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The Dynamics of Stock Market Participation

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THE DYNAMICS OF STOCK MARKET PARTICIPATION

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Abstract

We document novel facts on the exit and reentry margins of stock market participation by retail investors using detailed administrative data on every Norwegian resident from 1993 to 2016. Contrary to the conventional view that individuals either never or always participate in the stock market, we find that many households leave the stock market within just 2 years of entry. Such behavior is more prominent for people of low income, wealth, and educational attainment, and those of younger age. Estimation of a hazard function shows that there is negative duration dependence in exit probabilities: the longer households participate for, the less likely they are to exit. With respect to the reentry margin, over 30% of exiters subsequently return to the stock market, often just a year later. A structurally-estimated life-cycle model with participation costs fails to generate sufficient exits. Extending the model to allow for experience-based learning, whereby agents form beliefs over the equity premium based on their personal realized returns, improves the model fit of participation rates, conditional risky shares, and financial wealth-to-income ratios by over half, whilst also generating quick exits and a downward-sloping hazard function for exit. However, the model still struggles to generate enough reentry. Using granular portfolio holdings data, we show that poor initial returns are associated with quick exits from the stock market, while positive returns increase the likelihood of reentry in line with an experience effects channel.

Keywords: household finance, stock market participation, dynamics, experiences

JEL Classification: D14, D83, D84, E21, G11, G40, G50

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1 Introduction

Despite the large average return on equities relative to bonds, many households choose not to invest in the stock market (Mankiw and Zeldes (1991); Haliassos and Bertaut (1995); Campbell (2006)). While the literature has devoted significant attention to explaining why the aggregate participation rate lies below 100%, much less is known about the movements in and out of the stock market by individual investors. The conventional view is that individuals either never or always invest in the stock market; however, the data indicate that annual stock market exit rates are high, ranging from 5-10% in Norway. Exploring the decision to enter into or exit from the stock market is of first-order importance because portfolio choices matter for wealth inequality (Benhabib et al. (2011); Gabaix et al. (2016); Xavier (2021)), as well as the transmission of monetary policy (Melcangi and Sterk (2020)). Furthermore, analyzing these transitions can help to distinguish between the wide range of existing theories of participation that generate aggregate underparticipation, given that different models have opposing predictions for such individual-level movements. In this paper, we shed light on the dynamics of stock market participation by uncovering novel facts pertaining to exit and reentry at the individual level using detailed Norwegian administrative data, and assess the implications of our findings for theories of participation.

Studying individual-level changes in participation status is challenging because panel data on wealth holdings over a long time dimension are essential. We exploit Norwegian administrative tax records to overcome this challenge. As Norway levies a wealth tax, these records contain detailed wealth information for every member of the population. Our data span 24 years, which is significantly longer than similar administrative datasets from other countries and of higher frequency than most relevant longitudinal surveys. Individuals must file a tax return even if they hold no financial assets, which allows us to confidently identify periods of nonparticipation. This is a significant advantage relative to brokerage accounts data, where exit from such samples may simply reflect a transfer to another provider rather than a complete withdrawal from the stock market. Financial holdings are directly reported to the tax authority by the financial intermediaries themselves. Such third-party reporting alleviates concerns about measurement error that can arise when using self-reported measures of wealth. In addition, we can link the tax records to other administrative datasets,

thereby giving us additional information about each citizen that is typically not available in survey or brokerage accounts datasets.

Using the detailed Norwegian data, we document novel facts on two margins of stock market participation that have received less attention in the existing literature, namely the exit and reentry margins. First, we find that many individuals have very short spells in the stock market; that is, they stay in the market for only 1–2 years and then completely liquidate their stock holdings. 20% of all spells end within just 2 years of entry, and this behavior is not driven by involuntary participation coming from inheritances or employee stock options. This negates the conventional view that once people enter into the stock market, they should rarely exit. Our finding therefore builds on the high exit rates documented in [Hurst et al. \(1998\)](#), [Vissing-Jørgensen \(2002\)](#), and [Bonaparte et al. \(2023\)](#) by showing that these exits are particularly driven by recent entrants who invest for only a short period.

We then investigate whether the likelihood of a short spell, which is defined as a spell that results in complete exit within 2 years, is correlated with certain characteristics. Characteristics often linked to lower financial literacy, namely low income, wealth, and educational attainment ([Lusardi and Mitchell \(2011\)](#); [Behrman et al. \(2012\)](#)), are associated with an increased likelihood of having a short spell. We also find a strong, positive relationship between the share of financial wealth invested at entry and the likelihood of a short spell, meaning this behavior is not driven by people who initially invest small amounts into the stock market. With regard to age, short spells are more common amongst the youngest individuals, in line with the high exit and entry rates in this age category documented in [Fagereng et al. \(2017\)](#) and [Bonaparte et al. \(2023\)](#). Men are 20% more likely to exhibit such behavior compared to women, supporting existing evidence that men tend to trade excessively and display overconfidence ([Barber and Odean \(2001\)](#)). Furthermore, quick exits are significantly more likely among investors who enter into directly held stocks rather than mutual funds. To establish the degree to which liquidity shocks could force some investors to leave the stock market prematurely, we identify liquidity-related events in the data, such as house purchases and unemployment. There is a positive relationship between experiencing a liquidity need and short spells, suggesting that liquidity needs can play a role; however, approximately 85% of exiters do not experience such events at exit, which limits the degree to which this behavior can be explained purely by liquidity shocks.

To understand how the probability of exit evolves with time spent in the market, we estimate a hazard function for exit from participation using the methodology of [Alvarez et al. \(2021\)](#). Their approach exploits the presence of individuals with multiple participation spells to deal with unobserved heterogeneity that, if not properly accounted for, can bias the slope of the hazard function downwards ([Lancaster \(1979\)](#)). The hazard function is found to be downward sloping and convex, which means that the longer one stays in the stock market, the less likely they are to withdraw completely from the market. Together with the short spells result, this finding indicates that participation status is particularly fragile in the initial years following entry.

Moving onto the reentry margin, while most exiters do not reenter the stock market, we find that a nonnegligible fraction do with over 30% of exiters reentering within the following 4 years. They typically return to the same asset class (mutual funds or direct stockholding) that they previously invested in. Most reentry occurs soon after exit, often just a year later, and is more likely for high income and wealth individuals. We also estimate a downward-sloping and highly convex hazard function for reentry, implying negative duration dependence in reentry probabilities: the longer an individual has been away from the stock market, the less likely they are to return. After about a decade of nonparticipation, the likelihood of reentry is effectively zero.

We then consider the implications of our empirical findings for theories of stock market participation. In particular, we examine the extent to which a workhorse life-cycle portfolio choice model à la [Cocco et al. \(2005\)](#) can produce short-term dynamics. In this model, agents can invest in two financial assets, one risky (stocks) and the other safe (bonds), and they receive an exogenous labor income in every period that is stochastic during working life but constant in retirement. To generate a motive for nonparticipation, we augment the baseline model with participation costs, which are a popular explanation for limited participation in the stock market.¹ We consider two types of participation costs: the first follows [Gomes and Michaelides \(2005\)](#) and is an entry cost paid at the start of a new spell. This captures the time and effort spent searching for an account provider or learning fundamental

¹Under the core [Cocco et al. \(2005\)](#) model, there is full participation at all ages and thus no entry or exit dynamics. Full participation follows from standard portfolio theory, which states that as long as the expected equity premium is positive, everyone should invest at least a small amount in stocks ([Samuelson \(1969\)](#); [Merton \(1969, 1971\)](#)).

investment principles. The second is a per-period participation cost paid in every period in which one holds stocks, and represents the opportunity cost of time needed to monitor and rebalance one's investment portfolio every period or, alternatively, broker management fees (Vissing-Jørgensen (2002, 2003); Fagereng et al. (2017)). We also include a bequest motive to better match the wealth profile during retirement (Gomes and Michaelides (2005); Fagereng et al. (2017)), as well as a small probability of a large stock market crash (Fagereng et al. (2017)) to motivate exit, particularly in later life.

We structurally estimate parameters of the model to match life-cycle profiles of the stock market participation rate, conditional risky shares, and financial wealth-to-income ratios using simulated method of moments. Simulated life-cycle profiles show that this model underpredicts participation in early life, but overpredicts it in later life. Agents in the model need to build up wealth during their working life to justify paying the entry cost, which is estimated to be 1.22% of income (\approx \$500 in 2011 prices). Due to the low discount factor of 0.827, which is needed to better match the wealth profile, this takes time and means the participation rate remains close to zero until about age 40. Following entry, agents face a smaller per-period cost of 0.29% of income (\approx \$120) and generally have an increasing income profile, leading them to continue participating until retirement, after which point they start to exit. It therefore follows that there are minimal individual-level dynamics in the model with virtually all agents conforming to the “conventional” view of participation - you either never participate or you always participate upon entry.

To rationalize our empirical findings, we extend the model to allow for experience-based learning (EBL) à la Malmendier and Nagel (2011), whereby individuals do not know the true equity premium but form beliefs based on their own realized returns. This ingredient is motivated by the literature on memory and experience effects documenting how past experiences can have long-lasting effects on beliefs and actions.² Consistent with Foltyn (2020), the model with EBL more than halves the gap between the empirical target moments and the model-simulated moments. The participation rate profile shows the largest improvement in fit with the rise in participation occurring much earlier in life compared to the model without EBL. This occurs because we estimate much lower participation costs (an entry cost of

²See, for example, Greenwood and Nagel (2009); Malmendier and Nagel (2011, 2015); Andersen et al. (2019); Bordalo et al. (2020); Briggs et al. (2021); Afrouzi et al. (2023).

\approx \$290 and a per-period cost of \approx \$30), making it more appealing to invest in stocks at an earlier age. We also obtain declines in participation rates closer to the data, which is due to the presence of EBL. Our structural estimation shows that agents have recency bias as in [Malmendier and Nagel \(2011\)](#). Agents therefore put more weight on recent return realizations, which means that upon experiencing a poor return, they become more pessimistic and exit the market, leading to a gradual decline in participation rates. For conditional risky shares, we also obtain a better fit. The model without EBL underpredicts shares from age 50 onwards, partly because the higher participation costs mean participants are typically wealthier and therefore choose lower risky shares ([Jagannathan et al. \(1996\)](#); [Cocco et al. \(2005\)](#)). However, with beliefs, the individuals who select into participation are on average more optimistic and want a higher risky share.

Despite not being targeted in the structural estimation, the model with EBL is able to generate a distribution of spell lengths that is very close to the data. Some individuals will draw poor returns upon entry, making them more pessimistic about stock returns going forward and resulting in quick exit. We also obtain a downward-sloping hazard function. The intuition for this follows from the selection of who remains in the stock market. If a person has remained in the market for a long time, they must have experienced strong returns, otherwise the EBL force would have pushed them out of the market. As such, it will require a very negative return to make them sufficiently pessimistic such that they choose to exit in spite of the prior good experiences. Such an event is of low probability, and therefore, the model with EBL can generate negative duration dependence in exit probabilities. However, on the reentry side, while the model with EBL generates more reentry compared to the model without beliefs, it is still much less than observed in the data with just over 1% of individuals experiencing multiple spells in the model simulations compared to 12.5% in the data. This is because beliefs take time to recover under the estimated parameter values, by which time individuals are likely to be close to or already in retirement and have less desire to participate. For this same reason, amongst the set of agents that do reenter, reentry tends to occur over a decade after exit.

We conclude the paper by testing the experience effects channel. At the individual level, we exploit the detailed information on holdings of Norwegian listed stocks reported in the Shareholder Registry. As we do not observe information on specific mutual fund holdings,

we focus on the subset of people who only invest in listed stocks. We find that experiencing a negative return in the entry year is associated with a 21.6% (5.4 percentage points) increase in the probability of a short spell. We also find a positive link between experienced returns and the likelihood of reentry. These suggest that experiences can influence exit and reentry decisions. The experience-based model also predicts that young individuals should be more likely to have a short spell because they are more strongly affected by a poor return realization. This is a consequence of young agents having had fewer experiences in life, as they then place a higher weight on this (recent) bad experience. In line with this prediction, we show in the Norwegian data that short spells are more likely for younger individuals.

Our findings contribute to various strands of the literature. First, we contribute to the broad literature on underparticipation in the stock market by retail investors ([Mankiw and Zeldes \(1991\)](#); [Haliassos and Bertaut \(1995\)](#); [Vissing-Jørgensen \(2002, 2003\)](#); [Campbell \(2006\)](#); [Choi and Robertson \(2020\)](#)). We approach this puzzle from a dynamic perspective. While the literature typically divides the population into two groups, namely those who never invest in the stock market and those who continually invest, we find that many individuals fall into a third category of being *intermittent* participants, and argue that at least 20% of the population belongs to this group. Therefore, a snapshot of an individual's participation decision in a single year is not necessarily representative of their behavior in other years. While there are papers that have documented significant stock market entry and exit (e.g., [Hurst et al. \(1998\)](#), [Vissing-Jørgensen \(2002\)](#), and [Bonaparte et al. \(2023\)](#)), these papers typically look at exit decisions not conditional on time since entry. Our key contribution is therefore to exploit the long time dimension in the Norwegian data in order to explore how behavior changes over time since entry. We show that the high exit rates documented in these other studies are driven by new investors who exit very soon after entry, and provide novel evidence of negative duration dependence in exit probabilities.³ In addition, while studying individual-level exit is already challenging, the reentry margin is even more difficult to examine as it requires a long time dimension. Having panel data on the full population of Norwegians for 24 years allows us to give novel evidence on this margin of stock market participation.

³While our focus is on the speed of exit, others have linked exit to age ([Poterba and Samwick \(1997\)](#); [Ameriks and Zeldes \(2004\)](#); [Fagereng et al. \(2017\)](#)), house purchases ([Brandsaas \(2021\)](#)), income shocks ([Bonaparte et al. \(2023\)](#)), and portfolio characteristics ([Calvet et al. \(2009a\)](#)).

Second, we relate to the growing literature on memory and past experiences.⁴ [Malmendier and Nagel \(2011\)](#) document how stock market experiences at the cohort level can affect participation on both the intensive and extensive margins. Using expectations data from the UBS/Gallup survey, they argue in favor of a belief channel of experiences, whereby adverse experiences make individuals more pessimistic about equity returns. [Briggs et al. \(2021\)](#), in their study of how windfall wealth gains through lottery wins can affect stock market participation, argue that pessimistic beliefs can help to explain why participation does not increase following a win by as much as a life-cycle model with participation costs would predict. Our findings add to the literature by showing that personal experienced returns can influence the speed of stock market exit and the likelihood of reentry.

Third, we contribute to the literature on life-cycle portfolio choice models.⁵ We show that a structurally-estimated workhorse portfolio choice model of [Cocco et al. \(2005\)](#) with fixed participation costs struggles to generate the individual-level dynamics we observe in the data. Incorporating beliefs through experience-based learning à la [Malmendier and Nagel \(2011\)](#) like in [Foltyn \(2020\)](#) can improve the ability of these models to match profiles of participation rates, conditional risky shares, and wealth-to-income ratios. In addition to improving model fit along these targeted dimensions, we show that the model generates short spells and a downward-sloping hazard function for exit in line with the data.

Our results can have important implications for wealth accumulation. A growing literature has established a link between portfolio choices and wealth inequality ([Benhabib et al. \(2011, 2019\)](#); [Gabaix et al. \(2016\)](#); [Bach et al. \(2020\)](#); [Melcangi and Sterk \(2020\)](#); [Hubmer et al. \(2021\)](#); [Xavier \(2021\)](#)). We find that many individuals have intermittent spells in the stock market, so they may not remain in the stock market for long enough to attain the large average equity premium. Although efforts have been made to boost stock market participation (e.g., through tax incentives), our findings indicate that it is not simply about encouraging entry. Perhaps individuals need to be encouraged to continue participating for a prolonged period, particularly when faced with poor short-term returns. Furthermore, we find that individuals of low wealth are more likely than wealthier individuals to exit the stock market

⁴For an overview of the empirical and theoretical literature on how experiences and memory affect choices, see [Malmendier and Wachter \(2021\)](#).

⁵See, amongst others, [Cocco et al. \(2005\)](#); [Gomes and Michaelides \(2005\)](#); [Fagereng et al. \(2017\)](#); [Briggs et al. \(2021\)](#); [Catherine \(2021\)](#); [Choukhmane and de Silva \(2023\)](#).

soon after entry, which can further exacerbate the wealth gap between these two groups.

Outline: The paper is structured as follows. Section 2 describes the Norwegian data, while Section 3 documents our exit and reentry facts. Section 4 details the workhorse portfolio choice model and our augmented model with EBL. Section 5 shows the model results and provides empirical evidence in favor of experience effects. Section 6 concludes.

2 Data

We use Norwegian administrative data to conduct our analysis. Most administrative datasets contain information on income only. However, due to the existence of a wealth tax in Norway, our data also contain detailed information on end-year wealth holdings by broad asset class for every resident from 1993 to 2016. The Norwegian data are particularly well suited to studying individual-level dynamics in stock market participation relative to other datasets. First, to study dynamics, we need to be able to follow individuals over time. Compared to other datasets, our data provide this panel dimension with a longer time dimension.⁶ Second, a concern with brokerage accounts data is that exit from the sample does not necessarily mean an exit from the stock market. For example, if an individual simply switches providers, they would appear as an exiter in the brokerage accounts data. Reentrants could be difficult to identify if account numbers change between spells. The Norwegian data do not have this concern, as the tax data are based on overall holdings across all financial intermediaries. Third, brokerage data can have concerns with sample selection and nonrandom attrition, the latter of which is also a worry with longitudinal survey data. The Norwegian data cover the full population, and attrition should be due to death or emigration only. Fourth, financial institutions directly report information on wealth holdings to the tax authority, which eases concerns about measurement error.⁷ As such, evading taxes in Norway by underreporting asset holdings is very challenging.⁸ Last, we are able to link the tax

⁶As the wealth tax in Sweden ended in 2007, the Swedish data used by [Calvet et al. \(2007, 2009a,b\)](#) span 9 years (1999–2007 inclusive). The brokerage data of [Barber and Odean \(2000, 2001\)](#) cover 1991–1996.

⁷Residents are sent a prefilled tax form to approve. If they do not respond, then the tax authority assumes that the information is correct. In 2009, around 60% of tax payers did not respond ([Fagereng et al. \(2017\)](#)).

⁸As noted by [Fagereng et al. \(2017\)](#), one source of under-reporting would be if individuals hold but fail to disclose foreign investments. While asset holdings through Norwegian financial intermediaries are directly reported, this is not the case for foreign holdings. For Sweden, [Calvet et al. \(2007\)](#) argue that such holdings are likely to be a small portion of overall assets other than for the wealthiest individuals.

records to other administrative datasets, which contain additional information about each individual that is not necessarily available in survey or brokerage accounts data (e.g., demographics, employment history, and house purchases). This allows us to study whether the behaviors we find are linked to certain characteristics or events.

While the Norwegian data are particularly promising for our research objective, they have their shortcomings. The data provide us with asset holdings on December 31st of each year. As such, we are limited to participation decisions at the annual frequency, although it is worth noting that this is more frequent than most panel survey waves.⁹ We are, therefore, unable to capture within-year spells, although the presence of within-year spells would strengthen our result that short spells in the stock market exist. In addition, we do not have information on occupational or public pension wealth. In Appendix B.2, we argue that pensions are unlikely to affect our results. Last, we do not have information on the specific mutual funds held, though there is information on specific holdings of individual Norwegian stocks coming from the Shareholder Registry.

2.1 Data construction

We use the tax records to construct wealth by broad asset class and combine them to obtain measures of financial and real wealth. Financial wealth can be decomposed into the following asset classes: (a) cash and deposits (both domestic and foreign), (b) directly held listed stocks, (c) directly held unlisted stocks (typically private equity), (d) stock mutual funds, (e) money market funds, (f) financial wealth held abroad, and (g) other financial assets. Real wealth consists of housing and other real assets. We provide further details on the construction of the wealth variables in Appendix A.

Before proceeding with our analysis, we employ minimal sample selection to the raw data. First, we restrict attention to individuals aged 20 or over to ensure that the person is the main asset holder. Second, we exclude observations where the individual dies in that year. Third, we exclude people who never have financial wealth above \$500 (in 2011 prices) at any point in the sample period.

Our outcome of interest is stock market participation. We treat an individual as partici-

⁹For example, wealth information in the PSID was collected from 1984 at 5-year intervals until 1999, after which it began to be collected biennially.

pating in the stock market in a given year if the sum of directly-held listed stock holdings and equity mutual fund holdings exceeds \$150. We focus on stock market participation through nonretirement investment accounts because there is typically little turnover and trading activity in retirement accounts (Brunnermeier and Nagel (2008); Bonaparte et al. (2023)).

2.2 Descriptive statistics

Table 1 provides summary statistics at the individual level. The first block shows that there is an even split of men and women in the sample, and 35% of individuals have a college degree. The second block provides information on income and wealth holdings. The average individual has a total gross wealth holding of \$272,000, though the large standard deviation in asset holdings illustrates the vast heterogeneity in wealth across the population. The median wealth holding is about two-thirds of the mean holding, indicating a rightward skew in the wealth distribution. Nonfinancial wealth, of which the major component is housing, accounts for a larger share of total wealth than financial wealth does, with the average individual holding \$75,000 in financial wealth compared to \$200,000 in nonfinancial wealth. The mean amount of wealth held in public equity, measured as the sum of holdings in stock mutual funds and directly held stocks, is just under \$7,500. Indeed, the median individual does not hold any public equity, a finding that is indicative of broad aggregate underparticipation in the stock market in Norway. The third block further verifies this finding by showing that 25% of individuals invested in the stock market in 2016. Most participants invest in mutual funds rather than directly holding stocks. Conditional on participating in the stock market, 28% of financial wealth is in stocks on average.

Figure 1 plots the stock market participation rate in Norway over time. Less than 10% of the population owned stocks at the start of the sample. However, there was an acceleration in participation during the 1990s. Reasons include improved access to financial markets for retail investors, the rise of mutual funds, and the popularity of technology stocks during the dot-com bubble (Guiso et al. (2003)). After the bursting of the dot-com bubble, the participation rate dropped sharply from its peak of 32%. It stabilized until the financial crisis, but thereafter has shown a persistent decline, reaching 25% in 2016. Figure 2 plots the entry and exit rates over time.¹⁰ The sharp fall in participation in the early 2000s can be linked to a

¹⁰While an individual is treated as an entrant only if they invest at least \$150, an individual is classed as an

Table 1: Summary statistics

	Mean	Std. dev	P10	Median	P90	P99
<i>Demographics</i>						
Age (in years)	48.87	18.00	26	47	74	90
Male	0.51	0.50	0	1	1	1
Single	0.36	0.48	0	0	1	1
College degree	0.35	0.48	0	0	1	1
<i>Income and wealth (\$'000s)</i>						
Total income	41.06	63.20	17.63	36.51	64.45	135.22
Financial wealth	74.27	1,695.97	0.47	12.53	123.51	774.35
Financial wealth in public equity	7.44	233.43	0	0	9.52	132.23
Non-financial wealth	199.96	308.21	0	154.35	471.92	1,115.31
Gross wealth	271.59	1,745.58	1.11	182.81	570.79	1,640.21
Net wealth	180.88	1,724.07	-38.78	67.23	463.62	1,424.09
<i>Participation and wealth shares</i>						
Invest in stock market	0.25	0.43	0	0	1	1
Hold mutual funds	0.21	0.41	0	0	1	1
Hold listed stocks	0.08	0.27	0	0	0	1
Cond. risky share (of gross wealth)	0.09	0.17	0.00	0.02	0.26	0.87
Cond. risky share (of fin. wealth)	0.28	0.28	0.01	0.18	0.74	0.98
Observations	4.13m					

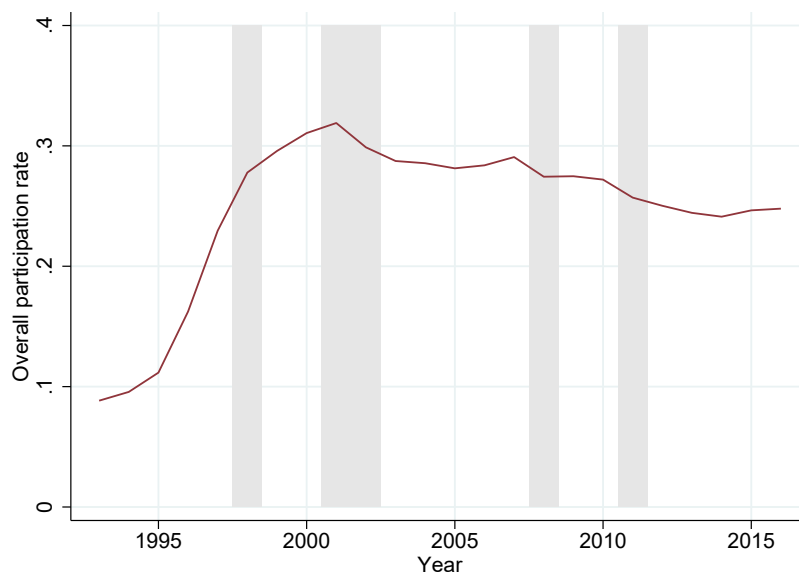
Notes. This table provides summary statistics using data from 2016. The first block gives summary statistics for demographic characteristics. *Single* is a binary variable equal to 1 if the individual is neither married nor cohabiting, and zero otherwise. The second block information on income and wealth measured in USD (in thousands) based on an exchange rate of \$1=8.62 NOK at the end of 2016. *Total income* is income from all sources. *Public equity* is measured as the sum of holdings in equity mutual funds and listed stocks. The third block gives summary statistics on stock market (i.e., public equity) participation and the share of wealth invested in public equity conditional on holding a nonzero amount of such wealth.

pronounced rise in the exit rate and a drop in the entry rate. Since the financial crisis, entry rates have been particularly low, which can explain the downward trend in the participation rate.

To get a sense of how much the conventional view that individuals either never or always participate in the stock market holds in the data, we divide individuals into three groups: *never participants*, who refrain from investing in public equity throughout the sample period; *always participants*, who are observed to have one single spell lasting at least 5 years; and *intermittent participants*, who have either one single spell in the stock market lasting less than 5 years or multiple spells. Figure H1 shows that over 20% of the Norwegian population can be characterized as intermittent participants, which implies that the conventional view does not apply for many individuals.

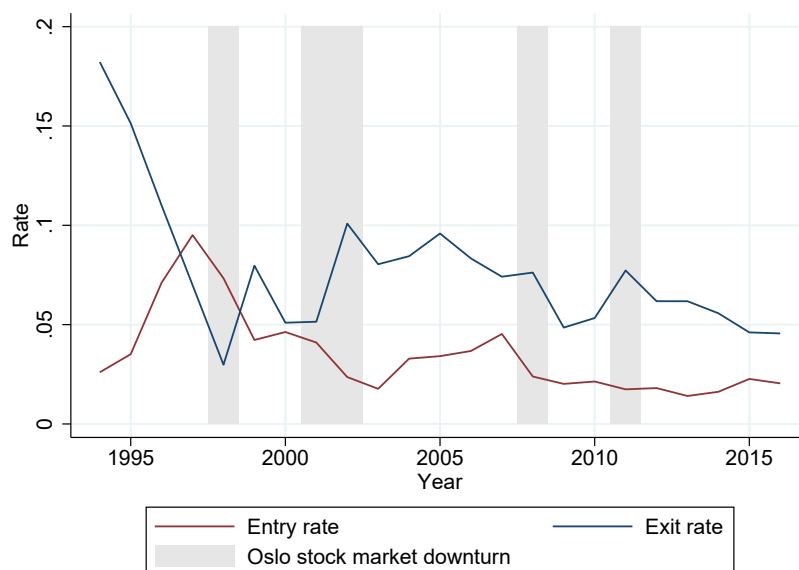
exiter if their holdings fall all the way to zero (i.e. complete exit from the stock market).

Figure 1: Stock market participation rate over time



Notes. This figure plots the participation rate in the stock market annually from 1993 to 2016.

Figure 2: Entry and exit rates over time



Notes. This figure plots the entry and exit rates for stock market participation. The entry rate in year t is the proportion of nonparticipants in year $t - 1$ who invest at least \$150 in the stock market in year t . The exit rate in year t is the proportion of participants in year $t - 1$ who sell all of their holdings in year t . The shaded areas are stock market downturn years in which the Oslo Børs Benchmark Index fell by at least 10%.

3 Empirical facts

In this section, we study and document novel facts pertaining to two margins of stock market participation using the Norwegian administrative data. Section 3.1 explores the exit margin, and shows that short spells in the stock market are common and linked to characteristics associated with low financial literacy. Section 3.2 studies the reentry margin, where we find that a nontrivial proportion of exiters do subsequently reenter the stock market.

3.1 Exit margin

3.1.1 Short spells are common

We begin by examining the distribution of spell lengths in the data. Figure 3 plots a histogram with the distribution of spell lengths based on spells beginning between 1994 and 2013 inclusive.¹¹ We restrict attention to spells starting by 2013 to ensure that participants have at least 3 years in which to exit. If, for example, 2015 entrants were also included, they would either have a 1-year completed spell or be right censored. Including such entrants would therefore artificially inflate the bars corresponding to a short spell length. The histogram shows a declining relationship between spell length and the proportion of observations. About 13% of all spells end in just 1 year, and 20% end within 2 years. We undertake a variety of robustness checks, namely analysis at the household level (Figure H2), excluding entrants who receive a gift or inheritance in the year of or before entry (Figure H3), removing individuals with stocks in the company they work for (Figure H4), dropping investors who invest a small sum at the point of entry (Figure H5), and only using the first (recorded) spell for each participant (Figure H6). In all cases, similar patterns emerge.

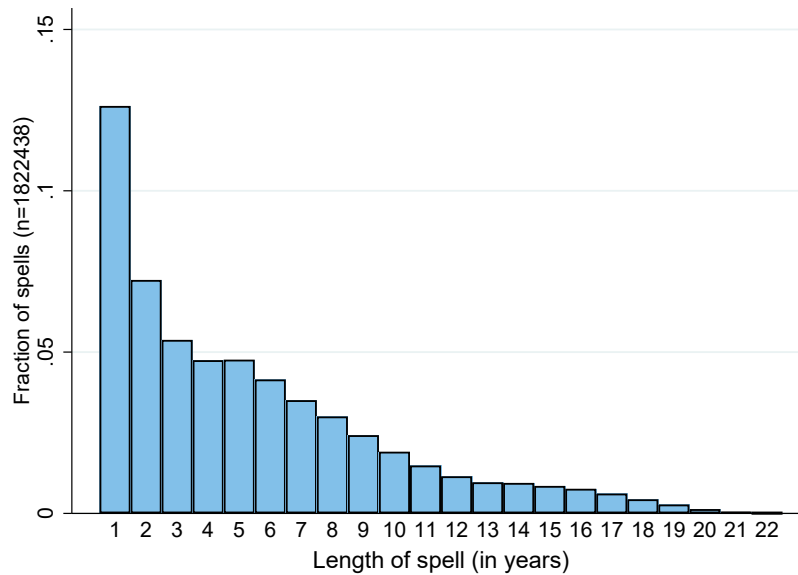
The next step is understanding whether short spells can be linked to observable characteristics. To do this, we estimate the following linear probability model:

$$\Pr(\text{spell ends within 2 years}) = \alpha + \delta_t + \beta' X_{it} + \epsilon_{it} \quad (1)$$

where δ_t denotes entry-year fixed effects and X_{it} is a vector of observable characteristics

¹¹Left-censored spells are excluded from this figure because a spell length cannot be computed for such spells. These spells are typically those that were already ongoing at the start of our data, though other reasons for left-censoring later in the sample could be immigration of an existing stockholder into Norway.

Figure 3: Distribution of spell lengths



Notes. This histogram plots the proportion of spells of different lengths in the Norwegian data. We take all spells beginning at any point from 1994 to 2013. The x-axis gives the spell length (in years), and the y-axis shows the proportion of spells belonging to a particular spell length. Right-censored spells are excluded from the plot, but are used in calculating proportions.

measured at the point of entry, such as age and wealth.

Table 2 shows the coefficient estimates from this estimation.¹² Quite interestingly, short spells are not more likely amongst those who put small amounts in the stock market. Instead, increasing the share of financial wealth invested in the stock market by 10pps *increases* the probability of a short spell by 1.3pps, which is a 6.4% increase in the probability when compared to the sample mean of 20%. This implies that this behavior is not concentrated amongst people who make small gambles. Men are 25% (4.9pps) more likely than women to have a short spell. This result relates to the existing literature on gender differences in confidence and trading behavior, which has found that men tend to be more overconfident and trade excessively, often to the detriment of their own returns (Barber and Odean (2001)).¹³ Regarding age, we see that short spells are more likely for the youngest age group (Figure H8). This finding is in line with Fagereng et al. (2017), who show that younger households tend to enter and exit frequently.¹⁴

¹²We find similar results if a probit model is used instead.

¹³Grinblatt and Keloharju (2009) study overconfidence using Finnish data and show that individuals with a high degree of self-confidence tend to have higher trading volumes.

¹⁴Figure H11 shows that short spells became much more likely during the early 2000s, a period that exhibited

Table 2: Determinants of short spells (≤ 2 years)

	(1)
Risky share (out of financial wealth)	0.128*** (0.001)
Homeowner	-0.019*** (0.001)
Male	0.049*** (0.001)
Unemployed	0.019*** (0.001)
Degree	-0.010*** (0.001)
Single	0.021*** (0.001)
Sample mean	0.20
Year FE	Yes
Wealth and income FE	Yes
Age group FE	Yes
Observations	1841303
R-squared	0.05

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This table shows the estimation of Equation 1. The dependent variable is a binary variable equal to 1 if the spell ends within 2 years, and zero otherwise. *Risky share* is the amount invested in public equity divided by total financial wealth. *Homeowner* is a binary variable equal to 1 if the participant owns their own property (either self-owned or ownership through housing cooperatives), and zero otherwise. *Single* is a binary variable equal to 1 if the participant is neither married nor cohabiting, and zero otherwise. *Unemployed* is a binary variable equal to 1 if the participant receives unemployment benefits at the point of entry, and zero otherwise. Entry year fixed effects are included. Age fixed effects by broad age group (20-29, 30-39, 40-49, 50-59, 60-69 and 70+), as well as income and wealth decile fixed effects are included. Observables are measured at the point of entry. Standard errors are clustered at the individual level. The regression uses data on entrants from 1994-2014.

Characteristics typically associated with lower financial literacy (low income, wealth, and education levels) are also linked to a higher prevalence of short spells.¹⁵ Having a college degree lowers the likelihood of exiting within 2 years by about 5% (1pp). Figures 4a and 4b show the impacts of income and wealth, respectively. We find a negative relationship between income and the probability of a short spell, with those in the bottom income decile having a 19% (3.7pps) higher probability of a short spell relative to the median. For wealth, the impact of low wealth is stronger. Entrants belonging to the bottom wealth decile are 28% (5.5pps) more likely to exit within 2 years relative to the median.¹⁶ The relationship between

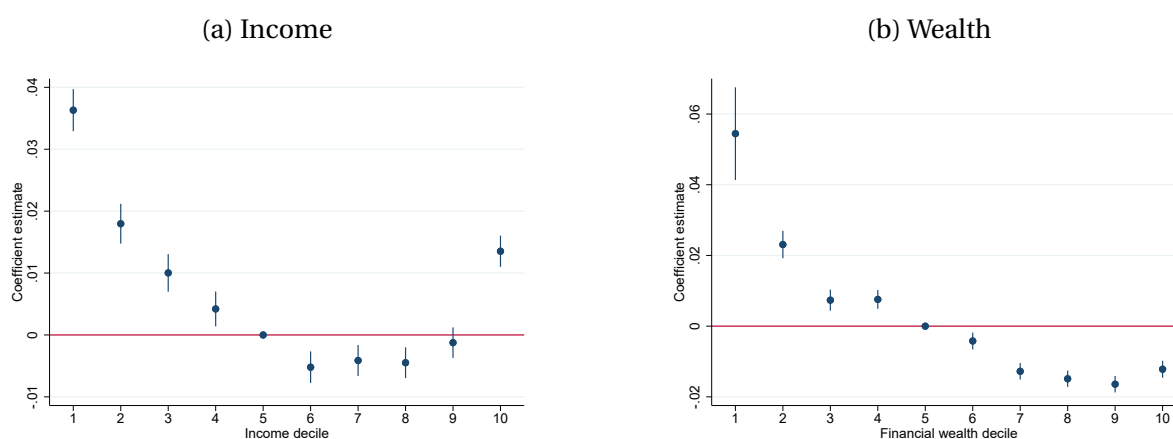
significant trading volumes and stock market in- and outflows associated with the build-up and subsequent bursting of the dot-com bubble (Ofek and Richardson (2003); Hong and Stein (2007)).

¹⁵Lusardi and Mitchell (2011) give evidence of a positive correlation between educational attainment and financial literacy. Behrman et al. (2012) find this as well and further show a positive correlation between wealth and financial literacy.

¹⁶Figure H7 plots the wealth distribution for short and longer-term spellers separately, and further shows

wealth and the probability of a short spell is convex, implying that the marginal impact of more wealth on this probability is declining and effectively becomes zero by the 7th decile. Calvet et al. (2009a) find that individuals with less income, wealth, and education are more likely to exit. Our findings therefore show that they are not just more likely to exit at any point. Rather, they are also more likely to experience a quick exit.

Figure 4: Impact of income and wealth on the probability of a short spell



Notes. This figure plots the coefficient estimates for the fixed effects on income (a) and financial wealth (b) deciles following the estimation of Equation 1. Variables are measured at the point of entry, and deciles are based on the full Norwegian population aged 20 and above in that year. The effects are estimated relative to the median group. 95% confidence intervals are shown. The red line represents a null relative effect.

Finally, we explore the degree to which liquidity needs could be driving these short spells.¹⁷ In principle, some individuals may exit the stock market due to, for example, job loss or unforeseen health expenses. Upon the “completion” of such liquidity needs, individuals may subsequently reenter the market. We therefore exploit the richness of the Norwegian data and identify liquidity-related events. In particular, we look at house purchases, divorce, unemployment, and a large drop in income of > 50% as our liquidity shocks.¹⁸ Figure H10 plots the proportion of exiters of different spell lengths experiencing at least one of these shocks in

that short spellers are more likely to belong to a lower wealth decile than longer-term participants.

¹⁷In Appendix B, we provide a discussion of other potential explanations, namely pensions, market timing, and tax optimization.

¹⁸Two other liquidity needs could be health shocks and education costs. However, higher education is free in Norway. While healthcare is not free, there is an annual deductible above which healthcare is free. This deductible is fairly small at NOK 2,460 in 2021 (\$410 in 2011 USD). Across OECD countries, Norway has the highest share of healthcare financed through government schemes and the largest per-capita spending on healthcare relating to long-term care (Cooper (2019)). As such, Norwegians in general do not seem to be susceptible to large financial costs linked to healthcare needs.

their exit year. For comparison, we also show the proportion of continuing participants experiencing a liquidity shock. There is some link between experiencing a liquidity shock and quick exits as the prevalence of these liquidity-related events is decreasing in spell length. This is in line with papers linking exit to house purchases (Brandsaas (2021)), marital status (Christiansen et al. (2015)), and unemployment (Basten et al. (2016)). However, it is worth noting that liquidity needs are unable to explain every short spell because if 15% of exiters leave due to one of these observed shocks, it means that 85% of exiters are leaving for other reasons.

It is important to emphasize that short spells are not exclusive to certain subgroups. Figure H9 shows the distribution of spell lengths by income, wealth, education, gender, and asset class. For example, while men are more likely to exit quickly (Figure H9d), about 17% of women still leave the stock market within 2 years of entry. It is also noteworthy from Figure H9e that the prevalence of short spells is particularly high for stock investors with just over 30% of their spells ending within 2 years compared to about 20% for fund investors.

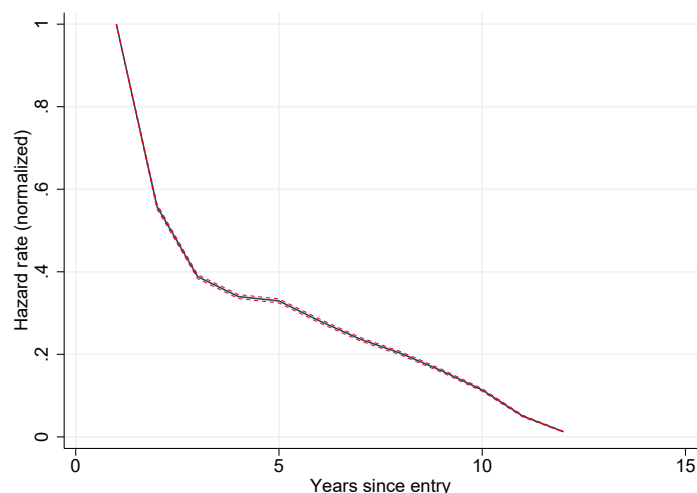
Our finding that short spells in the stock market are common can have important implications for wealth accumulation. Indeed, much of the policy focus has been on encouraging entry into the stock market (e.g., via tax incentives). However, we see that temporary participation is very common, so from a policy perspective, it is not only about encouraging entry into the stock market. It is also important to encourage participants not to exit impulsively so that they can earn the high equity premium on average.

3.1.2 Exit probability falls with spell duration

Are investors more likely to exit the stock market in the initial periods following entry or after staying in the market for a prolonged period? To answer this question, we estimate the hazard function for exit from participation. The hazard function $h_i(d)$ denotes the probability that individual i exits the market d years after entry, conditional on not exiting until then. A standard challenge with hazard function estimation is separating true duration dependence from (unobserved) heterogeneity. Estimating hazard functions based on pooled samples with heterogeneous individuals can lead to a downward bias in the slope of the hazard function because individuals who are less likely to “survive” exit the sample earlier than others (Lancaster (1979); Kiefer (1988)).

To address this concern, we apply the linear GMM estimator of [Alvarez et al. \(2021\)](#) and estimate a discrete-time proportional hazard model of duration. The main advantage of their approach is that it gives a consistent estimator of the slope of the hazard function, even in the presence of time-invariant individual heterogeneity. Their methodology does so by exploiting the presence of individuals with multiple spells in the stock market. The resulting limitation is that the set of people experiencing multiple spells used in the estimation can be fundamentally different from the rest of the population. However, similar patterns do emerge when using the full set of participants and instead estimating a Cox proportional hazards model (Figure H12). Further details on the [Alvarez et al. \(2021\)](#) approach are provided in Appendix D.

Figure 5: Baseline hazard function for exit from participation



Notes. This figure plots the estimated baseline hazard for exit from participation following the methodology of [Alvarez et al. \(2021\)](#) described in Appendix D. The dotted red lines denote 95% confidence intervals. The hazard rate at duration $d = 1$ is normalized to 1.

Figure 5 plots the estimated baseline hazard function. The hazard function is monotonically declining in duration, indicating negative duration dependence; that is, the longer one has been participating in the stock market, the less likely they are to exit completely at that point in time. As described in Appendix D, we are able to recover the slope of the baseline hazard rather than its level using the [Alvarez et al. \(2021\)](#) approach, so we normalize the hazard rate at $d = 1$ to 1. A striking feature of the hazard function is the steepness of the slope in the initial years following entry. The hazard rates at $d = 2$ and $d = 3$ are about 55% and 40% that of $d = 1$, respectively. By $d = 12$, the hazard rate is close to zero, suggesting that if an

individual remains in the market for a prolonged period, the likelihood of them completely withdrawing from the market is minimal. Combined with the fact that many stock market participants stay in the stock market for a short time, this finding indicates strong dynamics in the initial years following entry.

3.2 Reentry margin

3.2.1 Some exiters reenter the stock market

We now turn to understanding whether exiters ever reenter following exit. Figure 6 plots the distribution of the number of spells an individual experiences.¹⁹ 40% of the population never participates in stocks, while 48% are observed to participate just once, meaning that around 12% of the entire population has multiple spells. Hence, reentry does occur for a nonnegligible proportion of the population. Indeed, this finding negates the conventional view in the literature that upon entering the stock market, individuals should rarely leave. Here, we see that some people liquidate their stock holdings completely but subsequently reenter.²⁰ Figure H15 plots a time series of the reentry rate, and shows that since the late 1990s, the reentry rate has hovered between 20-40%. Therefore, while most exiters do not reenter, a nonnegligible proportion of them do.

We also find that investors tend to return to the same asset class in which they previously participated. Figure H14 shows that over 80% of reentrants who previously participated in funds choose to return to funds. Of those reentrants who previously invested in individual stocks, over 60% go back into direct stockholding. This result suggests that investors tend to divide themselves into types, namely fund investors and direct stockholders, with very few participating in both.

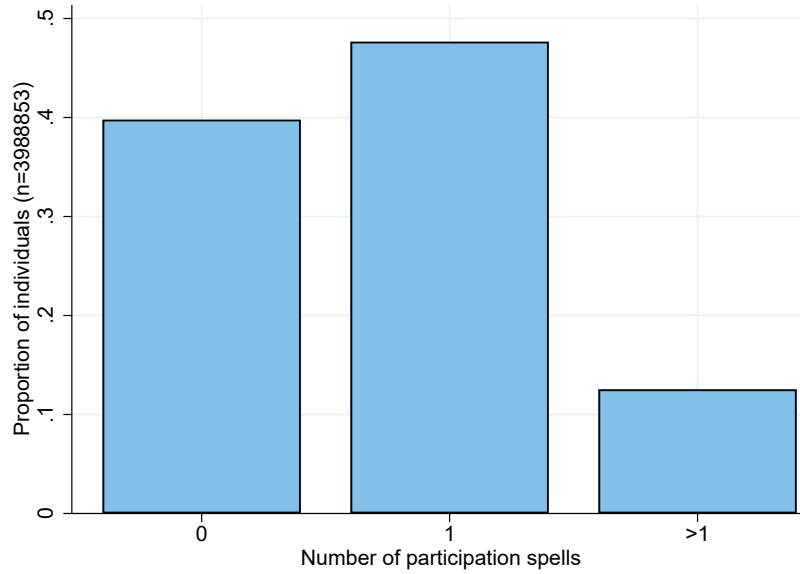
We now examine which characteristics are associated with reentry. For this purpose, we run the following linear probability model:

$$\text{Pr}(\text{reenter within 4 years}) = \alpha + \delta_t + \beta' X_{it} + \epsilon_{it} \quad (2)$$

¹⁹We restrict attention to individuals who appear in the data for at least 15 years, as those who appear for fewer years are likely to have either zero or one spell, which would skew the distribution to the left.

²⁰Figure H13 decomposes the entry rate into reentrants and new entrants, and shows that about one-third to one-half of entrants in a given year are reentrants.

Figure 6: Number of spells



Notes. This figure plots the distribution of the number of spells using individuals who appear in the data for at least 15 years.

where δ_t now denotes exit-year fixed effects. We use a fixed window of 4 years to reenter because those who exit early in the sample have more years remaining in which to reenter. A fixed window means all exiters have the same amount of time to reenter. Furthermore, to preview the findings in Section 3.2.2, most reentry occurs soon after exit, and so a 4-year window should capture a large proportion of reentry. To ensure that all individuals are observed for at least 4 years following exit, we restrict attention to those who leave the stock market by 2012.

Table 3 shows the coefficient estimates. Males are more likely to reenter by about 11% (3.8pps) relative to females, which again is in line with the overconfidence and excessive trading behavior of males documented in Barber and Odean (2001). We find that the characteristics found to be positively linked to entry in Calvet et al. (2009a) are also associated with a greater likelihood of reentry, namely having a college degree and being of high income (Figure H16a) and wealth (Figure H16b). Reentry is also most likely for the youngest age groups (Figure H17), in line with the finding in Fagereng et al. (2017) that permanent exit rises sharply after retirement.

Table 3: Determinants of reentry

	(1)
Homeowner	0.009*** (0.001)
Male	0.038*** (0.001)
Unemployed	-0.015*** (0.002)
Degree	0.037*** (0.001)
Single	-0.032*** (0.001)
Sample mean	0.35
Year FE	Yes
Wealth and income FE	Yes
Age group FE	Yes
Observations	1226078
R-squared	0.15

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This table shows the estimation of the linear probability model in Equation 2. The dependent variable is a binary variable equal to 1 if the exiter re-enters within 4 years following exit, and zero otherwise. *Homeowner* is a binary variable equal to 1 if the participant owns their own property (either self-owned or ownership through housing cooperatives), and zero otherwise. *Single* is a binary variable equal to 1 if the participant is neither married nor cohabiting, and zero otherwise. *Unemployed* is a binary variable equal to 1 if the participant receives unemployment benefits at the point of exit, and zero otherwise. Exit year fixed effects are included. Age fixed effects by broad age group (20-29, 30-39, 40-49, 50-59, 60-69 and 70+), as well as income and wealth decile fixed effects are included. Observables are measured at the point of exit. Standard errors are clustered at the individual level. The regression uses data on exiters from 1994-2012.

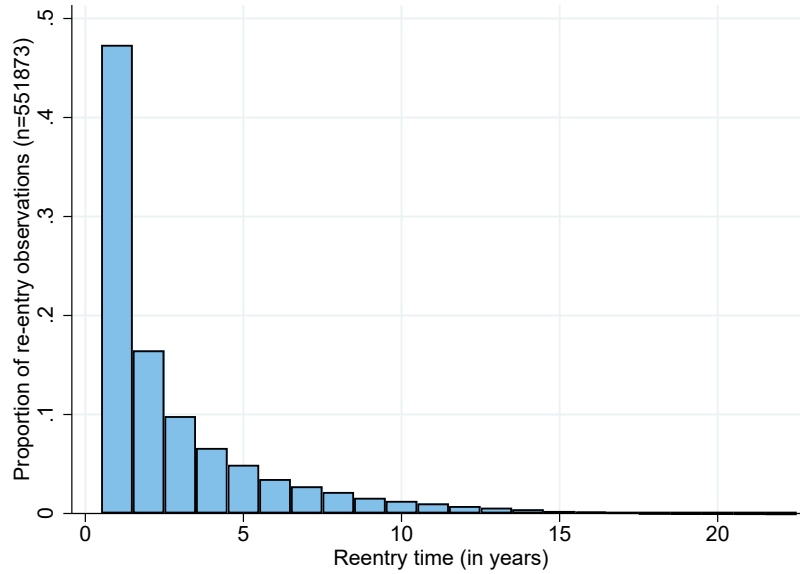
3.2.2 Reentry often occurs soon after exit

Conditional on occurring, how soon after exit do individuals reenter? Figure 7 plots the distribution of reentry times observed in the data. Almost half of all reentry occurs just 1 year after exit, indicating that reentry tends to be quick. Combined with the evidence for short spells given in Section 3.1.1, this implies that there is turnover between participation and nonparticipation states, with many individuals dropping out of participation spells after only a few years and some exiters reentering soon after exit. These findings are robust to excluding recipients of gifts or inheritances (Figure H18) and individuals holding stocks in the company they work for when they reenter (Figure H19).

3.2.3 Probability of reentry falls with time since exit

Our final fact studies how the likelihood of reentry changes with the duration since exit. The object of interest is a hazard function $h(d)$, which denotes the probability of reentering d

Figure 7: Distribution of reentry times



Notes. This histogram shows the distribution of reentry times in the Norwegian data.

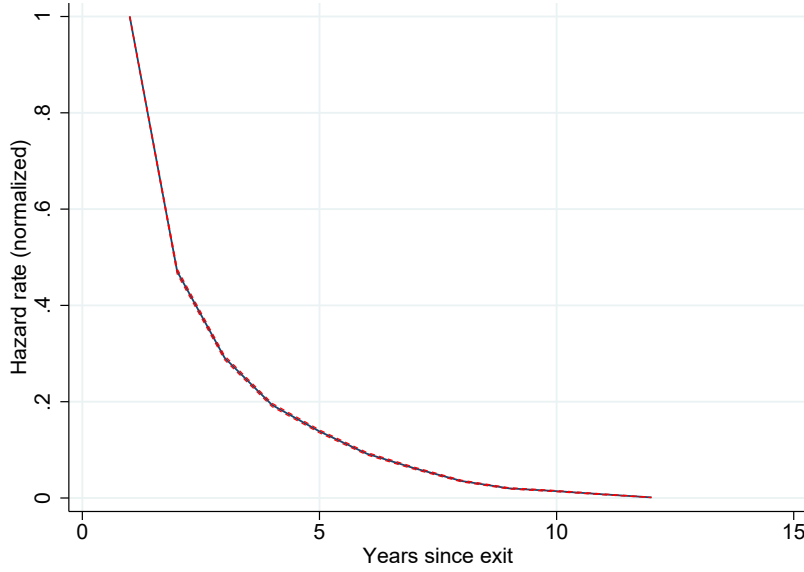
years after exit conditional on not having reentered until then. We exploit the fact that some individuals have multiple spells out of the stock market and again apply the GMM estimator of Alvarez et al. (2021). Figure 8 plots the estimated hazard function for reentry. The hazard function is downward sloping and highly convex, indicating negative duration dependence in reentry following exit: the longer it has been since one has been out of the stock market, the less likely they are to return. There is a sharp decline in the hazard rate in the initial years following exit, with the hazard rate at $d = 2$ being less than half that of $d = 1$. By $d = 12$, the hazard rate is very low, indicating that the likelihood of reentering is virtually zero by about a decade after exit.²¹

4 Model

Our empirical results established novel patterns of individual-level dynamics in stock market participation. This section first describes the workhorse portfolio choice model of Cocco et al. (2005) augmented with participation costs, and discusses the ability of the standard model to generate these dynamics. We then extend the model to allow for experience-based

²¹Similar patterns appear if we estimate a Cox proportional hazards model for reentry (Figure H20).

Figure 8: Baseline hazard function for reentry



Notes. This figure plots the estimated baseline hazard for reentry following exit using the methodology of Alvarez et al. (2021) described in Appendix D. The dotted red lines denote 95% confidence intervals. The hazard rate at duration $d = 1$ is normalized to 1.

learning à la Malmendier and Nagel (2011), whereby agents form beliefs over the equity premium based on their personal realized returns. While our model embeds the participation cost story of nonparticipation, we discuss alternative theories of participation in Appendix E, namely nonstandard preferences, risks faced by households, and cultural/social factors.

4.1 Model setup

4.1.1 Preferences

Individuals are born at age t_b and die for certain by age t_d . They have Epstein-Zin preferences over consumption C_{it} and next period cash on hand $X_{i,t+1}$ (Epstein and Zin (1989)):

$$V_{it} = \left[(1 - \beta)C_{it}^{1-\frac{1}{\psi}} + \beta \left(\pi_t E_t V_{i,t+1}^{1-\gamma} + \kappa (1 - \pi_t) E_t X_{i,t+1}^{1-\gamma} \right)^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right]^{\frac{1}{1-\frac{1}{\psi}}} \quad (3)$$

where ψ is the elasticity of intertemporal substitution, β is the subjective discount factor, and γ is the coefficient of relative risk aversion. π_t is the conditional survival probability (i.e. the probability of surviving to age $t + 1$ conditional on being alive at age t).

The second term in the next period utility captures a bequest motive of individuals with $\kappa \equiv (1 - \beta)^{\frac{1}{1-\psi}} \zeta^{\frac{1}{\psi-1}}$. This formulation of bequest motives follows [Kraft et al. \(2022\)](#), whereby the parameter ζ governs the strength of the bequest motive and corresponds to the terminal wealth-consumption ratio. Including a bequest motive provides an additional incentive to save, particularly during retirement, and thus helps to better match wealth dynamics during the latter period of life. Without a bequest motive, individuals would deplete their wealth following retirement at a faster rate than is observed in the data.

We follow [Gomes and Michaelides \(2005\)](#) and use Epstein-Zin preferences rather than power utility in order to separate out the effects of risk aversion and the elasticity of intertemporal substitution (EIS). A low degree of risk aversion implies less prudence, which induces less saving for precautionary reasons (as will be discussed in the next subsection, there are uninsurable shocks in the model). However, under power utility, the EIS is inversely proportional to the coefficient of risk aversion, and so the low risk aversion means a high EIS.²² As the expected return on the risky asset (stocks) exceeds that of the risk-free bonds, agents will choose to save more for retirement and bequest purposes, leading to conflicting effects on wealth accumulation. Using Epstein Zin, we can disentangle these two parameters.

4.1.2 Labor market

Life is split into working age ($t \leq t_r$) and retirement ($t > t_r$), where t_r denotes retirement age. In each period, individuals receive an exogenous income Y_{it} . During working age, labor income is stochastic and depends on a deterministic function of age $f(t)$ calibrated to capture the hump-shaped nature of earnings during working life, as well as a transitory component u_{it} and a persistent component p_{it} modeled as a random walk.

$$\ln Y_{it} = \ln f_t + p_{it} + u_{it} \quad \text{for } t \in \{t_b, \dots, t_r\}, \quad u_{it} \sim N(0, \sigma_u^2) \quad (4)$$

$$p_{it} = p_{i,t-1} + z_{it}, \quad z_{it} \sim N(0, \sigma_z^2) \quad (5)$$

Markets are incomplete and thus agents cannot insure against income shocks, nor the sur-

²²[Calvet et al. \(2021\)](#) show that the perfect negative correlation between risk aversion and EIS does not hold in the data with the two preference parameters exhibiting only weak negative correlation.

vival risk. It is useful to define the current level of permanent income $Y_{it}^p \equiv \exp(p_t) \cdot f_t$. During each year of retirement, agents receive a fraction ϕ_{ret} of their permanent income in the last year of working life. This means that upon reaching retirement age and realizing $Y_{it_r}^p$, they face no uncertainty over their income during this latter period of life.

$$\ln Y_{it} = \ln \phi_{ret} + \ln Y_{it_r}^p = \ln \phi_{ret} + \ln f_{t_r} + p_{it_r} \quad \text{for } t \in \{t_r + 1, \dots, T\}$$

4.1.3 Financial markets and participation costs

Individuals can invest in a riskless bond with a safe net return R_f or a risky asset (stocks) with a stochastic net return R_{it} determined by the following process:

$$R_{it} = \begin{cases} R_f + \mu + \epsilon_{it} & \text{with probability } 1 - p_{\text{tail}} \\ R_{\text{tail}}, & \text{with probability } p_{\text{tail}} \end{cases} \quad (6)$$

where μ denotes the average equity risk premium and $\epsilon_{it} \sim N(0, \sigma_\epsilon^2)$. Given evidence in [Fagereng et al. \(2017\)](#) that the correlation between income and stock return shocks is small and statistically insignificant, we treat ϵ_{it} as uncorrelated with the income shocks. We allow for a tail event return $R_{\text{tail}} < 0$ following [Fagereng et al. \(2017\)](#) as this can help to match participation rates during retirement. An implicit assumption here is that individuals have idiosyncratic return histories, which is supported by existing evidence on portfolio under-diversification by retail investors (e.g., [Calvet et al. \(2007\)](#); [Goetzmann and Kumar \(2008\)](#)).

Until now, there are no frictions to participating in the stock market, and so there would be full participation as long as $\mu > 0$ ([Samuelson \(1969\)](#); [Merton \(1969, 1971\)](#)). To provide a motive for nonparticipation, we augment the model with two types of stock market participation costs. The first is an entry cost (F_{it}^0), which must be paid at the start of any new spell. The entry cost can reflect time and money spent setting up an investment account, deciding on the initial portfolio, and learning fundamental investment principles. Such costs can help to explain why some people never participate in the stock market ([Gomes and Michaelides \(2005\)](#)). The second is a per-period cost (F_{it}^1) paid in each period where the agent chooses a positive quantity of stocks. This can capture the time spent monitoring one's portfolio and deciding whether to reallocate funds, as well as any fixed account man-

agement fees (Vissing-Jørgensen (2002)). Per-period costs can help to generate exit from the stock market (Fagereng et al. (2017); Bonaparte et al. (2023)).

We follow Gomes and Michaelides (2005) and assume that both costs are proportional to the level of permanent income ($F_{it}^d = \bar{F}^d Y_{it}^p$ for $d \in \{0, 1\}$). We primarily make this assumption for computational tractability. In particular, we can exploit the scale invariance of the problem and normalize the current level of permanent income Y_{it}^p to 1, thus reducing the number of state variables in the model by one. However, it can be motivated by the view that participation costs reflect the opportunity cost of time.

4.1.4 Budget constraint and optimization problem

Individuals choose consumption C_{it} and a risky asset share α_{it} . Agents cannot borrow or short sell, hence α_{it} is constrained to the unit interval. Cash on hand $X_{i,t}$ evolves according to the following budget constraint:

$$X_{i,t+1} = \tilde{R} \cdot (X_{it} - C_{it} - F_{it}^0 \mathbb{1}(\alpha_{i,t-1} = 0 \ \& \ \alpha_{it} > 0) - F_{it}^1 \mathbb{1}(\alpha_{it} > 0)) + Y_{i,t+1} \quad (7)$$

where $\tilde{R} \equiv 1 + R_f + \alpha_{it}(R_{it} - R_f)$ is the portfolio return. Exploiting homogeneity of the problem, we can scale the model by permanent income. Using a recursive formulation and defining lowercase letters as the variable normalized by permanent income (e.g., $x_{it} = \frac{X_{it}}{Y_{it}^p}$), the optimization problem can be written as:

$$V_t(x, \mathbb{1}(\alpha_{-1} > 0)) = \max_{C, \alpha} \left[(1 - \beta) c^{1 - \frac{1}{\psi}} + \beta (\pi_t E_{x'} V_{t+1}^{1-\gamma}(x', \mathbb{1}(\alpha > 0)) + \kappa (1 - \pi_t) E_{x'} x'^{1-\gamma})^{\frac{1 - \frac{1}{\psi}}{1-\gamma}} \right]^{\frac{1}{1 - \frac{1}{\psi}}} \quad (8)$$

subject to $c \geq 0$, $0 \leq \alpha \leq 1$, and non-negative savings $x - c - \bar{F}^0 \mathbb{1}(\alpha_{-1} = 0 \ \& \ \alpha > 0) - \bar{F}^1 \mathbb{1}(\alpha > 0) \geq 0$, and where:

$$x' = \tilde{R} \cdot (x - c - \bar{F}^0 \mathbb{1}(\alpha_{-1} = 0 \ \& \ \alpha > 0) - \bar{F}^1 \mathbb{1}(\alpha > 0)) \cdot \frac{1}{g_{t+1}^p} + \exp(u')$$

$$\tilde{R} \equiv 1 + R_f + \alpha_{it}(R - R_f) \quad , \quad g_{t+1}^p \equiv \frac{Y_{t+1}^p}{Y_t^p} \approx \exp\left(\frac{f_{t+1} - f_t}{f_t} + z'\right)$$

4.1.5 Allowing for experience-based learning

The model thus far assumes that agents have rational expectations. They know the returns process for stocks, and so poor realized returns do not alter their beliefs about future equity returns. However, a growing literature has shown that personal experiences can have long-lasting effects on individual beliefs and choices (Malmendier and Wachter (2021)). We therefore extend the model to allow for experience-based learning (EBL) à la Malmendier and Nagel (2011).²³ Following Malmendier and Nagel (2011, 2015), agents do not know the true average equity premium μ , but form beliefs over μ based on their experienced returns R_{it} .²⁴ Beliefs over μ , denoted by $\hat{\mu}_{it}$, evolve according to:

$$\hat{\mu}_{it} = \omega_t \hat{\mu}_{i0} + (1 - \omega_t) \sum_{k=1}^{t-1} g(k, \lambda, t) \cdot R_{it}^e \quad (9)$$

where t denotes age and $R_{it}^e \equiv R_{it} - R_f$ is the realized equity premium at age t for agent i . $\omega_t \equiv \frac{1}{1+t\iota}$ is the weight given to the prior belief, where ι is a parameter governing its strength.²⁵ We assume that the initial prior equals the true average equity premium for all individuals, $\hat{\mu}_{i0} = \mu \forall i$. $g(k, \lambda, t)$ denote experience weights with:

$$g(k, \lambda, t) = \frac{(t-k)^\lambda}{\sum_{k'=1}^{t-1} (t-k')^\lambda} \quad (10)$$

Under this formulation, experiences have long-lasting effects, but the weight given to each individual experience depends on age and elapsed time. If $\lambda > 0$, more recent experiences are given greater weight and agents exhibit recency bias, while $\lambda = 0$ means experiences are equally weighted. A negative value of λ means returns in early life have the strongest impact.

When individuals are in the stock market, their experience is simply the realized return on the equity component of their portfolio. When agents are not participating, we assume that they “experience” the market return and so $R_{it}^e = \mu$ when not in the market. This means

²³Some papers have shown that experience-based learning can also help to explain various asset pricing puzzles (e.g., Nakov and Nuño (2015); ADAM et al. (2016); Malmendier et al. (2020)).

²⁴Putting weight on personally-experienced outcomes relates to the availability bias of Tversky and Kahneman (1973).

²⁵Note that this weight is equivalent to the formulation in Malmendier et al. (2020) of $\frac{\tau}{\tau+t}$ with $\iota \equiv \frac{1}{\tau}$. We do this transformation so that $\iota \rightarrow 0$ means converging to the previous model without beliefs (as long as $\hat{\mu}_{i0} = \mu$). This limiting case of zero (rather than $\tau \rightarrow \infty$) is useful when estimating the model and providing bounds on parameter values for the Nelder-Mead local optimization routine (see Appendix F3).

that there is some reversion in beliefs following a bad return realization with the speed of reversion determined by λ and age. We also assume that agents display naïvety by not thinking that they will change their beliefs in the future when making decisions today, hence $\hat{\mu}_{i,t+1} = \hat{\mu}_{it}$ from the perspective of the individual. This simplification reflects cognitive limitations of agents when making such complicated investment decisions (Fiske and Taylor (2013)). It also simplifies the solution of the model as agents do not need to internalize the belief updating process when solving their decision problem. Note that beliefs will still evolve in accordance with Equation 9 when simulating the model.

Taken together, the optimization problem in the extended model with EBL is as follows:

$$V_t(x, \mathbb{1}(\alpha_{-1} > 0), \hat{\mu}) = \max_{C, \alpha} \left[(1-\beta)c^{1-\frac{1}{\psi}} + \beta(\pi_t E_{x'} V_{t+1}^{1-\gamma}(x', \mathbb{1}(\alpha > 0), \hat{\mu}) + \kappa(1-\pi_t) E_{x'} x'^{1-\gamma})^{\frac{1-\frac{1}{\psi}}{1-\gamma}} \right]^{\frac{1}{1-\frac{1}{\psi}}} \quad (11)$$

with the same constraints and evolution of cash on hand as before. Details on the model solution method are provided in Appendix F1.

4.2 Parameterization

We employ a two-step approach for calibrating the model. In the first step, we do an external calibration and set certain parameters to either existing values in the literature or values computed directly from our data. The second step involves estimating preference parameters, participation costs, and parameters of the belief updating process using simulated method of moments (SMM).

Table 4 summarizes the parameter values from external calibration. Individuals are born at age $t_b = 20$ and die for certain after age $t_d = 100$. The parameters relating to the stochastic component of the labor income process are taken from Fagereng et al. (2017), who estimate the process specifically for Norway. We estimate the deterministic component of the income process $f(t)$ ourselves using the approach described in Appendix F2. Financial market variables are also specific to Norway. The mean equity premium and standard deviation of stock returns are taken from Fagereng et al. (2017), who adjust the values in Dimson et al. (2008) to account for holdings of foreign equities by Norwegian retail investors. We use the estimated value of p_{tail} from Fagereng et al. (2017).²⁶ We also fit a Pareto distribution to financial wealth

²⁶Fagereng et al. (2017) argue that the frequency of tail events implied by their estimated probability $p_{\text{tail}} =$

of individuals aged 20, thereby obtaining scale and shape parameters. In our simulations, we draw initial wealths from this distribution.²⁷

This leaves 8 parameters that need to be estimated within the model: the preference parameters $(\beta, \gamma, \psi, \zeta)$, participation costs (\bar{F}^0, \bar{F}^1) , and the belief updating parameters (ι, λ) . Denoting θ as the parameter vector to estimate, SMM compares simulated moments $m(\theta)$ obtained in the model with equivalent empirical moments m , and selects the parameter combination $\hat{\theta}$ that minimizes the percentage difference between them. More formally:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} (m(\theta) - m)'W(m(\theta) - m) \quad (12)$$

where W is a weight matrix. We use three categories of target moments, namely the stock market participation rate, the conditional risky asset share, and financial wealth-to-income ratios. We compute each of these moments for every age from 20 to 85, leaving us with 198 target moments. Further details on the SMM procedure are provided in Appendix F3.

Table 4: Externally-calibrated parameters

Parameter	Description	Value	Source
<i>Institutional</i>			
t_r	Retirement age	67	Norwegian law
π_t	Cond'l survival probabilities	-	SSB Life Tables 2010
<i>Labor market</i>			
$f(t)$	Deterministic wage profile	-	Own calculations (Appendix F2)
ϕ_{ret}	Replacement ratio	0.842	Fagereng et al. (2017)
σ_z	Std. dev of permanent shock	0.110	Fagereng et al. (2017)
σ_u	Std. dev of temporary shock	0.152	Fagereng et al. (2017)
<i>Financial market</i>			
R_f	Risk-free return	0.0143	Klovland (2004)
μ	Average equity premium	0.0314	Fagereng et al. (2017)
σ_e	Std. dev of stock return	0.238	Fagereng et al. (2017)
R_{tail}	Tail event return	-0.485	Fagereng et al. (2017)
p_{tail}	Tail event probability	0.011	Fagereng et al. (2017)
<i>Initial wealth</i>			
$\alpha_{x_0}^{shape}$	Pareto shape (initial wealth)	0.881	Own calculations
$\alpha_{x_0}^{scale}$	Pareto scale (initial wealth)	2.894	Own calculations

Notes. This table shows the externally-calibrated parameter values used in our model simulations.

0.011 (1-2 tail events over one's lifetime) is in line with that implied by historical stock market crashes in Norway.

²⁷We take real financial wealth at age 20 and trim at the 99th percentile prior to fitting the Pareto distribution.

5 Model results

In this section, we discuss the estimated parameters and model simulations. We begin with a discussion of a model with only participation costs (no beliefs) and its ability to match the target moments, as well as our empirical findings on individual-level dynamics. We then analyze the impact of incorporating EBL in Section 5.2, before doing tests of the model predictions in Section 5.3.

5.1 Model without beliefs

Column 3 of Table 5 gives the estimated parameter values for a model without EBL, i.e. where participation costs act as the sole friction to participating in the stock market. We obtain a discount factor of $\beta = 0.827$. While this value is low relative to those used in macro models or estimates based on life cycle models of consumption-savings decisions (e.g., [Gourinchas and Parker \(2002\)](#)), this value is in the range of typical estimates from life cycle models of portfolio choice. For example, [Fagereng et al. \(2017\)](#) obtain estimates of β ranging from 0.75-0.83, while [Cooper and Zhu \(2016\)](#) get values between 0.76-0.90.²⁸ The low discount factor is needed to limit wealth accumulation such that the financial wealth profile over age is more in line with the data. We further obtain a moderate coefficient of relative risk aversion of 6.581, which is fairly close to the population average value of 7.57 found in [Calvet et al. \(2021\)](#) and also in line with existing estimates in the life cycle portfolio choice literature.²⁹ Our EIS is $\psi = 0.443$, which, when combined with our estimate of risk aversion, implies that the power utility restriction that γ and ψ are inversely related does not hold. As such, our estimates lend support to the Epstein-Zin formulation. Like in [Cooper and Zhu \(2016\)](#), [Fagereng et al. \(2017\)](#), and [Briggs et al. \(2021\)](#), we find a strong bequest motive that will help to slow down asset decumulation during retirement. For participation costs, we find entry costs of 1.22% of permanent income, which approximately amounts to $\approx \$500$ in 2011 prices. This is slightly lower than the 2% found in [Alan \(2006\)](#). The per-period partici-

²⁸Note that some papers obtain higher β estimates by adding further ingredients to the model. [Catherine \(2021\)](#) considers cyclical skewness of labor income shocks, and obtains β values ranging from 0.91-0.96. However, in a more standard model with participation costs but no cyclical skewness, they estimate lower discount factors of 0.67-0.88.

²⁹[Choukhmane and de Silva \(2023\)](#) note that existing estimates in the literature range from 4-14.4 with an average of 7.82.

pation cost is estimated to be 0.29% of permanent income, which is \approx \$120. This is within the range of estimates from [Fagereng et al. \(2017\)](#) of \$64-\$344, and slightly lower than estimates in [Vissing-Jørgensen \(2002\)](#) (\$300) and [Catherine \(2021\)](#) (\$250).

Table 5: Internally-estimated coefficients

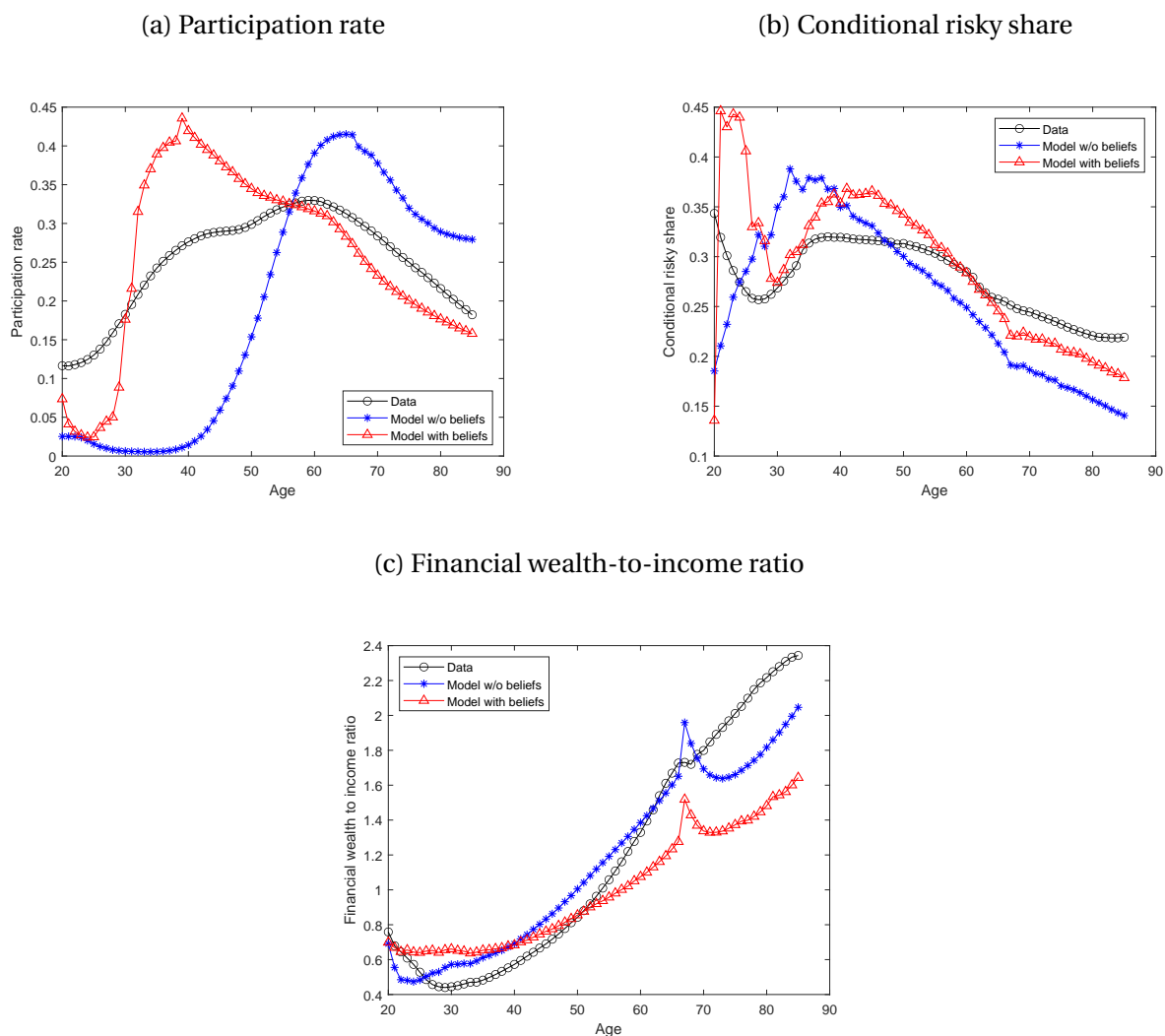
	Parameter	No EBL	With EBL
<i>Preference parameters</i>			
β	Discount factor	0.827	0.813
γ	Risk aversion	6.581	9.573
ψ	EIS	0.443	0.599
ζ	Bequest motive	4.600	4.330
<i>Participation costs</i>			
\bar{F}^0	Entry cost	1.22%	0.70%
\bar{F}^1	Per-period cost	0.29%	0.07%
<i>Belief updating</i>			
ι	Prior weight	-	0.029
λ	Experience weight	-	1.644
# of Moments		198	198
Objective function		29.67	13.83

Notes. This table gives the estimated parameter values for the models without (Column 3) and with experience-based learning (Column 4). Parameter values are estimated using simulated method of moments, and the objective function is calculated as in Equation 12. Participation costs are formulated as a percentage of permanent income (see Section 4.1.2). For more details on the estimation procedure, see Section 4.2 and Appendix E3.

Figure 9 shows the simulated life cycle profiles for our targeted moments, namely the stock market participation rate, conditional risky asset shares, and the financial wealth-to-income ratio. Without beliefs, the model underpredicts participation at a young age, but overpredicts participation in later life (Figure 9a). This occurs because the constraint to entering the stock market is payment of the entry cost. As individuals build up wealth during their working life, they start to cross the cash on hand threshold required to enter the stock market (Figure H21). However, this takes time and the participation rate is close to zero until about age 40. Once individuals eventually start to enter, they face the smaller per-period cost of participating. As they are continuing to build wealth over this period (as reflected by the increasing savings rate in Figure H22) and face an increasing income profile (Figure F1), they will typically remain in the stock market. Participation thus continues to increase until retirement age, after which individuals will start decumulating their asset holdings (but not completely due to the bequest motive). Hence, stock market participation begins to fall, but

still remains above levels in the data.

Figure 9: Life cycle profile of participation, risky shares, and wealth (targeted moments)



Notes. This figure plots the average life cycle profiles of the participation rate (panel a), the conditional risky asset share (panel b), and the financial wealth-to-income ratio (panel c) from the Norwegian data, the model without beliefs, and the model with EBL.

Figure 9b shows the life cycle profile of the conditional risky share. Average conditional shares initially rise in the first decade of life, though participation rates are essentially zero in this time. From age 40, average risky shares decline. The intuition for this follows from Jaggannathan et al. (1996), Cocco et al. (2005), and Gomes (2020). Labor income can be thought of as an implicit holding of the riskless bond given that labor income is a closer substitute to bonds than stocks (Heaton and Lucas (1997)). Over working age, the ratio of human capital (present value of future labor income) and financial wealth declines as individuals build

more wealth and you get closer to retirement, leading individuals to tilt their portfolios away from stocks. Beyond retirement, whether risky shares rise or fall with age depends on the rate by which human capital falls relative to financial wealth. Under our calibration, human capital falls at a faster rate than financial wealth because individuals have a bequest motive that encourages them to continue saving in retirement. Hence, average risky shares continue to fall with age.

The life cycle profile for wealth (Figure 9c) shows very similar patterns to the data. A low discount factor β is needed, otherwise agents in the model will accumulate too much wealth relative to the data. Individuals accumulate wealth during working age for precautionary reasons given that labor income risk is uninsurable, as well as for retirement because average incomes in retirement are less than in working life. There is a sharp spike just before retirement age. This reflects uncertainty about the level of permanent income that will prevail during retirement. Following retirement, wealth initially declines, partly reflecting the resolution of uncertainty over income, but also a reduction in average incomes during retirement that means agents save less. However, higher mortality and the presence of a bequest motive lead people to save and wealth to gradually increase once again.

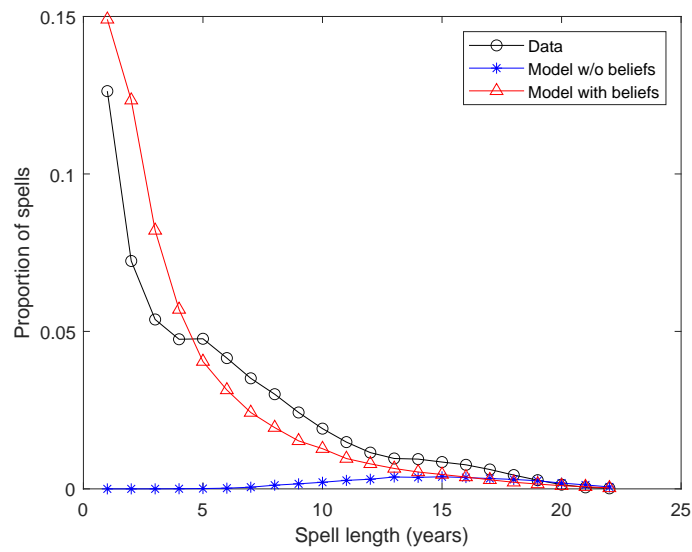
We now study whether the participation cost model is able to generate the individual-level dynamics found in the empirical analysis.³⁰ Figure 10 plots the distribution of spell lengths in the simulated model compared to the data. Unsurprisingly given the discussion on participation rates, the estimated model fails to generate short spells. Instead, once people enter, they generally do not exit until later life. Most spells thus end up as being right-censored. This is further reiterated in Figure 11, which shows that virtually no-one has multiple spells in the stock market.

5.2 Model with beliefs

We now consider the model with EBL. Column 4 of Table 5 shows the estimated parameter values. While the discount factor β and the bequest motive strength ζ hardly change, there is a sharp increase in risk aversion from $\gamma = 6.581$ to $\gamma = 9.573$. This is needed because with

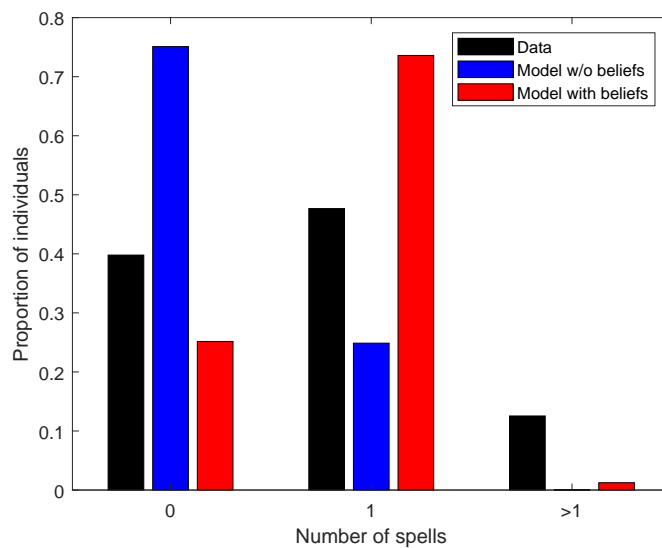
³⁰In this analysis, we censor the simulated agents in the same way as in the data. For example, someone born in 1990 would only appear in our data from 2010-2016 given the lower bound on age of 20 in the empirical analysis. As such, only their behavior from ages 20-26 will be used with the remaining ages treated as censored observations. The distribution of cohorts in the model is set to match that of the Norwegian data.

Figure 10: Distribution of spell lengths



Notes. This figure plots the distribution of spell lengths in the data (black line) compared to the models without (blue) and with (red) beliefs. Right-censored spells are excluded from the plot, but are used in calculating proportions.

Figure 11: Number of spells distribution



Notes. This figure plots the distribution of the number of spells in the data (black) compared to the models without (blue) and with (red) beliefs. In the model simulations, we restrict attention only to those agents who appear in the censored sample for at least 15 years to match the approach used in the empirical analysis.

beliefs, the individuals who will choose to participate in the stock market will on average be more optimistic. This optimism over the equity premium leads them to choose a greater risky share. The higher degree of risk aversion thus helps to dampen this increase in average shares and keeps them more in line with the data. We see that participation costs fall sharply. The entry cost almost halves from 1.22% to 0.7% of permanent income, while the per-period cost falls by three quarters from 0.29% to 0.07%. This occurs because adding beliefs provides another friction that can generate nonparticipation, namely pessimistic beliefs. As such, the model does not need to load as heavily on participation costs to keep people out of the stock market.

The EBL model adds two new parameters to the model, namely the prior weight ι and the experience weight λ . With $\iota = 0.029$, the prior belief has a long-lasting effect on beliefs. While the weight on the prior declines with age, it still remains high even in later life (Figure H23). We find an experience weight of $\lambda = 1.644$, which suggests that individuals have recency bias and overweight recent personal experiences. This value of λ lies within the range of estimates by [Malmendier and Nagel \(2011\)](#) of 1.3-1.9.

In terms of the targeted moments, the model with EBL provides an improved fit to the targeted moments with the objective function more than halving from 29.67 to 13.83.³¹ For participation (Figure 9a), we obtain a quicker rise in participation with a sharp increase in entry from around age 25. This occurs for two reasons: first, the lower participation costs means less wealth is needed to justify paying the costs, making it more appealing to invest. Second, the higher degree of risk aversion encourages more precautionary saving as individuals have greater prudence, though more risk aversion can also bring about the opposite effect by lowering optimal risky shares. However, the low participation costs can make it still worthwhile to invest, even when you select a low share. The participation rate does peak earlier compared to the data, which reflects the impact of bad experiences. An adverse return realization makes individuals pessimistic, an effect that is amplified due to recency bias. Consequently, some individuals will exit as soon as they experience a poor return, leading to a general decline in participation. The participation rate during retirement does, however, fit more closely now than without beliefs.

³¹[Foltyn \(2020\)](#) finds that incorporating EBL into a life cycle portfolio choice model can close half of the gap between model-generated participation rates and true rates in the data, though they find that the fit to average conditional risky shares does not improve.

For conditional risky shares (Figure 9b), the model tracks the data better than in the previous model, other than at the very early part of life. The large increase in average shares during early life is simply because those who choose to *continue* participating must have had a good return realization. Given the limited experiences that they have had thus far, this particular realization is given a large weight, thus generating very high risky shares. Thereafter, we see that average risky shares are typically larger than those found in the model without beliefs. Again, this is due to selection: those who choose to participate are, on average, more optimistic and thus choose higher risky shares.

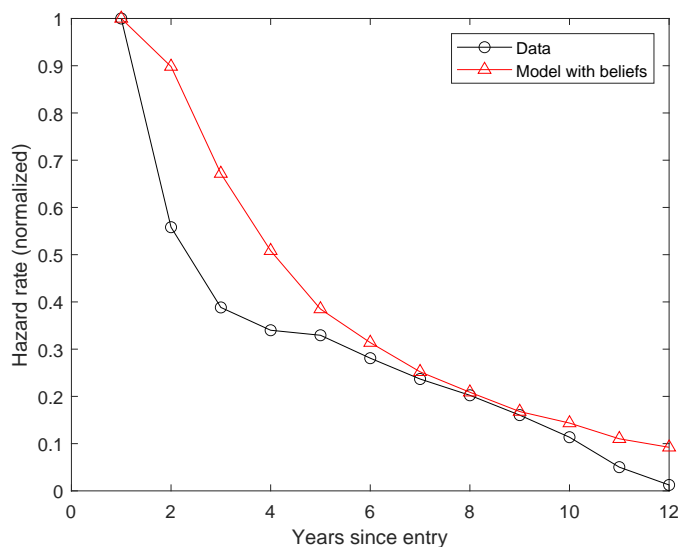
While the model with EBL does have the qualitative pattern of the empirical life cycle profile of financial wealth-to-income ratios, the quantitative fit is slightly weaker compared to a model with only participation costs. This difference is most stark from the end of working life, and reflects the impact of bad experiences generating some permanent exit and these agents consequently obtaining a lower return to their savings.

Turning to individual-level dynamics, which are not targeted in our estimation, we find that the model with EBL generates reasonable entry and exit rates of 1.85% and 5.77%, respectively. These numbers are in line with the rates found for Norway in Figure 2. Figure 10 shows that the model with EBL is able to produce a spell length distribution reasonably close to the data. Short spells occur because some individuals will draw poor initial returns, which lowers the expected return on stocks. The presence of participation costs can generate an additional margin of exit by further reducing the net gain from stock market participation. As such, following a poor return, the threshold wealth an individual needs to continue investing increases, which may drive some individuals out of the market even if they believe that stocks will outperform bonds on average. However, the very small per-period participation costs mean this amplification is weak.

We are also able to generate a downward-sloping hazard function (Figure 12). As time spent in the stock market increases, the fact that the agent has not yet left the market must mean that they performed well in their spell thus far, and therefore, they should be optimistic about the equity premium. Consequently, one requires a very low return to undo this confidence and be driven out of the market.

Figure 11 shows that the model with EBL generates a different distribution of number of spells. There are much fewer never participants in this model because participation costs

Figure 12: Hazard function for exit



Notes. This figure plots the hazard rate for exit under the model with beliefs (red) and the data (black). The hazard rate at 1 year after entry is normalized to 1 to facilitate comparison with the empirical hazard function, for which only the slope is identified.

are much lower. Given that individuals start with a prior belief equal to the true equity premium and they experience this value when not participating in the stock market, agents have a belief of $\mu = 3.14\%$ until their first participation spell. Consequently, the only friction to participating for a first time is the participation costs, and so their sharp reduction leads to much fewer never participants. The counter to this is that there are many more agents who experience one spell. In terms of reentry, the model with EBL does generate more multiple spellers relative to the model with only participation costs, for which effectively no-one reenters, but the amount of reentry remains much lower with just 1.2% of individuals experiencing multiple spells compared to 12.5% in the data. The reason for this is that while there is some reversion in beliefs over time because agents experience the average market return whenever they are not participating, under the estimated λ parameter, the speed of this reversion is not fast enough to bring exiters back into the stock market quickly.³²

³²This is illustrated in Figure H24, which plots the evolution of beliefs for an individual who enters the stock market at age 25, experiences a -20% return, and then permanently exits the market. By the time beliefs have “recovered”, agents are typically in the phase of life where they will not find it worthwhile to pay the entry costs given their cash on hand at that time. Plotting the distribution of reentry times in Figure H25 confirms that most reentry takes place at least a decade after exit, so we do not observe quick reentry as in the data.

5.3 Testing the model predictions

The model with EBL predicts that those who stop participating soon after entry should have weaker initial returns relative to those who stayed in the market for longer.³³ To test this, we use granular data from the Shareholder Registry, which tells us the specific Norwegian listed stocks held by an individual on December 31st of each year from 2004-2016. As we do not have information on specific mutual fund holdings, we focus on the subset of the population that only hold listed stocks. We compute annual returns following the methodology of Fagereng et al. (2020) described in Appendix G.

Table 6 gives the coefficient estimates from regressing a dummy variable of whether the spell ends within 2 years on a binary variable equal to 1 if the individual experienced a negative return in their entry year. When including the same set of controls as in the short spell regressions in Section 3.1.1 (Column 3), we find that experiencing a negative return in the entry year is associated with 21.6% (5.4pps) increase in the probability of the spell ending within 2 years.³⁴ We also see whether returns experienced during the spell affect the probability of reentry in Table 7, and find that there is a positive relationship between cumulative returns and the probability of reentry.

Table 6: Impact of entry year returns on probability of a short spell

	(1)	(2)	(3)
Negative return in entry year	0.057*** (0.003)	0.061*** (0.004)	0.054*** (0.004)
Sample mean	0.26	0.26	0.25
Year FE	No	Yes	Yes
Additional controls	No	No	Yes
Observations	76051	76051	72927
R-squared	0.00	0.01	0.06

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependent variable is a dummy variable equal to 1 if the individual's spell ends within 2 years, and zero otherwise. The explanatory variable of interest is a dummy variable equal to 1 if the annual return experienced in the entry year is negative. Details on the computation of returns are given in Appendix G. In Column 2, year fixed effects are included, and Column 3 adds the same set of controls used in the short spell regressions of Section 3.1.1. Returns are trimmed at the 1st and 99th percentiles of that year prior to estimation. Standard errors are clustered at the individual level.

The model with EBL also generates predictions on the impact of experiences by age. In particular, young people should be more strongly affected by an adverse return realization

³³At the aggregate level, we see that average risky shares fall during downturns (Figure H26), though part of this likely reflects passive drops in portfolio values rather than solely active changes in portfolio holdings.

³⁴Table HI shows that this relationship also holds when using a continuous measure of returns.

Table 7: Impact of experienced returns on probability of reentry

	(1)	(2)	(3)
Cumulative return during spell	0.025*** (0.006)	0.016* (0.006)	0.015* (0.006)
Sample mean	0.29	0.29	0.29
Year FE	No	Yes	Yes
Additional controls	No	No	Yes
Observations	19285	19285	18604
R-squared	0.00	0.01	0.05

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependent variable is a dummy variable equal to 1 if the individual reenters the stock market within 4 years. The explanatory variable of interest is the cumulative return experienced during the spell, which is computed as the product of annual returns. Annual returns are trimmed at the 1st and 99th percentiles of that year prior to estimation. Details on the computation of returns are given in Appendix G. In Column 2, year fixed effects are included, and Column 3 adds the same set of controls used in the reentry regressions of Section 3.2.1. Standard errors are clustered at the individual level.

because they have had fewer experiences, which results in them putting a greater weight on the most recent return. This is reflected in Figure H27, which shows that the likelihood of a spell ending within 2 years falls with age at entry. We found this pattern in the Norwegian data too (Figure H8).

We also look at what happens to safe financial asset holdings around exit. We focus on individuals who have a 1-year spell as pooling all spell lengths can contaminate the event studies as then both entry and exits can be mixed together. Figure H28a shows the evolution of the growth rate of safe financial asset holdings in the model. In the lead up to entry, the growth rate is increasing. Having accumulated enough wealth to justify paying the entry cost, agents then enter, which leads to a drop in safe financial asset holdings as agents choose to invest part of this in the stock market instead. However, upon exit, there is a sharp rise in safe financial asset growth. With a single year spell, these individuals likely experienced a poor return, which makes them more pessimistic about the stock market. They therefore would prefer to move their money into safe financial assets, hence there is a sharp temporary increase in the growth rate.³⁵ We find a very similar pattern in the Norwegian data (Figure H28b), implying that individuals tend to move their risky financial wealth into their safe bank account upon exit consistent with the experience-based model.

³⁵Figure H29 shows that upon exit, the savings rate remains at a similar level to pre-entry, suggesting that agents are switching between financial assets rather than reducing savings altogether.

6 Conclusion

While there is a large body of literature that studies why many individuals do not invest in stocks, much less is known about the dynamics of stock market participation by retail investors. How long do individuals stay in the stock market for? Is the probability of exit a function of time since entry? Do individuals reenter after exit, and if so, when? Using Norwegian administrative data, we document new facts regarding the exit and reentry decisions of individual investors. The unifying message from these facts is that short, multiple spells in the stock market are common. We show that a calibrated workhorse portfolio choice model with participation costs struggles to generate these patterns. Extending the model to allow for experience-based learning à la [Malmendier and Nagel \(2011\)](#), whereby individuals adjust their expected stock returns based on realized returns, is able to produce the quick exits observed in the data, though does not generate sufficient reentry. Our findings can have important implications for policies pertaining to encouraging stock market participation. In particular, they show that simply encouraging an initial entry is insufficient as poor experiences will drive some investors away. Instead, individuals should be encouraged to remain in the market for a more prolonged period in order to realize the equity premium on average.

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Online Appendix

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A Variable construction

Here, we describe the steps undertaken to translate the tax records into consistent measures of wealth by broad asset class. TR x.y denotes item x.y in the tax records based on 2016 item codings by the Norwegian Tax Administration (Skatteetaten). Note that while tax values are reported in the raw data, we translate these values into market values for our analysis. For financial wealth, we create the following subclasses:

- Cash and deposits are computed as the sum of deposits in Norwegian banks (TR 4.1.1), cash (TR 4.1.3), and deposits in foreign banks (TR 4.1.9).
- Directly held listed stocks are given by the value of listed Norwegian shares and equity certificates, bonds, etc. in the Norwegian Central Securities Depository (TR 4.1.7).
- Directly held unlisted stocks are given by capital in unlisted shares, share savings accounts, and securities not listed in the Norwegian Central Securities Depository (TR 4.1.8).
- Stock mutual fund holdings are given by the value of the share component in holdings of securities funds (TR 4.1.4).
- Money market/bond funds are given by the value of the interest component in holdings of securities funds (TR 4.1.5).
- Financial wealth held abroad is given by other taxable capital abroad such as foreign shares, outstanding claims, bonds, and endowment insurance (TR 4.6.2).
- Other financial assets are the sum of outstanding receivables in Norway (TR 4.1.6), the share of capital in housing cooperatives or jointly-owned property (TR 4.5.3), pension insurance and life insurance (TR 4.5.1 + TR 4.5.2), and other taxable capital, such as cryptocurrency (TR 4.5.4).

Real wealth can be decomposed into the follow:

- Housing wealth is the sum of housing owned through housing cooperatives (TR 4.3.2.2) and self-owned property (TR 4.3.2.1 + TR 4.3.2.3).

- Other real wealth is the sum of boats (TR 4.2.4), cars (TR 4.2.5), caravans (TR 4.2.6), holiday homes (TR 4.3.3.1 + TR 4.3.2.3), other real estate (TR 4.3.4 + TR 4.3.5 + TR 4.3.2.3), home contents and movable property (TR 4.2.3), fixtures and other business assets (TR 4.4.1 + TR 4.4.2 + TR 4.4.3 + TR 4.4.4), and real wealth abroad (TR 4.6.1 + TR 4.3.6.1).

B Potential explanations for short spells

B.1 Sophisticated market timing

Could the short-lived entry and exit observed in the data be driven by sophisticated market timers? Perhaps these individuals pursue short-term investment strategies and reenter whenever a promising investment opportunity arises. If this were the case, we would expect short spelling to be correlated with proxies for financial sophistication. However, as discussed in Section 3.1.1, short spelling is negatively correlated with characteristics typically associated with higher financial literacy (college education, income and wealth). Furthermore, we might expect higher returns for more sophisticated investors. However, in Section 5.3, we show that individuals who have a short spell have on average poorer initial returns compared to those who stay in the market for longer.

B.2 Pensions

One may worry that the existence of pension wealth could affect individuals' desire to actively invest in the stock market out of their nonpension wealth. In principle, a rational agent should consider their overall portfolio, comprising both pension and nonpension wealth, when deciding upon their optimal portfolio allocation. If, for example, one's pension wealth is already invested in the stock market, they may invest less (or nothing at all) out of nonretirement wealth. Therefore, nonparticipation out of nonpension wealth could simply be a rational choice given existing exposure through pensions.

If pensions are to be able to explain the dynamics, the following would need to be the case: 1) the desired risky asset share out of *total* wealth changes, and individuals adjust their nonpension holdings to achieve this new goal, and/or 2) exposure to the stock mar-

ket coming from pension wealth is changing at a high frequency, and individuals identify these changes and adjust their portfolio accordingly. Explaining frequent exit and (re)entry through this rebalancing channel is arguably difficult, as it requires individuals to regularly follow movements in their pension holdings and to actively rebalance accordingly. However, various papers have shown that portfolio adjustments are sluggish in both retirement and nonretirement accounts (Agnew et al. (2003); Ameriks and Zeldes (2004); Brunnermeier and Nagel (2008); Calvet et al. (2009); Karlsson et al. (2009)). In Appendix C, we provide a discussion of the Norwegian pension system and argue that the nature of the system is such that pensions are unlikely to explain the behaviors we observe.

B.3 Tax optimization

Could the quick exit and reentry from the stock market be due to tax optimization? Perhaps individuals choose to exit in order to reduce their tax liability in a given year. There are two tax margins that could be relevant here. The first is the wealth tax, whereby individuals are taxed on net wealth above a given threshold.¹ However, the majority of Norwegians do not reach the threshold. This is partly due to favorable tax treatments on certain asset classes. For example, the tax value on housing is 25% of its market value. Stocks and mutual fund holdings are given a valuation discount of 45% (in 2021), whereas cash and deposit account holdings are not given a discount. It is therefore actually better for wealth tax purposes to retain wealth in stocks and funds rather than liquidating and holding cash. Consequently, it is very unlikely that wealth tax considerations can explain entry and exit decisions for most Norwegian households. The second relevant tax is capital gains tax. In Norway, losses made from the sale of stocks and equity funds are tax-deductible, while gains above a risk-free return are taxed. One might be worried that the quick exit we observe is because individuals are liquidating their loss-making shares to reduce their tax liabilities.² However, capital gains taxation in Norway is tied to the realization for each individual security, not the performance of the overall portfolio. To explain the complete exit that we observe, we would need to see every security in one's portfolio making a loss. In addition, if tax incentives are driv-

¹In 2021, net wealth above 1.5m NOK (\approx \$250,000 in 2011 USD) was taxed at 0.85% (0.7% to the municipality and 0.15% to the state). The threshold is doubled for couples.

²Using US data, Odean (1998) shows that the prevalence of selling losing stocks is highest in December, which can be linked to the end of the tax year and attempts to reduce tax liability.

ing this behavior, we might expect to see reentrants purchasing the same stock when they return. While we do not observe specific mutual fund holdings, the Shareholder Registry provides information on direct stock ownership from 2004. We find that only 28% of directly held stocks owned just before exit are then repurchased upon reentry, meaning most reentrants are purchasing different securities. Therefore, we argue that tax-motivated selling is unlikely to drive our results.

C The Norwegian pension system

There are three main components to the Norwegian pension system: the first is the National Insurance Scheme (“*folketrygden*”), which is the basic public pension scheme. It ensures that everyone receives a minimum pension income. Furthermore, workers are guaranteed a supplement that is proportional to their income during working age.³ The system is defined-benefit in nature, so citizens face no stock market exposure through it. As such, the decisions to exit and enter the stock market cannot be attributed to portfolio rebalancing between private accounts and public pension wealth.

Second, there are occupational pensions. Public occupational pensions are also defined-benefit schemes. Hence, there is no stock market exposure through them.⁴ Private sector occupational pensions operate differently. Until 2001, only defined-benefit pensions existed. While defined-contribution pensions, for which the pension benefit depends on how well the contributions are invested, have been allowed since 2001, they did not gain momentum until 2006 when occupational pensions were made mandatory by law. Indeed, before 2006 occupational pensions were mainly provided by larger employers (OECD (2009)).⁵ One

³Under the current system, 18.1% of wages in each year of employment up to a certain ceiling is transferred to a pension account. This pension income is then indexed to nominal wage growth. Upon retirement, the accumulated amount is not given as a lump sum. Instead, an annual sum is given based on the expected number of years to be spent as a pensioner, which itself depends on when the individual starts withdrawing from their pension and life expectancy. While there are some differences based on year of birth, the overall premise of pensionable income being linked to employment earnings still holds. For further details, see [Fagereng et al. \(2019\)](#) and [Fredriksen and Halvorsen \(2019\)](#).

⁴Until 2020, the public occupational pension scheme was such that workers were entitled to the maximum pension after 30 years of service and can receive a pension equal to 66% of their pension base (final salary converted into a full-time equivalent) before adjustments for life expectancy. However, occupational pension earnings became similar to that in the National Insurance Scheme from 2020, in particular having a share of earnings each year be accumulated in a pension pot. However, this remained a defined-benefit system. For further details on public occupational pensions and the reforms, see [Fredriksen and Stølen \(2018\)](#).

⁵As of 2018, 90% of private sector employees are under a defined-contribution pension ([Fredriksen and](#)

may be concerned that because private sector defined-contribution occupational pensions have some exposure to the stock market, this could influence choices made in nonretirement investment accounts. However, Figure H11 shows that short spells in the stock market are not exclusive to the post-2006 period.

Third, individuals may have personal private pensions that they invest in. As payments into an Individual Pension Scheme (IPS) in Norway are tax deductible up to a certain limit, one can infer from the tax records whether an individual holds such pensions.⁶ Figure C1 provides a time series of participation in private pension accounts separately for the whole population and the subset of the population aged 60 and under (who are unlikely to have drawn from such pensions yet). In either case, the participation rates are in single digits, indicating that the vast majority of the population do not hold such accounts. To further ease concerns, we plot the proportion of exiters of different spell lengths who hold private pensions as of their exit year. If these schemes were driving our short spell result, we might expect to see a greater prevalence of private pensions among short spellers. However, Figure H30 shows the opposite. We also reproduce our spell length histogram but exclude any individual who at any point in the sample holds a private pension account. Figure H31 shows that our results are robust to this. We therefore believe that pension holdings cannot explain the short-term dynamics we observe.

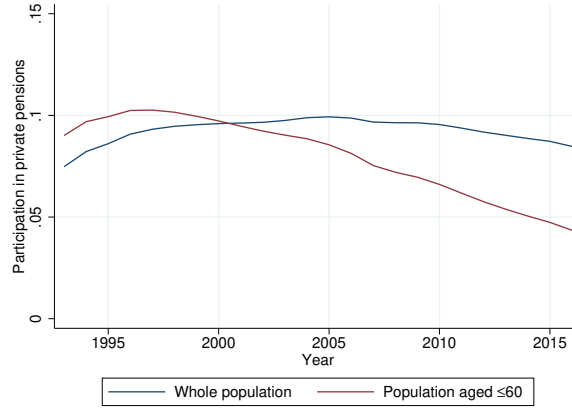
D Further details on the Alvarez et al. (2021) GMM estimator

The Alvarez et al. (2021) GMM estimator is based on the following environment. There is a proportional hazards data generating process for durations $d \in \{\underline{D}, \dots, \bar{D}\}$, where $h_i(d) = \theta_i b_d$. θ_i is the time-invariant frailty parameter specific to individual i and captures individual heterogeneity in hazard rates. b_d is the baseline hazard at duration d and is assumed to be common across individuals. The objective is to obtain an estimate of b_d , as this reflects true duration dependence rather than unobserved heterogeneity. Individual i experiences

Halvorsen (2019)).

⁶There are two relevant variables in the tax data. TR 3.3.5 records the deductible amount from payments into an IPS, while TR 4.5.1 indicates capital in an Individual Pension Account (IPA). Note that IPAs were replaced by the IPS in 2006, from which point new money could not be placed into one's existing IPA, and new IPAs could not be opened. We consider an individual to be a private pension contributor if they report a positive value for either of these two variables, either in the current year or in any past year.

Figure C1: Participation in private pensions over time



Notes. This figure plots a time series of participation in private pensions over time. The blue line gives the participation rate for the whole population, while the red line restricts attention to those aged 60 or under. An individual is said to be participating in private pensions in a given year t if they put money into a private pension either in the current year or in a past year. Participation has occurred if either of the following two items in the tax records is nonzero: TR 3.3.5, which records deductible payments to an Individual Pension Scheme (IPS), or TR 4.5.1, which records capital in an Individual Pension Account (IPA).

K^i spells, for which the measured duration of spells is $\zeta^i = \{\zeta_0^i, \zeta_1^i, \dots, \zeta_{K^i}^i\}$. Note that measured duration is not necessarily equal to the true length of the spell because of censoring. Assume that the spells $\zeta = (\zeta_0, \zeta_1, \dots, \zeta_K)$ are drawn from a proportional hazards model with a baseline hazard \mathbf{b}_0 . Defining

$$f_{d_1, d_2}^{[b]}(\zeta; \mathbf{b}) \equiv \sum_{(j, k): 1 \leq j \leq k \leq K} (b_{d_2} \mathbb{1}_{\zeta_j = d_1, \zeta_k \geq d_2} - b_{d_1} \mathbb{1}_{\zeta_j = d_2, \zeta_k \geq d_1})$$

then $\mathbb{E}[f_{t_1, t_2}^{[b]}] = 0 \forall \underline{D} \leq d_1 < d_2 \leq \bar{D}$ if and only if $\mathbf{b} = \lambda \mathbf{b}_0$ for some $\lambda > 0$. This gives $\frac{\bar{D}(\bar{D}+1)}{2}$ moment conditions, where $\bar{D} \equiv \bar{D} - \underline{D}$. It is important to note that under this procedure, we recover the baseline hazards \mathbf{b} up to a multiplicative constant, and so we normalize $b_1 = 1$. To estimate \mathbf{b}_0 :

$$\hat{\mathbf{b}}_0 = \arg \min_{\mathbf{b}} \left(\frac{1}{N} \sum_{i=1}^N f_{d_1, d_2}^{[b]}(\zeta^i; \mathbf{b}) \right)^T W \left(\frac{1}{N} \sum_{i=1}^N f_{d_1, d_2}^{[b]}(\zeta^i; \mathbf{b}) \right)$$

where W is a positive definite weighting matrix. We use two-step feasible GMM à la Hansen (1982). In the first step, we use the identity matrix as the weighting matrix. In the second step, we take our estimates from the first step, $\mathbf{b}_0^{(1)}$, and use $\hat{W}(\hat{\mathbf{b}}_0)^{-1}$ as the weighting matrix

in the second step where:⁷

$$\hat{W}(\hat{\mathbf{b}}_0) = \left(\frac{1}{N} \sum_{i=1}^N f_{d_1, d_2}^{[b]}(\zeta^i; \hat{\mathbf{b}}_0) f_{d_1, d_2}^{[b]}(\zeta^i; \hat{\mathbf{b}}_0)^T \right)^{-1}$$

There are several advantages of this approach. First, while [Honoré \(1993\)](#) provides continuous time identification results for duration models with multiple spells, the moment conditions used in the GMM estimator are based on discrete time identification results. Second, some approaches rely on specification of a frailty distribution. For example, [Nakamura and Steinsson \(2008\)](#) apply the empirical model of [Meyer \(1990\)](#) in their analysis of price spell duration and assume that the frailty parameter follows a gamma distribution for their baseline specification. [Heckman and Singer \(1984\)](#) note that misspecification of the frailty distribution can bias the hazard function. Instead, the approach of [Alvarez et al. \(2021\)](#) imposes no restrictions on the frailty distribution. Third, the GMM estimator is consistent when the number of individuals is large, and so it allows for a short time dimension. The latter is important in our setting given that we rely on annual data covering 24 years.

E Alternative theories of participation

E.1 Nonstandard preferences

Expected utility maximizers with standard preferences exhibiting second-order risk aversion (e.g., CRRA utility) should always be willing to invest some money in stocks as long as the expected risk premium is positive ([Haliassos and Bertaut \(1995\)](#)). This is because such individuals are effectively risk neutral for small risks and risk has no first-order effect. As such, a model where all agents exhibit second-order risk aversion would need to be augmented with additional ingredients to motivate nonparticipation, such as participation costs or background risks. Some papers have allowed for time-varying levels of risk aversion, with one popular method being to have habit-formation preferences. Such preferences generate a negative relationship between wealth and risk aversion.⁸ However, this

⁷[Hansen \(1982\)](#) show that $\hat{W}(\hat{\mathbf{b}}_0)$ converges in probability to $\Omega \equiv \mathbb{E}[f_{d_1, d_2}^{[b]}(\zeta^i; \mathbf{b}_0) f_{d_1, d_2}^{[b]}(\zeta^i; \mathbf{b}_0)^T]$ and that $W = \Omega^{-1}$ is the most efficient weighting matrix.

⁸These studies have typically used habit-formation preferences to help reproduce empirical patterns of equity premia (e.g., [Constantinides \(1990\)](#); [Campbell and Cochrane \(1999\)](#)).

will simply lead to time-varying risky asset shares with no impact on the extensive margin of participation as long as preferences still exhibit second-order risk aversion.⁹

To generate nonparticipation exclusively through preferences, first-order risk aversion is needed (Segal and Spivak (1990)).¹⁰ Under such preferences, individuals have a kink in the utility function at some certainty point, which can make risk aversion locally infinite and zero stockholdings an optimal outcome. To generate dynamics in participation, we would need some agents to exhibit time-varying first-order risk aversion (Gomes et al. (2021)). In addition, preferences would need to fluctuate at a reasonably high frequency to generate short-term dynamics. Empirical studies have typically found positive and significant autocorrelations in individuals' risk preferences, suggesting that preferences are moderately stable, although correlations are usually below 1 (Chuang and Schechter (2015); Dohmen et al. (2016)).¹¹

E.2 Risks faced by households

A strand of the literature studies how background risks, particularly labor income risk, can affect portfolio allocations. Theoretically, the impact of labor income risk depends on the nature of the risk (Vissing-Jørgensen (2002)). First, if labor income is riskless, this should lead to a higher investment in risky financial assets because such labor income is effectively equivalent to holding a riskless bond. Second, if labor income is risky but uncorrelated with stock returns, then individuals should tilt their portfolio away from stocks, as there is already risk coming from human wealth.¹² Third, if labor income is risky and correlated with stock returns, then there is a hedging component that runs with the opposite sign of the correlation. For example, if business cycle risk produces a positive correlation between labor

⁹Brunnermeier and Nagel (2008) empirically test whether wealth fluctuations affect risky asset shares and find no clear relationship, which they argue lends support to a CRRA model over a model with habit-formation preferences.

¹⁰A range of preferences exist that exhibit first-order risk aversion including, but not limited to prospect theory (Kahneman and Tversky (1979)), rank-dependent expected utility (Quiggin (1982); Epstein and Zin (1990)), disappointment aversion (Gul (1991); Ang et al. (2005); Routledge and Zin (2010)), news utility (Pagel (2018)), and ambiguity aversion (Gilboa and Schmeidler (1989); Cao et al. (2005)).

¹¹Part of these imperfect correlations could reflect measurement error (Schildberg-Hörisch (2018)).

¹²Fagereng et al. (2017b) studies the impact of uninsurable wage risk on portfolio shares using Norwegian data. They find a significant marginal effect of such risk on portfolio shares, although the economic impact is limited because the size of this wage risk is small. Vissing-Jørgensen (2002) finds a negative impact of non-financial income volatility on both the probability of stock market participation and the proportion of wealth invested in stocks conditional on participating.

income and stock returns, then the optimal portfolio choice requires one to reduce stockholdings (Haliassos and Bertaut (1995)). It is important to note that zero stockholding cannot be an optimal solution in the first two cases. Risky labor income that is uncorrelated with stock returns reduces the optimal portfolio share but would not push it to zero. However, Haliassos and Bertaut (1995) show that zero stockholding can be an optimal choice for sufficiently low wealth if labor income and stock returns are positively correlated, particularly if coupled with a no short-selling constraint. For a model to generate dynamics through labor income risk alone, we would require that 1) the correlation between labor income and stock returns is time-varying, and/or 2) wealth fluctuates around the participation threshold for some individuals, leading to entry and exit. The first can be hard to justify given that most individuals do not change jobs at a high frequency such that the underlying correlations could change. Regarding the second route, Figure H9b shows that short spells, while being relatively more likely for less wealthy individuals, still occur for high wealth groups at a nonnegligible frequency. In any case, empirical estimates for the correlation between labor income and stock returns are typically very close to zero, making such channels hard to rationalize from the data (e.g., Cocco et al. (2005); Fagereng et al. (2017a)).

E.3 Cultural and social environment

Cultural factors can influence an individual's beliefs and preferences, which in turn affect economic outcomes (Guiso et al. (2006)).¹³ Various papers have provided empirical evidence of a causal link running from cultural environments to savings behavior.¹⁴ While underparticipation in the stock market could be linked to cultural factors, these factors need to be time-varying to obtain dynamics in participation. However, Guiso et al. (2006) define culture as “*customary beliefs and values that ethnic, religious, and social groups transmit fairly unchanged from generation to generation*”. As such, cultural factors are very slow-moving and thus would not be able to reproduce the high frequency entry and exit that we observe.

However, social interactions could generate more frequent changes in beliefs and prefer-

¹³For example, ethnic origin has been shown to affect trust (Guiso et al. (2003)).

¹⁴Haliassos et al. (2017) study migrants to Sweden and find significant differences in financial behavior and the propensity to hold stocks based on the degree of cultural similarity to Sweden. Other papers that find significant effects of culture on financial behavior include Osili and Paulson (2008), Guin (2017), and Fuchs-Schündeln et al. (2020). However, some papers do not find such effects (Carroll et al. (1994, 1999)).

ences. [Shiller et al. \(1984\)](#) argue that investing is a social activity, and therefore, investment decisions can be affected by the actions of those one interacts with. A growing literature has provided empirical evidence for the influence of peers on financial behavior.¹⁵ In principle, communication between peers could lead to entry and exit. If my neighbor decides to leave the stock market – perhaps due to experiencing poor returns – this could induce me to also leave. If my neighbor claims that stock returns will be good in the near future, this might induce me back into the market. Testing these effects directly could be an interesting avenue for future research, although it seems unlikely that peer effects alone can explain all of the dynamics we observe for a variety of reasons. First, [Kaustia and Knüpfer \(2012\)](#) show that good stock returns experienced by local peers can positively affect an individual’s decision to enter the stock market. However, the authors do not find evidence of a discouragement effect following poor realizations, from which they infer that peers primarily share good outcomes with each other. Therefore, peer effects could struggle to explain exit. Second, it is difficult to rationalize the downward-sloping hazard functions through peers alone. Third, our focus is on the extensive margin of participation. We, therefore, require social interactions to generate complete exit rather than just exit from a particular stock. One could imagine individuals discussing particular stocks, and perhaps a bad return experienced by a peer may deter them from also investing in that security. However, it may not necessarily put the person off investing in other stocks or funds.

F Model solution and estimation

F.1 Solution method

We first specify exogenous grids for cash on hand, risky shares, and, in the case of the model with experience-based learning (EBL), beliefs. For (normalized) cash on hand, we specify a grid with more gridpoints at lower values due to the greater curvature of the value function and the larger mass of individuals in this region. The grid for risky shares is equally spaced in the unit interval. For beliefs, we draw values from a truncated normal distribution with

¹⁵[Hong et al. \(2004\)](#) show that households who report interacting with their neighbors and attending church are more likely to participate in the stock market even after controlling for individual characteristics and personality traits. [Brown et al. \(2008\)](#) find a causal link between individual stockholding and the average participation of the individual’s community, which they argue occurs through word-of-mouth communication.

the mean set at the true average equity premium μ and a standard deviation of 6%. To avoid having redundant gridpoints for beliefs, we truncate below at 0%. We can do this because for a given cash on hand and past participation status, anyone with negative or zero beliefs would choose the same decision rules because agents are risk averse and do not believe their beliefs will change in the future. We use the method of [Tauchen and Hussey \(1991\)](#) to discretize the labour income and stock return processes. We have five states for each of the income shocks and six states for the stock return process (five states for when the agent does not experience the tail event, plus the tail event return R_{tail}).

To solve the model, we use backward induction. In the final year of life t_d , agents know they will die next period ($\pi_{t_d} = 0$), and so the value function at age t_d is given by :

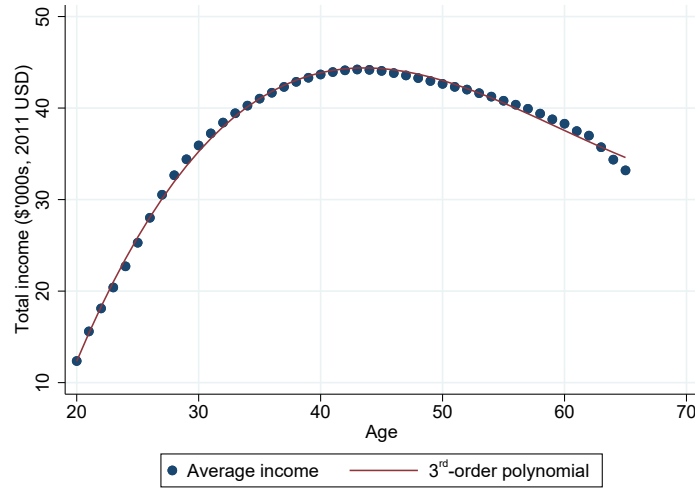
$$V_{it_d} = \left[(1 - \beta) C_{it_d}^{1 - \frac{1}{\psi}} + \beta \left(\kappa E_{t_d} X_{i,t_d+1}^{1-\gamma} \right)^{\frac{1 - \frac{1}{\psi}}{1-\gamma}} \right]^{\frac{1}{1 - \frac{1}{\psi}}}$$

For each combination of cash on hand, beliefs and past participation status, we compute V_{it_d} for different feasible choices of consumption and risky share. We then find the combination of consumption and risky share that generates the highest utility. For values of future cash on hand that do not lie on the grid, we evaluate the next period value function using cubic spline interpolation. We repeat this for all combinations of the state variables. Note that in the case without a bequest motive ($\kappa = 0$), the value function at age t_d simplifies down to $V_{it_d} = (1 - \beta)^{1 - \frac{1}{\psi}} C_{it_d}$. The decision rule then becomes trivial: agents simply consume all of their available cash on hand in the final period of life and choose not to save in either asset. This procedure gives us a terminal condition for conducting backward induction, using which we can solve the problem for age $t_d - 1$ and so on.

F.2 Estimation of life cycle profiles in the Norwegian data

For labor income, we use the broad variable of income from all sources in the Norwegian data and restrict attention to those aged 65 or below. We first regress total income in logs on age and year dummies, and extract the fitted values. After exponentiating these fitted values, we calculate the average for each age across our sample. We then regress these averages on a third-order polynomial of age and store the coefficients. We use this estimated third-order polynomial as the function $f(t)$ in the model (see Section 4.1.2).

Figure F1: Estimated age-dependent component of income $f(t)$



Notes. This figure plots average total income by age and the fitted third-order polynomial.

For the participation rate, conditional risky share, and financial wealth-to-income ratios, we regress each variable on age and year dummies. We take the fitted values and compute the mean of the fitted values for each age from 20 to 85. These averages constitute the life cycle profile for each variable. The conditional risky share is computed only for stock market participants, and is the ratio between total wealth invested in the stock market and financial wealth. Financial wealth-to-income ratios are the ratio between financial wealth and total income from all sources.

E.3 SMM estimation procedure

We use an approach similar to Brandsaas (2021). Using our model without beliefs, we first do a global search and draw 12,000 parameter vectors from a 6-D hypercube using a Sobol sequence. For each parameter draw, we compute the objective function as in Equation 12. We then do a local search using the Nelder-Mead method, taking the parameter vector that minimizes the objective function in the global search as our initial guess.

Given the sharp increase in computation time when adding beliefs to the model, we start directly with local search for the model with EBL as a global search would be too time intensive. We use the Nelder-Mead parameter values from the model without beliefs as our initial guess for the preference and participation cost parameters, and use $\iota = 0.05$ and $\lambda = 0$

as guesses for the belief updating parameters.

G Computing returns using the Shareholder Registry

To compute a measure of returns for individuals who invest in listed stocks, we make use of data from the Shareholder Registry, which tells us holdings of listed and unlisted stocks of companies registered in the Norwegian Central Securities Depository (VPS) as of December 31st of each year. The Shareholder Registry is available from 2004, and we restrict attention to holdings of listed stocks. Our approach to computing returns, r_{it} , follows [Fagereng et al. \(2020\)](#):

$$r_{it} = \frac{y_{it}}{w_{i,t-1} + \lambda \cdot F_{it}} \quad (1)$$

The numerator is income from listed stock holdings, and is the sum of three components: the first is the capital gain, and is computed as:

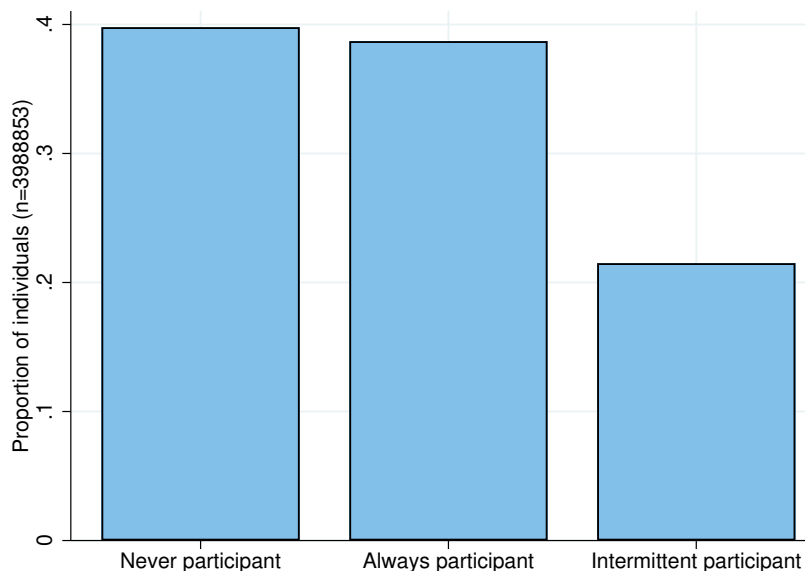
$$\text{Capital gain}_{it} = \sum_k (p_{12/31,t}^k - \bar{p}_t^k)(x_{i,12/31,t}^k - x_{i,12/31,t-1}^k) + (p_{12/31,t}^k - p_{12/31,t-1}^k)x_{i,12/31,t-1}^k \quad (2)$$

where k denotes a particular stock, $p_{12/31,t}^k$ is the market price of security k on December 31st of year t , \bar{p}_t^k is the geometric mean of the daily prices of security k in year t , and $x_{i,12/31,t}^k$ is individual i 's holdings of security k on December 31st of year t . Price data is obtained from Datastream. The second term is dividends received from VPS-registered companies, and is directly reported in the Shareholder Registry. The third term is dividends from non-VPS-registered companies and is reported in TR 3.1.7.

The denominator follows [Dietz \(1968\)](#). It is the sum of the total value of holdings on December 31st of year $t - 1$, denoted by $w_{i,t-1}$, and net flows during the year, F_{it} . As we do not observe the specific date of inflows and outflows, we follow [Fagereng et al. \(2020\)](#) and assume that flows occur on average in the middle of the year. We therefore take $\lambda = \frac{1}{2}$. Flows are computed as $F_{it} = w_{it} - w_{i,t-1} - \text{Capital gain}_{it}$. In computing returns, we make appropriate adjustments for stock splits.

H Additional tables and figures

Figure H1: Types of individuals



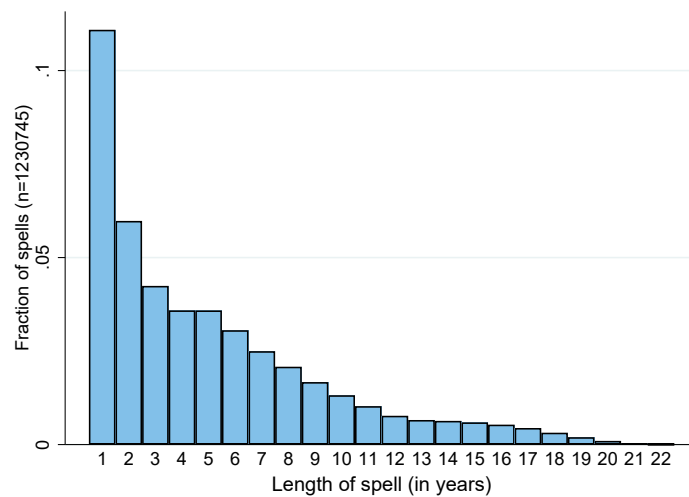
Notes. This figure divides individuals into three categories based on their lifetime stock-market exposure and plots the percentage of the population belonging to each of these three groups. “Never participant” contains individuals who never hold any stocks. “Always participant” covers people who are observed to have one single spell lasting at least 5 years, plus any individuals with right-censored or left-censored spells. “Intermittent participant” contains individuals with one single spell known to last less than 5 years and people who have multiple spells in the stock market. This figure includes only individuals observed in the data for at least 15 years.

Table H1: Impact of entry year returns on probability of a short spell

	(1)	(2)	(3)
Entry year return	-0.022*** (0.005)	-0.014 (0.007)	-0.021** (0.007)
Sample mean	0.26	0.26	0.25
Year FE	No	Yes	Yes
Additional controls	No	No	Yes
Observations	76051	76051	72927
R-squared	0.00	0.01	0.05

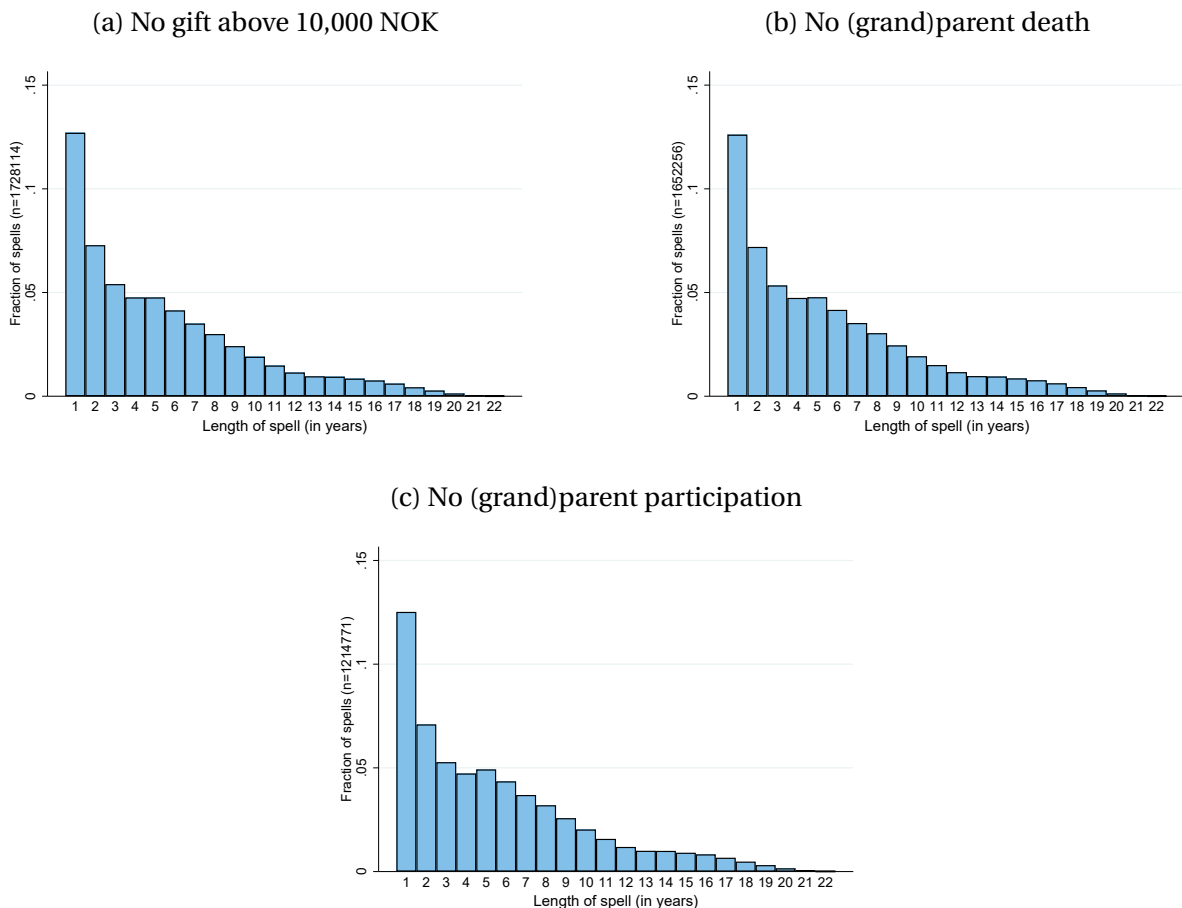
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The dependent variable is a dummy variable equal to 1 if the individual's spell ends within 2 years, and zero otherwise. The explanatory variable of interest is the nominal return experienced in the entry year. Details on the computation of returns are given in Appendix G. In Column 2, year fixed effects are included, and Column 3 adds the same set of controls used in the short spell regressions of Section 3.1.1. Returns are trimmed at the 1st and 99th percentiles of that year prior to estimation. Standard errors are clustered at the individual level.

Figure H2: Spell length distribution at the household level



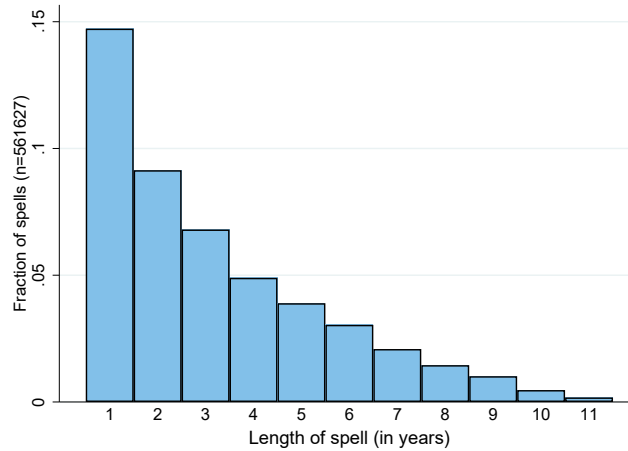
Notes. This histogram plots the proportion of spells of different lengths in the Norwegian data based on the household-level balance sheet. A household is treated as participating in the stock market in year t if household-level holdings of public equity exceeds \$150. We take all spells beginning at any point from 1994-2013. The x-axis gives the spell length (in years) and the y-axis shows the proportion of spells belonging to a particular spell length. Right-censored spells are excluded from the plot, but are used in calculating proportions.

Figure H3: Spell length distribution (robustness to gifts/inheritance)



Notes. This histogram plots the proportion of spells of different lengths in the Norwegian data for different subsamples intended to deal with concerns that short spells are driven by gifts and inheritances. For all panels, we take spells beginning at any point from 1994-2013. The x-axis gives the spell length (in years) and the y-axis shows the proportion of spells belonging to a particular spell length. Right-censored spells are excluded from the plot, but are used in calculating proportions. Panel (a) excludes all individuals who receive a gift or inheritance above 10,000 NOK (based on tax records) in the year of or before entry. Panel (b) excludes all entrants who experience the death of a parent or grandparent in the year of or before entry. Panel (c) excludes all entrants for whom a parent or grandparent participated in the year of or before entry.

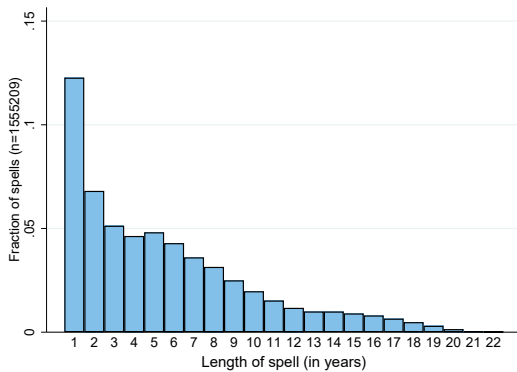
Figure H4: Spell length distribution excluding employee stocks



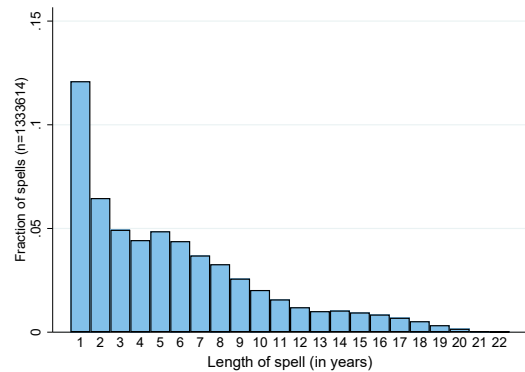
Notes. This histogram plots the proportion of spells of different lengths in the Norwegian data excluding entrants who hold stocks in the company they work for. Such individuals are identified using the Shareholder Registry and demographic information about place of work. We take all spells beginning at any point from 2004-2013 (Shareholder registry data begin in 2004). The x-axis gives the spell length (in years) and the y-axis shows the proportion of spells belonging to a particular spell length. Right-censored spells are excluded from the plot, but are used in calculating proportions.

Figure H5: Spell length distribution excluding small investors

(a) Invest > \$500

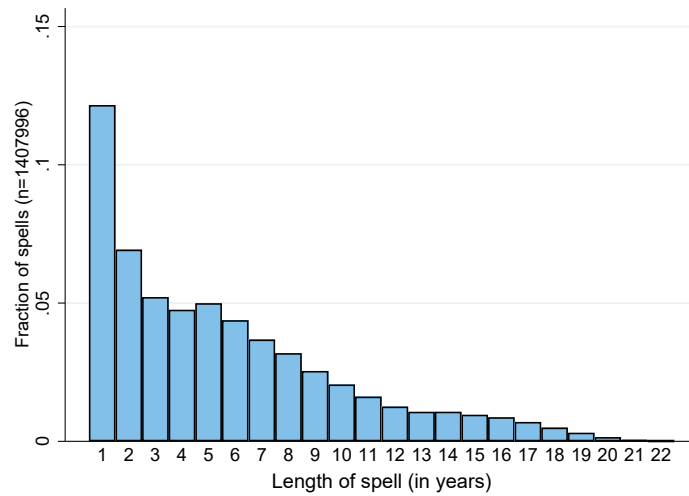


(b) Invest > \$1000



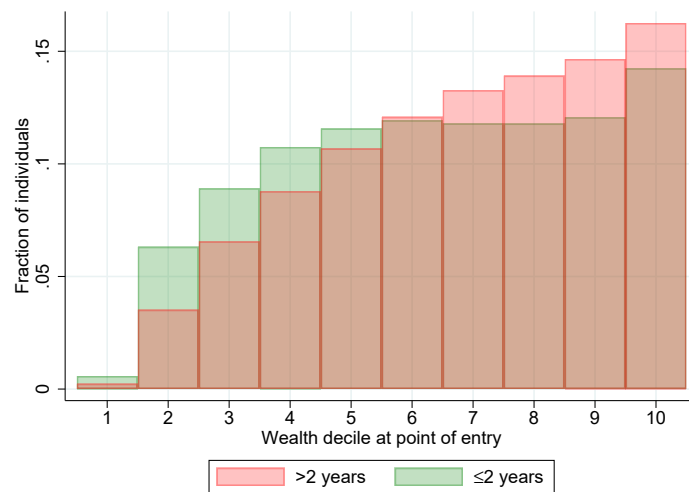
Notes. This histogram plots the proportion of spells of different lengths in the Norwegian data excluding entrants who invest a “small” amount of money at the point of entry. The left panel only uses individuals who invest at least \$500 at the point of entry, while the right panel requires an investment of at least \$1,000. For both panels, we take spells beginning at any point from 1994-2013. The x-axis gives the spell length (in years) and the y-axis shows the proportion of spells belonging to a particular spell length. Right-censored spells are excluded from the plot, but are used in calculating proportions.

Figure H6: Spell length distribution using only first spells



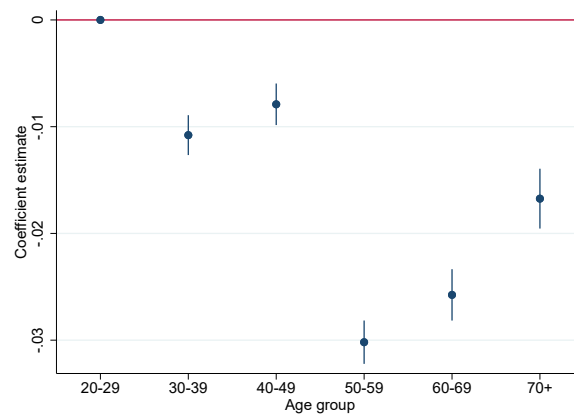
Notes. This histogram plots the proportion of spells of different lengths in the Norwegian data using only the first recorded spell of a given participant. We take all first spells beginning at any point from 1994-2013. The x-axis gives the spell length (in years) and the y-axis shows the proportion of spells belonging to a particular spell length. Right-censored spells are excluded from the plot, but are used in calculating proportions.

Figure H7: Wealth distribution by spell length



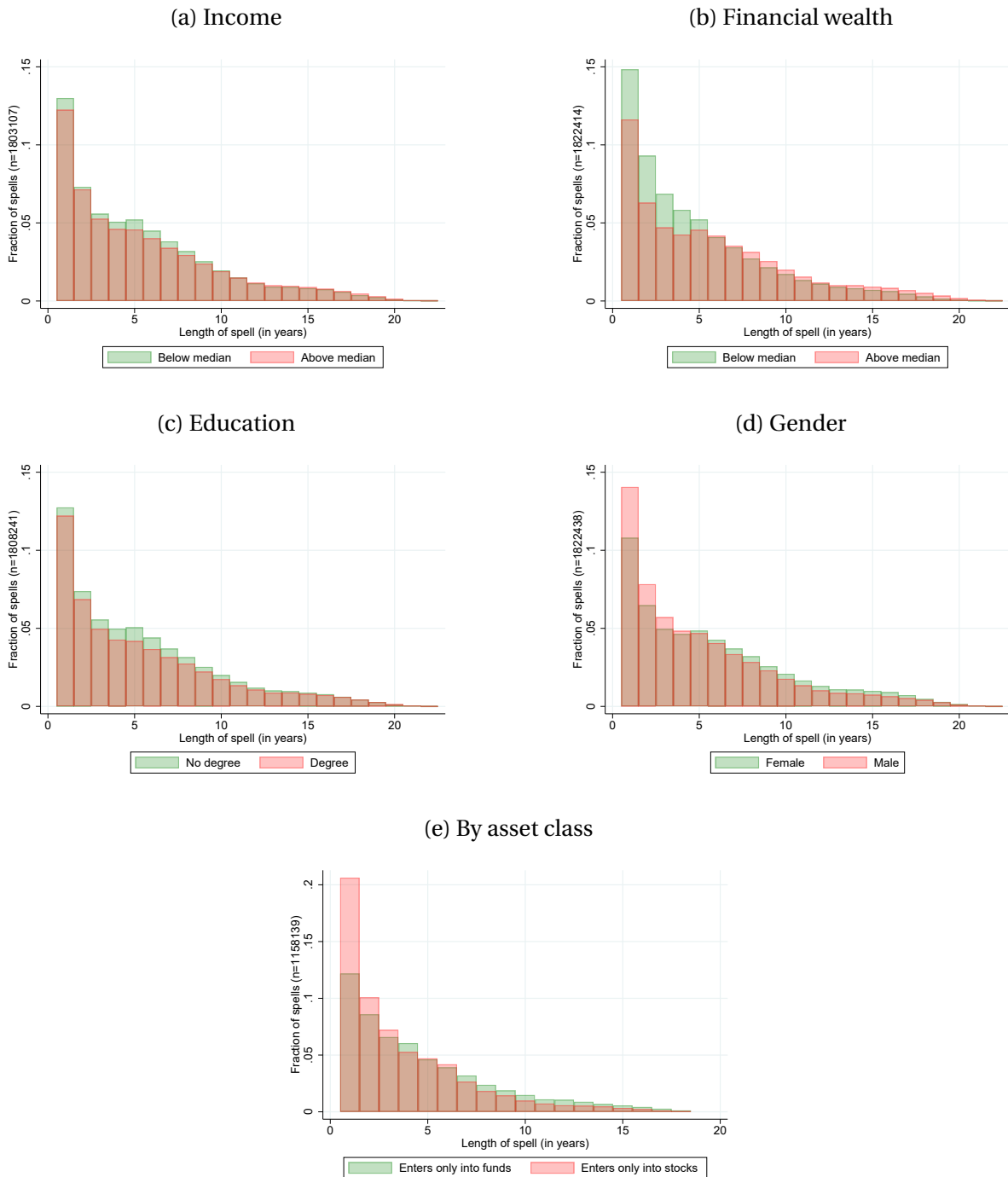
Notes. This figure plots the proportion of stock market participants belonging to different wealth deciles as measured at the point of entry, separately for short spellers (participate for ≤ 2 years) and longer-term participants (> 2 years).

Figure H8: Impact of age on the probability of a short spell



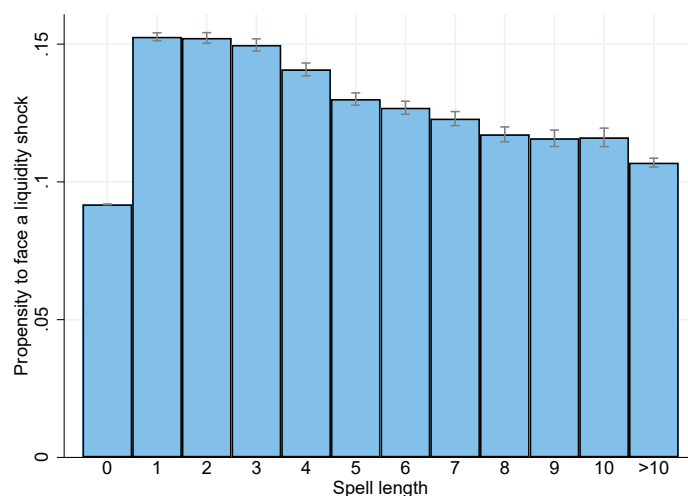
Notes. This figure plots the coefficient estimates for the fixed effects on age following estimation of Equation 1. Age is measured at the point of entry and individuals are grouped into 10-year bins. 95% confidence intervals are shown. The red line represents a null relative effect.

Figure H9: Spell length distribution by observable characteristics



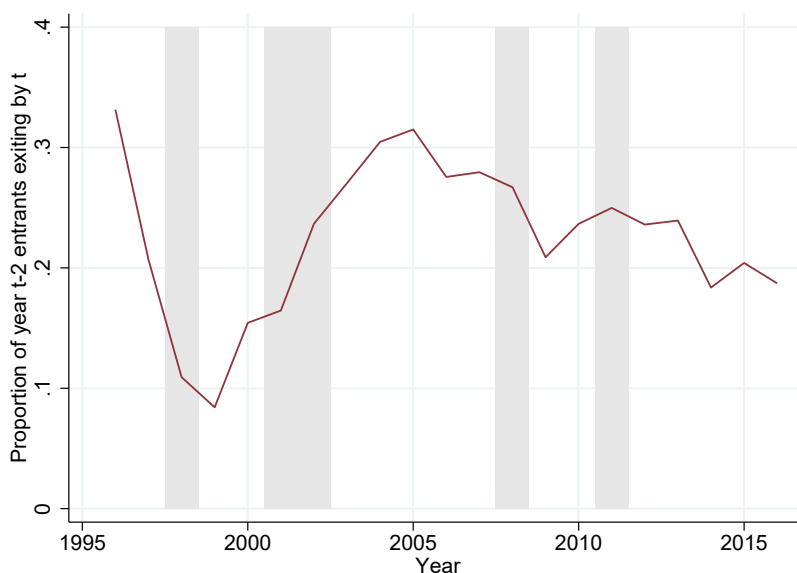
Notes. This histogram plots the proportion of spells of different lengths in the Norwegian data for different observable characteristics, namely income (a), wealth (b), education (c), and gender (d). Panel (e) looks at individuals who enter into mutual funds vs. directly held stocks. For this panel, we exclude those entrants who choose to invest in both at the point of entry. For panels (a) to (d), we take all spells beginning at any point from 1994-2013, while for panel (e) we use spells starting from 1999-2013 as we cannot separate fund and stock holdings in the tax data until 1998. The x-axis gives the spell length (in years), and the y-axis shows the proportion of spells belonging to a particular spell length. Right-censored spells are excluded from the plot, but are used in calculating proportions.

Figure H10: Prevalence of liquidity shocks in exit year by spell length



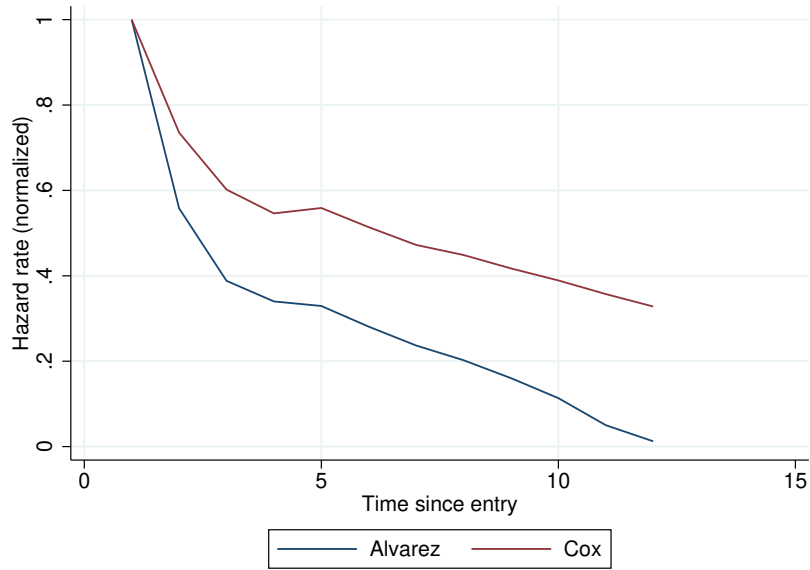
Notes. This figure shows the proportion of exiters of different spell lengths experiencing at least one of four potential liquidity needs in the exit year. The four shocks considered are buying a house (observed in housing transactions data), divorce, unemployment (inferred through receipt of unemployment benefits), and a large fall in income of > 50%. The far-left bar (spell length of zero) gives the prevalence of liquidity shocks over nonexit observations (i.e. continuing participants). The far-right bar groups all exiters with spell lengths above 10 years. 95% confidence intervals are shown.

Figure H11: Prevalence of short spells over time



Notes. This figure plots the proportion of year $t-2$ entrants who leave the stock market by year t . The shaded areas are stock market downturn years in which the Oslo Børs Benchmark Index fell by at least 10%.

Figure H12: Cox proportional hazard function for exit from participation

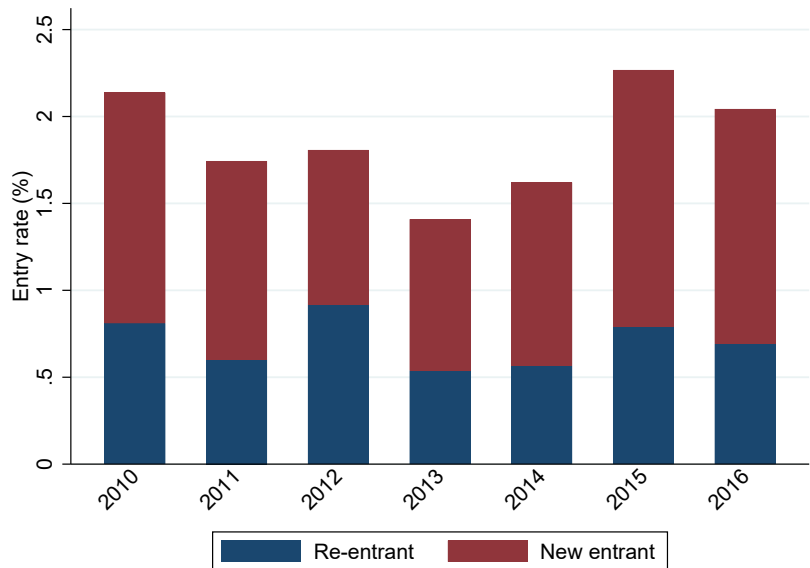


Notes. This figure plots the baseline hazard for exit from participation estimated using a Cox proportional hazards model, which takes the form:

$$h_i(d) = \exp(X_i\beta)b_d$$

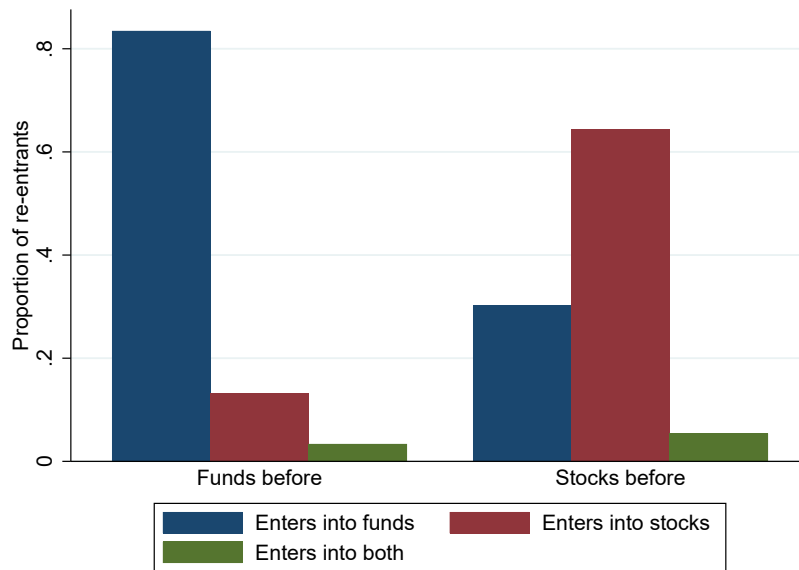
where X_i is a set of individual characteristics and b_d is the baseline hazard. X_i contains the same controls as in Table 2. The baseline hazard estimated using the Alvarez et al. (2021) methodology (see Section 3.1.2) is also shown. To facilitate comparison with the Alvarez et al. (2021) hazard function, the Cox baseline hazard has been normalized to 1 at duration $d = 1$.

Figure H13: Decomposition of entry rate into reentrants and new entrants



Notes. This figure decomposes the stock market entry rate in a given year into two components: entry by former participants (“Re-entrant”) and new entrants who have not participated before. The entry rate in year t is the proportion of nonparticipants in year $t - 1$ who enter in year t .

Figure H14: Reentry into different asset classes by previous asset class choice



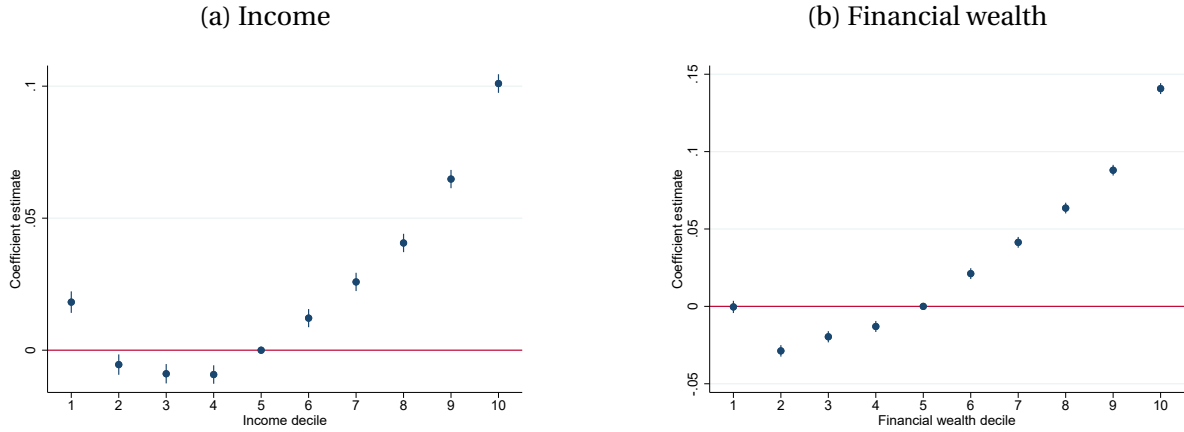
Notes. This figure plots the proportion of reentrants going into funds, stocks or both by the choice of funds vs. stocks in their previous spell.

Figure H15: Reentry rate over time



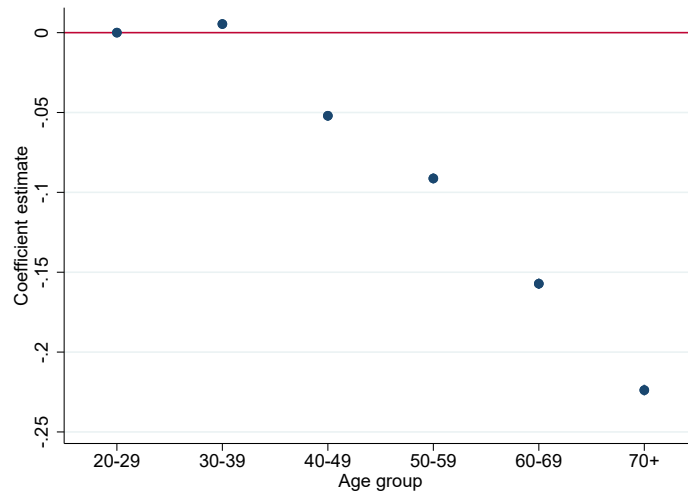
Notes. This figure plots the proportion of exiters of a given year who reenter within the next 4 years. The shaded areas are stock market downturn years in which the Oslo Børs Benchmark Index fell by at least 10%.

Figure H16: Impact of income and wealth on the probability of reentry



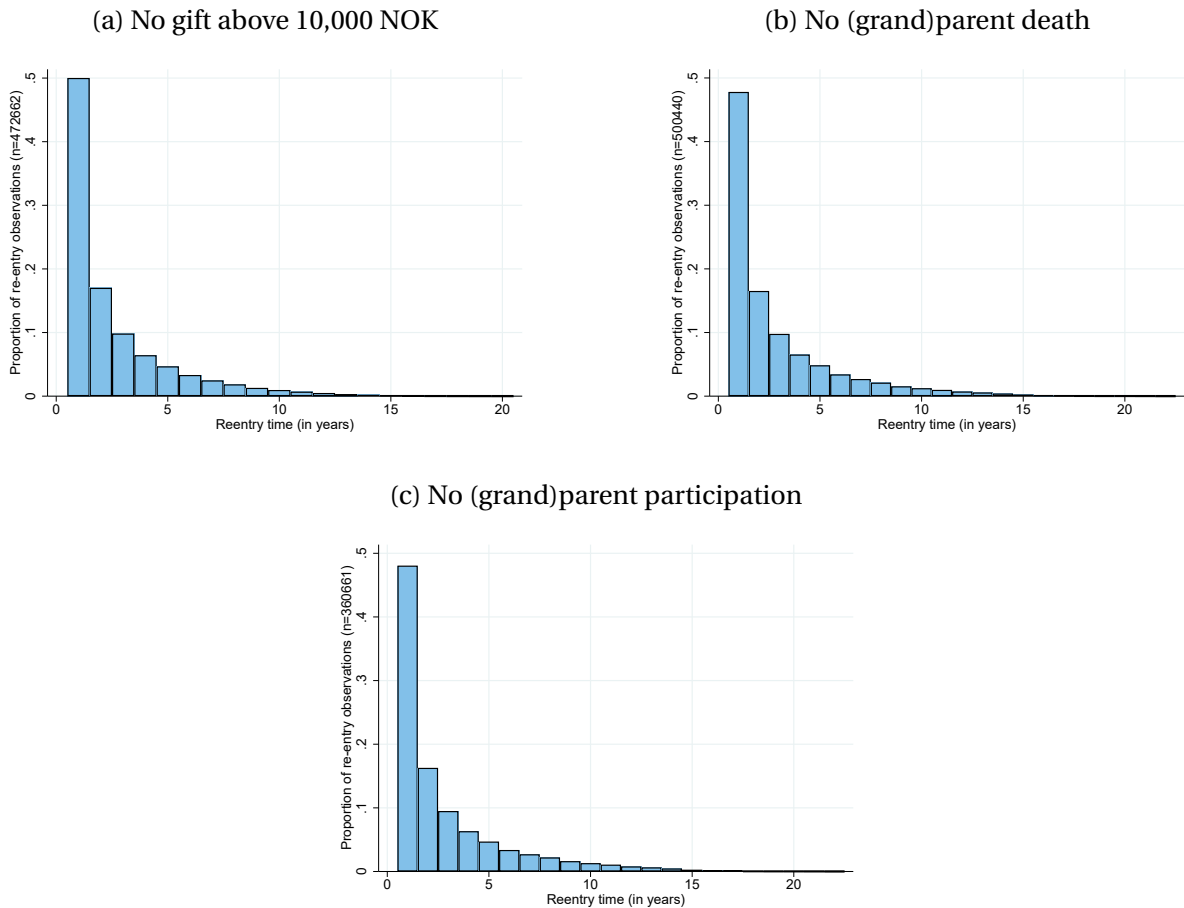
Notes. This figure plots the coefficient estimates for the fixed effects on income (A) and wealth (B) deciles following the estimation of Equation 2. Variables are measured at the point of exit, and deciles are based on the full Norwegian population aged 20 and above in that year. The effects are estimated relative to the median group. 95% confidence intervals are shown. The red line represents a null relative effect.

Figure H17: Impact of age on the probability of reentry



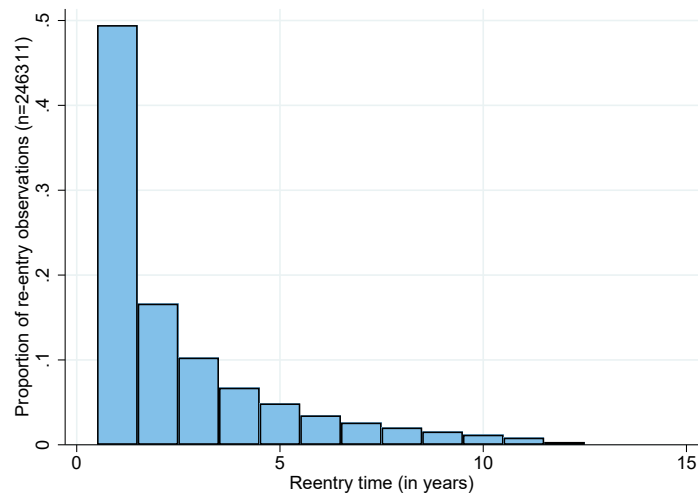
Notes. This figure plots the coefficient estimates for the age group fixed effects following estimation of Equation 2. Age is measured at the point of exit, and individuals are grouped into 10-year bins. 95% confidence intervals are shown. The red line represents a null relative effect.

Figure H18: Distribution of reentry times (robustness to gifts/inheritance)



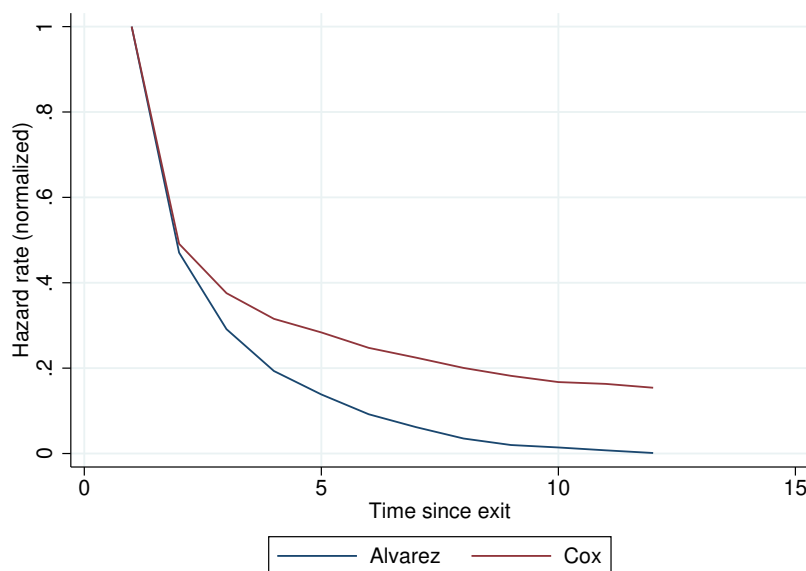
Notes. This histogram shows the distribution of reentry times in the Norwegian data for different subsamples intended to deal with concerns that short spells are driven by gifts and inheritances. The x-axis gives the reentry time (in years) and the y-axis shows the proportion of reentry observations belonging to a particular length. Panel (a) excludes all reentrants who receive a gift or inheritance above 10,000 NOK (based on tax records) in the year of or before reentry. Panel (b) excludes all reentrants who experience the death of a parent or grandparent in the year of or before reentry. Panel (c) excludes all reentrants for whom a parent or grandparent was participating in the year of or before reentry.

Figure H19: Distribution of reentry times (excluding employee stocks)



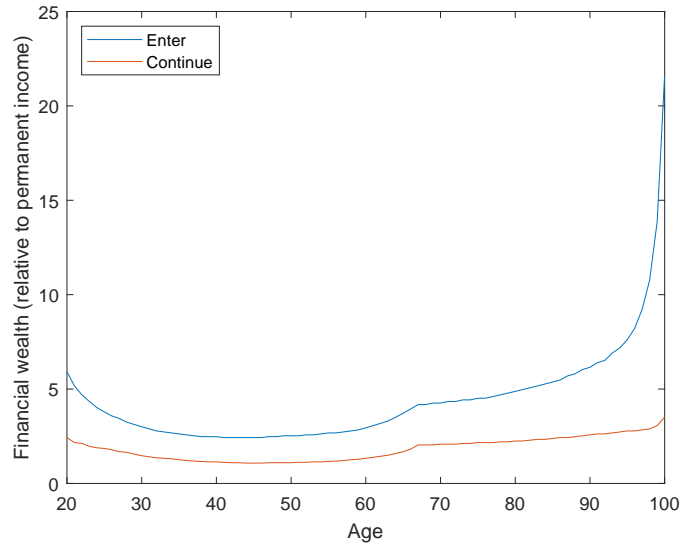
Notes. This histogram shows the distribution of reentry times in the Norwegian data excluding reentrants who hold stocks in the company they work for. The x-axis gives the reentry time (in years) and the y-axis shows the proportion of reentry observations belonging to a particular length. As the Shareholder Registry data are only available from 2004, we only consider reentry observations where the year of reentry is no earlier than 2004.

Figure H20: Cox proportional hazard function for reentry



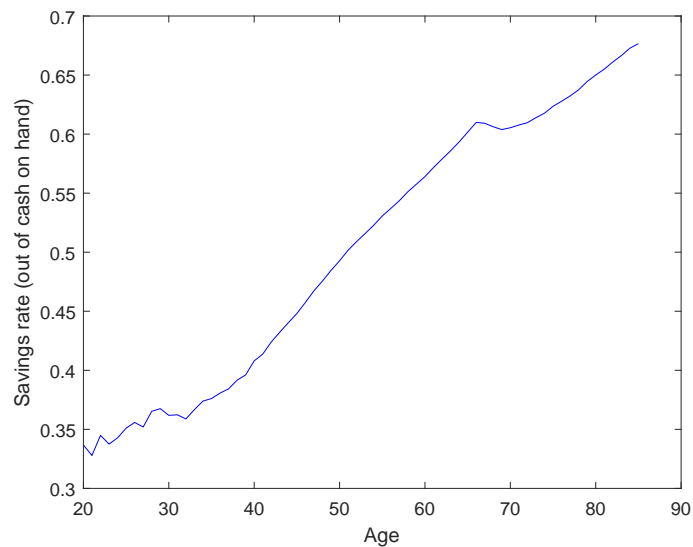
Notes. This figure plots the baseline hazard for reentry following exit estimated using a Cox proportional hazards model. We control for homeownership status, gender, unemployment status, education, marital status, financial wealth, income, and age for the Cox estimation. The baseline hazard estimated using the Alvarez et al. (2021) methodology (see Section 3.2.3) is also shown. To facilitate comparison with the Alvarez et al. (2021) hazard function, the Cox baseline hazard has been normalized to 1 at duration $d = 1$.

Figure H21: Cash on hand thresholds for stock market participation in model without beliefs



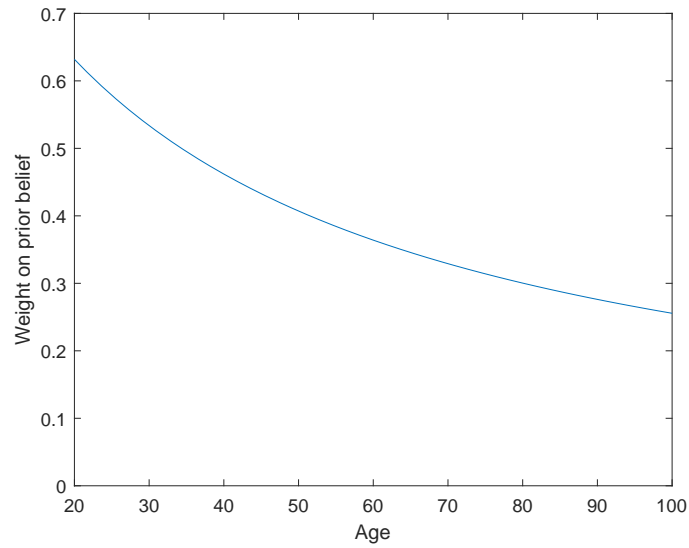
Notes. This figure plots the minimum cash on hand required to either enter into (blue line) or continue participating (orange line) in the stock market for the model without beliefs. This is based on simulations using the estimated parameter values in Table 5.

Figure H22: Savings rate profile in model without beliefs



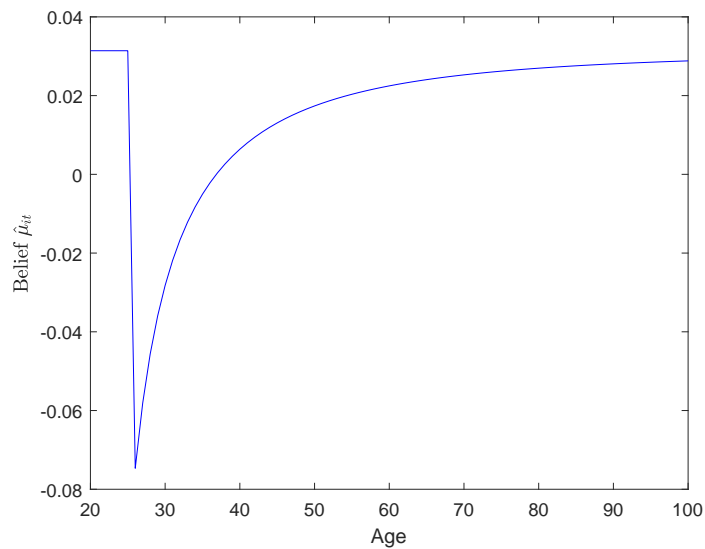
Notes. This figure plots the mean savings rate (out of cash on hand) over age in the model without beliefs.

Figure H23: Weight on prior belief



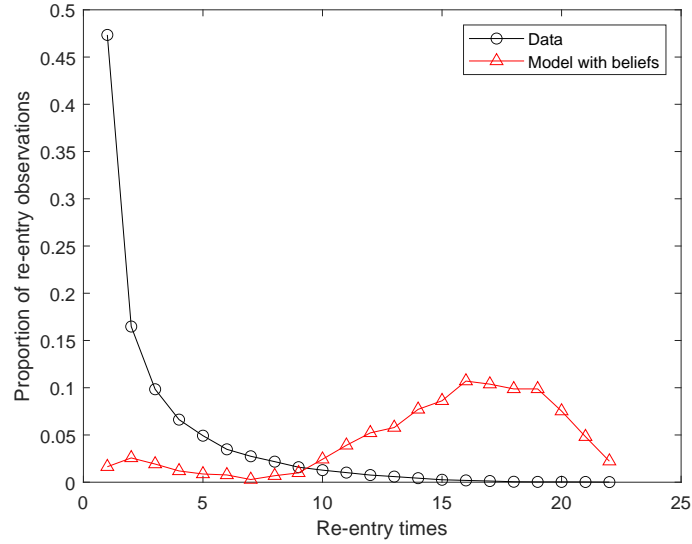
Notes. This figure plots the weight on the prior belief as a function of age, $\omega_t = \frac{1}{1+t\iota}$, at the estimated parameter value of $\iota = 0.029$.

Figure H24: Time taken for beliefs to revert after a poor return



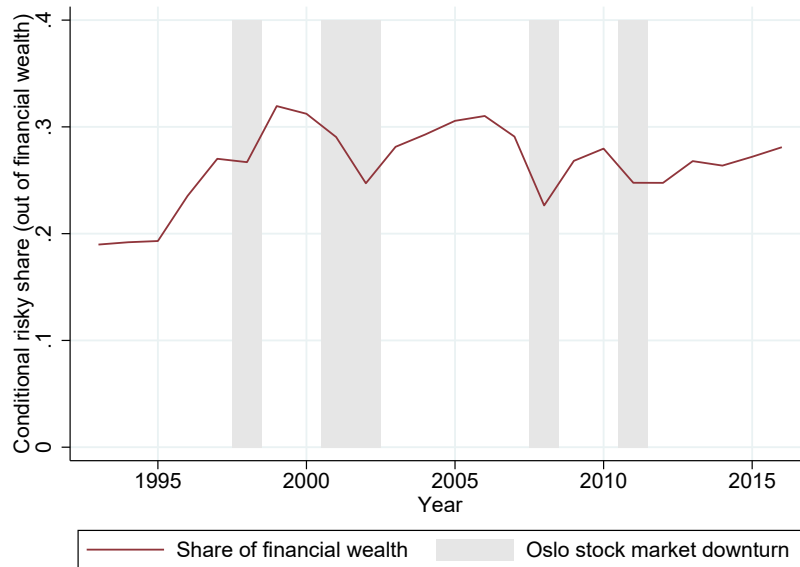
Notes. This figure plots the evolution of beliefs for an individual who enters the stock market for the first time at age 25, experiences a -20% return, and then exits at age 26, remaining out of the market for the rest of their life. Parameter values for belief updating are the estimated values in Column 2 of Table 5.

Figure H25: Distribution of reentry times



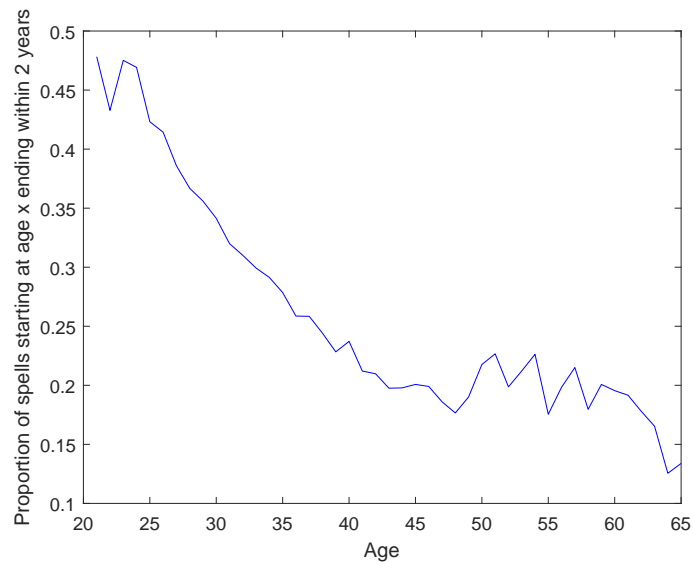
Notes. This figure plots the distribution of reentry times under the model with beliefs (red) and the data (black).

Figure H26: Average conditional risky share over time



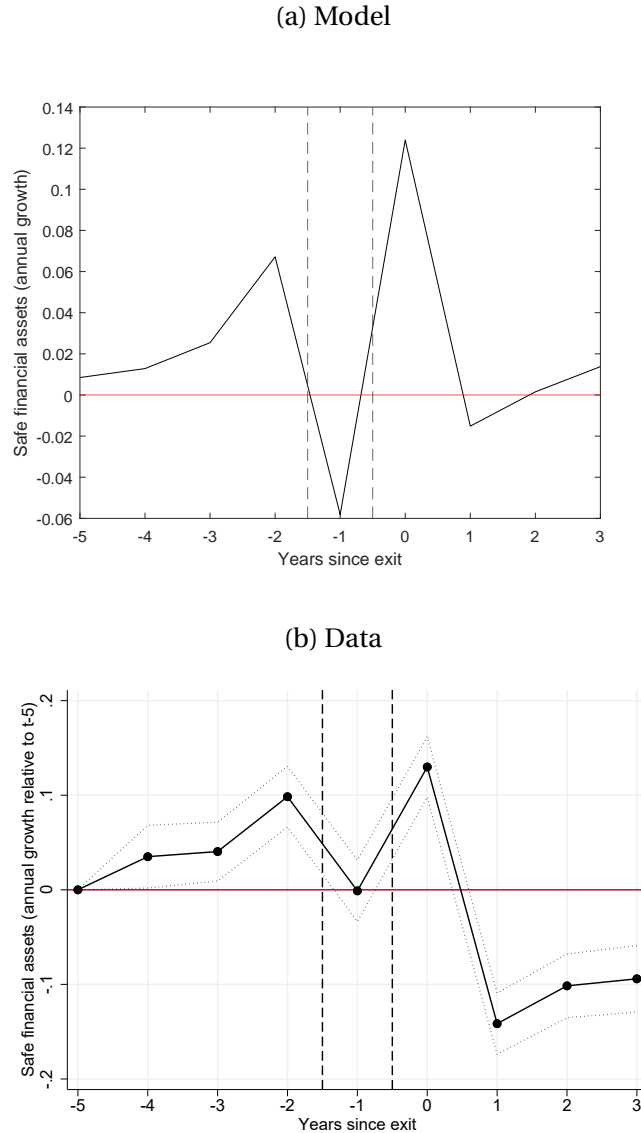
Notes. This figure plots the average conditional risky share over time. The shaded areas are stock market downturn years in which the Oslo Børs Benchmark Index fell by at least 10%.

Figure H27: Likelihood of a short spell by age at entry for model with beliefs



Notes. This figure plots the proportion of spells starting at an age x that end within 2 years for the model with beliefs.

Figure H28: Average safe financial asset growth around entry/exit (1 year spellers)

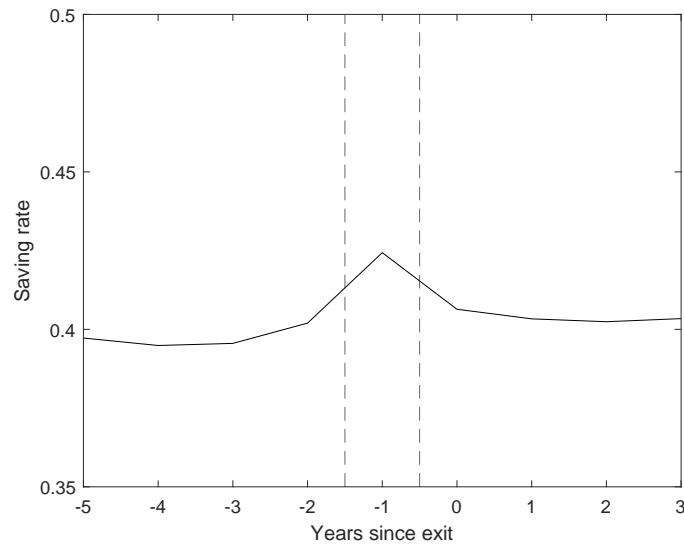


Notes. This figure plots the evolution of safe financial asset growth around exit for people who had a 1-year spell in the simulated model with EBL (panel a) and in the Norwegian data (panel b). For the model, we look at the first stock market exit event for each agent and plot the average growth of safe financial asset holdings in each year, ranging from 5 years before the exit to 3 years after the exit. For the data, we also take all individuals for whom the first spell lasted 1 year. The figure plots the β^h coefficient estimates from the following regression:

$$y_{it} = \alpha_i + \gamma_t + \sum_{h=-5}^3 \beta^h \mathbb{1}\{t = E_i + h\} + \epsilon_{it}$$

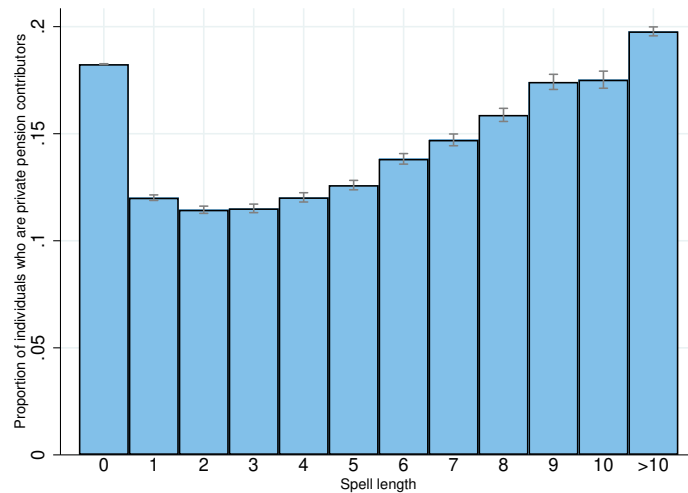
where y_{it} is the annual growth rate of safe financial asset holdings, α_i are individual fixed effects, and γ_t are year fixed effects. E_i denotes the year in which individual i exits the stock market, and $\mathbb{1}\{t = E_i + h\}$ is an indicator variable equal to 1 if the year t equals h years after the exit event. The $h = -5$ case is omitted, and so coefficients tell us the growth rate in year t relative to year $E_i - 5$. Growth rates are trimmed at the 5th and 95th percentiles of each year prior to estimation, and we restrict attention to those who invest at least \$5,000 in the stock market. For both panels, the dotted vertical lines reflect the periods just before entry and exit (one year later).

Figure H29: Average savings rate around entry/exit (1 year spellers) in model with beliefs



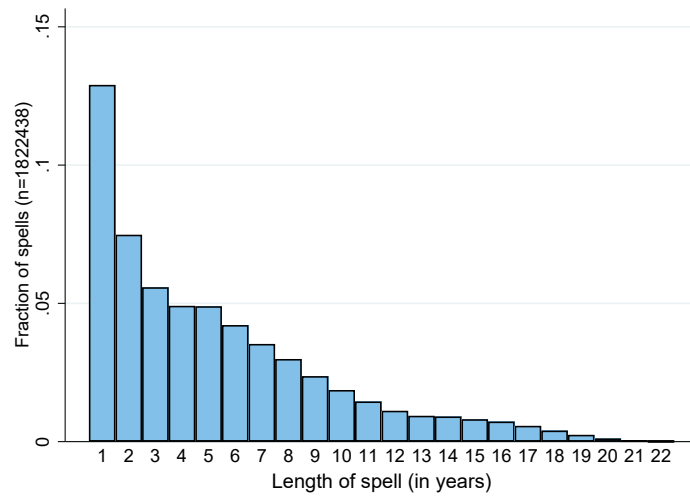
Notes. This figure plots the evolution of the savings rate (total savings divided by cash on hand) for people who had a 1-year spell in the simulated model with EBL. We look at the first stock market exit event for each agent and plot the average savings rate in each year, ranging from 5 years before the exit to 3 years after the exit. The dotted vertical lines reflect the periods just before entry and exit (one year later).

Figure H30: Prevalence of private pensions amongst exiters by spell length



Notes. This figure shows the proportion of exiters of different spell lengths participating in private pension accounts as of their exit year. An individual is said to be participating in private pensions in their exit year if they put money into a private pension either in the current year or in a past year. Participation has occurred if either of the following two items in the tax records is nonzero: TR 3.3.5, which records deductible payments to an Individual Pension Scheme (IPS), or TR 4.5.1, which records capital in an Individual Pension Account (IPA). The far-left bar (spell length of zero) gives the prevalence of private pensions shocks over nonexit observations (i.e. continuing participants). The far-right bar groups all exiters with spell lengths above 10 years. 95% confidence intervals are shown.

Figure H31: Spell length distribution excluding individuals with a private pension account



Notes. This histogram plots the proportion of spells of different lengths in the Norwegian data excluding individuals who at any point in the sample hold a private pension account. Participation has occurred if either of the following two items in the tax records is nonzero: TR 3.3.5, which records deductible payments to an Individual Pension Scheme (IPS), or TR 4.5.1, which gives capital in an Individual Pension Account (IPA). The x-axis gives the spell length (in years) and the y-axis shows the proportion of spells belonging to a particular spell length. The far-right bar gives the proportion of these spells that are right censored.

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