House of Finance
SAFE
Working Paper Series

Andreas Fagereng - Charles Gottlieb - Luigi Guiso

Asset Market Participation and Portfolio Choice over the Life-Cycle

SAFE Working Paper No. 115

Non-Technical Summary

This paper studies the portfolio allocation of households over the life cycle following for 15 years a large random sample of Norwegian households using error-free data on all components of households' investments drawn from the Tax Registry. Using this unique dataset, we provide new empirical evidence on the life cycle pattern of households' asset participation and their stocks holdings. In contrast to existing empirical evidence, our empirical exercise shows that both participation in the stock market and the portfolio share in stocks, have important life cycle patterns. Stock market participation is limited at all ages but follows a hump-shaped profile, which peaks around retirement; the share invested in stocks among the participants is high and flat for the young but households start reducing it as retirement comes into sight. This suggests a double adjustment as people age: a rebalancing of households' portfolio away from stocks as they approach retirement, and stock market exit after retirement.

In the model section of the paper, we show that existing life cycle models can account for households portfolio rebalancing away from stocks as they age, but not for the hump-shaped pattern of participation. We show that augmenting these models with a reasonable per period participation cost can generate limited participation among the young but not enough exit from the stock market among the elderly. However, if we introduce a small probability of a large loss when investing in stocks, our model is able to generate a joint pattern of participation and of the risky asset share that resembles the one observed in the data. Based on this model structure, we estimate unobserved parameters, namely risk aversion, participation cost and the probability of tail event that allows our model to best replicate the patterns identified in the data. Our structural estimation reveals that the parameter combination that fits the data best is one with a relatively large risk aversion, small participation cost and a yearly large loss probability in line with the frequency of stock market crashes in Norway.

Asset Market Participation and Portfolio Choice over the Life-Cycle*

Andreas Fagereng
Statistics Norway

Charles Gottlieb
University of Cambridge

Luigi Guiso
EIEF & CEPR

First draft: September 2011
This version: June 2015

Abstract

We study the life cycle of portfolio allocation following for 15 years a large random sample of Norwegian households using error-free data on all components of households' investments drawn from the Tax Registry. Both, participation in the stock market and the portfolio share in stocks, have important life cycle patterns. Participation is limited at all ages but follows a hump-shaped profile which peaks around retirement; the share invested in stocks among the participants is high and flat for the young but investors start reducing it as retirement comes into sight. Our data suggest a double adjustment as people age: a rebalancing of the portfolio away from stocks as they approach retirement, and stock market exit after retirement. Existing calibrated life cycle models can account for the first behavior but not the second. We show that incorporating in these models a reasonable per period participation cost can generate limited participation among the young but not enough exit from the stock market among the elderly. Adding also a small probability of a large loss when investing in stocks, produces a joint pattern of participation and of the risky asset share that resembles the one observed in the data. A structural estimation of the relevant parameters that target simultaneously the portfolio, participation and asset accumulation age profiles of the model reveals that the parameter combination that fits the data best is one with a relatively large risk aversion, small participation cost and a yearly large loss probability in line with the frequency of stock market crashes in Norway.

*We would like to thank Árpád Ábrahám, Jerôme Adda, Juan-Carlos Conesa, Maria Gustafsson, Elin Halvorsen, Jonathan Heathcote, Dirk Krueger, Kim Peijnenburg, Facundo Piguillem, Arvid Raknerud and Marno Verbeek for helpful comments and suggestions. We are grateful to Joao Cocco for making the code of his life cycle model available to us, and to Bernt Arne Ødegård for providing us with ISIN-codes and end of period prices of the Oslo Stock Exchange. We thank seminar participants at the University of Frankfurt, University of St. Gallen, University of Cambridge, EIEF, University of Oxford, European University Institute, European Central Bank, Statistics Norway, Norges Bank, NHH Bergen, ESEM 2011, SED 2012, IIPF 2013 and EALE 2014. We are grateful to NETSPAR for financial support. Andreas Fagereng also thanks the Norwegian Research Council for support through grant #184563. Charles Gottlieb gratefully acknowledges research support from the Research Center SAFE, funded by the State of Hessen initiative for research LOEWE.

1 Introduction

Over the past decade a number of contributions have re-examined the life cycle behaviour of investors' portfolio. Inspired by empirical findings from novel microeconomic data on households portfolios, several papers have provided new models of the life cycle portfolio of individual investors that go beyond the seminal models of Mossin (1968), Samuelson (1969) and Merton (1969).

These earlier contributions have two sharp predictions: first, even in a dynamic setting, individuals should, at all points in their life-cycle invest a share of their wealth in risky assets. That is, independently of age, all investors should participate in the stock market - an extension of the participation principle in a static setting to a dynamic context. Second, assuming complete markets and in the absence of labor income, the share invested in the risky asset should be age-invariant. Thus, the portfolio, either described by the ownership of risky assets or by their share in total wealth, exhibits no life cycle pattern. However, the absence of rebalancing over the life cycle predicted by these earlier models is not robust to the (realistic) presence of human capital. As shown by Merton (1971), the presence of tradeable human capital in a complete market setting implies that since human capital is riskless and tradeable, it plays the same role as a large endowment of riskless bonds. It therefore creates a strong incentive to invest in risky securities when abundant, that is early in the life cycle, and to rebalance away from them as people get older and their human wealth shrinks. Importantly, this basic implication carries over to more complex environments that feature non-insurability of labor income and incomplete markets, as shown by several computational models of life cycle portfolio investments that amend the Samuelson-Merton model in one or more dimensions to add doses of realism.[1] All these models uniformly predict that individuals should rebalance toward a safer portfolio as they approach retirement and the driving force is the life cycle pattern of human capital.[2] On the other hand, without additional assumptions, they still imply that people should participate in the stock market.

In contrast, microeconomic data on household portfolios seem to show two remarkable features: first, not only participation in the stock market is limited at all ages but it tends to follow a life cycle pattern - in many instances a hump-shaped

[1]See Gomes and Michaelides (2003), Gomes and Michaelides (2005), Heaton and Lucas (1997),Gakidis (1998), Michaelides and Haliassos (2002), Storesletten, Telmer, and Yaron (2007), Campbell and Viceira (2001), Viceira (2001), Cocco, Gomes, and Maenhout (2005), Davis, Kubler, and Willen (2006), Benzoni, Collin-Dufresne, and Goldstein (2007), Polkovnichenko (2007) and Gomes, Kotlikoff, and Viceira (2008).

[2]A declining life cycle portfolio profile may be generated also by other features than just the life cycle of human capital. For instance, Bodie, Merton, and Samuelson (1992) show that accounting for endogenous labor supply decisions can induce the young to invest more in stocks because greater labor market flexibility offers insurance against financial risks. A downward sloping age-portfolio profile can be generated by departure from CRRA utility (Gollier and Zeckhauser, 2002), by life cycle patterns of risk aversion and background risk, as well as predictability of stock returns (Kandel and Stambaugh, 1995; Campbell and Viceira, 1999, 2002). These factors may certainly contribute to induce a rebalancing motive over the life cycle but none is as uncontroversial as the life cycle of human capital.

one (see Haliassos, Guiso, and Jappelli, 2001). Second, the share invested in stocks tends to vary little with age, though in this case the specific empirical pattern is more controversial. Summarizing evidence for several countries, Haliassos et al. (2001) argue that the age profile of the share of risky assets conditional on participation is relatively flat, though in some instances "there does seem to be some moderate rebalancing of the portfolio away from risky securities" as people age. Thus, a reasonable characterization of the empirical findings is that participation in risky assets follows a hump-shaped profile while the share invested varies little, if at all, with age. But how solid is the evidence on which this characterization rests? The empirical finding that people do not rebalance their risky portfolio share over the life cycle sounds particularly puzzling because rebalancing is implied by an indisputable fact of life - the decrease in the stock of human capital as people age. It is also in contrast with recent evidence that human capital drives financial risk-taking positively Calvet and Sodini (2014).

While the lack of participation is a robust feature of the data, there are at least three reasons to doubt the empirical patterns over age in both participation and the portfolio share. First, most of the available evidence is obtained from cross sectional data. Hence, inferences on the age pattern of the portfolio must be drawn from comparisons of portfolio holdings of individuals of different age, rather than of the same individual as his age varies. If individuals of different age differ in unobservables that are correlated with age, the estimated age pattern may reflect the former not the latter, in particular, cohort effects. Panel data may help sorting this out: though adding an extra source of variation to the data (time) also adds the need to model it, if one can impose reasonable restrictions on time effects one can then distinguish the effect of age from that of year of birth. Second, most studies ignore the fact that the risky portfolio share is only defined for the participants in the risky assets markets and that participation in assets markets is an endogenous choice. Thus, uncontrolled selection, if correlated with age, may be responsible for the failure to find evidence of rebalancing in the risky share. Third, evidence so far is based primarily on household surveys which are notoriously subject to measurement problems. Most importantly, measurement and reporting errors are likely to be correlated with age, hiding age patterns when present in the true data. For instance, this could arise because wealth is correlated with age and the wealthy may have a stronger motive to under-report or not-report specific assets (such as stocks). Hence, age profiles of the risky portfolio share (and participation) may appear flatter than they actually are.

One important exception is Ameriks and Zeldes (2002) who try to circumvent these problems by using a panel of TIAA-CREF contributors covering 13 years of data.[3] Thus, they can in principle distinguish between age, time and cohort effects.

[3]Agnew, Balduzzi, and Sundén (2003) also use a four year panel data set of about 7,000 people in a 401k retirement accounts and can thus distinguish age and time effects. They find that the risky portfolio share is decreasing in age. However, this result is obtained restricting cohort effects to zero; in addition, since they fit a Tobit model, no distinction is made between the optimal share and the participation decision. Thus it is unclear whether the age pattern stems from people exiting the market or lowering their share. Since they look at allocations in a 401k plan alone, all

Because they use administrative data, non-reporting and under-reporting of assets in the program is not a major issue. Using a variety of identifying assumptions to separate age, time and cohort effects and distinguishing between ownership of stocks and conditional shares, they conclude that a good characterization of the portfolio life cycle is one where the life-cycle of stock market participation is hump shaped and the conditional share in stocks shows little action over the life cycle. Thus, in their view, most of the life cycle portfolio changes take place on the extensive rather than on the intensive margin.

While their results mark a clear progress in the literature, a number of open issues related in part to the data remain. First, TIAA-CREF reports only assets contributed to the program, not the complete portfolios of these individuals. Furthermore, the part left out is not negligible - retirement assets amount to less than 30% of total household financial assets in the 1998 Survey of Consumer Finances (SCF) - and there is no obvious reason why the portfolio allocation in pension savings should be the same as the allocation in other financial assets or follow the same age profile (indeed it does not, see Guiso and Sodini, 2013). Second, the data refer to individuals and not to households. If the asset allocation is a joint family decision, this may result in biased estimates. Third, participants at TIAA-CREF belong to a selected group of the population - typically employees at institutions of higher education - which have markedly different characteristics compared to a representative population sample. Since the estimated portfolio life-cycle reflects the age pattern of portfolio-relevant household (or individual) variables, such as the age profile of human capital and of its riskiness, if these profiles differ across groups also the profiles of their portfolios will be different. Hence, they may not be a good characterization of the average investor in a population. Finally, dynamic portfolio patterns of pension assets from a defined contribution plan such as TIAA-CREF may be constrained by the rules of the plan, potentially resulting in less pronounced age patterns than in overall portfolios which reflect allocations of constraint-free financial wealth.

In this paper, we try to overcome these problems. We have assembled a new database drawing on administrative records from the Norwegian Tax Registry (NTR). Because Norwegian households are subject to a wealth tax, they have to report to the tax authority all their asset holdings, real and financial, item by item at the level of the single instrument as of the end of year. We have drawn a random sample of 20% (about 164,000) of the 1995 population of Norwegian households and then followed these households for 15 years up until 2009 - the latest year for which we could obtain the data. This dataset reports the complete portfolio of Norwegian people and is similar in structure and content to the one used by Calvet, Campbell, and Sodini (2007) but spans many more years - an essential feature when studying the life cycle profile of portfolio allocation. Being of administrative source, measurement error is minimized. The main cause of non-reporting or under-reporting should stem from incentives to evade the wealth tax, but the way the wealth tax is collected in Norway, as we argue in Section 2, suggests that tax evasion is unlikely to be an issue. Finally,

the issues raised about the Ameriks and Zeldes (2002) data extend to their data too.

since the whole population of Norwegian taxpayers has to report to the NTR, there is little attrition in the panel - apart from that due to death, migration to another country or divorce.

Taking into account the endogeneity of the participation decision and modelling cohort effects directly, we find that both participation in the stock market and the portfolio share in stocks show important life cycle patterns. As in other studies, we also find little assets decumulation after retirement and a hump-shaped life cycle profile in participation (besides limited stock market participation at all ages). But we also find that conditional shares decline significantly with investors' age. Specifically, the portfolio share in risky assets is high and fairly constant in the earlier and mid phases of the life cycle at a level just below 50%. As retirement comes into sight, households start rebalancing their risky asset share gradually but continuously at a pace of little less than one percentage point per year until they retire (around age 65). In retirement investors who remain in the stock market keep the share fairly flat at around 30%. On the other hand, participation in the stock market rises rapidly with age when young, reaching a value of around 60% at age 45 and stays roughly constant or slightly increasing until retirement. As soon as investors leave the labor market and retire, they start exiting the stock market as well.

Our data suggest a double adjustment as people age with a very specific timing: a rebalancing of the portfolio away from stocks *before* households reach retirement; exiting the stock market *after* retirement. Existing calibrated life cycle models can account for the first behaviour but not the second.[4] We show that extending the model of Cocco et al. (2005) to incorporate a (relatively large) per period participation cost generates substantial limited participation among the young but not enough exit after retirement. However, adding also a small probability of a large loss when investing in stocks (a "disaster" event) close to the frequency of large collapses in the Norwegian stock market over the past century, the model predicts a joint pattern and level of participation and the risky asset share over the life cycle similar to the one observed in the data, with early rebalancing of the share and pronounced exit from the risky asset market after retirement.

Numerical simulations reveal that a combination of small participation costs, small probability of a large loss and a relatively large risk aversion can explain well the shape and location of the life cycle profile of stock market participation and the risky asset share of the average household. Furthermore, when we estimate the parameters using an extended version of the model that also allows for a bequest motive to target simultaneously the age profile of participation, the portfolio share and the level of wealth, we match reasonably well the three profiles though the

[4]Some models have addressed the issue of limited participation among the young by allowing for a once and for all fixed cost of participation (Alan, 2006), or for long run co-integration between labor income and stock market returns (Benzoni et al., 2007) or for costly access to the loans market (Davis et al., 2006). None of these models, however, can deal with exit from the stock market as people retire. Hence they cannot explain the hump shape in participation over the life cycle and the timing of rebalancing in the optimal share and in participation that we observe in the data. In addition, these models tend to predict a far too high share in stocks among the stockholders at some point over the life cycle.

model still generates more financial wealth decumulation during retirement than we observe in the data.

The rest of the paper is organized as follows. Section 2 discusses the Norwegian registry data and presents descriptive evidence of the portfolio life cycle pattern. Section 3 lays down the methodology for estimating the life cycle portfolio profile and presents the estimation results. Section 4 shows how an extended calibrated life cycle model can account for the pattern of the portfolio that we observe in the data. Section 5 presents the properties of the model and the outcome of the model estimation. Section 6 summarizes our contribution and draws implications for future research.

2 Data

The empirical study of household portfolio allocations over the life cycle has formidable data requirements. Ideally, one needs data on households' complete portfolio holdings over a long time span, free of measurement and reporting errors. The NTR data that we use in our empirical analysis come very close to meet these requirements. Because households in Norway are subject to a wealth tax, they are required to report every year their complete wealth holdings to the tax authority. We merge this information with administrative records of individual demographic characteristics and information on earnings from the same source and obtain a unique panel data set spanning the years from 1995 to 2009.

2.1 The Norwegian administrative data

Each year, before taxes are filed in April, employers, banks, brokers, insurance companies and any other financial intermediary send both to the individual and to the tax authority, information on the value of the asset owned by the individual and administered by the employer or the intermediary, as well as information on the income earned on these assets. In case an individual holds no stocks, the tax authority pre-fills a tax form and sends it to the individual for approval; if the individual does not respond, the tax authority considers the information gathered as approved. In 2009, as many as 2 million people in Norway (60% of the tax payers) belonged to this category.[5] If the individual owns stocks then he has to fill in the tax statement - including calculations of capital gains/losses and deduction claims. The statement is sent back to the tax authority which, as in the previous case receives all the basic information from employers and intermediaries and can thus check its truthfulness and correctness.[6] Stockholders are treated differently because the government wants to save on the time necessary to fill in more complex tax statements and to reduce the risk of litigation due to miscalculated deductions on

[5]See Norwegian Tax Administration annual report:
`http://www.skatteetaten.no/Upload/annual-report-2009.pdf`

[6]Internet brokers offer to their costumers calculations of realized returns over the previous year for free.

capital losses and taxes on capital gains.[7] This procedure, particularly the fact that financial institutions supply information on their customer's financial assets directly to the tax authority, makes tax evasion very difficult, and thus non-reporting or under-reporting of assets holdings very likely to be negligible.[8]

Tax statements on both labor income in the previous year and asset holdings, as of December 31 of the previous year, are filed separately by each taxpayer in the population even for married couples. Besides information on assets, the administrative data contains information on demographic characteristics of all individuals as well as an identifier for the family they belong to. Thus, we can aggregate assets at the household level. For our purposes, we define a household as a married couple (or a cohabiting couple possibly with children) and identify its age (and other characteristics such as education) with that of the husband. The term "cohort" refers to the year of birth of the husband. In order to extract a large but still computationally manageable sample, we first retain all households defined as above with both spouses alive as of 1995 and with at least 3,000 NOK of financial assets (480 USD at 1995 prices). We then randomly sample 20 percent of them obtaining an initial reference sample of 164,015 households which we follow over the subsequent 15 years until 2009. Households who exit the sample because individuals die, or migrate or divorce are not replaced. Overall, the sample contains 1,804,115 household-year observations.[9]

We focus on the financial portfolio and distinguish between bank deposits, treasuries and bonds, stocks (of listed and non-listed companies), mutual funds and money market funds.[10] Following the literature, we consider a two asset-portfolio and define risky financial assets as the sum of mutual funds with a stock component and directly held stocks; the rest - the sum of bank deposits, money market funds and bonds - is classified as risk-free assets. Financial assets are the total of these categories.[11]

Table 1 provides summary statistics for the whole household sample in 1995. Household average age is 51 years. High school diploma is the most common ed-

[7] Since year 2000 all this is done electronically; prior to 2000 tax reports were done on paper forms.

[8] The only exception is if households own and do not report foreign investments. Calvet et al. (2007) discuss this issue for Sweden and conclude that unreported foreign investments represent a modest fraction of households' assets - except perhaps for the very wealthy.

[9] The quality of this data is similar to that in the Swedish data studied by Calvet et al. (2007). Until 2007, Sweden like Norway collected taxes on both individual income and wealth. In 2007, however, Sweden abandoned the wealth tax, leaving Norway as the only Scandinavian country with this arrangement.

[10] Very few households (67 observations in the whole sample) hold more sophisticated instruments such as futures and options. We exclude them from the sample.

[11] Private old age pensions were not widespread in Norway during our observation window. All Norwegian citizens are entitled to a state pension from the age of 67 in accordance with the National Insurance Act. The financing of this system is through a Pay-as-you-go system, but it is currently undergoing reforms and evolving towards a defined contribution system to be fully implemented by 2025. Furthermore, early retirement schemes are widespread in Norway and workers may be eligible for these from the age of 62, see e.g. Vestad (2013). Pension benefits are indexed to the average wage growth of the economy.

Table 1: Descriptive Statistics, 1995

	Full Sample				Balanced Panel Sample			
	Obs	Mean	Std Dev	Median	Obs	Mean	Std Dev	Median
Demographics:								
Age Husband	164,015	50.88	14.14	49	106,369	47.67	11.64	47
Age Wife	164,015	48.12	14.01	47	106,369	45.00	11.40	45
Share Less High School Education	164,015	0.22			106,369	0.18		
Share High School Education	164,015	0.53			106,369	0.55		
Share College Education	164,015	0.24			106,369	0.27		
Household Size	164,015	3.24	1.19	3	106,369	3.44	1.17	3
Asset Holdings in USD:								
Financial Wealth	164,015	38,270	106,975	11,884	106,369	38,169	111,865	11,348
Stocks	164,015	12,797	91,438	0	106,369	14,386	97,230	0
Mutual Funds	164,015	1,173	3,895	0	106,369	1,245	3,989	0
Safe Assets	164,015	24,297	37,678	9,734	106,369	22,536	35,575	9,139
Net worth	164,015	120,354	143,051	97,543	106,369	116,213	142,199	93,318
Participant share:								
Risky Assets	164,015	0.33	0.47	0	106,369	0.35	0.48	0
Stocks	164,015	0.23	0.42	0	106,369	0.25	0.43	0
Mutual Funds	164,015	0.22	0.41	0	106,369	0.23	0.42	0
Mean share participants:								
Risky Assets	54,519	0.32	0.30	0.20	37,770	0.33	0.31	0.22
Stocks	54,519	0.23	0.31	0.05	37,770	0.24	0.32	0.06
Mutual Funds	54,519	0.09	0.15	0.03	37,770	0.09	0.15	0.04
Attrition:	58,863							
Share Death		0.62						
Share Migration		0.13						
Share Divorce/Separation		0.25						
Mean yearly attrition rate:		0.03	0.00					
Age at Exit		62.63	16.83					

Note: This table displays summary statistics for the main sample of married households in the first year of observation, 1995. In addition, the table provides summary statistics for the sample of households that remain in the panel throughout, until 2009. Where applicable, values are reported in 1995 USD. Education is missing for less than one percent of the sample.

ucational level, which is attained by 53% of the sample, while 26% hold a college degree. The average Norwegian household holds around 38,000 USD (1995 prices) in financial assets. Net worth, the sum of financial assets and real estate net of debt, amounts to 120,000 USD, of which about 2/3 is real estate.[12] The financial portfolio of the average household is mostly composed of safe assets which account for 63% of average financial assets. We define a participant in the risky financial assets market to be a household with at least 160 USD (1995 prices) of risky assets. The participation rate in risky asset markets amounts to 33% (37% if we include all those with positive risky assets), reflecting 23% of the population holding stocks directly and 22% percent participating via mutual funds. Thus, back in 1995 mutual funds were not as widespread as direct stock-holding among Norwegian households. Among participants, the average portfolio share in risky assets is 32% while mutual funds account for 9%; a similar figure for the total share prevails in other European countries, as documented in Haliassos et al. (2001). Needless to say, over our sample period, asset markets worldwide and in Norway experienced both booms and busts and the mutual fund industry expanded significantly making it easier for many households to participate in the risky asset market, e.g. by lowering participation costs, offering more diversified investments and spreading information about mutual fund investments.

Although there is attrition in the sample at an average annual rate of 3%, we can track 2/3 of the households sampled in 1995 all the way until 2009. The main reason for exiting the sample is death of one spouse (62%), which is consistent with the high average age at exit (63 years, see bottom of Table 1). To get a sense of the importance of attrition for the composition of the sample, the right part of Table 1 displays summary statistics in 1995 for the balanced sample - households that are present continuously from 1995 to 2009. Balanced panel households are not surprisingly younger in 1995 and slightly better educated. However, the value of asset holdings, portfolio allocation and risky asset market participation are similar across the two groups suggesting that attrition is fairly random.

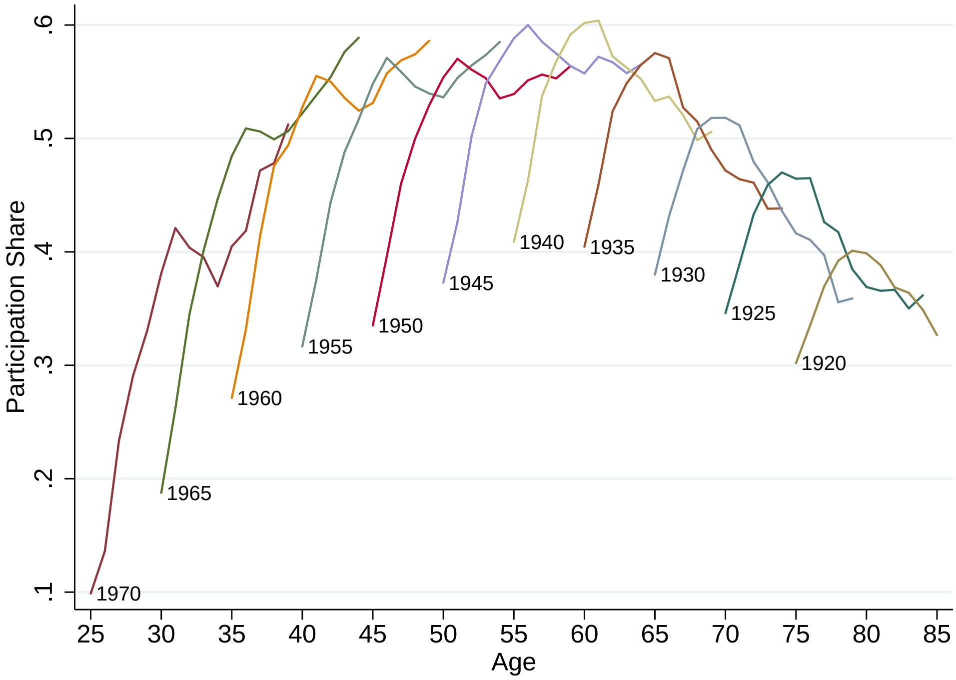
2.2 Portfolio life cycle patterns by cohort: descriptive evidence

Figure 1 plots the age participation profile in the risky assets market for selected cohorts spaced by 5-year intervals, beginning with the cohort born in 1970, aged 25 in 1995, the first sample year. Since we are able to follow each cohort for 15 years, just plotting the raw data provides a good picture of the life cycle portfolio pattern.

Consider the first cohort born in 1970 whose members are 25 years old in 1995; only slightly more than 10% of them were participating in risky asset markets in 1995. However, subsequently the share of participants in this cohort increases sub-

[12]The value of real estate is a proxy based on the reported tax values of Norwegian households, and is not updated every year. To obtain our estimate, we divide the reported tax value of real estate by 0.25. This follows the guidelines of the Norwegian Tax Authorities, which state that the tax value of real estate shall not exceed 30% of its market value.

Figure 1: Participation shares in risky asset markets



Note: This figure plots the mean participation rates in risky asset markets at observed age for selected cohorts over the period 1995-2009.

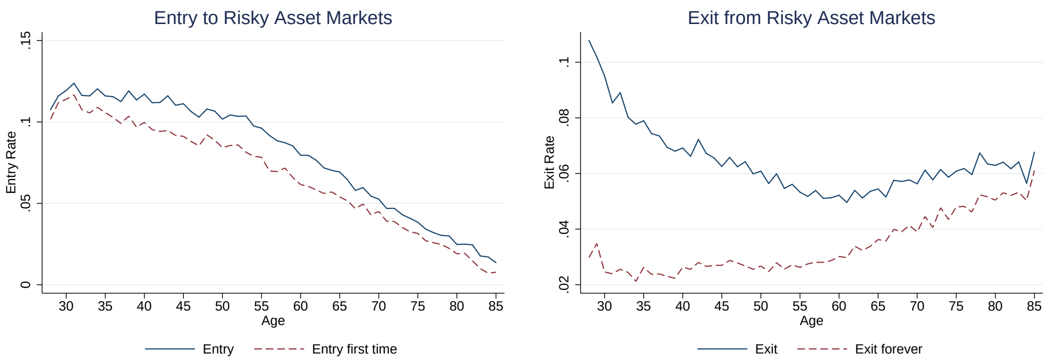
stantially, and five years later when this cohort ages 30, almost 50% of the households own risky financial assets. Clearly, this pattern is consistent with a marked age effect (an increase in participation with age), with strong time effects (an increase in participation due to favourable improvements in market conditions, e.g. the boom of the mutual funds industry), as well as with a cohort-specific pattern. If this were the only cohort observed, these effects would be hard to disentangle as time and age evolve in parallel and we only observe one cohort. We could not make any claim on whether the increase in participation rate is cohort-specific, a pure age effect, or it reflects a common time trend that affects all cohorts in the years 1995-2009.

The next plotted cohort - households born in 1965 - reveals a steep increase in average participation during the first years of our sample also for these households. This suggests that the increase in participation over age/time is unlikely to be cohort specific. But it is still unclear whether it is due to an age-effect, or to a common time trend. Comparing the evolution of participation across cohorts suggests that time effects are likely to be important; for instance, all cohorts experience a marked increase in participation during the first years of our sample, even those born in 1920 - who are 75 in 1995 - and thus typically exit the risky asset market. And a drop during the 2001 recession even among those born in the 1960's and 1970's who are typically entering the stock market. This graphical evidence also suggests that cohort effects are likely to play an important role. In fact, compared to younger

Table 2: Definitions of stock market entry and exit

Measure 1:	
Entry:	The fraction of households who do not hold stocks at age *a* that enter the risky asset markets at *a+1*.
Exit:	The fraction of those who are stockholders at age *a* who exit the market at age *a+1*.
Measure 2:	
Entry:	The fraction of households who **has never held any stocks** up until the age *a* that enter the risky asset markets at *a+1*.
Exit:	The fraction of those who are stockholders at age *a* who exit the market at age *a+1* and **never re-enters** the stock market.

Figure 2: Entry and exit rates to/from risky asset markets



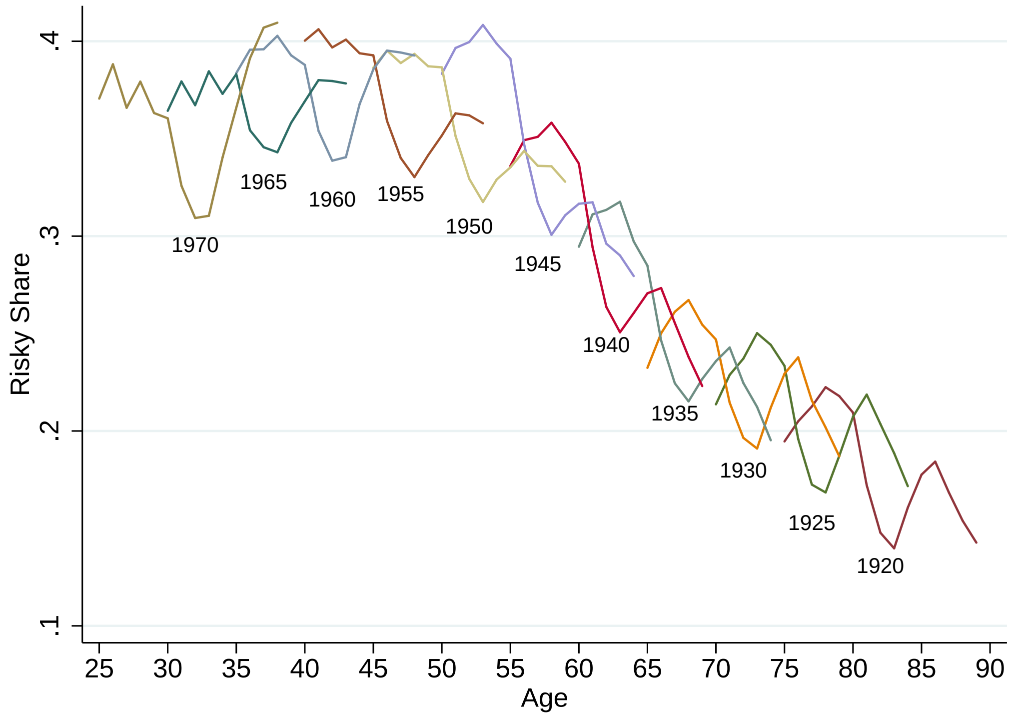
Note: These figures plot entry and exit rates into risky asset markets. The left panel depicts entry and exit frequencies, allowing for re-entry/exits, whereas the right panel documents frequencies of first time entry and once and for all exits.

cohorts, older cohorts at the same age, have lower participation rates. In Section 3, we describe our empirical strategy to separate age and time effects and test for the presence of cohort effects.

As a next step in the descriptive analysis of the life cycle patterns of participation, we consider two measures of entry into and exit from the stock market, as defined in Table 2. These two measures are plotted in Figure 2 for the same selected cohorts. The first measure refers to entry (exit) in a given year, regardless of the household's past (future) participation pattern. The second, reports entry (exit) that was not preceded (followed) by a previous entry (a subsequent exit). The second measure captures first-time entry and permanent exit.

First-time entry is very high at the beginning of the life cycle, with a peak at 13%, and drops steadily thereafter. It is lower than total entry particularly for middle aged households. Instead permanent exit is low at the beginning of the life

Figure 3: Risky share of financial wealth by cohort



Note: This figure plots the average risky shares of households' financial portfolios conditional on participation, for selected cohorts at each age they are observed.

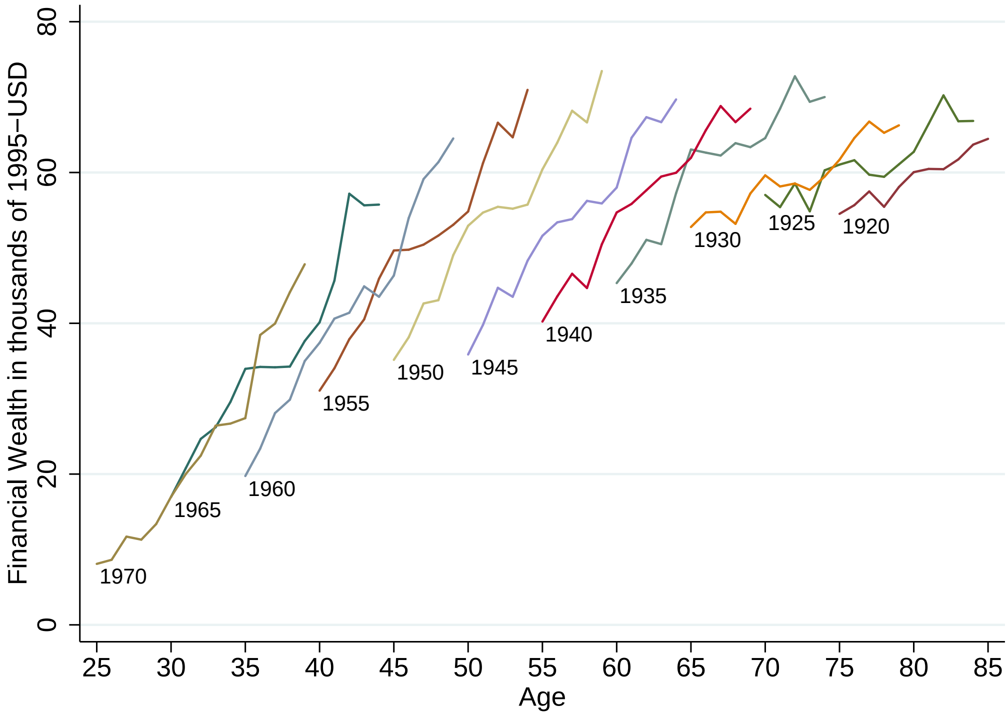
cycle and increases sharply after retirement.[13] By comparing the two measures, Figure 2 highlights that early in life temporary entry and exit are very common phenomena. Among households in their early 30's, 13% enter the stock market and most of them enter for the first time. On the other hand, the fraction of young households that sells all risky financial assets to return to the stock market later in life is almost five times the fraction of households that exit permanently. The existence of intermittent participation suggests a role for per period participation cost and it will be interesting to see whether our extended model that allows for this type of costs can reproduce the observed pattern of entry and exit.[14]

Figure 3 plots the risky financial share among households who participate in the stock market for the same cohorts as in Figure 1. We refer to it as the conditional share. Looking at the overall age pattern the picture suggests that once people enter, they invest a relatively large share in risky assets, hold it fairly constant over the early part of the life cycle and reduce it as they age. A comparison

[13]Because of the limited time span of our data, the second measure of entry and exit may be affected by censoring. Censoring should bias upward both the first time entry rate measure at young age, and the permanent exit rate measure at old age.

[14]The higher variability at the two ends of the age range both in Figure 2 and in Figure 3 reflects the fact that at the two ends of the age distributions there is limited number of observations.

Figure 4: Financial wealth by cohort



Note: This figure plots the average financial wealth for selected cohorts at each age they are observed. Values are in 1995 USD, and the wealth profiles are corrected for mortality, following Attanasio and Hoynes (2000), as outlined in Section 3.

across cohorts suggests less pronounced cohort effects than those that seem to characterize the participation profile. On the other hand, the pattern of the conditional share over time across cohorts reveals strong time effects, reflecting movements in stock prices that are only partially undone by active rebalancing, as suggested by Calvet, Campbell, and Sodini (2009). Instead, the raw data for the risky share suggest that there is substantial rebalancing over the life cycle, in particular as households approach retirement.

To complete the description, Figure 4 shows the profile of the households financial wealth for the same cohorts as in Figure 3. To account for the bias induced by the well known correlation between wealth and mortality we have adjusted the value of households assets using the methodology in Attanasio and Hoynes (2000).[15]

[15]Following Attanasio and Hoynes (2000), we define the death of either husband or wife as the death of the household. Further, we split our sample in each year and age group (using the age of the husband) by wealth percentile. Using observations across years we then estimate the probability of survival with a logit model as a function of the wealth percentile and age with interactions up to the 3rd polynomial. We allow the polynomials to differ with age by inserting 4 splines in wealth and we control for household education. We use the regression estimates to calculate the survival probability from one year to the next. We repeat this procedure for all the years of our sample,

This adjustment is necessary also to make the life cycle wealth profile of the data comparable to that generated by the model that we propose in Section 3 - as no relationship between mortality and wealth exists in the model. The plotted profile suggests that for young cohorts financial assets are sharply increasing with age and time; furthermore, younger cohorts tend to be wealthier than older ones. The figure also suggests only a mild (if any) decumulation of financial wealth in old age. In Section 3 we estimate the age wealth profile accounting for cohort and time affects.

3 Estimation

The descriptive evidence suggests the existence of marked life cycle patterns for both the participation decision and the risky share of household's portfolio conditional on participation as well as for financial assets. However, it does not deal with two key issues: the endogeneity of participation in risky assets and the separation of time, age and cohort effects. In this section, we discuss how we address these issues in order to pin down the age profile of participation in the market for risky assets, of the risky assets portfolio share for the participants and that of the level of financial assets.

3.1 Methodology: limited asset market participation

It is well established that not all households participate in risky asset markets. Empirical studies of the life cycle profile of household portfolios has, so far, neglected the endogeneity of participation when estimating the life cycle profile of the portfolio share (Ameriks and Zeldes, 2002). This is unfortunate because unaccounted selection can bias the relation between the optimal share and age, for instance hiding it. Also calibrated life cycle models have, until recently, ignored limited participation in risky asset markets by abstracting from participation costs. Later, we will remedy this deficiency by introducing a per period participation cost in a standard life cycle portfolio model that already allows for several other realistic features.

Empirically, we deal with the joint decision of whether to participate and how much financial wealth to allocate in risky assets using a Heckman selection model. To do so, we estimate a probit model for the household participation in the risky assets market and a share equation for the participants accounting for selection. To achieve identification, we let the participation decision to be affected by (the lagged value of) the overall lifetime wealth of the individual, obtained summing accumulated assets and an estimate of the individual stock of human wealth (see the Appendix in Section A.1.2 for details about the estimation of human wealth), and impose that lifetime wealth does not affect the financial portfolio share conditional

and compute the cumulative survival probabilities for each household. Finally, we use the inverse of these probabilities to weigh the observations of our wealth regression. The relationship between survival and wealth is strongly positive in the data; hence, the wealth of poorer households that survive until old age will be weighted up. These weighted observations are plotted by cohort in Figure 4.

on participation. This exclusion restriction is inspired by Merton (1971) whose model implies that in the presence of labor income, risky assets holdings as a share of total lifetime wealth is constant over the life cycle and thus independent of lifetime wealth. The financial portfolio share in risky assets depends on the *ratio* of human to financial wealth which evolves over the life cycle but not on the *level* of lifetime wealth. Hence, controlling for age to account for the life cycle of human to financial wealth, the share should be unaffected by total lifetime resources.[16] We impose this restriction.[17] Of course, with a fixed participation cost the decision to participate will depend on the level of individual wealth (Vissing-Jorgensen, 2002).

3.2 Methodology: treatment of cohort effects

Even though we observe households' investments and wealth over a substantial portion of their life span, it is well known that it is not possible, without additional restrictions, to identify cohort, time and age effects. This issue is extensively discussed in Ameriks and Zeldes (2002) in the context of estimates of the life cycle profile of portfolio choice. In fact, calendar time, age and year of birth are linearly related. Since at the heart of the identification problem is the linear relationship "calendar year"="age" + "year of birth", most solutions have proceeded by making

[16]Let $s(a)$ denote the share of financial wealth ($W(a)$) invested in risky assets by an individual aged a and $H(a)$ his stock of human capital. In Merton (1971) the share of risky assets as a fraction of lifetime wealth $W(a)+H(a)$ is
$\frac{s(a)W(a)}{W(a)+H(a)} = \frac{r_p}{\gamma\sigma_r^2}$
where r_p denotes the equity premium, σ_r^2 the variance of stock returns and γ the investor relative risk aversion. This share is constant over age; on the other hand, $s(a) = \frac{r_p}{\gamma\sigma_r^2}(1+\frac{H(a)}{W(a)})$ varies over the life cycle because the ratio of human capital to financial wealth $\frac{H(a)}{W(a)}$ varies with age. Thus, capturing $\frac{H(a)}{W(a)}$ with a set of age dummies, $s(a)$ is unaffected by the level of human wealth or that of financial wealth.

[17]The restriction holds true in the context of the Merton (1971) model; whether it is still true once one relaxes the assumptions on which it builds, in particular the complete markets assumption, is hard to tell because there is no closed form solution to the model. One may think that with uninsurable income risk, presumably investors with more cash on hand can stand background risk more easily, suggesting that cash on hand can reduce the effect of background risk on the risky portfolio share, which would invalidate the exclusion restriction. To check how important this may be, we have used the simulated data generated by the model in Section 4 and run regressions of the portfolio share on a full set of time dummies and cash on hand accounting for endogenous participation. We find that cash on hand has a positive and strong effect on participation (one standard deviation increase in cash on hand increases the probability of participation in the stock market by 10 percentage points - about 25% the mean participation rate. On the other hand it has a negative but very small effect on the share. A one standard deviation increase in cash on hand lowers the risky share by 1.6 percentage points. Since its mean is around 40%, this is a tiny effect. Thus, though the exclusion restriction does not hold literally, it seems to hold approximately. An alternative exclusion restriction that is implied by the theory would be to use information on per period participation costs in the probit regression. Finding valid measures of individual participation costs is very difficult and we have not, so far, been able to come up with a convincing one. Thus, rather then trying unconvincing proxies for participation costs, we have preferred to impose an identifying restriction that simulations suggest is, economically speaking, not far from what literal validity requires.

assumptions or using prior information so as to break this multicollinearity, allowing the use of standard regression techniques. One strategy that has been followed is to re-specify the model to make it non-linear or to estimate it in first differences; another is to impose parametric restrictions; a third to replace the dummies that capture one of the effects with variables meant to capture a causal mechanism for that effect.[18] Here we rely on both the second (impose parametric restrictions) and the third strategy (model cohort effects explicitly) to identify the age profile of the portfolio and the third to identify the age wealth profile.

As for the parametric restrictions, we rely on Deaton and Paxson (1994) and impose that time effects sum to zero once the variables have been de-trended. Since our data cover several years, we should be able to separate trend and cycle, and thus be reasonably confident about the decomposition of age, time and cohort effect based on this restriction (Deaton, 1997).

To implement the other strategy to identify the age profile of participation and share in risky assets, we build on recent research by Giuliano and Spilimbergo (2014), which indicates that generations who grew up in recessions have systematically different socio-economic beliefs compared to generations who grew up in booms - suggesting important year of birth effects on beliefs and preferences. Even closer to the spirit of our approach is the study by Malmendier and Nagel (2011), who show that households with experience of higher stock market returns early in life are more likely to participate in the stock market and, conditional on participation, invest a higher fraction of their wealth in risky assets. Furthermore, when asked, they report a higher willingness to bear risk, possibly because early experiences have enduring effects on risk preferences. This evidence suggests that one can rely on variation in experienced stock market returns among members of our sample to model cohort effects. Accordingly, we will use stock market returns (a weighted average of the Oslo Stock Exchange (OSE) and the MSCI World Index) experienced during the household heads' youth (between ages 18 and 25, as in Giuliano and Spilimbergo, 2014) as our proxy for cohort effects.[19] As we will show, these returns significantly affect the decision to enter the risky assets market and to a lesser extent the conditional risky share. Thereby we can identify unrestricted time and age effects.

To pin down the age wealth profile, we follow Kapteyn, Alessie, and Lusardi (2005) and Jappelli (1999) and use a measure of the general macroeconomic conditions at the time an individual entered the labor market as proxies for cohort effects and allow for unrestricted time effects. Long-term effects on individuals careers of the macroeconomic condition faced by an individual at time of entering the labor

[18]The use of one or another strategy is context specific and the choice depends on what assumption appears reasonable in the given context. Some recent papers propose generic, contest-independent solutions. One is suggested by Yang, Fu, and Land (2004) and Yang, Schulhofer-Wohl, Fu, and Land (2008) who propose what they call the intrinsic estimator. Another is introduced by Browning, Crawford, and Knoef (2012) who show that when the range of the variable(s) of interest is bounded, the time, age and cohort effects are partially identified in the sense they are confined to a closed convex set. They then propose using a maximum entropy estimator to achieve point identification within that set.

[19]See Appendix A.2 for more details on the weights.

market have been recently documented both for the US (Oreopoulos, von Wachter, and Heisz, 2012) and for Norway (Liu, Salvanes, and Sørensen, 2012).

3.3 Model specification

We specify the following two equation model for the share of financial wealth invested in stocks conditional on participation, s_{iact}, and for the decision to participate P_{iact} by household i, aged a, belonging to cohort c in year t:

$$s_{iact} = \beta_a A_a + \beta_c C_c + \beta_t D_t + \beta_0 Trend + \theta Z_{iact} + \theta_2 \lambda_{iact} + \varepsilon_{iact} \quad (1)$$

$$\begin{aligned} prob(P_{iact} = 1|x) &= prob(P^{\star}_{iact} > 0|x) \\ &= prob(\delta_a A_a + \delta_c C_c + \delta_t D_t + \delta_0 Trend + \vartheta Z_{iact} + \vartheta_2 L_{iact} + \eta_{iact} > 0) \end{aligned}$$

where P_{iact} is a dummy variable taking value 1 for households with positive risky assets and zero otherwise, P^{*}_{iact} is the unobserved latent variable triggering participation when positive, A_a, C_c and D_t denote dummies for age, cohort and time, $Trend$ is a time trend, Z_{iact} a vector of individual controls (family demographics and a home ownership dummy to account for interactions between portfolio composition and housing (Cocco, 2005)), λ_{iact} the inverse Mills ratio computed from the participation equation and L_{iact} an estimate of lifetime wealth; ε_{iact} and η_{iact} are error terms.

When we use the Deaton and Paxson (1994) method to tell age, time and cohort effects apart, we also impose the restriction $\sum \beta_t = \sum \delta_t = 0$; when we model cohort effects as a function of experienced stock market returns (R_c), we replace C_c with R_c, and set $\beta_0 = \delta_0 = 0$. Assuming η_{iact} is normally distributed, we estimate the above model using a two stage Heckman estimator.

As for the financial wealth profile we estimate the model

$$w_{iact} = \gamma_a A_a + \gamma G_c + \gamma_t D_t + +\psi Z_{iact} + \nu_{iact} \quad (2)$$

where w_{iact} is the value of the financial assets of household household i, aged a, belonging to cohort c in year t, G_c is a measure of the macroeconomic conditions faced by cohort c when it entered the labor market, and the other variables have the same meaning as before.

3.4 Results from estimating life cycle patterns

3.4.1 Risky asset market participation and conditional share

Table 3 reports the estimates of the Heckman selection model. Age and time effects as well as the coefficients of the other controls are, for brevity, not reported. The first two columns show the estimates using the Deaton and Paxson (1994) restriction. In the participation equation (first column) the time trend is positive, significant and economically important; it implies that in the final year of the sample the average participation rate is 18 percentage point higher than at the beginning of the sample. The trend is negative and statistically significant but economically small in the conditional share estimate. Unrestricted cohort effects are significant both for the participation decision and for the risky asset share, but particularly for the former (see the χ^2 test at the bottom of the table). Interestingly, the probability that the household participates in the market for risky assets is strongly affected by the level of lifetime wealth, which suggests that the identifying strategy is, as expected, both consistent with the presence of fixed participation costs and powerful. In addition, the significance of the Mills ratio suggests the importance of adjusting for selection to obtain consistent estimates of the age profile of the conditional share.

Columns 3 and 4 show the estimates obtained by modelling cohort effects explicitly. Cohort effects captured by stock market returns experienced in youth have a positive and significant effect on the participation decision but not on the share of financial wealth invested in risky assets among the participants. Economically, investors who grow up in years of low stock market returns (5th percentile of the historical return distribution) are 6.12 percentage points less likely to own risky assets compared to investors exposed in youth to high stock market returns (95th percentile of the historical return distribution). The effect of lifetime wealth on participation and of the Mills ratio on the conditional share is essentially the same as when imposing the Deaton and Paxson (1994) restriction.

The age profiles for participation and the portfolio share obtained from the estimated Heckman model using the these two strategies are plotted in the two panels of Figure 5.[20] Independently of the method used to separate age from time and cohort effects, the figures document a distinct hump-shaped age pattern of asset market participation over the life cycle. Among younger households, the participation rate (right scale) increases steadily until the age of approximately 40, and then much more gradually, peaking when households are in their 60's, just prior to retirement. At peak the participation rate is around 60%. From then on participation in the risky asset market drops almost linearly until the age of 80. The age pattern of the conditional risky share is remarkably different. The share starts high at very young age and remains relatively constant for about a decade; from then on individuals rebalance the share in risky assets first gradually and then somewhat faster until retirement (around age 65), when the risky share stabilizes. During the transition, the share is reduced at a speed of around half of a percentage point a year (if the cohort proxy is used or 2/3 of a percentage point using the Deaton and Paxson (1994) restriction), half of the speed of adjustment that is typically recommended by practitioners.

The most interesting feature of the two profiles is the timing of the portfolio adjustment along the two margins - the intensive margin of the share invested in risky financial assets and the extensive margin of participation in risky assets. Our

[20]Obviously, since the value of lifetime wealth depends on age it contributes to confer a lifetime profile to the participation rate, in addition to the effect that the age dummies have on it. Figure 5 reflects this.

estimates show that consistent with life cycle portfolio models with labor income, households do limit exposure to the stock market by rebalancing their financial portfolio as they approach retirement and the stock of human capital falls. But they adjust also along the other margin, by leaving the stock market altogether as they age. However, this adjustment starts to take place only after the household retires, exactly when the adjustment along the intensive margin stops. The pattern and the timing of this double adjustment that we document empirically is the focus of the life cycle portfolio model developed in Section 4.

When we contrast the life cycle profiles of the share and participation estimated applying the two methods, we see that they deliver very similar participation profiles. However, the Deaton and Paxson (1994) method predicts a significantly higher conditional particularly among the young.

Since the age profiles of human capital differ in level and shape according to education (see Appendix A.1.2), these differences may result in different portfolio share and participation profiles though their main qualitative features should be preserved since human wealth declines with age independently of education. As a robustness check, we have estimated the model presented in Section 3.3 separately for three education groups imposing the Deaton and Paxson (1994) restriction (results are similar using the other method). More educated households tend to participate more and to invest larger shares in risky assets conditional on participation. However, the age profile of the share and participation preserve the dual adjustment pattern that we have documented for the whole sample, with the conditional share being relatively flat in the middle ages and then declining until retirement and the participation profile being hump shaped with exit from the stock market beginning only after households have already adjusted the share and are close to retire or just retired.

Finally, we apply the same methodology to separate age from year and cohort effects in the entry and exit patterns shown in Figure 2. We regress the two different measures of entry in and exit from the risky asset market on age dummies, cohort dummies and calendar year fixed effects imposing the Deaton-Paxson restriction discussed in 3.2. The estimated profiles are reported in Figure 6. Interestingly, once we account for cohort and time effects, the entry age profiles are hump shaped with a peak around age 40 while the exit age profiles are somewhat U-shaped.

3.4.2 Financial wealth profile

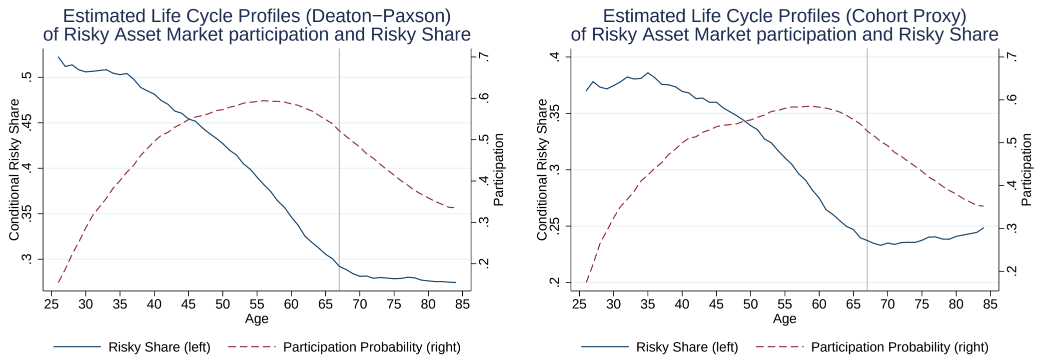
Obtaining the complete picture of the life cycle portfolio choice of households also involves estimating the wealth profiles of the households. We estimate the life cycle portfolio of household financial wealth, while controlling for the real estate wealth. Our left hand side is the level of financial wealth multiplied by the inverse of the estimated survival probabilities, in order to clean for the bias induced by the well known correlation between wealth and mortality (Shorrocks, 1975). We model cohort effects with the macroeconomic conditions faced by the cohort when entering the labor market measured by the deviation from trend of GDP per capita at the ages between 15 and 30 for each cohort. Similarly to Kapteyn et al. (2005) and

Table 3: Heckman selection model

	Deaton-Paxson		Cohort Proxy	
	Participation	Share	Participation	Share
Trend	0.012***	-0.003***		
	(0.001)	(0.001)		
Youth Stock Return			0.361***	-0.070
			(0.017)	(0.080)
Lag Total Wealth	4.107***		4.186***	
	(0.148)		(0.030)	
λ_{iact}		-0.186***		-0.186***
		(0.001)		(0,001)
Observations	1,804,115	886,189	1,804,115	886,189
Joint sign. tests				
Year χ^2 (12)	1575.79***	882.70***		
Cohort χ^2 (59)	7644.51***	19.17***		

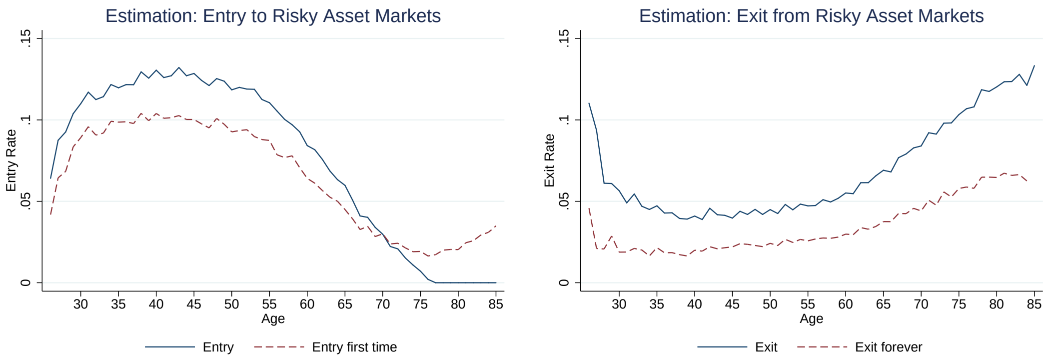
Note: This table displays the two estimated Heckman selection models (discussed in section 3.2) for asset market participation and the conditional risky share. Lagged total wealth is the sum of financial and Human Wealth (in 100.000 of 1995 USD), and λ is the inverse Mills ratio / non-selection hazard. Coefficients in the selection equation are calculated marginal effects of the underlying probit-regression. For presentational purposes, calendar year fixed effects and family size coefficients are not reported here, age coefficients and marginal effects are displayed in Figure 5. Standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Figure 5: Estimation: risky asset market participation & risky share



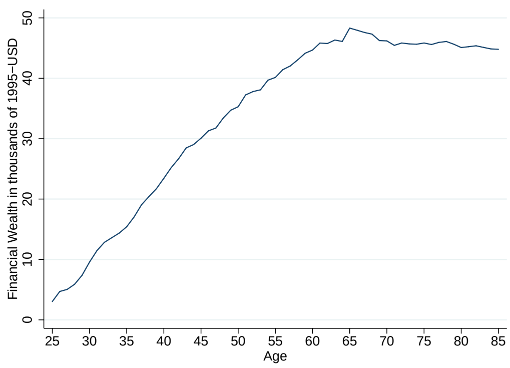
Note: The left panel of the figure plots the life cycle patterns for both the risky asset market participation and the conditional risky share of financial wealth coming from the Heckman selection equation applying the Deaton and Paxson (1994) methodology reported in columns 1 and 2 in Table 3. The right panel applying the cohort-proxy methodology reported in Table 3, columns 3 and 4. For the Selection/Participation Equation, we plot the marginal values of the estimated underlying probit equation, and for the risky share, the age coefficients of the outcome equation in the Heckman model.

Figure 6: Life cycle patterns of entry and exit from risky asset markets



Note: These figures plot the estimated life cycle patterns of entry to and exit from risky asset markets, defined by two different measures in Table 2 imposing the Deaton-Paxson restriction of zero-sum time effects (see Section 3.2).

Figure 7: Life cycle pattern of financial wealth



Note: This figure plots the estimated life cycle pattern of financial wealth, when correcting for differences in mortality, following Attanasio and Hoynes (2000), and proxying for cohort effects with deviations from trend GDP-per-capita at early ages (Kapteyn et al., 2005; Jappelli, 1999). Values are in 1995 USD.

Jappelli (1999) we also find that these cohort effects are significant and economically important for the wealth levels of the household later in life. The estimated life cycle profile of the financial wealth is shown in Figure 7. It is steeply increasing earlier in life and, as typical in this literature (e.g. Kapteyn et al., 2005; Jappelli, 1999), it shows only mild asset decumulation after retirement, a well documented empirical fact (e.g. Bernheim (1987)). In the model below we try to capture this feature by allowing for survival risk as well as for a bequest motive.

4 Model

The previous sections have established novel stylized facts about the life cycle profile of Norwegian households' asset market participation and portfolio composition. Existing calibrated life cycle models can account for the rebalancing of the risky share away from stocks over the life cycle, but not for the joint patterns of adjustment of the share and the participation in the risky assets market. In this section, we present a life cycle model that can account for the broad features of the life cycle profile of portfolio allocations along both margins and in one version also for the wealth accumulation profile.

To facilitate comparisons with the literature, we use the workhorse portfolio choice model of Cocco et al. (2005) but add two features. First, we allow for a fixed per-period stock market participation cost; this provides a motive for exiting the stock market as people age besides inducing limited participation in the stock market at early ages.[21] Second, we allow for a probability of a negative tail event when investing in stocks, a "disaster" event.[22] There are two well established ways in the literature to interpret this tail event. One interpretation is that stocks are (more than other financial instruments) subject to frauds and investors receive less than full legal protection giving rise to limited trust as in Guiso, Sapienza, and Zingales (2008). An alternative interpretation, pursued by Barro (2006) and Rietz (1988) argues that households anticipate rare but big losses due stock market crashes - that is they attach a small positive probability to disasters that entail large stock market losses. We will stick to this interpretation and support it by showing that, based on past stock market history, Norwegian households have good reason to attach a small probability to large stock market losses whose distribution across households

[21] Some exit from the stock market after retirement may occur even without a per period participation cost if households liquidate stocks in bulk to finance durable consumption purchases or to face unusual lumpy expenses e.g. for health care (Alan, 2006). In general, however, absent participation costs, one should see a decumulation of both stocks and bonds and very little exit.

[22] Alan (2012) also studies the life cycle portfolio allocation allowing for participation costs and a disaster probability and estimates it structurally on US data, using pseudo panel data constructed using various cross sections of the US Survey of Consumer Finances. She finds that the model fits the data poorly. As she notices when compares the simulated profile and that in the data, "What is particularly disturbing in this figure is that the model persistently generates a hump shape for shares and participation that does not exist in the data." However, it may be that it is not the model that needs to be amended but rather the data that are unable, due to the shortcomings of survey data discussed in the introduction, to reveal the true life cycle portfolio pattern.

we calibrate on observed individual losses during the 2008 crash.[23] As we will see, the tail event is key for the model to generate enough exit from the stock market after retirement as well as to help addressing the "too" high conditional shares in risky assets at young and middle ages that a workhorse portfolio choice model typically generates.[24] We proceed with the description of the model.

4.1 Households

In the model economy, households work from age T^b until age T^r, after which households retire. Households face uncertainty in the number of years they live (T). We model this component as in Hubbard, Skinner, and Zeldes (1995) and denote p_a the probability that the household is still alive at age $a+1$ conditional on being alive at a. Households' objective function is the sum of discounted life time utility:

$$E \sum_{a=T^b}^{T} \underbrace{\delta^a (\prod_{j=0}^{a-2} p_j)}_{\beta_a} U(c_{i,a}) \tag{3}$$

where $c_{i,a}$ is the consumption of household i at age a and δ the discount factor, and β_a the age-dependent effective discount factor that takes into account the probability of death. We assume the utility function is of the CRRA type; the degree of risk aversion is denoted γ.

[23]This does not mean that financial fraud risk plays no role. It may, but because no systematic data on financial frauds are available we are unable to bring reliable evidence to bound its frequency and loss size. A few recent papers suggest that in the US financial frauds may be relatively frequent and costly to stockholders and that investors respond to perceptions of fraud risk by adjusting stockholdings (see Giannetti and Wang (2014) and Dyck, Morse, and Zingales (2010, 2013)).

[24]There are two alternative sources of tail risk that in principle matter for life cycle savings and portfolio decisions. First, large, infrequent drops in labor income such as those resulting from unemployment spells. Second, large shocks to health expenditure. The first source can help explain low shares invested in stocks at young age (Cocco et al., 2005)) but does not generate exit at old age. Furthermore, Norway provides substantial unemployment insurance which reduces the relevance of this source of tail risk at least in our case. In fact, Fagereng, Guiso, and Pistaferri (2015) find very small effects on stock investments of employment risk originating from firm bankruptcies in Norway.

Concerning large health shocks, they matter more at old age and could in principle help explain stock market exit and portfolio composition after retirement (Yogo, 2009). But while this type of risk is likely to be important in several countries, it is unlikely to in Norway because the Norwegian health system is quite generous and offers substantial insurance. It grants universal coverage and has the highest health expenditure per capita ($5400 in 2010) in Europe. About 85% of health expenditures are covered by public insurance, with out of pocket expenses being limited to 15% of the total. The latter reflect some gaps in the range of benefits (e.g. routine dental care services for adults are excluded), but older and disabled people are covered (see Ringard, Sagan, Saunes, and Lindahl (2013) for details).

4.2 Market structure

Financial markets are incomplete - households smooth consumption over the life cycle by holding a riskless asset and possibly a risky asset. The riskless asset can be thought of as a real bond and has a time-invariant return r_f. We denote the amount of bonds a household i holds at age a with $b_{i,a}$. Whereas the riskless asset can be purchased and sold at no cost, we impose a fixed per-period participation cost q to hold risky assets. The amount of risky asset held by household i at age a is denoted $s_{i,a}$. The risky asset has a time-dependent real return r_t and a risk premium denoted r_p

$$r_t = r_f + r_p + \nu_t, \quad \nu \sim \mathcal{N}(0, \sigma_r^2). \tag{4}$$

where ν_t is the period t innovation to stock market returns drawn from a normal distribution. To account for the possibility of stock market crashes we alter the stock return structure in order to allow for such events. With a probability $(1 - p_{tail})$ the return of the risky asset will be drawn from the above stock return process (4); with a probability p_{tail} from

$$\tilde{r}_t = r_{tail} + \epsilon_t, \quad \epsilon \sim \mathcal{N}(0, \sigma_{\tilde{r}}^2). \tag{5}$$

where $r_{tail} < 1$ is the average return and $(1-r_{tail})$ the average loss proportion, in case of disaster. We assume that the loss following a stock market disaster is not the same for everyone but is drawn from a distribution centred around the mean loss with variance $\sigma_{\tilde{r}}^2$. This way we capture the fact that households hold heterogeneous stock portfolios and thus suffer heterogenous losses following a stock market crash. The process for stock return in case of disaster is based on evidence that combines data on the frequency of stock market crashes in Norway and on the empirical distribution of losses on stock investments suffered by Norwegian stockholders during the 2008 stock market crash as described in Section 4.6 and Appendix A.3.

Finally, we assume that households can't borrow against future labor income and that the quantities of the two assets held are non-negative.

$$s_{i,a} \geq 0, \quad b_{i,a} \geq 0. \tag{6}$$

These constraints ensure that the share $\alpha_{i,a}$ of financial wealth invested in risky assets at age a, is non-negative and $\alpha_{i,a} \in [0, 1]$.

4.3 Household problem

4.3.1 Household budget constraints

Households start a period with a certain amount of labor income $(w_{i,a})$ and financial wealth $(x_{i,a})$. Then households decide how much to consume $(c_{i,a})$ and to save in bonds $(b_{i,a+1})$ if they don't participate in the stock market, and how much to consume and save in bonds and equity $(s_{i,a+1})$, if they choose to participate in the stock market. Finally, they compare the indirect utility from participation and non-participation, and decide whether to enter (stay) or exit the stock market.

The budget constraint of a working age household reads as:

$$c_{i,a}+\mathbf{1}_{i,a+1}(s_{i,a+1}+q)+b_{i,a+1}=w_{i,a}+(1+r_a)\mathbf{1}_{i,a}s_{i,a}+(1+r_f)b_{i,a}, \quad a=T^b,...,T^r \tag{7}$$

where $\mathbf{1}_{i,a+1}$ is an indicator variable taking value 1 if household i participates in the stock market at age $a+1$ and 0 if not; $w_{i,a}$ stands for the age-dependent labor income.

The retired households' budget constraint reads as follows:

$$c_{i,a}+\mathbf{1}_{i,a+1}(s_{i,a+1}+q)+b_{i,a+1}=\phi_{ret}w_{i,T^r}+(1+r_a)\mathbf{1}_{i,a}s_{i,a}+(1+r_f)b_{i,a}, \quad a=T^r+1,...,T \tag{8}$$

Equation (8) is isomorphic to (7) with the key difference that labor income is now time-invariant: Retirement income is a fixed share ϕ_{ret} of the last working-age labor income of the household.

Finally, households maximize their objective function (3) subject to the above constraints (7)-(8).

4.3.2 The labor income process

During their working age, households face uncertainty with regard to their labor income. The labor income process consists of two components: a deterministic component and an idiosyncratic stochastic component:

$$\log(w_{i,a})=f(a)+v_{i,a}+\epsilon_{i,a}, \quad a=T^b,...,T^r \tag{9}$$

The deterministic component $f(a)$ is a function of age; the stochastic component is the sum of an idiosyncratic temporary shock $\epsilon_{i,a}\sim\mathcal{N}(0,\sigma_\epsilon^2)$ and a persistent shock $v_{i,a}$ that follows a random walk:

$$v_{i,a}=v_{i,a-1}+u_{i,a} \tag{10}$$

where $u_{i,a}$ is distributed as $\mathcal{N}(0,\sigma_u^2)$.

In contrast, during retirement household labor income is assumed to be deterministic. Households' retirement income is a constant fraction ϕ_{ret} of the labor income in the last year of a households' working life.

$$\log(w_{i,a})=\log(\phi_{ret})+f(a=T^r)+v_{i,T^r}, \quad a=T^r+1,...,T \tag{11}$$

The labor income processes is estimated from our dataset. Details on the estimation of the age-dependent component of labor income and the variances of the transitory and permanent shocks to labor income are in the Appendix A.1.1.

4.3.3 Recursive formulation

The household problem presented above has a set of control variables $\{c_{i,a}, s_{i,a+1}, b_{i,a+1}, \mathbf{1}_{i,a+1}\}_{a=T^b}^{T}$ and a set of state variables $\{x_{i,a}, z_{i,a}\}_{a=T^b}^{T}$. We denote $V_a^{in}(x, z)$ the indirect utility of a a-year old household who participates in the stock market, has permanent labor income level z and financial wealth amounting to x,[25] and is the solution to the following maximization problem:

$$V_a^{in}(x, z) = \max_{c,s',b'} U(c) + \beta_{a+1} E_{z',\tilde{r},r} V_{a+1}(x', z') \tag{12}$$

where

$$x' = \begin{cases} (1 + r_f)b' + (1 + r)s' \text{ with probability } (1 - p_{tail}) \\ (1 + r_f)b' + (1 + \tilde{r})s' \text{ otherwise.} \end{cases} \tag{13}$$

The Bellman equation $V_a^{out}(x, z)$ is the indirect utility of a a-year old household who does not invest in risky assets, has a permanent labor income z and financial wealth x. It is computed by solving the following maximization problem:

$$V_a^{out}(x, z) = \max_{c,b'} U(c) + \beta_{a+1} E_{z'} V_{a+1}(x', z') \tag{14}$$

where

$$x' = (1 + r_f)b'. \tag{15}$$

The budget constraint of the household reads as follows:

$$c + \mathbf{1}'(s' + q) + b' = w + x, \tag{16}$$

The Bellman equation $V_a(x, z)$ for the household problem pins down the participation decision of the household:

$$V_a(x, z) = \max_{\mathbf{1}'=\{1,0\}} \left[V_a^{in}(x, z); V_a^{out}(x, z)\right]. \tag{17}$$

The optimal policy correspondence $\mathbf{1}'(x, z)$ for the participation decision is obtained as follows:

$$\mathbf{1}'(x, z) = \begin{cases} 1 & \text{if } \overline{x} \in X_p(z) \\ 0 & \text{otherwise.} \end{cases} \quad \text{where } X_p(z) \equiv \{\overline{x}(z) : V_a^{in}(x, z) > V_a^{out}(x, z)\}. \tag{18}$$

The maximization problem of the retired households is analogous to the above formulation with the only difference that the uncertainty with regard to the realization of the income shocks is shut down and retirement income is a constant fraction ϕ_{ret} of the permanent component of last working age year labor income.

[25] We drop the indices i and a, to lighten the notation, and index one period ahead variable as x' instead of x_{a+1}.

4.4 Bequest Motive

In one version of the model we allow households to obtain utility also from bequests according to a standard warm-glow bequest motive. This brings to the fore a third motive for intertemporal trade besides the life-cycle consumption smoothing and precautionary motive. The bequest motive gives our model more flexibility when we try to match concurrently the participation, asset allocation and financial wealth life cycle profiles that we estimate in Section 3.4.2; in particular the bequest motive helps matching wealth dynamics during retirement. With the bequest motive the household value function becomes

$$V_a(x,z) = \frac{c^{1-\gamma}}{1-\gamma} + \beta E_{z',\tilde{r},r}\left[p(a+1|a)V_{a+1}(x',z') + (1-p(a+1|a))\frac{b}{1-\gamma}\left(\frac{x'}{b}\right)^{1-\gamma}\right] \tag{19}$$

where b is the strength of the bequest motive and $p(a+1|a)$ is the conditional survival probability.

4.5 Solution method

The problem is solved by backward induction. Given the terminal condition, the policy functions and the value function in the final period T are trivial: households consume all their wealth (in the no bequest case), and the value function corresponds to the utility function. We substitute this value function in the Bellman equation and compute the policy functions one period backward. We do this for 75 periods, from $T = 100$ to age $T_b = 25$. We discretize the state space for the financial wealth state variable. Both the labor income process and the stock return process are discretized using the method of Tauchen and Hussey (1991). Using this solution method for a set of parameters, we obtain policy rules that we use to simulate an artificial panel of N agents (10,000 in our case).

4.6 Parametrization

Table 4 reports the parameters that we have either fixed or estimated outside our model. In accordance with Norwegian law we set the retirement age (T^r) at 67 for all households. The risk free rate (r_f) is set at 1.8% as documented by Dimson, Marsh, and Staunton (2008) for Norway.[26] The equity premium (r_p) and the standard deviation of returns on stocks are computed taking into account the exposure of Norwegian households to foreign stocks. As discussed in Appendix A.2, Norwegian households hold on average 80% of their portfolio in national stocks and the remainder in international stocks. Ødegaard (2007) documents that the correlation of returns is 0.6. Based on this information and the equity premium reported in Dimson et al. (2008) for Norway and the World, we compute an equity premium of

[26] These are historical values for the (average) risk free rate.

Table 4: Parameterization

Parameter		Value	Source
Retirement age	T^r	67	Norwegian Law
Risk free return	r_f	0.018	Dimson et al. (2008)
Risk premium	r_p	0.034	Dimson et al. (2008)
Stock return Std deviation	σ_r	0.229	Dimson et al. (2008)
Tail Risk Return	r_{tail}	0.515	Table A4
Tail Risk Std deviation	$\sigma_{\tilde{r}}$	0.06	Table A4
Variance of transitory shocks	σ_t^2	0.023	Table A1
Variance of persistent shocks	σ_p^2	0.012	Table A1
Replacement Ratio	ϕ_{ret}	0.842	Table A2
Shape of Pareto Distribution for x_0	μ_{x_0}	0.4521	Wealth at age 25
Scale of Pareto Distribution for x_0	σ_{x_0}	5711.7	Wealth at age 25

3.4% and a standard deviation of the stock returns of 0.23. The conditional survival probabilities (p_a) are obtained from the Population Tables of Statistics Norway.[27]

The last five parameters in Table 4 are estimated from our dataset. The age profile and the variances of permanent (σ_p^2) and transitory shocks (σ_t^2) to labor income are obtained by applying to our measure of disposable household labor income the decomposition used by Carroll (1997) and Cocco et al. (2005) (See Appendix A.1.1 for details).[28] Our estimates of the variances of labor income shocks are very close to those obtained by Blundell, Graber, and Mogstad (2015) who use the same data source, but a different methodology.

The replacement rate ϕ_{ret} is pinned down by computing the ratio of mean pension income five years after retirement and mean labor income five years prior to retirement. The age profile of labor income is obtained from the fitted age polynomial for all the population as documented in Table A2.

For the purpose of our simulations, we require an estimate of the wealth of the households at age 25. For this, we fit a Pareto distribution to the financial wealth distribution of households aged 25 in our sample, and obtain an estimate of the shape μ_{x_0} and scale σ_{x_0} parameters, which we then use to randomly assign initial wealth to households.

The return (loss) structure in the event of disaster defined by r_d and σ_d^2 is fixed to the returns observed in the 2008 stock market crash. We provide further evidence on stock market crashes in Norway in the following subsection and use it to hint at a value of probability p_{tail} when we simulate the model and to judge the reasonableness of this parameter estimates in Section 5.3.

The remaining parameters, namely the discount factor (β), the risk aversion parameter (γ) and the participation cost (q) are in a first stage parametrized to

[27]Table 5 Life tables, 2010 Statistics Norway

[28]In Table 4, we report only the variances of permanent and transitory shocks to labor income for the whole population. Appendix A.1.1 shows the estimates by education group.

standard values in the literature to illustrate the key mechanisms of the model.[29] In Section 5.3 we will estimate these parameters as well as the tail event probability p_{tail}.

4.6.1 Stock market crashes in Norway

From 1920 to 2010, there have been 7 medium/large stock market crashes in Norway, with drops in the Oslo stock exchange index between around 25 and 50%; and 5 large crashes if we restrict to drops in the index of at least 30%.[30] Depending on the definition, this amount to roughly one stock market crash every 13 or 23 years, implying that a household that owns stocks can experience several large losses in her stock portfolio over the life cycle. As we document in the Appendix A.3 (Table A3), 48% of the households in our sample have directly experienced 5 medium/large (drop in the index $\geq$ 25%) stock market crashes over their life cycle (from age 18 onwards) and 87% of them have been exposed to at least 3 crashes. The average number of experienced medium/large crashes over their life cycle is 3.9 and 2.2 that of large crashes ($\geq$ 30%). Depending on the age group, the fraction of experienced medium/large crashes over a Norwegian expected lifetime (82 years) ranges between 1.2% and 3.2%, and that of large crashes between 0.6% (for the very young) and 1.6% for the older cohorts. Hence, an informed guess of what a reasonable value of the tail event probability may be is between 0.6% and 3.2%. In the simulations below for illustrative purposes we set $p_{tail} = 2\%$ - about the mid point of the previous range; in Section 5.3 we will estimate it.

Furthermore, since households tend to hold different risky portfolios (Calvet et al., 2007), just counting the number of crashes in the index may understate the frequency they experience large losses in the stock portfolio and their average size. In fact, because households are imperfectly diversified, losses on the risky portfolio tend to reflect also idiosyncratic risk. We document the importance of imperfect diversification for tail risk using data on single stock investments available since 2006 to compute the returns on the risky portfolio of each household. Focusing on the 2008 collapse, we find that virtually all households loose on their risky portfolio. The average loss is 48.5% (somewhat less than the drop in the Oslo stock market index (54%)) but the range of the cross sectional distribution is almost as large, with 1% of the households loosing 70% of the value of their investment (See Appendix A.2, Table A4). Idiosyncratic portfolio risk also implies that some households may suffer "disasters" even in years when the stock market does well on average. For instance, in 2007, despite an average return on the Oslo stock market index of 11.4%, 1 percent of the households incur a loss larger than 27% and in 2009 (average annual return of 43%) one percent of the households experience a loss of at least 13% . In

[29] In particular we set $\beta = 0.96$, $\gamma = 10$ (as in Cocco et al. (2005), $q = 0.3$, which amounts to 300 US$ in 1995 prices, and $p_{tail} = 0.02$. For comparison with the literature we use the model without a bequest motive.

[30] These figures are very similar when using the combined index of the Oslo Stock Exchange and the MSCI World discussed in Appendix Section A.2, except for the crisis of 1998 when the combined index fell by about 20%.

other words, because of idiosyncratic risk, individual portfolio tail risk tends to be more frequent than the tail risk associated with the market portfolio and the size of the loss larger. We try to account for this by setting the average loss $(1 - r_{tail})$ to 0.485 and its standard deviation σ_d to 0.06 (Table 4). It is important to stress that while accounting for heterogeneity in returns on the stock portfolio adds some realism, we obtain the same results if we set $\sigma_d = 0$.

5 Results

This section provides the solution to the model, and gives the economic intuition behind the decision rules of the households. To facilitate comparisons with the literature, our analysis builds on Cocco et al. (2005) and shows how the introduction of the per period participation cost and the idiosyncratic tail-event probability contribute to explaining the stylized facts outlined in Section 5.3. This benchmark model has no bequest motive.

5.1 Policy Functions

The four panels of Figure 8 plot the optimal portfolio share invested in risky assets conditional on participating in the stock market as a function of financial wealth at a given age. Each panel plots the optimal portfolio share for three versions of the model without a bequest motive: first, the Cocco et al. (2005) model parametrized to Norwegian data, second the same model augmented by a fixed per period participation cost, and finally the fully fledged model as described in Section 4, with participation decision, a disaster probability and idiosyncratic loss following disaster.

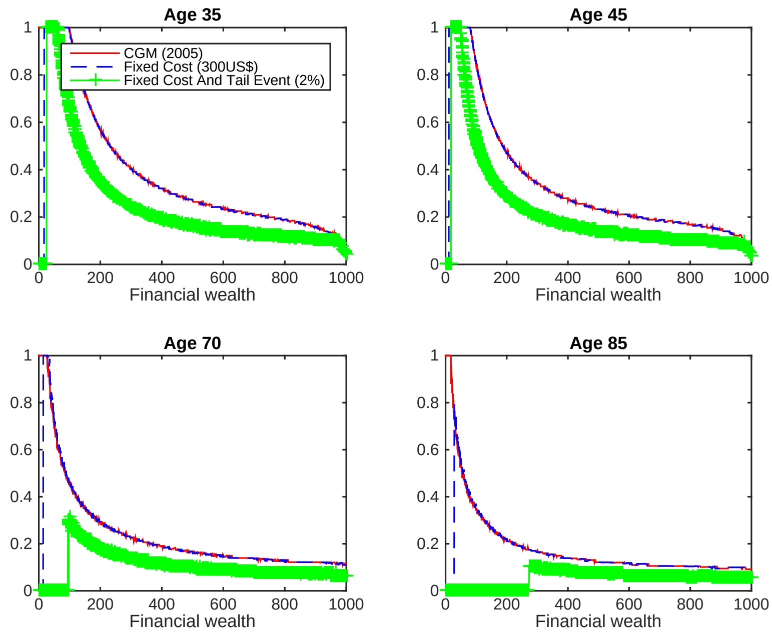
In all cases the optimal portfolio rule is decreasing with both financial wealth, and age, a pattern that is consistent with the literature (amongst others Merton (1971)). The key driver is the importance of human capital (discounted stream of future labor income) relative to accumulated wealth. During working age, since shocks to labor income are uncorrelated with stock market returns, the deterministic component of labor income mimics the pay-off of a risk free asset. Therefore, for a given level of human wealth, households with low levels of financial wealth have a relatively large amount of future income from risk free assets (relative to their financial wealth) and thus invest more aggressively in stocks than wealthier households. A higher level of financial wealth reduces the relative importance of the bond-like human wealth leading households to rebalance their financial portfolio by investing less in stocks relative to their financial wealth.

As for the negative correlation with age, this follows from the same logic. The portfolio rule is less aggressive when agents grow older because the capitalized value of labor income drops with age, and households compensate for this drop in bond-like wealth by reducing their relative holding of risky financial assets.

The inclusion of a per-period participation cost introduces a wealth-participation threshold (Figure 9).[31] The wealth threshold of participation is mildly U-shaped

[31] The participation thresholds can also be visualized in Figure 8 where they are the vertical

Figure 8: Policy functions - conditional risky share

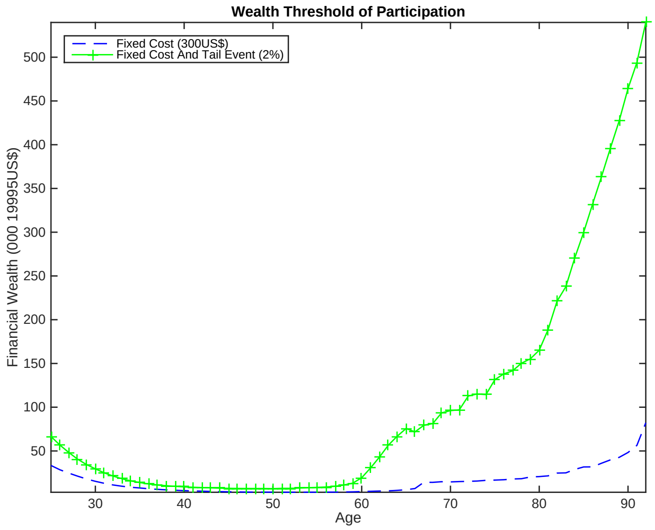


with respect to age. The main drivers behind the U-shaped pattern of the participation threshold are jointly the hump-shaped labor income process, the age dependent discounting factor, and the rebalancing channel (young households seeking to hold equity more aggressively than older households). At very early working age, accumulated assets are low, which contains the benefit of participating (grabbing the equity premium) below its per-period cost. A high human wealth and greater financial wealth later on imply a higher optimal risky share which makes stock market participation more worthwhile, leading to a drop in the age-dependent wealth threshold which remains low for long. With increased age, households discount the future more (because of higher mortality risk), choose a lower optimal risky share, and have lower human wealth as labor shrinks and the working horizon shortens. These three facts jointly make participation less worthwhile for old households and consequently increases the wealth threshold of participation.

The introduction of the disaster probability has three distinct effects. First, from Figure 8 one can notice that for given level of cash on hand the disaster probability has a somewhat stronger effect on the optimal risky share of younger households relative to older households. This asymmetry arises because the high level of human wealth relatively to financial wealth among younger households increases their optimal risky share above that of older households, meaning that they have more to lose from a disaster event, and therefore respond with a stronger reduction in their optimal risky share than older households to the introduction of a tail risk. Second, the disaster probability makes stock market participation less attractive by reducing the expected return from holding stocks, which explains why at all ages

cut-off line of the conditional risky share policy functions.

Figure 9: Wealth threshold of participation as a function of age



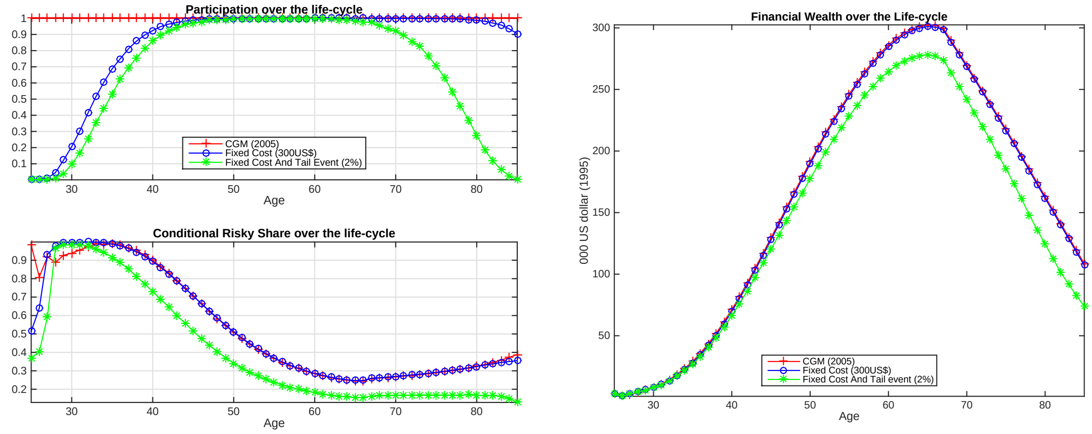
the wealth threshold of participation is higher than the threshold from the model with participation cost only (See Figure 9). Third, as clearly shown in both Figure 8 and 9 the interplay between the participation cost and the tail event probability in discouraging participation is strikingly stronger for older households than younger ones. The interplay between the disaster event and the participation cost on stock market participation is well understood in the stylized model presented in Guiso et al. (2008). However, its age dependent aspect, presented here, is novel. This asymmetry is driven by two facts. First, because retired households rely heavily on accumulated assets to finance their consumption, a disaster event would hurt them substantially more than young households. Second, retired households choose a substantially lower optimal risky share, implying that they need to invest substantially more than young households to benefit from the equity premium and cover the participation cost.

Overall, the policy functions show that the fixed per period participation cost can induce stock market entry and exit over the life-cycle, leaving the conditional risky share unaffected, whereas the tail event probability has both an impact on the average behavior of the participation margin and the conditional risky share. These differential responses of the share and participation will ease the identification of the disaster probability and the participation cost when we estimate them in Section 5.3.

5.2 Simulations

To highlight the role of per period participation costs and the disaster probability for the age profiles of participation and the conditional share, Figure 10 plots the average stock market participation rate (upper-left panel) and the average conditional risky share (lower-left panel) of simulated panels of 10,000 households from

Figure 10: Model simulations



(a) Intensive and extensive margin **(b)** Financial wealth

three models (without bequest motive): the Cocco et al. (2005) model calibrated to Norwegian data, the above model with a per period fixed stock market participation cost without tail risk and the above model presented with both endogenous participation and the tail event risk.

There are a number of interesting features that emerge from the top-left panel of Figure 10. First, as to be expected, in the absence of participation costs, the participation rate is at 100 %, meaning all households hold stocks at all ages. Second, introducing a fixed per period participation cost generates limited participation. This effect is marked among the young because of their low levels of cash on hand. The per period cost generates also exit among the elderly, giving rise to a hump-shaped participation profile. However, for the assumed level of participation cost (300 US dollars, as estimated for the US by Vissing-Jorgensen (2002)) the hump in participation is much less pronounced and exit from the market takes place at a much later age than observed in the data. This property does not change even if we double the participation cost suggesting that a reasonable participation cost is not sufficient to produce exit at the time and rate that we observe. Third, when we also add the small disaster probability the simulated profile shows more rapid exit which starts a few years after retirement - a feature that is consistent with the data - while leaving the pattern of participation among the young barely affected. This is because the disaster probability affects the participation rate of old households substantially more than that of younger households, a reflection of the age dependence of the participation threshold depicted in Figure 9 and discussed in the previous subsection.

The lower-left panel of Figure 10 plots the average conditional risky share of the simulated panel by age. There are three noteworthy features. First, adding participation costs to the Cocco et al. (2005) model leaves the level of the conditional share and its age profile little affected. The share is very (and unrealistically) high - hitting 100% - at relatively young age but households start rebalancing gradually until retirement. Second, introducing the small tail event probability lowers the conditional share at all ages except very early in life when the the stock of human wealth is so high that households are borrowing constrained. On the other hand, the pattern of rebalancing as households approach and foresee retirement is unchanged. Third, as in the data, rebalancing of the risky share starts much before households start exiting the stock market.

The right panel of Figure 10 plots the average accumulated financial wealth of the simulated panel over the life cycle. The introduction of the disaster probability lowers the average accumulated wealth at all ages relative to the Cocco et al. (2005) model. In fact, given the modified return structure of the risky asset, households tilt their financial wealth towards the safe asset (at all ages) as depicted in the policy functions. As a result of this, the average return on their financial wealth is lower, which thereby lowers the average accumulated wealth over the life cycle.

Looking jointly at the simulated life cycle profile of participation and of the conditional share reveals that the participation cost and the small probability tail event can together reproduce qualitatively, with one exception, the pattern and timing of portfolio adjustment along the intensive and the extensive margins documented in Section 3. The exception is that while the conditional share at the beginning of the life cycle is flat in the data (See Figure 5), it is increasing in the model. However, the model replicates well the joint pattern of life cycle rebalancing and exit. A key finding in the Norwegian data is that households *first* start reducing the conditional risky share before retirement, and *later*, after retirement, they begin exiting the stock market. This qualitative ability of the model to reproduce the empirical timing of the double adjustment is the main contribution of this section of the paper. We now move to assessing the ability of our model to quantitatively reproduce the empirical patterns identified in Section 3.

5.3 Estimation

We use indirect inference to estimate a set of unobserved parameters κ. We proceed as follows. For a given draw of parameters κ, we solve the model and simulate an artificial panel based on which we compute some moments, denoted $\Theta_M(\kappa)$. We define our loss function as the squared difference between the model moments $\Theta_M(\kappa)$ and the data moments Θ_D relative to the data moments obtained from our empirical analysis. Rather then relying on a partial identification procedure to pin down the parameter combination that minimizes the loss function, we approximate the loss function $L(\kappa)$ defined as follows

$$L(\kappa) = \sum_{i=1}^{N} \frac{(\Theta_M(\kappa) - \Theta_D)^2}{\Theta_D}$$

where N denotes the number of data points that we try to match. The loss function is approximated on a Smolyak sparse grid using the Smolyak Polynomial function following Judd, Maliar, Maliar, and Valero (2014).[32] Using the approximated

[32]We approximate the loss function on 2433 points - with a dimensionality d=5 and an approx-

Table 5: Structural estimation of parameters

	Estimation 1	Estimation 2	Estimation 3
Discount factor (β)	0.84	0.79	0.79
Risk aversion (γ)	15.25	11.48	7.3
Participation cost (q, *in 1995 US$*)	507.03	154.95	117
Probability of tail event (d, %)	-	1.50	1.64
Bequest motive (b)	-	-	0.5
Value of objective function($L(\kappa^{\star})$)	1'192.21	1'062.02	1'184.1
Nr. of targeted moments (N)	118	118	177

Note: The targeted data moments are those estimated using the Deaton-Paxson methodology in Section 3. In Estimation 1 and 2, we target the average participation rate and the average conditional risky share of households between 26 and 85. In Estimation 3, we augment the targeted moments with the average financial wealth of households between 26 and 85.

loss function, we can compute the global minima for each model configuration and targeted dimensions (investment behavior alone or together with financial wealth accumulation).

We now proceed with the discussion of the structural estimations. First, we estimate parameters that allows the model without bequest motive (presented in Section 4) to best match the life cycle profile of stock market participation and the conditional share. In this exercise we do not target the age-wealth profile because, contrary to the data (see Figure 7), this model generates substantial wealth decumulation after retirement (Figure 10). We next present the set of parameter estimates that matches best both households' average investment behavior over the life cycle (the extensive and the intensive margin) as well as the households' average age profile of financial wealth using the model with a bequest motive outlined in Section 4.4. This model predicts slower wealth decumulation and has thus a better chance of matching the observed financial wealth profile.

5.3.1 Portfolio Choice

Our estimation identifies the set of parameters $\kappa = [\beta, \gamma, q, p_{tail}]$ that allows the model to match the conditional risky share and the participation rate over the life cycle best $\Theta_D = [\alpha_a, \mathbf{1}_a]$.

Table 5 summarizes our findings. Estimation 1 and Estimation 2 refer to the standard model without a bequest motive. Estimation 3 to the model with a bequest motive targeting also the financial wealth profile. To better appreciate the role played by the tail event, in Estimation 1 we switch off the disaster event ($p_{tail} = 0$). We subsequently estimate it in Estimation 2 and 3. Our point estimate for the probability of the tail event is 1.50% in Estimation 2 and 1.64% in estimation 3, meaning that over their lifetime, households expect to experience between 1 and

imation level μ=4, 2433 points are selected by the Smolyak rule (Smolyak, 1963) from the set of unidimensional nested points.

2 tail risk events. These estimates are remarkably close to those implied by the frequency of historical stock market crashes in Norway discussed in Section 4.6.1.[33]

Table 5 instructs us that a relatively low disaster probability enhances the quantitative performance substantially. Compared to Estimation 1, Estimation 2 shows a loss function 15% lower. Most importantly, comparing Estimation 1 and Estimation 2 shows clearly that a disaster probability allows to obtain more moderate estimates of the degree of risk aversion and a much lower participation cost. When instead of forcing $p_{tail} = 0$ we let it take the estimated value of 1.5%, the estimated relative risk aversion drops from 15 to around 11.5 a value that is more in line with the literature (for instance Cocco et al. (2005) use a γ of 10). And the participation cost drops from $482.03 to $154.95 per year (at 1995 prices) which agrees with recent evidence about the effects on stock market participation of wealth increases.[34]

To further appreciate the role of the tail event, Figure 11 contrasts the model-generated age profiles using the set of estimated parameters in Estimation 1 and 2 and the data-estimated profiles. In both cases the model simulated profiles approximate our stylized facts well, at least qualitatively. In particular, they reproduce closely the hump-shaped pattern of the participation rate and capture the differential timing when people start rebalancing the share and exiting the stock market.

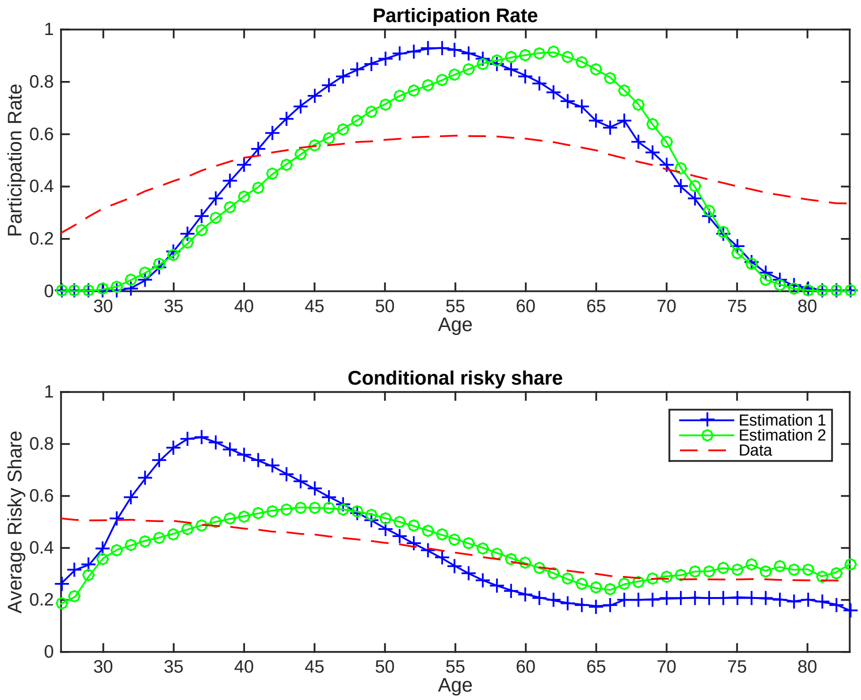
Yet, when the disaster probability is set at zero, exit from the stock market starts much earlier than in the data (the peak in participation occurs more than 10 years before retirement) and the level of the conditional share at younger ages far exceeds the observed one. Allowing for a small disaster probability improves both margins. First, it delays the peak in participation and aligns the timing of exit from the stock market with that in the data; second it lowers considerably the conditional portfolio share in risky assets, while preserving significant rebalancing.

On the other hand, the estimate of the other preference parameter, the discount rate, is little affected. Our estimate of the discount rate is around 0.8, much lower than the values typically used in calibrations of life cycle consumption portfolio models, but not at odds with models of buffer stock savings such as Deaton (1991). In these models, consumers facing idiosyncratic labor income risk and liquidity constraints accumulate precautionary savings to buffer income shocks. Impatience is necessary to limit the accumulation of liquid assets and make liquidity constraints relevant. In our case, a high discount rate is necessary to contain assets accumulation and through this channel discourage (costly) stock market participation. This

[33]Barro (2006) pools historical data for 35 countries and defines a macroeconomic "disaster" as a drop in GDP of at least 15% in a year; he obtains estimates a disaster probability of 1.75%.

[34]Briggs, Cesarini, Lindqvist, and Östling (2015) try to identify the causal effect of wealth on stock market participation using large random assignments of lottery wins in Sweden. They find effects that are inconsistent with the relatively high values of participation costs in the literature. In a calibration exercise they show that a combination of low participation costs and pessimistic beliefs about stock market returns can explain the observed empirical responses. This conclusion parallels ours: a combination of low participation cost and a small probability of a large loss can better explain limited participation. As we notice below, our model highlights that tail event beliefs are important not only to rationalize limited participation, but also to account for the timing of participation over the life cycle, as well as for limiting the puzzling high share in stocks at young age.

Figure 11: Estimation 1 and 2.



fits well our focus on the accumulation of liquid assets in Section 3.4.2.

In sum, from our first set of structural estimations we learn that to square jointly the intensive and the extensive margin of portfolio choice over the life cycle, the best parameter combination entails a low per-period participation cost to generate entry/exit dynamics; a low discount factor to limit liquid asset accumulation and discourage participation, a relatively high risk aversion parameter to match observed conditional risky share and a small idiosyncratic disaster probabilities to match the timing of exit from the stock market and the level of the conditional share particularly at young age.

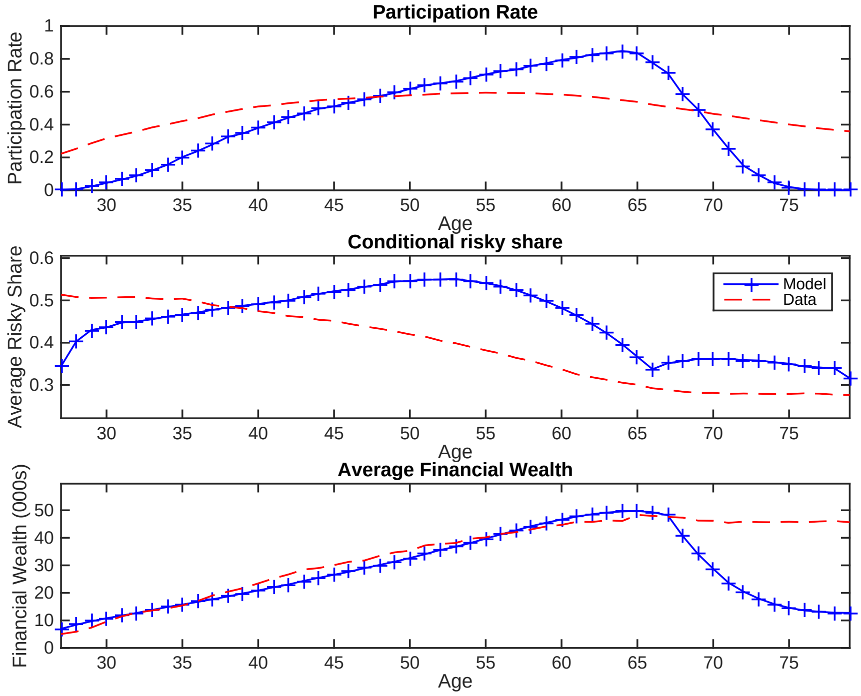
These conclusions, however, are obtained trying to match the life cycle participation and assets allocation profiles without any attempt to match also the wealth accumulation profile. In the following section we aim at explaining the three dimensions jointly.

5.3.2 Extensive, Intensive Margin, and Financial Wealth

We estimate a set of parameters $\kappa = [\gamma, \beta, q, p_{tail}]$ that allows the model with bequest motive (see Section 4.4), which we fix at b=0.5, to match jointly the investment behavior (conditional risky share and the participation rate over the life cycle) and the average financial wealth accumulated over the life cycle $\Theta_D = [\alpha_a, \mathbf{1}_a, x_a]$.

The third column of Table 5 summarizes the findings of our structural estimations. A comparison of the two sets of estimates (Estimation 2 and Estimation 3) reveals that introducing a bequest motive brings the estimated risk aversion param-

Figure 12: Estimation 3



eter down to 7.3, even closer to values used in the literature. Indeed, with a bequest motive, observed asset accumulation can be matched with a weaker precautionary motive, and thus a lower risk aversion (and prudence). There is instead no effect on the discount rate while the estimated tail probability - 1.64% - is only slightly higher than in Estimation 2. Interestingly, an even lower participation cost (117 dollars instead of 155) is enough to match the pattern of participation. In sum, targeting also the wealth profile together with the participation and portfolio profiles delivers more realistic parameter estimates.

Figure 12 shows the model-generated and the empirical profiles using the parameters in Estimation 3. There are a number of noteworthy features. First, the model with bequest tracks very well the financial assets profile until retirement but even this model predicts more assets decumulation at old age than observed in the data (bottom panel). Second, as shown on the first two panels, even when we target the financial wealth profile the model is able to reproduce the salient features of the age participation profile and the conditional risky share that we observe in the data. The age participation profile is hump-shaped and exit starts around retirement. Furthermore, compared to Estimation 2, the model profile is closer to the empirical profile. Third, the conditional share profile shows substantial rebalancing starting earlier in life and a level of the share that is not far from that observed in the data. Compared to Estimation 2 rebalancing starts later and the share has a more pronounced hump shape than in the data.

Overall both the model with and without bequest are able to capture the basic features of the portfolio profile. However, both models generate too little participation in the stock market at early age and too fast exit later in life than we observe in the data. In addition, the model features lower shares in stocks among the younger participants than seen in the data. Thus, though our estimated models perform well in matching the broad pattern of the timing of rebalancing and participation over the life cycle and that of liquid assets accumulation, they are still probably too stylized to fit the data closer.

6 Conclusion

Over the past decade, many scholars have used calibrated models to study life cycle portfolio allocations, departing from the simplifying assumptions of early generations models and adding realistic features of households environments. Among them, uninsurable income risk, non-tradeable human capital and borrowing constraints. Despite these (and other) complications, these models uniformly predict that households should at a certain point before retirement start lowering exposure to the stock market in order to compensate for the decline in the stock of human wealth as people age, which in this models acts mostly as a risk-free asset. Finding empirical evidence in support of this rebalancing, however, has been hard. We have argued that this is likely to be due to data limitations, both because a proper treatment of the issue requires long longitudinal data and because the information on assets needs to be exhaustive and free of measurement error. Combining administrative and tax registry data from Norway, we are fulfilling these requirements and find that households do indeed manage their portfolio over the life cycle in a way that is consistent with model predictions. We find that they adjust their financial portfolios along two margins: the share invested if they participate in the stock market and the decision whether to stay or leave the market altogether. They tend to enter the stock market early in life as they accumulate assets and tend to invest a relatively large share of financial wealth in stocks. As they start foreseeing retirement, they rebalance their portfolio share, reducing it gradually. Around retirement, they start adjusting on the other margin, exiting the stock market. This double adjustment pattern along the intensive and extensive margin with its clear timing cannot be explained by any of the available life-cycle portfolio models. However, an extension of these models that incorporates a small per period participation cost and a small probability of a large loss when investing in stocks is able not only to generate the double pattern of adjustment but also to replicate the profiles of stock market participation and portfolio shares observed in the data.

A Appendix

A.1 Earnings variances and human wealth

To estimate the variance of permanent and transitory shocks to labor income and the value of a households human wealth, we rely on a broad measure of household labor income obtained from tax records by summing the labor income of the two spouses for all households in our portfolio sample. The income data cover the same time span we observe the households portfolio. As in Carroll (1997), we define labor income as the sum of after-tax earnings at the household level. Besides earnings, it includes capital income and transfers (including sickness money, compensation for maternity leave, benefits paid during unemployment spells and pensions). Values are in 1995 USD - converted using the 1995 NOK/USD exchange rate. The statutory retirement age in Norway is 67, in practice however, a number of arrangements allow workers to retire earlier.[35] Our measure is then deflated using the growth in the National Insurance Scheme basic amount, which is used to adjust payments of unemployment insurance and pensions.[36]

A.1.1 Variance of permanent and transitory shocks to labor income

Following Carroll (1997) and Cocco et al. (2005), we estimate the following model for (log) labor income, $Y_{i,a,t}$ for household i, aged a at time t :

$$\log(Y_{i,a,t}) = \alpha + \beta(X_{i,a,t}) + \theta_a + \gamma_t + \varepsilon_{i,a,t} \tag{20}$$

where α is a constant, $X_{i,a,t}$ a set of demographic controls (such as household size), θ_a a full set of age dummies, γ_t the calendar year fixed effects and $\varepsilon_{i,a,t}$ the error term capturing shocks to labor income. We estimate the model separately for three different levels of educational attainment of the household (using husband education), as well as for the whole sample of non-retired households.[37]

To estimate the variance components of the income process, we follow the procedure in Carroll and Samwick (1997) and Cocco et al. (2005) and assume that labor income innovations can be decomposed as the sum of a permanent and a transitory shock, with variances σ_u^2 and σ_η^2 respectively. Using the estimated model we compute for each observation prediction errors d-years ahead -denoted $\widehat{\varepsilon}_{id}$ - for various d starting from the base year (1995); then, noticing that $var(\widehat{\varepsilon}_{id}) = d\sigma_u^2 + 2\sigma_\eta^2$, we retrieve the two variances from an OLS regression of $var(r_{id})$ on d and a constant

[35]In Norway, the actual average retirement age is around 64. See e.g. `http://ec.europa.eu/economy_finance/publications/publication14992_en.pdf`. Early retirement schemes are widespread in Norway and workers may be eligible for these from the age of 62, see e.g. Vestad (2013)

[36]See The Norwegian Labour and Welfare Administration, `http://www.nav.no/English/Membership+in+The+National+Insurance+Scheme` for more information on the basic amount, 'grunnbeløpet'.

[37]In fact, we cut the sample at the age of 65, to avoid variability in income coming from early retirement from influencing our results.

term. The estimates are shown in Table A1. The variance of transitory shocks is larger than that of permanent shocks for all education groups as well as the total sample, with some differences in its extent. We do not find large differences in the size of the variances across education groups with a tendency of households with High-School education to face lower labor income uncertainty than either households with less than high school of households with a college degree. Compared to Cocco et al. (2005), we find much lower values of the transitory components.[38] There are two possible explanations. The first is that workers in Norway are covered by a generous social insurance scheme which dampens the labor income effects of temporary shocks. The second that, differently from Cocco et al. (2005) who use PSID surveys, we use administrative records. Hence there is much less scope for measurement errors which otherwise inflates the estimated variance of transitory shocks.

Table A1: Income variance decomposition and correlation with stock return

	<High School	High School	College	All
Transitory	0.026	0.015	0.029	0.023
	(9.97)	(6.76)	(11.89)	(16.5)
Permanent	0.013	0.011	0.011	0.012
	(17.44)	(19.12)	(17.73)	(31.11)
Stock Market	0.017	0.045	0.005	0.008
	(0.48)	(0.34)	(0.75)	(0.50)

Note: The table reports estimates of the variance of permanent and transitory labor income shocks. The estimation is based on the error terms from estimating the labor income process in Figure 13. The procedure is based on the method in Carroll and Samwick (1997), which is also used in Cocco et al. (2005). T-values in parentheses.

Our estimates of the variance of permanent and transitory shocks are instead very close to those of Blundell et al. (2015) based on the same Norwegian data that we use, but obtained using a different methodology and excluding income from self employment. Unlike us, they allow for age-varying variances, finding that the earnings variances follow a U-shaped profile. Variances are higher at the very beginning of the (working) life cycle (particularly for high education workers) and essentially age-invariant for many years before retirement when they increase again. Our estimates are similar to their for middle aged households.

[38]The estimates of the income variance are highly dependent on very low income realizations of few households. In previous contributions this has been taken care of by excluding households with realized incomes below some threshold, justifying the choice with the need to limit the influence of measurement error. Since we use highly reliable administrative records we retain the whole sample, including households with very low income realizations.

Table A2: Labor income process: Age polynomials

	Less High School	High School	College	All
Age	0.0418	0.0375	0.112	0.0572
$Age^2/10$	-0.0231	-0.0176	-0.0689	-0.0308
$Age^3/100$	0.00587	0.00454	0.0212	0.00888
$Age^4/1000$	-0.101	-0.0906	-0.337	-0.161
$Age^5/10000$	0.0749	0.0735	0.208	0.117
Constant	3.576	3.657	3.415	3.566
Observations	61	61	61	61
r^2	0.995	0.996	0.988	0.995

Note: The table shows the coefficients of 5th order polynomial that approximates labor income as a function of age for various population groups.

Finally, we also computed the correlation between labor income and stock market returns on the Norwegian stock market. A negative correlation would represent a hedging opportunity for the households, as argued in Bodie et al. (1992). Table A1 shows that the correlation tends to be positive but very small and never statistically significant. This confirms the results in Cocco et al. (2005) for the United States.[39]

A.1.2 Human wealth

To obtain an estimate of the human wealth of a household of age a we estimate Equation 13 on the whole sample of households aged between 25 and 80 and separately for the three education groups. We then retrieve the age dummies and regress them on a 5th order polynomial. The age effects (solid lines) and the fitted polynomials are plotted in Figure 13. Table A2 shows the estimated 5th order polynomial.

The income profiles by educational attainment are consistent with the evidence in the literature showing much steeper profiles for high education workers. To compute lifetime wealth we proceed as follows. Let $G_e(a)$ denote the estimated 5th order polynomial in age for log income for a households with education level e. Assuming that all the household characteristics apart from age will not change in the future the labor income (or pension benefits) at age $a + \tau$ of a household with education level e and age a can be calculated using the function $G_e(a)$ as follows:

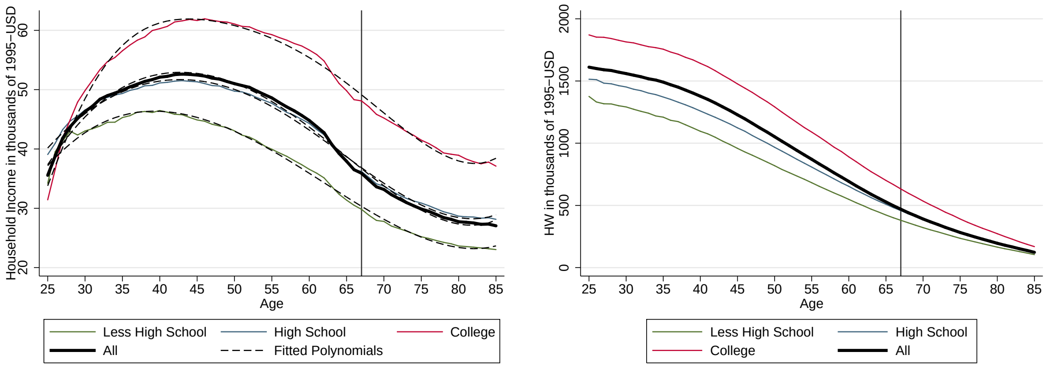
$$L_e(a+\tau) = L_e(a)\frac{\exp(G_e(a+\tau))}{\exp(G_e(a))} \tag{21}$$

The human wealth for a households of age a is then computed as:

$$H_{e,a} = L_e(a) + \sum_{\tau=1}^{T-a} p(a+\tau|a)\frac{L_e(a+\tau)}{(1+r)} \tag{22}$$

[39]The same holds for a combined measure of returns from the S&P 500 and the Oslo stock exchange, as discussed in Appendix Section A.2.

Figure 13: Life cycle profiles of labor income and human wealth



Note: The left panel of the figure plots the estimated labor income processes by educational level and for the full sample, coming from equation 20 estimated on the different sub-samples. The right panel displays the life cycle profiles of human wealth, calculated as described in Guiso and Sodini (2013) (Equations 21 & 22) based on the income polynomials in the left panel.

where $p(a+\tau|a)$ is the probability of surviving to age $a+\tau$ conditional on survival to a, from the population tables of Statistics Norway[40] and r is a risk free rate, which we set at 0.02. For each household we obtain an estimate of $H_{e,a}$ for each age of household in the sample.

A.2 Household stock market exposure

Norwegian households are exposed to both domestic and foreign stock markets. The main channel through which households are exposed to international stock markets is by buying share of mutual funds. We use a weighted average of the Oslo Stock Exchange and the MSCI World Index both when we in Section 3.4 proxy cohort effects with previous stock market returns, but also when we calibrate the equity risk in the model (Section 4.6).4.6).[41] Our data information on wealth held abroad is not perfectly measured. For the later years of the sample period we observe the sum of wealth abroad, which also includes assets like housing. In 2009, 4.7% of our sample has reported wealth abroad above zero. When we exclude these households from the empirical analysis our results are not affected. In our data we only observe the aggregate value of a households mutual funds each period, we do not observe the exact composition of the households mutual fund portfolio. However, we have gathered information on mutual funds registered in Norway and their aggregate allocation of assets between Norway and abroad.[42] Over the sample period from 1995 to 2009 this fraction is on average 28% in foreign stocks. Taking the product

[40]See `http://ssb.no/en/dode/`

[41]The MSCI World Index is available since 1969. Before this we use the S & P 500 as proxy for foreign stock market returns.

[42]This information is obtained from the Norwegian Fund and Asset Management Association, `http://www.vff.no/Internett/English/`

of this and the mutual fund share of risky assets at the household level, we get an international exposure of 20% in Norwegian portfolios. Hence, our weighted average is one with weight of 0.8 to the OSE and 0.2 to the MSCI World Index. In calibrating the equity risk we apply the returns (relative to bills) and standard deviation from Table 3 in Dimson et al. (2008). Furthermore we use a covariance between the value weighted OSE and the MSCI world of 0.6, as found in Ødegaard (2007). This yields the equity premium of 3.4 and the standard deviation of 0.229, see Table 4.

A.3 Tail risk: Stock market collapses in Norway

Since 1920 - the oldest substantial drop in the Oslo stock market experienced in the life time by at least some of the people in our sample - there have been other six stock market crashes (drops in stock market index of 25% or more) including the 2008 collapse: 1920 (34%), 1921 (32.7%), 1974 (34.2%), 1977 (25.5%), 1998 (28.9%), 2002 (30.2%) and 2008 (53.5%). Hence, Norwegians have had several opportunities over their life cycle to directly experience large losses in their stock investments. Table A3 shows the fraction of households in our sample that over their life cycle (above the age of 18) have experiences up to n medium/large stock market drops (drops $\geqq$ 25%) or to large drops (drops $\geqq$ 30%). 48% of the households have been exposed to 5 medium/large stock market crashes and to 3 large crashes during their lifetime, and the mean number of medium/large crashes experienced is 3.9 and that of large crashes 2.2.

This suggests that, while large drops in the stock market are indeed infrequent, the frequency, even that directly experienced by the households in the sample is non-negligible.

Furthermore, since households tend to hold different risky portfolios (Calvet et al., 2007), losses on the risky portfolio tend to reflect also idiosyncratic risk. Because of this, just looking at the return on the index may understate the tail risk households experienced and learned over their life cycle. First, they may experience substantial losses more frequently than a counting of the crashes in the stock market index may suggest; second, for some people the size of the losses in a crash year may far exceed the average loss in the index. To document this we exploit the fact that starting in 2006 we know for each household the value of every directly held stock in her portfolio and the ISIN code. Accordingly, we have computed the individual returns on their risky portfolio. As we do not observe the individual mutual fund the household invests in we have approximated returns in mutual funds with a weight between the Oslo Stock Exchange and the MSCI World Index, using the information on the aggregate asset allocation of mutual funds in Norway (see Section A.2). Table A4 shows the cross sectional distribution of these returns for the years 2007-2010.

Focusing on 2008, the table shows that virtually all households loose on their risky portfolio. The average loss is 48.5% - little less than the drop in the Oslo stock market index (54%) – but the range of the cross sectional distribution is almost as large, with 1% of the households loosing 70% of the value of their investment. Idiosyncratic portfolio risk also implies that some households may suffer “disasters”

Table A3: Large stock market drops experienced by households

Number of drops	Total Life cycle	Age bracket 18-36	Age bracket 18-42	Age bracket 18-55
	Experience of medium/large drops $\geqq$ 25 %:			
0	1.52	39.97	24.89	5.45
1	2.28	18.85	8.77	6.22
2	8.90	41.01	63.25	39.21
3	22.04	0.17	3.09	24.03
4	17.49			19.46
5	47.77			5.63
Mean	3.9	1.0	1.4	2.66
Median	4	1	2	3

Number of drops	Total Life cycle	Age bracket 18-36	Age bracket 18-42	Age bracket 18-55
	Experience of large drops $\geqq$ 30%:			
0	4.37	53.36	35.40	8.36
1	17.99	46.47	61.52	54.42
2	29.88	0.17	3.09	31.59
3	47.77			5.63
Mean	2.2	0.5	0.7	1.3
Median	2	0	1	1

Note: The table displays the distribution of number of large stock market drops (in the upper panel marked drops of more than 25% in a year, and in the lower drops of more than 30%) experienced by the households in the sample, for various age groups; above the age of 18 (column 2) , between ages 18 and 36 (column 3), between ages 18 and 42 (column 4) and between ages 18 and 55 (column 5).

Table A4: Cross sectional distribution of the return on the risky asset part of the household portfolios in 2008

Percentile	Net Return (in %)
1st	-70%
5th	-58.6%
10th	-56.4%
25th	-55.3%
50th	-47.8%
75th	-47.0%
90th	-46.7%
95th	-41.0%
99th	-29.8%
Mean	-48.5%
Range	-40.2%
Std. Dev.	6.0%

Note: The table shows the cross sectional distribution of the return on the risky asset part of the household portfolios in 2008.

even in years when the stock market does well on average. For instance, in 2007, despite an average return on the Oslo stock market index of 11.4%, 1 percent of the households incur a loss larger than 27% and in 2009, when the average annual return is 43%, one percent of the households experience a loss of at least 13%. In other words, because of idiosyncratic risk, individual portfolio tail risk tends to be more frequent than the tail risk of the market portfolio and the size of the loss larger larger.

Notice that in our model, the disaster probability reflects individual idiosyncratic risk; in fact, in each period a small fraction of the households, randomly, drawn, incurs a significant loss. This can be seen as a simple way of capturing the limited diversification of households portfolios, due, for instance, to partial (and heterogeneous information) as in Merton (1987).

References

AGNEW, J., P. BALDUZZI, AND A. SUNDÉN (2003): "Portfolio Choice and Trading in a Large 401(k) Plan," *American Economic Review*, 93, 193–215.

ALAN, S. (2006): "Entry costs and stock market participation over the life cycle," *Review of Economic Dynamics*, 9, 588–611.

——— (2012): "Do disaster expectations explain household portfolios?" *Quantitative Economics*, 3, 1–28.

AMERIKS, J. AND S. ZELDES (2002): "How do household portfolio shares vary with age," *TIAA-CREF Working Paper*, 112.

ATTANASIO, O. P. AND H. W. HOYNES (2000): "Differential mortality and wealth accumulation," *Journal of Human Resources*, 1–29.

BARRO, R. J. (2006): "Rare Disasters and Asset Markets in the Twentieth Century*," *The Quarterly Journal of Economics*, 121, 823–866.

BENZONI, L., P. COLLIN-DUFRESNE, AND R. S. GOLDSTEIN (2007): "Portfolio Choice over the Life-Cycle when the Stock and Labor Markets Are Cointegrated," *The Journal of Finance*, 62, 2123–2167.

BERNHEIM, B. D. (1987): "Dissaving after retirement: Testing the pure life cycle hypothesis," in *Issues in pension economics*, ed. by Z. Bodie, J. Shoven, and D. Wise, University of Chicago Press, 237–280.

BLUNDELL, R., M. GRABER, AND M. MOGSTAD (2015): "Labor Income Dynamics and the Insurance from Taxes, Transfers, and the Family," *forthcoming Journal of Public Economics.*

BODIE, Z., R. MERTON, AND W. SAMUELSON (1992): "Labor supply flexibility and portfolio choice in a life cycle model," *Journal of Economic Dynamics and Control*, 16, 427–449.

BRIGGS, J., D. CESARINI, E. LINDQVIST, AND R. ÖSTLING (2015): "Wealth and Stock Market Participation: Estimating the Causal Effect From Swedish Lotteries," *Working Paper.*

BROWNING, M., I. CRAWFORD, AND M. KNOEF (2012): "The age-period cohort problem: set identification and point identification," *Cemmap Working Paper.*

CALVET, L. E., J. Y. CAMPBELL, AND P. SODINI (2007): "Down or Out: Assessing the Welfare Costs of Household Investment Mistakes," *Journal of Political Economy*, 115, 707–747.

——— (2009): "Fight or Flight? Portfolio Rebalancing by Individual Investors," *The Quarterly Journal of Economics*, 124, 301–348.

CALVET, L. E. AND P. SODINI (2014): "Twin Picks: Disentangling the Determinants of Risk-Taking in Household Portfolios," *The Journal of Finance*, 69, 867–906.

CAMPBELL, J. AND L. VICEIRA (1999): "Consumption and Portfolio Decisions

When Expected Returns Are Time Varying," *The Quarterly Journal of Economics*, 114, 433–495.

Campbell, J. Y. and L. M. Viceira (2001): "Who Should Buy Long-Term Bonds?" *American Economic Review*, 91, 99–127.

——— (2002): *Strategic Asset allocation: Portfolio Choice for Long-Term Investors*, Oxford University Press.

Carroll, C. (1997): "Buffer-stock saving and the life Cycle/Permanent Income Hypothesis," *The Quarterly Journal of Economics*, 112, 1–55.

Carroll, C. and A. Samwick (1997): "The nature of precautionary wealth," *Journal of Monetary Economics*, 40, 41–71.

Cocco, J. (2005): "Portfolio Choice in the Presence of Housing," *The Review of Financial studies*, 18, 535–567.

Cocco, J. F., F. Gomes, and P. J. Maenhout (2005): "Consumption and portfolio choice over the life cycle," *Review of Financial Studies*, 18, 491–533.

Davis, S., F. Kubler, and P. Willen (2006): "Borrowing costs and the demand for equity over the life cycle," *The Review of Economics and Statistics*, 88, 348–362.

Deaton, A. (1991): "Saving and Liquidity Constraints," *Econometrica*, 59, 1221–1248.

——— (1997): *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy*, World Bank Publications.

Deaton, A. S. and C. Paxson (1994): "Saving, growth, and aging in Taiwan," in *Studies in the Economics of Aging*, University of Chicago Press, 331–362.

Dimson, E., P. Marsh, and M. Staunton (2008): "The worldwide equity premium: a smaller puzzle," *Handbook of the Equity Risk Premium*, 467–514.

Dyck, A., A. Morse, and L. Zingales (2010): "Who blows the whistle on corporate fraud?" *The Journal of Finance*, 65, 2213–2253.

——— (2013): "How pervasive is corporate fraud," *Rotman School of Management Working Paper*.

Fagereng, A., L. Guiso, and Pistaferri (2015): "Back to Background Risk?" *Working Paper*.

Gakidis, H. E. (1998): "Portfolio Choice with Uninsurable Labor Earnings," Ph.D. thesis, MIT.

Giannetti, M. and T. Y. Wang (2014): "Corporate Scandals and Household Stock Market Participation," *Working Paper*.

Giuliano, P. and A. Spilimbergo (2014): "Growing Up in a Recession: Beliefs and the macroeconomy," *Review of Economic Studies*, 81(2), 787–817.

Gollier, C. and R. Zeckhauser (2002): "Time Horizon and Portfolio risk," *Journal of Risk and Uncertainty*, 3, 195–212.

GOMES, F. AND A. MICHAELIDES (2003): "Portfolio Choice with Internal Habit Formation: A Life-Cycle Model with Uninsurable Labor Income Risk," *Review of Economic Dynamics*, 6, 729–66.

——— (2005): "Optimal Life-Cycle Asset Allocation: Understanding the Empirical Evidence," *The Journal of Finance*, 60, 869–904.

GOMES, F. J., L. J. KOTLIKOFF, AND L. M. VICEIRA (2008): "Optimal Life-Cycle Investing with Flexible Labor Supply: A Welfare Analysis of Life-Cycle Funds," *American Economic Review*, 98, 297–303.

GUISO, L., P. SAPIENZA, AND L. ZINGALES (2008): "Trusting the Stock Market," *The Journal of Finance*, 63, 2557–2600.

GUISO, L. AND P. SODINI (2013): "Household Finance. An Emerging Field," *Handbook of the Economics of Finance*.

HALIASSOS, M., L. GUISO, AND T. JAPPELLI, eds. (2001): *Household Portfolios*, MIT Press.

HEATON, J. AND D. LUCAS (1997): "Market frictions, savings behavior, and portfolio choice," *Macroeconomic Dynamics*, 1, 76–101.

HUBBARD, R., J. SKINNER, AND S. ZELDES (1995): "Precautionary Saving and Social Insurance," *The Journal of Political Economy*, 103, 360–399.

JAPPELLI, T. (1999): "The Age-Wealth Profile and the Life-Cycle Hypothesis: a Cohort Analysis With a Time Series of Cross-Sections of Italian Households," *Review of Income and Wealth*, 45, 57–75.

JUDD, K. L., L. MALIAR, S. MALIAR, AND R. VALERO (2014): "Smolyak method for solving dynamic economic models: Lagrange interpolation, anisotropic grid and adaptive domain," *Journal of Economic Dynamics and Control*, 44, 92–123.

KANDEL, S. AND R. STAMBAUGH (1995): "On the predictability of stock returns: An asset-allocation perspective," *The Journal of Finance*, 51, 385.

KAPTEYN, A., R. ALESSIE, AND A. LUSARDI (2005): "Explaining the wealth holdings of different cohorts: Productivity growth and Social Security," *European Economic Review*, 49, 1361–1391.

LIU, K., K. G. SALVANES, AND E. Ø. SØRENSEN (2012): "Good skills in bad times: Cyclical skill mismatch and the long-term effects of graduating in a recession," Tech. rep., Institute for the Study of Labor (IZA).

MALMENDIER, U. AND S. NAGEL (2011): "Depression Babies: Do Macroeconomic Experiences Affect Risk Taking?" *The Quarterly Journal of Economics*, 126, 373–416.

MERTON, R. (1971): "Optimum consumption and portfolio rules in a continuous-time model," *Journal of Economic Theory*, 413, 373–413.

MERTON, R. C. (1969): "Lifetime Portfolio Selection under Uncertainty: The Continuous-Time Case," *The Review of Economics and Statistics*, 51, 247.

MICHAELIDES, A. AND M. HALIASSOS (2002): "Calibration and computation of house- hold portfolio models," in *Household Portfolios*, ed. by L. Guiso, M. Haliassos, and T. Jappelli, MIT Press.

Mossin, J. (1968): "Optimal Multiperiod Portfolio Policies," *The Journal of Business*, 41, 215–229.

Ødegaard, B. A. (2007): "Asset pricing at the Oslo Stock Exchange. A source book," *Manuscript, BI Norwegian School of Management, available at http://finance. bi. no/˜ bernt.*

Oreopoulos, P., T. von Wachter, and A. Heisz (2012): "The short-and long-term career effects of graduating in a recession," *American Economic Journal: Applied Economics*, 4, 1–29.

Polkovnichenko, V. (2007): "Life-cycle portfolio choice with additive habit formation preferences and uninsurable labor income risk," *Review of Financial Studies*, 20, 83–124.

Rietz, T. (1988): "The equity risk premium: A solution," *Journal of Monetary Economics*, 22, 117–131.

Ringard, Å., A. Sagan, I. S. Saunes, and A. K. Lindahl (2013): "Norway. Health system review," *Health Systems in Transition*, 15.

Samuelson, P. (1969): "Lifetime Portfolio Selection By Dynamic Stochastic Programming," *The Review of Economics and Statistics*, 51, 239–246.

Shorrocks, A. F. (1975): "The age-wealth relationship: a cross-section and cohort analysis," *The review of Economics and Statistics*, 155–163.

Smolyak, S. A. (1963): "Quadrature and interpolation formulas for tensor products of certain classes of functions," in *Dokl. Akad. Nauk SSSR*, vol. 4, 123.

Storesletten, K., C. Telmer, and A. Yaron (2007): "Asset Pricing with Idiosyncratic Risk and Overlapping Generations," *Review of Economic Dynamics*, 10, 519–548.

Tauchen, G. and R. Hussey (1991): "Quadrature-based methods for obtaining approximate solutions to nonlinear asset pricing models," *Econometrica: Journal of the Econometric Society*, 371–396.

Vestad, O. L. (2013): "Labour Supply Effects of Early Retirement," *Labour Economics*, 25, 98–109.

Viceira, L. M. (2001): "Optimal Portfolio Choice for Long-Horizon Investors with Nontradable Labor Income," *The Journal of Finance*, 56, 433–470.

Vissing-Jorgensen, A. (2002): "Towards an explanation of household portfolio choice heterogeneity: nonfinancial income and participation cost structures," *NBER Working Paper.*

Yang, Y., W. Fu, and K. Land (2004): "A methodological comparison of age-period-cohort models: the intrinsic estimator and conventional generalized linear models," *Sociological Methodology*, 34, 75–110.

Yang, Y., S. Schulhofer-Wohl, W. Fu, and K. Land (2008): "The Intrinsic

Estimator for Age-Period- Cohort Analysis : What It Is and How to Use It," *American Journal of Sociology*, 113, 1697–1736.

Yogo, M. (2009): "Portfolio choice in retirement: Health risk and the demand for annuities, housing, and risky assets," *NBER Working Paper*.

Recent Issues

No. 114	Nicole Branger, Christian Schlag, Lue Wu	**'Nobody is Perfect': Asset Pricing and Long-Run Survival When Heterogeneous Investors Exhibit Different Kinds of Filtering Errors**
No. 113	Bettina Brüggemann, Jinhyuk Yoo	**Aggregate and Distributional Effects of Increasing Taxes on Top Income Earners**
No. 112	Shafik Hebous, Alfons J. Weichenrieder	**On Deficits and Symmetries in a Fiscal Capacity**
No. 111	Alfons J. Weichenrieder, Fangying Xu	**Are Tax Havens Good? Implications of the Crackdown on Secrecy**
No. 110	Dirk Krueger, Alexander Ludwig	**On the Optimal Provision of Social Insurance**
No. 109	Tobias Tröger	**Regulatory Influence on Market Conditions in the Banking Union**
No. 108	Sascha Baghestanian, Paul Gortner, Baptiste Massenot	**Compensation Schemes, Liquidity Provision, and Asset Prices: An Experimental Analysis**
No. 107	Daniel Powell, Marc Steffen Rapp	**Non-Mandatory Say on Pay Votes and AGM Participation: Evidence from Germany**
No. 106	Baptiste Massenot, Stéphane Straub	**Informal Sector and Economic Development: The Credit Supply Channel**
No. 105	Vilen Lipatov, Alfons J. Weichenrieder	**A Decentralization Theorem of Taxation**
No. 104	Sascha Baghestanian, Baptiste Massenot	**Predictably Irrational: Gambling for Resurrection in Experimental Asset Markets?**
No. 103	Massimiliano Caporin, Loriana Pelizzon, Francesco Ravazzolo, Roberto Rigobon	**Measuring Sovereign Contagion in Europe**
No. 102	Iñaki Aldasoro, Iván Alves	**Multiplex interbank networks and systemic importance: An application to European data**
No. 101	Marcel Grupp	**On the Impact of Leveraged Buyouts on Bank Systemic Risk**
No. 100	Marcel Grupp	**Taking the Lead: When Non-Banks Arrange Syndicated Loans**