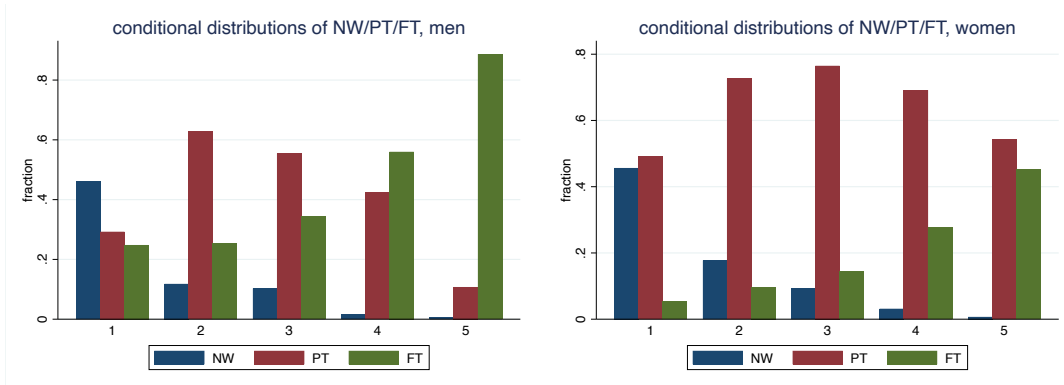


Figure 6 shows how retrospective responses are distributed across different values of FDZ employment records. This distribution implicitly defines the measurement error in employment. We see that probability of reporting “full-time work” (FT) in SOEP increases with the FDZ employment record, while probability 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 matching the theoretical model, that I discuss in Section 6, to the data, I assume that model-generated labor supply outcomes correspond to FDZ records. To make them comparable with SOEP, I augment those outcomes with the measurement error as in Figure 6.

Figure 6

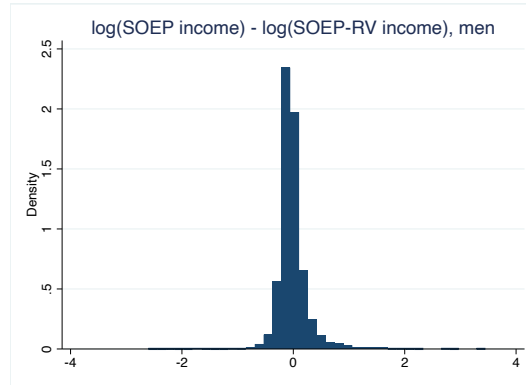


4.3.2 Measurement Error in Income

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. On average, reported values are very close to the true ones with a big mass of responses concentrated around zero measurement error. However, there is a lot of dispersion: one standard deviation away from the mean corresponds to a measurement error of 28%. I will add this measurement error to the “true” income process when I simulate the theoretical model in Section 6.2.

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 relate retirement decisions to cumulative labor history (how much people work when they are 30-49) and to asset holdings, conditional on recent wages, health, and other demographic characteristics.

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.

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. 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 status is another important variable to consider. It is directly related to retirement through lower productivity, and it can be correlated with savings through health expenditures (De Nardi, French, and Jones (2010)).

For my analysis, I use Cox proportional hazards model with the following specification:

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

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 2nd and 3rd quartiles of the asset distribution are almost as likely to retire as those in the 1st quartile. However, those at the 4th 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, though the coefficient is marginally significant.

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			

The model's ability to explain the retirement hazard is given by its concordance ratio. When we compare the model with and without labor history (Columns 1 and 2), the concordance ratios are almost the same. So labor history brings no extra information to the model, which means that it does not reflect preference heterogeneity.

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 the presence of both preference heterogeneity and employment constraints.

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 identify the extent of preference heterogeneity, I run regressions for retirement hazard on the simulated data. While the model matches the relationship between assets and retirement, it generates a counterfactual result for the correlation between labor history and retirement.

I then augment the model with employment constraints. That helps replicate both empirical findings: a negative correlation between wealth and retirement hazard, and a positive correlation between past employment and retirement hazard.

6.1 Setup

I set up an annual life-cycle model with endogenous retirement. 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 I 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:

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

where agent's utility depends on consumption c_{it} , hours worked h_{it} , and bequest value $b_i(a_{i,T+1})$. The agent chooses 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.

For computational purposes, I discretize labor choices. In particular, I allow for 5 discrete values: $h \in \{0; 0.25; 0.5; 0.75; 1\}$. This largely captures 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.

Consumption consists of both 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 a decline in labor force participation, as seen in the data. It can reflect declining health, among other factors.

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

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

where $h_{it}^h = h_n(1 - h_{it})$ and $c_{it}^h = c_n h_{it}^h$. I assume that a 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, in line with evidence from the SOEP (Bonsang and van Soest (2020)). To match the share of part-time employment, I include a fixed cost of work θ_h (e.g. commuting cost). Notice, this 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. The 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 differ across people. 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 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 is:

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

where P_{it} is a pension benefit paid out only if the person is older than 65 years old and retired. To capture elements of the German pension system, the benefit is determined as a function of past average labor income $PAI_{i,t-1}$. At the time the worker becomes eligible, the pension 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 recursive form. 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 by comparing the value of staying in the labor force versus 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 $t = 1, \dots, T - 1$ and for a particular preference type:

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

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

where $V_{w,it}$ is the value of not retiring and $V_{R,it}$ – value of being retired. These values are in turn defined as follows:

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

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

To calculate policy functions, I start from period T and solve the value function backwards. At time T , the value functions, for both retired and non-retired individuals, equal the sum of contemporaneous utility and bequest value:

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

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

6.2 Simulation

I simulate the model for 65 periods (equivalent to ages 20-85) for 10.000 individuals. The retirement age is defined as the age at which the person stops working. This definition allows to treat the data and the model in the same way. Notice, that it does not have to coincide with the age of 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 and each age prior to retirement, 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 how correlated the errors are with the SOEP-RV income records. I regress the measurement errors described in Section 4.3 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: $\log(err_{it}) = -0.2\log(w_{it}) + \gamma$, 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:

$$\begin{aligned} y_{it} &= z_{it} + v_{it} \\ z_{it} &= \rho z_{i,t-1} + \epsilon_{it} \end{aligned}$$

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 an 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.

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

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

$$\begin{aligned}
E(y_j, y_j) &= E(z_j + v_j, z_j + v_j) \\
&= E(z_j^2) + E(v_j^2) \\
E(y_j, y_{j+h}) &= E(z_j + v_j, z_{j+h} + v_{j+h}) \\
&= E(z_j z_{j+h} + z_j v_{j+h} + v_j z_{j+h} + v_j v_{j+h}) \\
&= E(z_j z_{j+h}) = E(z_j (\rho z_{j+h-1} + \epsilon_{j+h})) \\
&= \dots = E(\rho^h z_j^2 + \sum_{i=0}^{h-1} z_j \epsilon_{j+h-i}) = \rho^h E(z_j^2),
\end{aligned}$$

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: $\rho = 0.98, \sigma_{z_0}^2 = 0.18, \sigma_\epsilon^2 = 0.02, \sigma_v^2 = 0.08$. This implies a highly persistent income process with significant wage heterogeneity at the beginning of working life.

6.3.2 Parameter values

Table 3 summarizes the externally calibrated parameter values. The real interest rate is set to 2%, with discount rate $\beta = \frac{1}{1+r}$. The intertemporal elasticity, $\frac{1}{\sigma_\epsilon}$, equals to $\frac{1}{2}$. Share of non-working hours in home production is set to 0.25, in line with the evidence from Bonsang and van Soest (2020). The bequest function parameters, excluding the bequest motive, are taken from De Nardi (2004). The pension multiplier is set 0.6 to match an average replacement ratio of 60%. The 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.

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

Table 3: Parameter values

parameters	meaning	value
r	real interest rate	0.02
β	discount factor	0.98
ρ	persistence of income process	0.98
$\sigma_{z_0}^2$	variance in initial heterogeneity at age 25	0.18
σ_ϵ^2	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	2
h_n	fraction of non-working hours used in home production	0.25
σ_b	elasticity in bequest function	1.5
ψ_b	scaling parameter in bequest function	11.6
ξ_1	how disutility increases with age	2
θ_h	fixed cost of work	0.2
\bar{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_j^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 targeted moments 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, the relationship between assets and retirement hazard, and the relationship between recent wages and retirement. Initially, I do not target the relationship between labor history and retirement in order to illustrate the importance of preference heterogeneity for matching the correlation between assets and retirement hazard, and the resulting counterfactual correlation between past employment and retirement. When I consider the full model with both preference heterogeneity and employment shocks, the relationship between labor history and retirement will be a key moment.

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 follow 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. Lastly, 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 almost half of the population have high disutility of labor and low bequest motive (44%). Those with high disutility of labor and high bequest motive constitute the smallest group (7%).

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
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 the model fits the data well.

Table 5: Targeted moments, w/o constraints

	model	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, key insights on preference heterogeneity come from how well the model matches the correlations between assets and retirement hazard and between labor

history and retirement. I run the same survival analysis regressions on the model-generated data as on the SOEP in Section 5, with the results summarized in Table 6.

Table 6: Retirement hazard, model without constraints

	data (1)	data (2)	model (3)	model (4)	model (5)
more than 1800hrs		0.18 (0.11)		-0.87 (0.03)	-0.14 (0.03)
log past wage	0.11 (0.05)	0.11 (0.05)	0.83 (0.02)	0.76 (0.02)	0.08 (0.03)
2nd quart assets	0.11 (0.09)	0.10 (0.09)	0.06 (0.03)	0.16 (0.04)	0.37 (0.04)
3rd quart assets	0.02 (0.09)	0.00 (0.09)	-0.32 (0.03)	-0.04 (0.04)	1.21 (0.04)
4th quart assets	-0.18 (0.09)	-0.20 (0.09)	-0.76 (0.04)	-0.42 (0.04)	2.56 (0.06)
control for preferences	–	–	NO	NO	YES
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

Columns 1 and 2 replicate the empirical results from Section 5, while columns 3 and 4 show results from running the same regressions on the model-generated data. Comparing columns 2 and 4, we conclude that the relationship between assets and retirement hazard in the model is qualitatively similar to the one in the data. Both in the model and in the data wealthier people retire later, contrary to what a standard wealth effect would predict. In the model, this relationship is explained by the preference heterogeneity. Indeed, once I control for preferences in column 5, the correlation between wealth and retirement hazard turns positive. 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 the 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, notice the difference between the data result in column 2 and the model result in column 4. Contrary to the data, the model generates 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 does not hold in the data. Comparing columns 3 and 4, we can notice that the concordance ratio increases significantly when labor history is added to the regression model. This is because past employment 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 face labor market constraints, their labor outcomes 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 will 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 the household problem must account for the stochastic labor market constraints. I assume the constraints have three realizations: the person might be 1) unemployed, 2) able to find only a part-time job, or 3) able to freely choose their hours. 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. In the presence of these constraints, preferences should have a diminished role in determining one’s labor market history, while fully affecting retirement decisions.

The employment shocks increase overall uncertainty, adding to stochastic income risks. As a result, we can anticipate a stronger precautionary motive forcing people to work more and save more.

I assume that the constraints follow a Markov process, with realizations of the employment shocks that depend on the most recent realizations. This brings 6 new parameters that need to be calibrated – transition probabilities across different realizations of the labor market constraints.

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

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:

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

$$V_{w,it}^j(a_{it}, w_{it}, PAI_{i,t-1}) = \max_{a_{i,t+1}, h_{it}^m} u(c_{it}, h_{it}) + \beta \left[p_{ju} EV_{i,t+1}^u(a_{i,t+1}, w_{i,t+1}) + p_{jp} EV_{i,t+1}^p(a_{i,t+1}, w_{i,t+1}) + p_{jf} EV_{i,t+1}^f(a_{i,t+1}, w_{i,t+1}) \right], \quad (11)$$

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 are the same as in the model without constraints:

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

7.1 Calibration: Labor Constraints

To calibrate the probabilities of employment shocks, I bring in additional moments. First of all, these moments include the 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 also exploit the fraction of nonemployed people who report a reservation wage that is lower than their recent income. In the absence of employment constraints, we would expect that nearly all nonemployed would have a high reservation wage, indicating low willingness to work. However, in the data 66% of nonemployed report a reservation wage below their past income, suggesting that they are willing to work but are likely constrained.

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

Notice that the model with labor market constraints requires essentially just two types: 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 two remaining combinations of preferences.

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. I present these results in Table 8.

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	corr(ϕ^h, ϕ^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

The model with labor constraints requires much smaller heterogeneity in disutility of labor, and a slightly lower heterogeneity in bequest motives, relative to the model without labor constraints. This is not surprising, since in the absence of labor market constraints, preference heterogeneity plays the major role in explaining the employment variation. As a result, preferences need to be much more dispersed. When we introduce labor market constraints into the model, these constraints create additional variation in employment outcomes which reduces the role of preferences. Bequest motive heterogeneity is still crucial to explain the relationship between assets and retirement hazard and is almost unaffected by the constraints.

Another result we get is that disutility of labor and bequest motive are correlated: those with large bequest motive are more likely to have lower disutility of labor. This means that the two sources of heterogeneity reinforce each other. Those who have large bequest motive work more in order to accumulate more assets. At the same time, they have lower disutility of labor which increases their incentives to work. As a result, they save even more.

To get a better sense of how different the preferences actually are, we can compare the consumption profiles of the four types. Figure 8 shows mean life-cycle consumption paths conditional on disutility of labor and bequest motive. The figure indicates that people with strong bequest motive consume about 35% less in their 60s and 70s than people with a weak bequest motive. Conditional on bequest motive, the consumption profiles are very similar across different values of disutility of labor, indicating that heterogeneity in disutility of labor is not substantial.

Figure 8: Mean life-cycle consumption

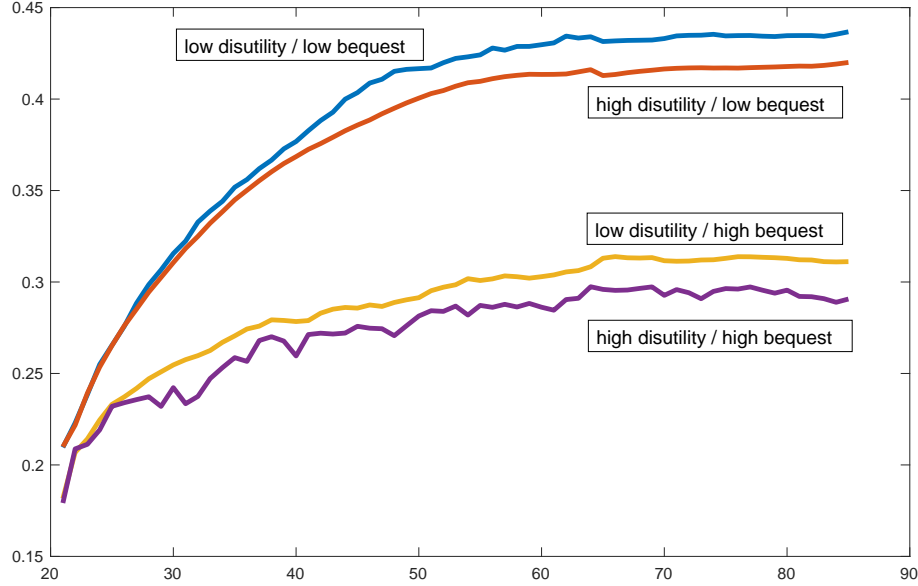


Table 9 shows calibrated transition probabilities across different realizations of the labor market constraints. We see that all the realizations are persistent, which contributes to generating the employment variation. People who get the “full choice”, have a 98% probability of getting the full choice again the following year. Unemployment and partial choice are also persistent but have a lower, 69%, probability of repeating the following year.

Table 9: Calibrated transition matrix

	unemployment	partial choice	full choice
unemployment	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

Table 10 compares the data moments to the model-generated ones. Overall, the model matches the data well. It slightly overestimates the shares of those who stay in part-time employment and in unemployment. At the same time it underestimates the share of constrained people among nonemployed, as captured by the fraction of non-workers with low reservation wage.

Table 10: Targeted moments, with constraints

	model	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

To understand the role of constraints, we can look at how well the model matches the correlations between assets and retirement hazard, and between labor history and retirement hazard. Table 11 presents the results. Columns 1 and 2 correspond to the data and to the full model. Notice, that the model now matches both the relationship between wealth and retirement and between past employment and retirement.

The full model now generates a positive relationship between labor history and retirement

hazard, meaning that working more is associated with earlier retirement even in the presence of preference heterogeneity. Remember, that this was not the case in Section 6, when the model did not have labor market constraints. Column 3 shows the results when the probability of “full choice” is set to 100%. Comparing Columns 2 and 3, we see that shutting down the constraints indeed changes the relationship between labor history and retirement hazard. Since in Column 3 preference heterogeneity is not muted by the employment shocks, those who work more in their prime age – work more in their later years as well. This generates a negative correlation between past employment and retirement hazard, which is counterfactual to the data. It implies that the relationship between past employment and retirement is key to identify the employment constraints.

As discussed in Section 6, heterogeneity in bequest motives masks the standard wealth effect and ensures that wealthy people retire later. Comparing Columns 2 and 4 illustrates this point. In Column 4 both bequest motive and disutility of labor are set to their mean values. Notice that in this case the relationship between assets and retirement hazard is what we would expect in a standard model: people with more assets are more likely to retire earlier.

Table 11: Retirement hazard, roles of preferences and shocks

	data (1)	full model (2)	no shocks (3)	no heterogeneity (4)
more than 1800hrs	0.18 (0.11)	0.14 (0.02)	-0.45 (0.04)	0.12 (0.06)
log past wage	0.11 (0.05)	0.63 (0.02)	0.68 (0.02)	-0.54 (0.03)
2nd quart assets	0.10 (0.09)	0.14 (0.03)	0.02 (0.03)	0.02 (0.03)
3rd quart assets	0.00 (0.09)	-0.01 (0.03)	-0.11 (0.03)	0.23 (0.03)
4th quart assets	-0.20 (0.09)	-0.35 (0.03)	-0.49 (0.03)	1.30 (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

These results imply that having preference heterogeneity is crucial to ensure that wealth-

ier people retire later. On the other hand, the constraints are key to explain the lack of correlation between preferences and past employment.

8 Implications

8.1 Sources of Employment Variation

Having established that the constraints are important for matching the moments, the next step is to quantify the relative roles of the preference heterogeneity and the constraints for the employment outcomes.

Table 12 shows probabilities of each of the employment outcomes conditional on the realizations of the constraints. The first row of the table tells us that almost everyone who got the full choice realizations is choosing full time work, with very few people choosing part-time work or non-employment. Similarly, almost all the workers with partial choice work part-time, with very few choosing not to work. And the unemployed do not have any choice other than not working. These results suggest that the majority of employment outcomes are driven by the constraints, rather than by heterogeneity in observable or unobservable characteristics.

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	0.0575	0.0004
unemployed	0	0	0.0432

Next, I quantify the relative roles of constraints and preferences for overall variation in cross-sectional employment. I calculate the employment variation as the standard deviation of log average hours worked at 30-49. Table 13 compares labor supply variation under three scenarios: in the model with constraints and preference heterogeneity, in the model without constraints, and in the model without constraints and without preference heterogeneity.

In the full model calibrated in Section 7, employment variation equals 0.10. The “no chocks” case shows what the variation would be if there was just the preference heterogeneity and no labor market constraints. For this scenario, I solve and simulate the model

without labor market constraints, keeping the preference heterogeneity and other parameters at the levels calibrated for the full model. Shutting down the constraints suppresses 50% of total employment variation, showing that the constraints play crucial role in explaining total employment variation. To see how important preferences are for the remaining variation, I remove preference heterogeneity by setting disutility of labor and bequest motive to their mean values, calculated in Table 8. The employment variation in “no shocks/no heterogeneity” is 0.04, meaning that preferences account for 10% of total variation ($\frac{0.01}{0.1}$). The remaining variation of 0.4 is explained by differences in wage shocks and assets.

Table 13: Decomposing employment variation

	full model	no shocks	no shocks/no heterogeneity
variation in observed hours	0.10	0.05	0.04

To summarize, the results suggest that the constraints play a much bigger role than preferences in the employment outcomes, explaining 50% of total employment variation.

8.2 Welfare Implications

Now that we have established the importance of employment constraints, we can think about their welfare costs. To what extent would an agent i be better off if they did not face any constraints? To get the answer to this question I calculate welfare for the full model with the constraints and for the same model but with the constraints shut down. I then compare the two welfare measures using the 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.

Formally speaking, I need to find Δ_i such that:

$$\sum_{j=1}^T \beta^{j-1} \frac{[c_{it}(1 + \Delta_i)]^{1-\sigma}}{1 - \sigma} - V_i^h + V_i^{beq} = V_i'. \quad (13)$$

Noting that $\sum_{j=1}^T \beta^{j-1} \frac{c_{it}^{1-\sigma}}{1-\sigma} = V_i^c$ ³, we get an expression for Δ_i :

$$\Delta_i = \left(\frac{V_i' + V_i^h - V_i^{beq}}{V_i^c} \right)^{\frac{1}{1-\sigma}} - 1. \quad (14)$$

I calculate Δ_i for each individual, and 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%. The mean is so much bigger than the median because a relatively small fraction of the population experience persistent unemployment shocks, driving up the average welfare cost. The welfare costs arise not only from the direct loss of income, but also from backloading consumption due to precautionary motives.

9 Conclusion

Employment variation unexplained by observable characteristics can be driven by preferences, such as disutility of labor and bequest motives, or exogenous labor market constraints. This paper proposes a new way to disentangle these channels by exploiting rarely-used empirical moments – correlations between assets and retirement hazard and between work history and retirement hazard.

The signs of these two moments differ depending on the presence of preference heterogeneity and labor market constraints. In a standard model without preference heterogeneity, we can expect people at the top of asset distribution to retire earlier due to the wealth effect. However, in the presence of preference heterogeneity, those with more assets might also postpone retirement, for example, because of a strong bequest motive. This masks the standard wealth effect and can turn the empirical relationship between assets and retirement hazard

³Eq. 13 is equivalent to: $(1 + \Delta_i)^{1-\sigma} V_i^c - V_i^h + V_i^{beq} = V_i'$.

negative.

What does this imply for the relationship between past employment and retirement? If preferences differ across people, we should expect that those who work more earlier in life retire later. This is because high labor supply people choose to provide more labor both when they are young and when they are older. However, the correlation between preference types and labor history weakens if labor market constraints are present at the same time. 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 use 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 wealthy people retire later and that those who work more in prime-age retire earlier. Given the identification strategy described above, this suggests that both preference heterogeneity and labor market constraints are present.

To quantitatively disentangle the two channels, I set-up a life-cycle model with endogenous retirement decisions and calibrate it to match important moments related to retirement and employment. I start with a model without labor market constraints and show that the relationship between assets and retirement helps to identify preference heterogeneity. In particular, to match that relationship the model requires strong heterogeneity in both disutility of labor and in bequest motive. With the calibrated heterogeneity, there is a strong negative correlation between past employment and retirement hazard which is counterfactual to the data.

After adding the employment shocks, the model is able to replicate both the negative relationship between assets and retirement and the positive relationship between employment and retirement hazard. With the labor market constraints present, the model no longer requires strong heterogeneity in disutility of labor. However, the relationship between assets and retirement still pins down significant heterogeneity in bequest motives. Despite this preference heterogeneity, the model with labor market constraints can generate a small 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 sequentially shutting down labor constraints and 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 the labor market constraints are costly in terms of consumption, which raises further questions about an appropriate insurance against these shocks.

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.

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10 Appendix

10.1 SOEP-RV vs SOEP sample

Table 14 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 14: 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

10.2 Robustness to other specifications

Table 15: Retirement hazard with two groups in work history, men

	1	2	3	4
1600-1800 hrs			0.83 (0.13)	0.76+ (0.13)
less than 1600 hrs			0.83 (0.16)	0.74+ (0.16)
log past wage	1.08+ (0.04)	1.12* (0.05)	1.11* (0.05)	1.03 (0.04)
2nd quart assets		1.12 (0.09)	1.11 (0.09)	1.04 (0.09)
3rd quart assets		1.02 (0.09)	1.00 (0.09)	0.91 (0.09)
4th quart assets		0.83+ (0.09)	0.82* (0.09)	0.69*** (0.09)
bad health	1.39*** (0.07)	1.37*** (0.07)	1.38*** (0.07)	1.39*** (0.07)
married	1.07 (0.07)	1.10 (0.07)	1.09 (0.07)	1.12 (0.07)
years of schooling	0.93*** (0.01)	0.93*** (0.01)	0.93*** (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 16: Retirement hazard with continuous work history, men

	1	2	3	4	5
log work history	1.859** (0.250)	2.537*** (0.347)	2.641*** (0.362)	2.511** (0.362)	1.733 (0.359)
log past wage		0.973 (0.038)	1.034 (0.044)	1.032 (0.044)	1.114** (0.046)
2nd quart assets			1.052 (0.086)	1.043 (0.086)	1.108 (0.087)
3rd quart assets			0.930 (0.085)	0.913 (0.086)	1.003 (0.087)
4th quart assets			0.712*** (0.088)	0.695*** (0.090)	0.817** (0.093)
bad health	1.198*** (0.052)	1.517*** (0.064)	1.387*** (0.069)	1.386*** (0.069)	1.377*** (0.069)
married				1.119 (0.073)	1.091 (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 17: Retirement hazard with two groups in work history, women

	1	2	3	4	5
more than 1800hrs	1.114** (0.053)	1.036 (0.067)	1.046 (0.071)	1.049 (0.071)	1.091 (0.072)
log past wage		1.050 (0.051)	1.066 (0.054)	1.080 (0.054)	1.156** (0.058)
2nd quart assets			1.102 (0.105)	1.098 (0.106)	1.146 (0.107)
3rd quart assets			1.105 (0.105)	1.060 (0.108)	1.110 (0.109)
4th quart assets			1.050 (0.106)	1.000 (0.112)	1.099 (0.114)
bad health	1.130** (0.062)	1.334*** (0.082)	1.340*** (0.087)	1.341*** (0.087)	1.323*** (0.087)
married				1.172** (0.081)	1.151* (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

* p < 0.1, ** p < 0.05, *** p < 0.01