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%.

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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, someone with stronger bequest motives and who cares more about leaving inheritance to their kids will also work more. Another explanation emphasizes that some of the 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. Secondly, retirement is an additional margin of labor supply which means that it captures any permanent preference heterogeneity. Thirdly, retirement is a voluntary choice and hence it is not contaminated by exogenous employment shocks. 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 asset distribution to retire earlier due to the wealth effect. To rationalize the fact 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 effect: those with lower disutility of work would have 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, 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 ex-ante heterogeneity, but introduced idiosyncratic wage shocks which generate heterogeneity in asset holdings and spousal earnings.

Since then there has been a big discussion around 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 luxury good to overlapping generation model, which helps to generate upper tail of 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) further 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.

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.

Retirement literature is mostly 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 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 intertemporal elasticity of substitution which is usually estimated using prime age labor supply. 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 much additional information about retirement decision once assets, wages, and all the demographic characteristics are accounted for. We can expect to see zero or slightly positive relationship between labor history and retirement hazard. Positive coefficient can arise because if relationship between assets and retirement is misspecified, there will be some residual variation in assets positively correlated with both retirement hazard and work history.

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. If at the same time bequest motive is negatively correlated with disutility of labor (which I will show to be true in the theoretical model) – higher assets would be associated with even lower willingness to retire. Hence, unobservable preferences create omitted variable bias and distort the wealth effect. In this case, we would expect the relationship between assets and retirement hazard to be negative (at least for higher quartiles). This idea is illustrated in the 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 this implies negative relationship between labor history and retirement hazard, because those with higher disutility of labor and/or smaller bequest motive will work less and will have higher probability to retire (will retire earlier) – this is illustrated on Figure 1b.

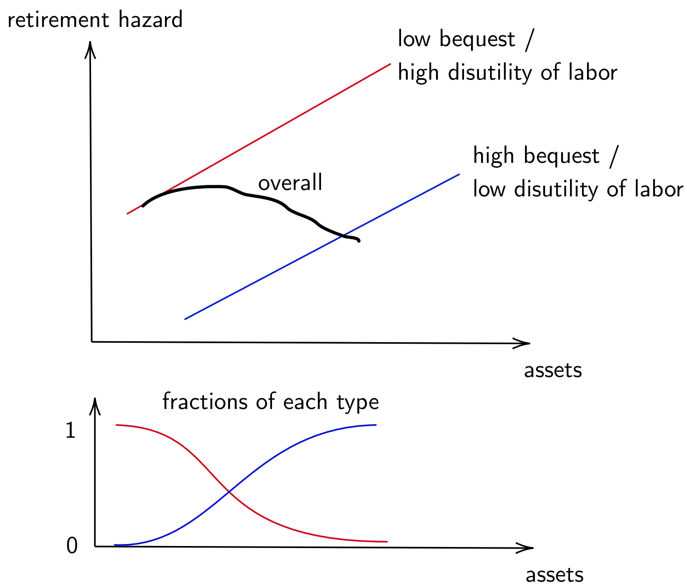
However, in the presence of labor market constraints preference heterogeneity will not be fully reflected in employment (some people will be pushed off labor supply curve). This means that the relationship between labor history and retirement is going to become either less negative or even positive.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

I summarize all 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.

Therefore, looking jointly at these two moments in the data can help us distinguish between different cases.

Figure 1: Role of preference heterogeneity

(a) assets and retirement hazard



(b) work history and retirement hazard

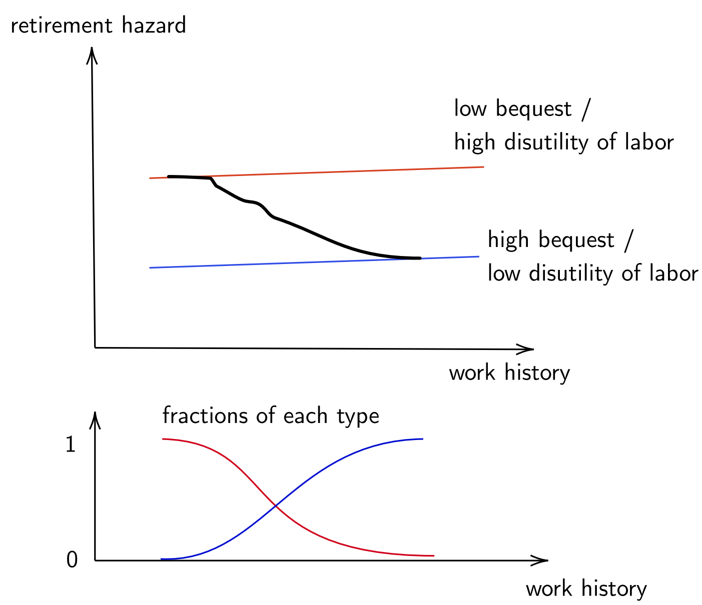


Table 1: Identification strategy

	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 that I am using for the empirical analysis and for generating the moments to calibrate the model.

4.1 SOEP

For my empirical analysis I use 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. This means that I need information on people from when they are 30 years old. At the same time I am interested in connecting their labor histories to retirement decisions which implies I need to observe those people into the older ages as well.

Most datasets do not allow to track adequate number of people for that many years. Advantage of SOEP is that it contains retrospective information on employment for everyone entering the sample, which is crucial for relating retirement decisions to earlier labor supply. Moreover, 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 beginning of respondents' careers. Since SOEP respondents provide their pension identifiers on a voluntary basis, only 20% of SOEP observations can be linked to SOEP-RV. This makes SOEP-RV insufficient to carry out full empirical analysis, however it provides a unique opportunity to quantify the extent of measurement error in both employment history and earnings. I will describe SOEP-RV dataset in more details later.

Retirement decision is a crucial aspect of my analysis, so I restrict my sample to people whom I observe in the sample when they are more than 50 years old. I choose this age threshold since at this age employment share starts declining meaning that people start transitioning into retirement.

Below I introduce how I define two of the key variables of my analysis: retirement age and labor market history. Relationship between these variables will help me identify to what extent people are pushed off their labor supply curves and to better understand the relative roles of preferences vs labor market constraints in lifetime employment variation.

4.1.1 Retirement age

I define retirement as exiting the labor force without coming back. For this definition it does not matter whether those individuals receive retirement pension or not, what matters is that they are no longer working.

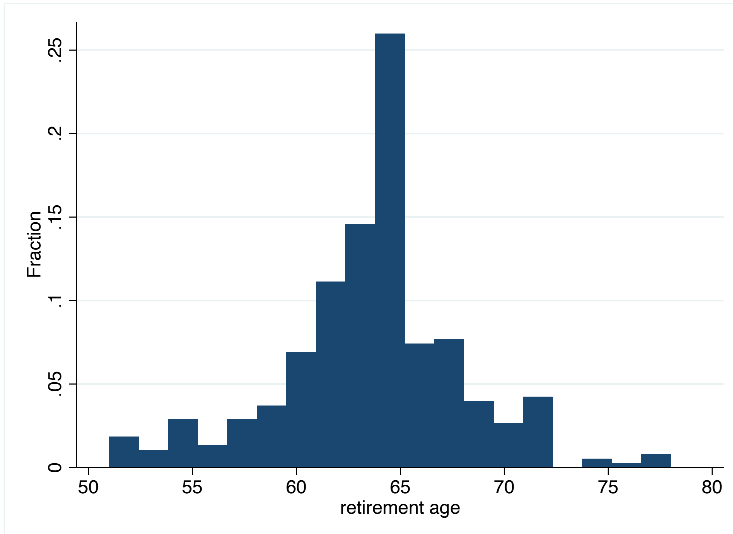
To identify retired people in the data, I look at those who are older than 50 and apply the following two rules:

- 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

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

Figure 2: distribution of retirement ages for men, SOEP



4.1.2 Labor market history

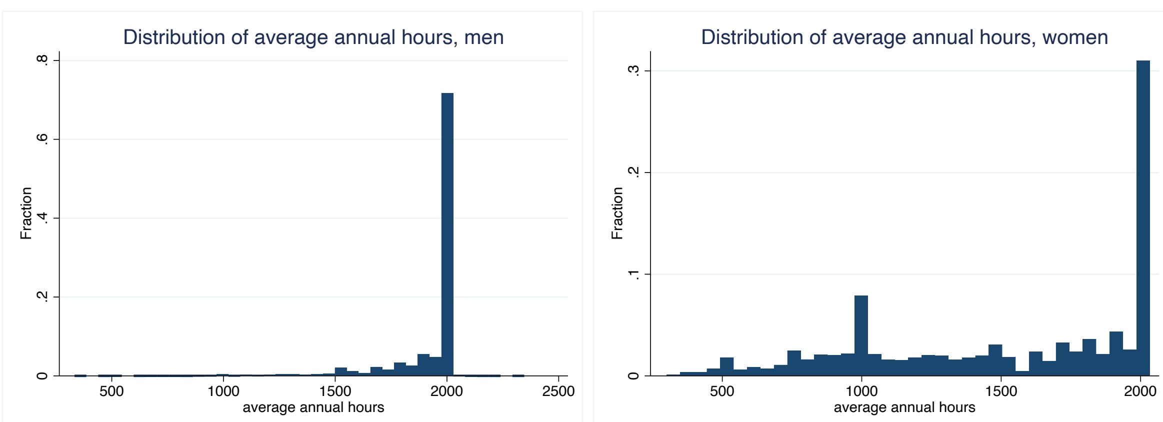
The other key variable is labor market history. I am interested in how much people work from 30 to 49 years old. The 30 years old threshold is chosen to make sure that periods of studying do not show up as non-employment, and 49 years old is chosen to make sure that no one starts retiring yet. For as many years as I see the individuals in the survey between ages 30 and 49, I use the contemporaneous information from the survey. However, for most individuals the observed period will not go back as far as to their 30s. For those ages where I do not see the respondents, I use retrospective data.

For each person who first enters the survey at any age, the survey collects information which is related to their life and labor market activity prior to entering the survey. In particular, the respondents need to answer whether they were employed full-time, part-time, not employed, studying, etc at each of the previous ages back to when they were 15 years old. This data does not allow to distinguish between people who worked 60 hours vs 40 hours, but allows to 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). In such cases, I assume that the year was split equally between the two statuses and use the average value for that year.

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 mostly be focusing 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

Retirement decision depends on many characteristics that are important to control for. 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. Information on assets is available every 5 years, so I collect information for those years when assets are available and impute with the lagged assets for other years. In my regression I enter assets as a quartile in the distribution. Health is also collected every 5 years. The respondents are asked how they evaluate their health from very bad to very good – I then classify the answers into a dummy for bad health. 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 SOEP, which adds another source of measurement error. To make model and empirical results comparable with each other, I am recovering measurement error processes from the data.

To do that, I utilize the newly available project SOEP-RV which is a collaboration between SOEP and the Research Data Centre of the German Pension Insurance (FDZ-RV). The project is 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. Those records include monthly employment spells and income starting from 14 years old until the most recent SOEP survey, among other variables. However, they do not contain any information regarding occupations or assets.

Original FDZ dataset contains information about the whole population, however, not all SOEP respondents agreed to publicly share their pension record identifiers. This means that only a subsample of SOEP can be merged with administrative records. The overlap is 20% of SOEP sample. This makes the 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. I will explain how I work with the measurement error when I talk about the model. There might be a concern about how representative SOEP-RV is since SOEP participants choose whether to provide pension identifier data. In the Appendix I provide descriptive statistics for SOEP respondents who are in SOEP-RV and they look comparable to each other.

Information about employment comes from the records on the "number of days recorded with compulsory contributions from employment subject to social insurance contributions or self-employment in the respective month". Income comes from "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

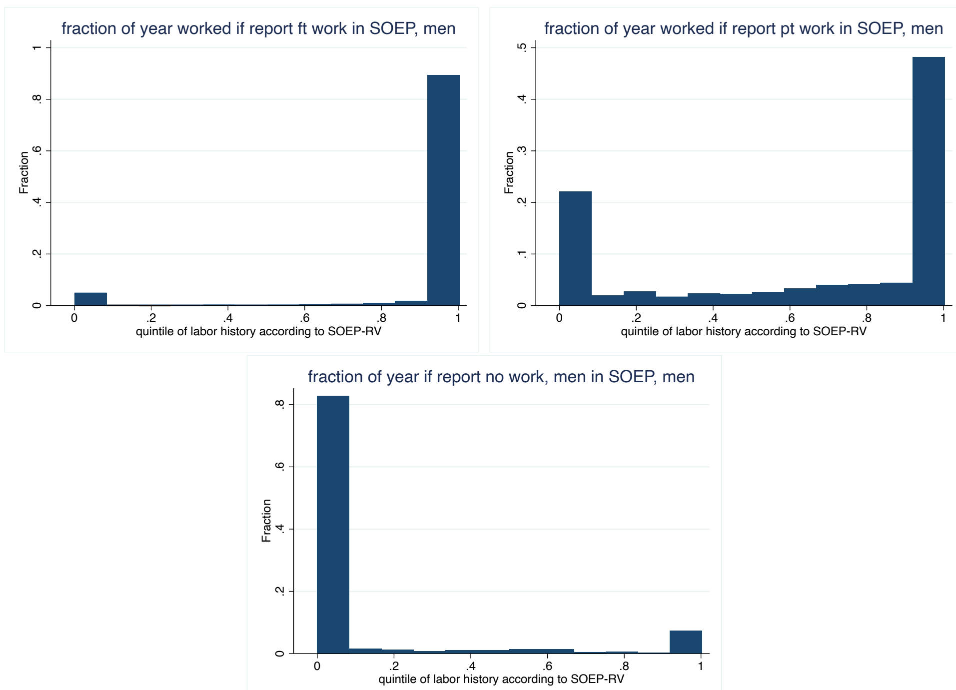
One complication with FDZ is that the dataset records spells only for those occupations that are covered by public pension system. This excludes civil servants who do not make contributions to pension system, and those who are covered by occupation-specific pension – doctors, lawyers and architects. For these occupations, records show up as missing values which makes it impossible to determine if a person did not work in that month or they worked but in an occupation that does not imply contributing to the public pension system. And since SOEP does not track information about occupations in retrospective data (only in the contemporaneous data) and FDZ does not contain that information at all, I do not know what was their occupation in the past.

To get as close to true employment spells as possible, I use information available to me from SOEP survey. In particular, I look at the mode of occupations held by the person in the survey years, at the first job the person had in their life (there is a corresponding question in SOEP) and at the job held at the time of the first interview. I exclude those for whom those occupations were civil servants, doctors, lawyers and architects. I also exclude self-employed who can contribute to the pension system but are not required to. These excluded occupations together make up 13% of the sample. I remove them from my analysis of measurement error, however everyone except for civil servants and self-employed are still part of main empirical analysis.

To infer measurement error in retrospective data, I need to compare annual values (aggregated from monthly information) from FDZ to retrospective annual values from SOEP. I calculate what fraction of the year SOEP respondents are working according to administrative records, and look at the distribution of those fractions conditional on what they report in SOEP retrospective data.

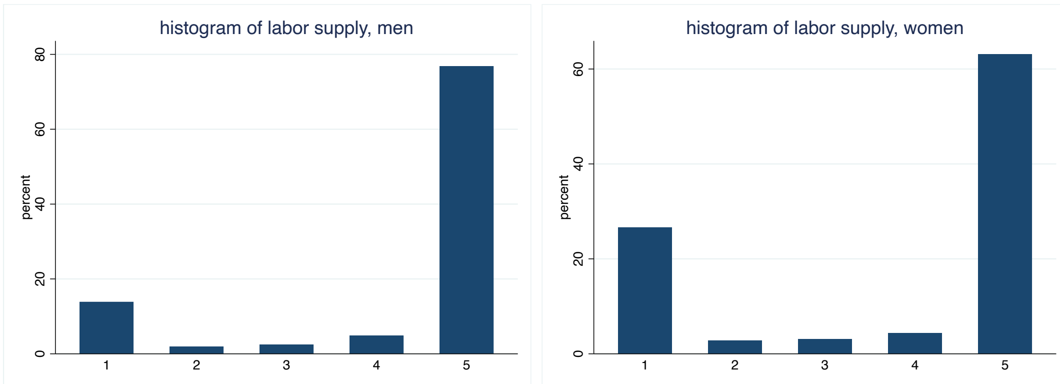
Figure 4 shows that 90% of those who report that they worked full-time work for the full year and 85% of those how reported not working really did not work. The actual employment of those who reported part-time work is much more dispersed, which makes sense because part-time workers are more flexible in their contracts. Overall, these figures suggest that retrospective data is highly correlated with the true employment patterns, however, with some probabilities people misreport their past employment spell.

Figure 4



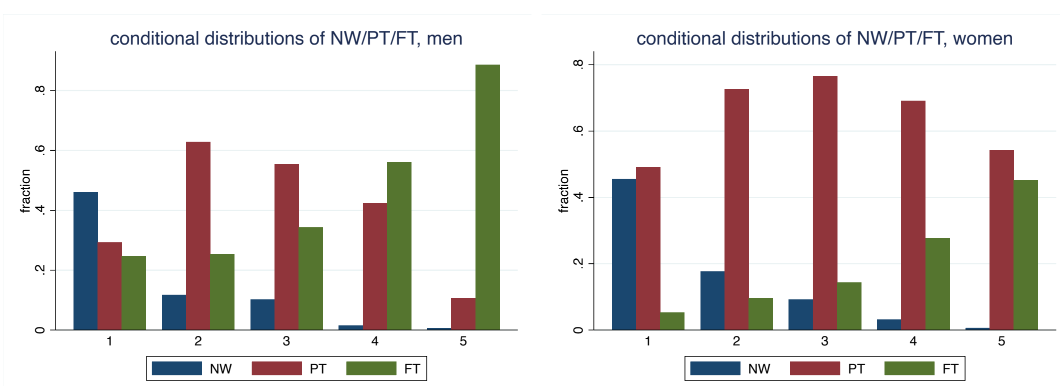
The next step is to quantify the measurement error. To do that, I split yearly labor supply from FDZ into 5 equal bins, and look at how SOEP responses are distributed depending on how much the person worked that year. Figure 5 plots the distribution of men and women over different values of labor supply.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

Figure 5



Note that in retrospective SOEP data people are asked whether they worked full-time, part-time or not at all in each of the years preceding their first SOEP survey. Sometimes they report several different values in the same year, e.g. full-time and non-working. I assign entries with such multiple responses to part-time work. Figure 6 shows how retrospective responses are distributed across different of yearly employment. This distribution implicitly defines the measurement error in employment. We see that as the fraction of the year worked goes up, probability of responding full-time work goes up and probability of responding no-work goes to zero. These patterns hold for both men and women but, not surprisingly, part-time work plays a bigger role for women.

Figure 6

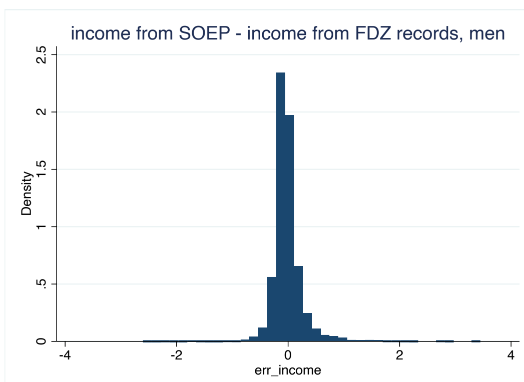


4.3.2 Measurement Error in Income

Income values recorded based on pension insurance contributions are closer to the true income process than self-reported SOEP responses. I directly compare the values reported in SOEP and recorded in FDZ, and define the 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 monthly, I use the same month for both datasets. Each year values above a known year-specific threshold are censored in FDZ but not in SOEP. To avoid comparing those censored values, I am looking only at the values that are below censoring threshold in FDZ.

Figure 7 plots a histogram of the 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.

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. The most natural approach is to run an OLS regression of retirement age on earlier labor market history, however this empirical strategy has some problems. Retirement is a right-censored variable which means that while some people will be observed at retirement, others will still be not retired at the last wave of the survey. By applying OLS, I would have to throw those observations out but not being retired at a certain age also contains a lot of information about underlying behavior. For this reason, I want to use a methodology that is able to handle right-censored data.

To deal with right-censored data, I rely on survival analysis tools. The most popular model is Cox proportional hazards model. However, it requires regressors to be fixed at initial point in time which would not allow me to capture how retirement hazards change with time-varying wages and assets. For that purpose I use a Cox model with time-varying regressors.

Figure 3 showed that distribution of labor histories for men is very concentrated: more than 50% of people work full-time all 20 years from 30 to 49. I split people in two groups based on how much they work and define a dummy variable $wkhist$, where $wkhist = 1$ for those who on average worked at least 1800 hours a year, and $wkhist = 0$ otherwise. In the Appendix, I present results with different splits and larger number of groups and show that results are not fundamentally different and the key sign of the relationship between labor supply and retirement hazard remains the same. I also show that using a continuous variable (log of cumulative labor history) gives similar qualitative results but it is harder to interpret.

Assets are split in four quartiles, with each quartile denoted as $assets^j$.

Health is important factor of retirement decision because it reduces productivity. At the same time it increases expected health expenditures and can affect savings (De Nardi, French, and Jones (2010)). This means that is correlated both with asset holdings and retirement decisions and is important to control for.

Below is the specification that I use for my analysis:

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

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, birth year.

I run this specification for men, but 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 presence of preference heterogeneity. 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 there is preference heterogeneity but at the same time there are employment constraints that prevent preference heterogeneity from mapping to the labor history.

6 Model

To quantify the relative role 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 of the empirical moments 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 argue that the combination of the empirical facts together with a life-cycle model can help us identify heterogeneity in disutility of labor and bequest motives and tell us how much of the employment variation is explained by being on the labor supply curve versus off the labor supply curve.

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:

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

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 decide 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 use SOEP-RV as described later in the paper. This will make the results comparable to the data.

I assume that consumption consists of two components: market consumption c_t^m (which enters the budget constraint) 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. In particular, it starts increasing at $\bar{t}$ (calibrated to be 50 years old) – this generates decline in labor force as we see it in the data. This increase in disutility can be motivated by gradual decline in health as people get older.

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

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

where $h_t^h = h_n(1-h_t)$ and $c_t^h = c_n h_t^h$. 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 those hours. This suggests 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 workers, I include fixed cost of working θ_h (e.g. commuting cost). Notice, that it affects disutility of labor only if the person is engaged in market work ($h_{it}^m > 0$).

In this specification ϕ_i^h reflects disutility of labor, where higher values are associated with valuing leisure more.

Bequest motive follows De Nardi (2004): $b(a_{T+1}) = \phi^b(1 + \frac{a_{T+1}}{\psi_b})^{1-\sigma_b}$. Higher ϕ_i^b indicates stronger motive for leaving bequests.

I allow ϕ_i^h and ϕ_i^b to be different across people, and the goal will be to estimate the extent of this heterogeneity and its role for employment variation. For simplicity I will consider two groups: (ϕ_1^h, ϕ_1^b) and (ϕ_2^h, ϕ_2^b).

6.1.2 Budget constraint

Individual income comes from wage income and pension if eligible (older than retirement age of 65 years old). The budget constraint then looks as following:

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

where b_t 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 carry past average labor income $PAI_{i,t-1}$. Each period I update it to account for the most recent labor income. At the time the worker becomes eligible for pension, the pension benefit equals: $b_{it} = pPAI_{i,t-1}$, where p is a multiplier that will be calibrated to match 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}.

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

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 and PAI_{t-1} is past average labor income accumulated until t. Value functions are dependent on the preference type (ϕ^h, ϕ^b) – I will solve the optimization problem separately for each type.

At every age a non-retired individual chooses whether to retire or not by comparing the value of staying in labor force and retirement. Since the retirement is an absorbing state, once the person retires they get value of a retiree every period and do not have any uncertainty anymore.

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

$$V_t(a_t, w_t, PAI_{t-1}, R_{t-1} = 0) = \max_{R_t} \{V_{wt}(a_t, w_t, PAI_{t-1}), V_{Rt}(a_t, PAI_{t-1})\}$$

$$V_t(a_t, w_t, PAI_{t-1}, R_{t-1} = 1) = V_{Rt}(a_t, PAI_{t-1})$$

where V_{wt} is the value of not retiring and V_{Rt} – value of being retired.

$$V_{w,t}(a_t, w_t, PAI_{t-1}) = \max_{a_{t+1}, h_t} u(c_t, h_t) + \beta EV_{t+1}(a_{t+1}, w_{t+1}, PAI_t)$$

$$V_{R,t}(a_t, PAI_{t-1}) = \max_{a_{t+1}} u(c_t, 0) + \beta V_{R,T+1}(a_{t+1}, PAI_{t-1})$$

At time T, the value for both retired and non-retired consists of contemporaneous utility and bequest value:

$$V_{w,T}(a_T, w_T) = \max_{a_{T+1}, h_T} u(c_T, h_T) + \beta b(a_{T+1})$$

$$V_{R,t}(a_t) = \max_{a_{T+1}} u(a_{T+1}, 0) + \beta b(a_{T+1})$$

To solve the model, I start from period T and solve backwards. I discretize the state space and use grid search method to find optimal solutions.

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 realized wage shocks.

While in the model we can see the exact age when a person decides to retire, in the data we cannot do that. To make the model and the data consistent with each other, I define retirement age in the model exactly as in the data. Hence, retirement age is defined as the age after which the person is never seen working. Notice that it could coincide with the age at which the agent decides to retire but could also be earlier than the retirement decision.

To make the model-generated data as comparable to the data as possible, I add measurement error both to employment outcomes and wages as defined in Section 4.3. The model-generated 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 their true outcome in line with the conditional distributions from Figure 6.

To augment the model with measurement errors in income I first look at whether those errors are correlated with actual income values in the data and how dispersed they are. I regress the errors on the actual income recorded in the administrative data (restricting to not top-coded values). After examining the residuals from this regression, I find that they are normally distributed with $\mu = 0$ and $\sigma = 0.3$. So the log of measurement error can be represented as: $log(err_{it}) = 1.6 - 0.2 \times log(w_{it}) + \gamma$, where $\gamma \sim N(0, 0.3)$.

I add this measurement error process to the wage realizations in the model according to $w_{it}^{obs} = w_{it} exp(err_{it})$.

6.3 Calibration: No Labor Constraints

In this section I describe how I calibrate the unknown parameters for the model without labor market constraints. Adding those constraints requires calibrating extra parameters using additional moments, and I will explain those later in the paper.

6.3.1 Estimating income process

I assume the following income process[1]:

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

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

[1] tried ARMA(1,1) process as well with similar goodness of fit, but chose the process with fewer parameters

where y_{ti} – residual log income (after accounting for education, age, gender, year), z – permanent component with $\epsilon \sim N(0, \sigma_\epsilon)$, v – temporary and $\sim N(0, \sigma_v)$, and $z_0 \sim N(0, \sigma_{z_0})$. All of the innovation terms are orthogonal to each other. Parameters that need to be estimated are: $\rho, \sigma_\epsilon, \sigma_v, \sigma_{z_0}$.

Following extensive literature, I estimate permanent and transitory errors by fitting auto-covariance function. In the presence of measurement error estimating transitory component is challenging. However, since I use administrative dataset for recovering income process I can assume measurement error to be zero and it makes estimating transitory shocks much easier.

Theoretical moments are calculated as follows (individual indexes omitted to simplify notations):

$$\begin{aligned} E(y_j, y_j) &= E(z_j + v_j, z_j + v_j) \\ &= E(z_j^2) + E(v_j^2) \end{aligned}$$

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

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 from the data, and pick parameters that minimize the distance between theoretical autocovariances and the empirical ones.

I estimate the parameters to be: $\rho = 0.98, \sigma_{z0}^2 = 0.18, \sigma_\epsilon^2 = 0.02, \sigma_v^2 = 0.08$.

6.3.2 Parameter values

Table 13 summarized 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 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
r	interest rate	0.02
β	discount factor	0.98
ρ	AR coeff in income process	0.98
$\sigma^2_{z_0}$	variance in initial heterogeneity at age 25	0.18
σ^2_{ϵ}	variance in innovation of permanent shocks	0.02
σ^2_{v}	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 fn	1.5 (De Nardi 2004)
ψ_b	scaling parameter in bequest function	11.6 (De Nardi)
ξ_1	how disutility incr	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^h_1, ϕ^h_2	values for disutility of labor	SMM
ϕ^b_1, ϕ^b_2	values for bequest motive	SMM
π_{ij}	share of type (ϕ^h_i, ϕ^b_j)	SMM
ξ_2	how disutility increases with age	SMM
c_h	productivity of home production	SMM

I jointly calibrate a vector of parameters $(\phi^h_1, \phi^h_2, \phi^b_1, \phi^b_2, \pi_{11}, \pi_{12}, \pi_{21}, \xi_2, c_h)$ 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 of average hours worked at 30-49, mean and standard deviation of 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. For my SMM procedure 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, choose 15 best-fitting initial vectors. Then I use simplex local search method to solve for the minimum around each of those points while increasing the number of grid points in assets. 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 calibration results for the parameters calibrated by SMM. We can see that the model requires a lot of heterogeneity in both disutility of labor and bequest motive. We can also see that the biggest fraction of the simulated population is the group that has high disutility of labor and low bequest motive – they constitute 45%. On the other hand, the smallest group is the ones with high disutility and high bequest motive (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
w/o constraints	2.04	4.28	1718.18	2.26	0.25	0.07	0.23	0.44	21.95	0.16

The table below shows how well the model matches the moments (excluding the coefficients from retirement hazard regression), and the results are very close to the data.

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 I mentioned before, the key insights come from whether the model can qualitatively match correlations between assets and retirement hazard and between labor history and retirement. The table below shows how well the model reproduces empirical regressions results, using the model data.

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, I present results for data and model in two columns: one without labor history and one with labor history. This helps to understand what information labor history brings to the regression model in each case. We can see that the relationship between assets and retirement hazard in the model is qualitatively similar to the one in the data: instead of the standard wealth effect we see that those with more assets retire later. In the last column of the regression table, I control for the preference type – and the coefficients on assets change to the standard monotonically increasing relationship. This tells us that preference heterogeneity is necessary to qualitatively replicate the empirical relationship between assets and retirement hazard. In other words, bringing in the relationship between assets and retirement is useful to identify preference heterogeneity in the data.

We can also notice that the coefficient on wage is different from what we would expect in a standard model when substitution effect dominates. In the model with preference heterogeneity if a person with high wage has the same assets as a person with low wage – that is because the person with high wage has low bequest motive and high disutility of labor, while the person with low wage – high bequest motive and low disutility of labor. Moreover, low bequest motive and high disutility of labor will force the first individual to retire earlier than the one who has lower wage. As a result, preference heterogeneity confounds not only the relationship between assets and retirement hazard, but also the relationship between wage and retirement hazard.

Now we can look at what that preference heterogeneity implies for the correlation between labor history and retirement hazard. Having that heterogeneity results in a strong negative relationship between early labor supply and retirement hazard – this result goes against the data. Hence, there is a conflict between matching the relationship between assets and retirement hazard and between work history and retirement. Another thing to notice is that in the model concordance ratio goes up significantly when labor history is added, because it adds extra information about preferences and hence helps better explain retirement decisions. In the data, adding work history to the regression almost does not change the concordance ratio meaning that work history does not contain any information useful for predicting retirement.

This suggests that either preference heterogeneity is overestimated in the model or it does not map to earlier labor supply in the data, or both. This can be because younger workers are pushed off their labor curves and their preferences are not fully reflected in their actions. 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 will explore this idea by adding stochastic labor market constraints to the model described earlier. I will show that having those constraints indeed breaks the tight connection between preferences and labor history.

7 Adding Labor Market Constraints

A reason why preference heterogeneity might not map to employment outcomes is that people are subject to exogenous labor market constraints which 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". BLS defines such part-time workers as those 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, even though people would like to work different amount of time, they cannot do that due to employment constraints that they get.

Now consider adding such labor constraints to the model. The constraint has three realizations: 1) unemployment, 2) choice between non-employment and part-time employment, and 3) full choice (same as in the model without employment shocks). Realization of the constraint becomes a new state variable that affects current choices. In this scenario, preferences should have less role in determining labor market history but at the same they will still largely affect retirement decision.

The core of the model is the same as before, but now utility-maximization is modified to account for different realizations of the constraints. I assume that the constraints follow Markov process, which brings 6 new parameters to the model – transition probabilities across different realizations of labor market constraints.

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

That means that future value will be an expectation over different realizations of the constraints, with probabilities dependent on current realization.

If a person gets full choice outcome their contemporaneous decision looks the same as before. However, due to uncertainty about future labor market constraints, the decisions will be different than in the full choice model without labor constraints. For example, precautionary motive can make people choose to overwork compared to no-constraint case in order to accumulate more assets and to protect themselves against potential unemployment in the future. If they get a part-time realization, they can choose any option between 0 and 0.5 units of work. And if they get an unemployment draw, they cannot work at all at the current period.

The value functions for each realization are as following, where $j \in \{f, p, u\}$ stands for full choice, partial constraint (only choose between 0 and 0.5), and unemployment:

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

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

where $V_{w,it}^{j}$ – value function of a non-retired individual i at age t who received constraint realization j for this period, and $V_{R,it}^{j}$.

If the person has already retired, there is no more uncertainty over wages and constraint realization, so value function is the same as in the model without constraints:

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

7.1 Calibration: Labor Constraints

I solve the model same way as before, while incorporating expectations over different labor market constraints. To calibrate transitional probabilities between constraint realizations I bring in extra moments – empirical flows between non-employment, part-time employment and full-time employment from SOEP retrospective data.

To speak more directly to how many people are constrained, I bring in another moment: share of people who are nonemployed and whose reservation wage is lower than the recent income. The idea behind this moment is that those who are not employed and who has low reservation wage (e.g. lower than their previous income) are more likely to be constrained than those who have high reservation wage. Reservation wage data comes from SOEP questionnaire, and for simplicity I look only at those who report their reservation wage as corresponding to a full-time job. I calculate the analogous reservation wage in the model as the minimum wage at which the person would be willing to work full-time. I can then compare these reservation wages to the past incomes both in the data and in the model.

With labor 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 effects of preference heterogeneity required by relationship between assets and retirement decision.

Repeating the calibration strategy from the previous section, I get the following results. The table shows the comparison between two models: without labor markets (same as in the previous section), and with labor 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

We can see that in both models there is a lot of heterogeneity in bequest motives. However, adding the labor constraints adds a lot of employment variation so there is less need for 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. There are only 7% contributed to the remaining two types.

Since the four preference types are allocated very differently in population, it is hard to gauge the amount of overall heterogeneity in each case without taking those shares into account. Moreover, disutility of labor increases after 50 years old, which means that mean and variance of disutility of labor are age-dependent. To get an idea about overall heterogeneity and to make it comparable across the two calibrations, I calculate mean and variance of disutility of labor and of bequest motive parameter at ages 30 and 60, mean and variance of bequest motive, and the correlation between the two types of heterogeneity.

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.

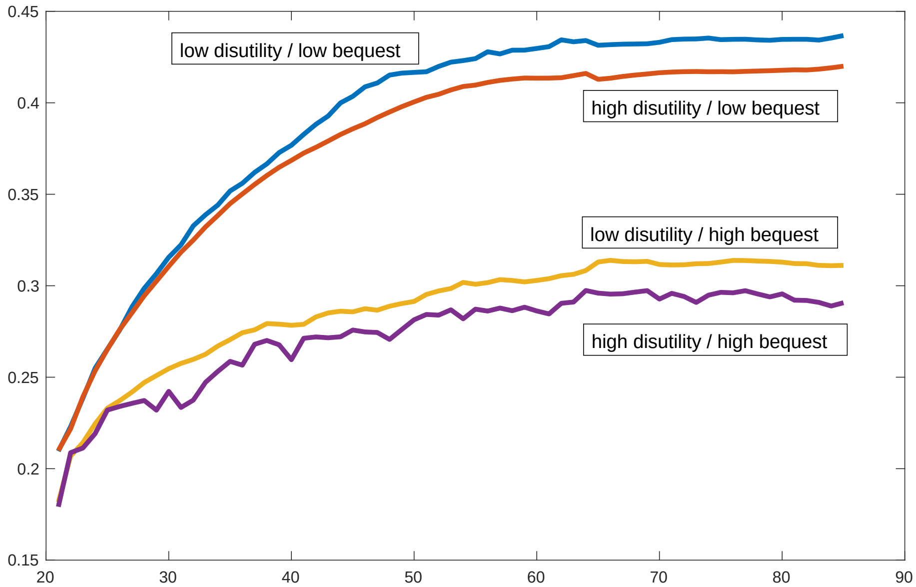
To get a better sense of how different the "high" and "low" bequest motives are, we can

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

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 probabilites 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:

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

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 the majority of employment variation – 83% of the residual lifetime variation which cannot be explained by wages and assets. 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.

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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

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