European University Institute
Department of Economics

Three Essays in Household Finance

Andreas Fagereng

Thesis submitted for assessment with a view to obtaining the degree of Doctor of Economics of the European University Institute

Florence
April 2012

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Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute
DOI: 10.2870/403

Abstract

This thesis contains three chapters relating to the field of household finance. In the first chapter household life cycle investment behaviour is investigated using a panel of Norwegian administrative data and tax records. Dealing with selection and identification issues, the data suggests a double adjustment as people age: a rebalancing of the portfolio away from stocks as households approach retirement, and a peak in stock market participation around the time when they reach retirement. A theoretical model predicting these life cycle patterns of investment behavior is then provided. This is achieved by extending existing models with a per period participation cost in risky asset markets and a small perceived probability of being cheated.

In the second chapter the relation between household financial asset holdings and unemployment is investigated. Consistent with a simple theoretical model, the data shows increased savings and a shift towards safer assets in the years leading up to unemployment, and depletion of savings during unemployment. This suggests that at least some households can foresee and prepare for upcoming unemployment, which indicates that private savings can complement publicly provided unemployment insurance.

The final chapter identifies the causal effect of lump-sum severance payments on non-employment duration in Norway by exploiting a discontinuity in eligibility at age 50. A severance payment worth 1.2 months' earnings lowers the fraction re-employed after one year by six percentage points. This effect is decreasing in wealth, which supports the view that the effect of severance pay should be interpreted as evidence of liquidity constraints. Finding liquidity constraints in Norway, despite its equitable wealth distribution and generous welfare state, suggests they are likely to exist also in other countries.

Fagereng, Andreas (2012), Three Essays in Household Finance
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Contents

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

Part I

Introduction

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Introduction

This thesis consists of three papers covering topics in household finance. In parallel with households becoming more and more integrated and involved in financial markets, the attention to household finance in the literature has been increasing. Decisions made by households in their encounters with financial markets are increasingly important for their utility and welfare outcomes. In most developed countries, populations are ageing, hence financial choices made at early ages will affect the households increasingly as they e.g. approach retirement age. The emergence of the mutual funds industry in the late 1990s lowered the threshold for entering risky asset markets, and made ever more households enter and hence enable the exposure of their financial wealth to higher risk and possible higher returns in the long run. These issues relate directly to the topic of the first chapter, on household life cycle investment behaviour. The papers are listed in the chronological order in which I started working on them, and are now briefly discussed in turn:

Chapter 1, joint work with Charles Gottlieb[1] and Luigi Guiso[2] focuses on households life cycle investment choices. This relates specifically to the decision of entry into risky asset markets and conditional on entry, what fraction of the total financial portfolio the household invests in risky assets. Models of life cycle portfolio choice with labor income uniformly predict that investors should reduce their portfolio share in stocks as they age because human capital, which acts a bond, becomes a smaller component of household total wealth. Despite this rather indisputable fact of diminishing human wealth over the life cycle, the prediction has not yet found empirical support. We study the life cycle portfolio allocation using a random sample of 75,000 households drawn from the Norwegian Tax Registry followed over 15 years which contains exhaustive and error-free information on all components of households' investments. We find that both participation in the stock market and the portfolio share in stocks have important life cycle patterns. Participation is limited at all ages but follows a hump-shaped profile which peaks around retirement; as households retire and begin decumulating wealth, they start exiting the stock market. The share invested in stocks among the participants is high and flat for the young but investors start reducing it slowly as retirement age gets closer. Our data suggest a double adjustment as people age: a rebalancing of the portfolio away from stocks as they approach retirement, and stock market exit after retirement. Existing calibrated life cycle models can account for the first behavior but not the second. We show that extending the models in Gomes, Kotlikoff, and Viceira

[1]Then affiliated with the European University Institute (EUI), now Oxford University.
[2]Then affiliated with the EUI, now The Einaudi Institute for Economics and Finance.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

(2008) and Gomes and Michaelides (2003) to incorporate reasonable per period participation costs can generate a joint pattern of participation and the risky asset share over the life cycle similar to the one observed in the data. In addition, if we add a small perceived probability of being cheated when investing in stocks, the model predicts a share in stocks much closer to the one observed in the data.

Chapters 2 and 3 are joint projects with Christoph Basten[3] and Kjetil Telle[4], and focus on the labor market and household finance, with very direct implications for public policy. As Chapter 1 they both make use of Norwegian administrative data. Chapter 2 uses these data to track the paths of income, wealth and holdings in different asset classes around the year of job loss to verify the predictions from a simple model with inter temporal savings. Panel data techniques and the complementary use of information on plant downsizings allow us to find clear evidence that households start to accumulate additional savings and to reallocate these to less risky and more liquid asset classes from about 2 years before their job loss, subsequently deplete these and further savings to cushion consumption while unemployed, and finally start rebuilding their savings to the initial level, all within +/- 4 years of their job loss.

Chapter 3 investigates closer the duration of job search and liquidity constraints. We look at the responsiveness of job search (non-employment) duration, which can be interpreted as a form of consumption, to quasi-randomly assigned lump-sum severance payments. We identify the causal effect of lump-sum severance payments on non-employment duration in Norway by exploiting a discontinuity in eligibility at age 50. We find that a severance payment worth 1.2 months' earnings at the median lowers the fraction re-employed after a year by six percentage points. The prior literature has interpreted such effects as evidence of liquidity constraints, but have had no means of actually verifying this claim. Data on household wealth enable us to show that the effect is decreasing in prior wealth, which supports the view that the severance pay effect should be interpreted as evidence of liquidity constraints. Finding liquidity constraints in Norway, despite its equitable wealth distribution and generous welfare state, means they are likely to exist also in other countries.

[3]Then affiliated with the EUI, now the KOF Swiss Economic Institute, ETH Zurich.
[4]Statistics Norway.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute
DOI: 10.2870/403

Part II

Chapters

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute
DOI: 10.2870/403

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

Chapter 1

Asset Market Participation and Portfolio Choice Over the Life Cycle

With Charles Gottlieb and Luigi Guiso

1.1 Introduction

Over the past 10 years a number of contributions have re-examined the life cycle behaviour of investors' portfolio. Inspired by empirical findings from novel microeconomic data on households portfolios, several papers have provided new models of the life cycle portfolio of individual investors that go beyond the seminal models of Mossin (1968), Samuelson (1969), Merton (1969) and Merton (1971).

These earlier contributions have two sharp predictions: first, even in a dynamic setting, individuals should, at all points in their life-cycle invest a share of their wealth in risky assets. That is, independently of age, all investors should participate in the stock market - an extension of the participation principle in a static setting to a dynamic context. Second, assuming complete markets and in the absence of labor income, the share invested in the risky asset should be age-invariant. Thus, the portfolio - either described by the ownership of risky assets or by their share in total wealth - exhibits no life cycle pattern. However, the absence of rebalancing over the life cycle predicted by these earlier models is not robust to the (realistic) presence of human capital. As shown by Merton (1971), the presence of tradeable human capital in a complete market setting implies that since human capital is riskless and tradeable, it plays the same role of a large endowment in riskless bonds. Hence, it creates a strong incentive to invest in risky securities when abundant, that is early in the

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute
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life cycle, and to rebalance away these as people get older and their human wealth shrinks. Importantly, this basic implication carries over to more complex environments that feature non-insurability of labor income and incomplete markets, as shown by several computational models of life cycle portfolio investments reviewed in Section 1.2 that amend the Samuelson-Merton model in one or more dimensions to add doses of realism. All these models, uniformly predict that individuals should rebalance their portfolio as they approach retirement and the driving force is the life cycle pattern of human capital. On the other hand, without specific additional assumptions, they still imply that people should participate in the stock market.

In contrast to these models, microeconomic data on household portfolios seem to show two remarkable features: first, not only participation in the stock market is limited at all ages but it tends to follow a life cycle pattern - in many instances a hump-shaped one, as documented for several countries by Haliassos, Guiso, and Jappelli (2001). Second, the share invested in stocks tends to vary little with age, though in this case the specific empirical pattern is more controversial. Summarizing evidence for several countries, Haliassos, Guiso, and Jappelli (2001) argue that the age profile of the share of risky assets conditional on participation is relatively flat, though in some instances "there does seem to be some moderate rebalancing of the portfolio away from risky securities" as people age. Thus, a reasonable characterization of the empirical findings is that participation in risky assets follows a hump-shaped profile while the share invested varies little, if at all, with age. But how solid is the evidence on which they rest? The finding that people do not rebalance their portfolio share over the life cycle sounds particularly puzzling since it is implied by an indisputable fact of life - the decrease in the stock of human capital as people age.

While the lack of participation is a robust feature of the data, there are at least three reasons to doubt the empirical patterns over age in both participation and the portfolio share. First, most of the available evidence is obtained from cross sectional data. Since in a cross section one has to compare portfolio holdings from individuals of *different* ages at a point in time, one cannot separate age effects from cohort effects and thus any pattern observed in either risky assets participation or the portfolio share may not reflect a life-cycle effect, but differences across individuals in the particular cohort they belong to. Second, most studies ignore the fact that the risky portfolio share is only defined for the participants in the risky assets markets and that participation in assets markets is an endogenous choice. A third issue is that this evidence comes primarily from household surveys which are notoriously subject to measurement problems. Most importantly, measurement and reporting error may be correlated with age giving rise to age patterns even when not present (or hide them when present) in the true data. This would arise for instance if under-reporting or non-reporting

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

of specific assets is correlated with wealth levels which in turn are correlated with age. Furthermore, since stocks are less widely held, lying about them in surveys is more likely, because it is more difficult to detect the lie than if one lies on safe assets. Hence, erroneous age effects may appear in the portfolio shares.

One important exception is Ameriks and Zeldes (2002). They try to circumvent these problems by using a panel data of TIAA-CREF contributors covering 13 years of data.[1] Since for each individual in their sample they have observations for many periods, they can in principle distinguish between age, time and cohort effects. The data being of administrative origin, non-reporting and under-reporting of assets in the program is not a major issue. Using a variety of identifying assumptions to separate age, time and cohort effects and distinguishing between ownership of stocks and conditional shares, they conclude that a good characterization of the portfolio life cycle is one where time and age effects play an important role, the life-cycle of stock market participation is hump shaped and the conditional share in stocks shows little action over the life cycle. Thus, in their view, most of the life cycle portfolio changes take place on the extensive margin not on the intensive margin.

While their results mark a clear progress in the literature, a number of open issues related in part to the data remain. First, TIAA-CREF reports only assets contributed to the program, not the complete portfolios of these individuals. Furthermore the part left out is not negligible - retirement assets are less than 30% of total household financial assets in the 1998 SCF - and there is no obvious reason why the portfolio allocation in pension savings should be the same as the allocation in other financial assets or follow the same age profile (indeed it is not, see Guiso and Sodini (Forthcoming 2012)). Second, the data refer to individuals and not to households. If the asset allocation is a joint family decision, this may result in distorted estimates. Third, participants at TIAA-CREF are from a selected group of the population - typically employees at institutions of higher education - which have marked different characteristics compared to a representative population sample. Since the estimated portfolio life-cycle reflects the age pattern of portfolio-relevant household (or individual) variables, such as the age profile of human capital and that of its riskiness, if these profiles differ across groups also the profiles of their portfolios will be different. Hence, they may not be a good characterization of the average investor in a population. Finally,

[1] Agnew, Balduzzi, and Sundén (2003) also use a four year panel data of about 7,000 people in a 401k retirement accounts and can thus distinguish age and time effects. They find that the portfolio share is decreasing in age. But this result is obtained restricting cohort effects to zero; in addition, since they fit a Tobit model, no distinction is made between the optimal share and the participation decision. Thus it is unclear whether the pattern stems from people exiting the market or lowering their share. Since they look at allocations in a 401k plan alone, all the issues raised about the Ameriks and Zeldes (2002) data extend to their data too.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

dynamic portfolio patterns of pension assets from a defined contribution plan such as TIAA-CREF may be constrained by the rules of the plan, potentially resulting in less pronounced age patterns than in overall portfolios which reflect allocations of unconstrained financial wealth.

In this paper, we try to overcome these problems. To reach this goal, we have assembled a new database drawing on administrative data from the Norwegian Tax Registry (NTR). Since Norwegian households are subject to a wealth tax, they have to report to the tax authority all their asset holdings, both real and financial, item by item at the level of the single instrument as of the end of year. We have drawn a random sample of about 75,000 Norwegian households from the 1995 population and then followed these households for 15 years up until 2009 - the latest year for which we could obtain the data. This truly unique dataset reports the complete portfolios of Norwegian people and is similar in structure and content to the one used by Calvet, Campbell, and Sodini (2007) but spans more years - a relevant feature when studying the portfolio life cycle. Being of administrative source, measurement error is minimized. The main source of non-reporting or under-reporting should stem from incentives to evade the wealth tax, but in light of the way the wealth tax is collected, tax evasion is unlikely to be an issue in Norway as we will argue in Section 1.3. Because taxes are filed individually, information on asset holdings is at the individual level but can be aggregated at the family level since a family code is available. Finally, since the whole population of Norwegian taxpayers has to report to the NTR, there is very little attrition in the panel - the only reasons to exiting it being either divorce, death or emigration to another country.

Taking into account the endogeneity of the participation decision and modelling directly cohort effects through specific variables that capture relevant experiences in individuals formative years, we find that both participation in the stock market and the portfolio share in stocks show important life cycle patterns. As in other studies, we also find a hump-shaped life cycle profile in participation (besides limited stock market participation at all ages). But we also find that conditional shares decline significantly with investors' age. Specifically, the portfolio share is high and fairly constant in the earlier and mid phases of the life cycle at a level just below 50%. As retirement age comes within households' sight - roughly 15 years before retirement - households start rebalancing their stock market share gradually but continuously by little less than one percentage point per year until they leave the job market (around age 65). During retirement investors who remain in the market keep the share at around 30% fairly flat or slightly increasing. On the other hand, participation in the stock market rises rapidly with age when young reaching a value of around 70% at age 40 and stays roughly constant until retirement age. As soon as investors leave the labor market and

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

retire, they start exiting the stock market as well.

Our data suggest a double adjustment as people age with a very specific timing: a rebalancing of the portfolio away from stocks *before* households reach retirement; exiting the stock market *after* retirement. Existing calibrated life cycle models can account for the first behaviour but not the second. We show that extending the models by Gomes, Kotlikoff, and Viceira (2008) and Gomes and Michaelides (2003) model to incorporate reasonable per period participation costs can generate a joint pattern of participation and the risky asset share over the life cycle similar to the one observed in the data. In addition, if we add a small perceived probability of being cheated when investing in stocks, the model predicts a share in stocks much closer to the one observed in the data.

The rest of the paper is organized as follows. Section 1.2 reviews the life cycle portfolio literature highlighting its core implications for the life cycle pattern of the participation and risky portfolio share. Section 1.3 discusses the Norwegian Registry data and presents descriptive evidence of the portfolio life cycle pattern. Section 1.4 lays down the methodology for estimating the life cycle portfolio profile and presents the estimation results. Section 1.5 shows how an extended calibrated life cycle model can account for the pattern of the portfolio that we observe in the data. Section 1.6 presents the results of this paper and Section 1.7 summarizes the contribution of this paper and draws implications for future research.

1.2 An Overview of the Literature

Inspired by empirical findings from novel microeconomic data on household finances, over the past decade several papers have provided new models of optimal portfolio rebalancing over the life cycle that go beyond the seminal dynamic framework of Merton (1969), Merton (1971), Mossin (1968) and Samuelson (1969). The Merton-Mossin-Samuelson (MMS) models generate two sharp predictions. First, individuals should participate in risky asset markets at all ages - a proposition that extends the participation principle to a dynamic context. Second, the share invested in the risky asset should not vary over the life cycle. The implications of the MMS models are in contrast both with the limited participation that we observe in the data at all ages and with the widespread advice of the financial industry practitioners to invest substantially in stocks when young and reduce the exposure to the stock market when older. Yet, these earlier contributions were not meant to provide sharp predictions about realistic features of the data but rather to establish the benchmark conditions under which a long term investor would choose “myopically” - i.e. show no life cycle pattern in his investments. As Samuelson (1969) points out, “[A] lifetime model reveals that investing

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

for many periods does not itself introduce extra tolerance for riskiness at early, or any, stages of life". One needs the MMS assumptions of no labor income, unpredictable stock returns, constant relative risk aversion and time-separable preferences, in addition to long time horizon, to obtain that the optimal portfolio risky share does not vary with wealth and age.

In fact, as shown by Merton (1971), adding to the model tradeable human capital in a complete market setting generates a strong rebalancing motive in the financial risky share. Since human capital is riskless and tradeable, it plays the same role as a large endowment in riskless bonds. Hence, it creates a strong incentive to invest in risky securities when human capital is abundant, that is early in the life cycle, and to rebalance away from stocks as people get older and their human wealth diminishes. The simple presence of human capital - an indisputable feature of any realistic model of household portfolio decisions - seems to be enough to provide a rationale for the practitioners' advice to rebalance the portfolio away from stocks as people age.

Merton (1971)'s result is obtained in a complete market setting with tradeable human capital; this allows him to obtain neat closed-form solutions. A new recent wave of papers has reconsidered the Merton (1971) model relaxing the assumption of complete markets and tradeability of human capital (see Gomes and Michaelides (2003), Gomes and Michaelides (2005); Heaton and Lucas (1997); Gakidis (1998); Haliassos, Guiso, and Jappelli (2001);Haliassos and Michaelides (2002); Storesletten, Telmer, and Yaron (2007); Campbell and Viceira (2001); Viceira (2001); Cocco, Gomes, and Maenhout (2005); Davis, Kubler, and Willen (2006); Benzoni, Collin-Dufresne, and Goldstein (2007); Gomes, Kotlikoff, and Viceira (2008)). Because markets are incomplete and labor income is uncertain and non-tradeable, these models do not have closed form solutions and have to be solved numerically. A representative example of this literature is Cocco, Gomes, and Maenhout (2005). They develop, numerically solve and simulate a life cycle model of consumption and portfolio choice which allows for non-tradeable and uncertain labor income as well as many other features that characterize a typical household environment such as bequest motives, mortality risk, non-standard preferences, uncertain retirement income and catastrophic labor income shocks. They calibrate the labor income process with data from the PSID and estimate average consumption and assets allocation by simulating the model over 10,000 households. A robust prediction of this and all the other models in this literature is that the portfolio share invested in stocks has a strong life cycle profile. Thus, Merton (1971)'s rebalancing implication holds true not only when labor income is tradeable and certain but also when it is non-tradeable and subject to uninsurable risk.[2]

Despite that the prediction according to which households should rebalance their portfolio as they approach retirement rests on an uncontroversial fact, namely the decline in human capital as people age, it has been hard to find it in the data, as we have argued. This is likely to be the reflection of limitations in the data that we are able to overcome using the Norwegian dataset, and we find evidence that is indeed consistent with the prediction that households should rebalance their financial risky portfolio as they approach retirement.

While the shape of the age profile of the portfolio share in stocks predicted by these models resembles the one we find in the data, there are two important differences between these models' predictions and our findings. First, the new models generate much higher shares in stocks, particularly at the beginning of the life cycle and in the middle ages, than those seen in the data among the stockholders. Second, they often do not give rise to limited participation and to exit from the stock market as people age. In particular, our evidence suggests a double adjustment as people age: as they approach retirement, they rebalance their portfolio away from stocks but continue to stay in the market; after retirement they stop rebalancing but start exiting the market. Some models have addressed the issue of limited participation among the young by allowing for a once and for all fixed cost of participation (Cocco, Gomes, and Maenhout 2005), or for long run co-integration between labor income and stock market returns (Benzoni, Collin-Dufresne, and Goldstein 2007) or for costly access to the loans market (Davis, Kubler, and Willen 2006). None of these models, however, deals with exit from the stock market as people retire. Hence they cannot explain the hump shape in participation over the life cycle and the timing of rebalancing in the optimal share and in participations that we observe in the data. In addition, these models tend to predict a far too high share in stocks among the stockholders at some point over the life cycle. To better mirror the data, we propose a simple extension of the Cocco, Gomes, and Maenhout (2005) model enriched with two ingredients: a per period participation cost and a trust friction. This model is able to generate a hump shaped pattern of stock market participation that peaks at retirement and declines thereafter. This pattern is the consequence of the hump-shaped wealth age profile: when young, wealth is typically increasing and thus gradually more and

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

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

more consumers will cross the wealth thresholds that triggers entry into the stock market. After retirement, people begin to decumulate assets and at some age the level of assets left is too low for it to be worthwhile to pay the per period cost and remain in the market, hence they exit.[3] At the same time, the age profile of the share among the stockholders is relatively high and flat at young age, but as people foresee retirement, they start rebalancing the portfolio. Limited trust - modelled as an individual specific small probability that the investor is cheated and looses the money invested in stocks - helps lower the portfolio share in stocks, bringing it closer to the one observed in the data.

1.3 Data

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

1.3.1 The Norwegian Administrative data

Each calendar year, before taxes are filed in April, employers, banks, brokers, insurance companies and any other financial intermediary send both to the individual and to the tax authority, information on the value of assets individuals own, as well as information on the income earned on these assets. In case an individual holds no stocks, the tax authority pre-fills a tax form and sends it to the individual for approval; if no answer is given, it is perceived as an approval of the information gathered by the tax authority. In 2009, as many as 2 million individuals in Norway (about 60% of the tax payers) belonged to this category.[4] If the individual holds stocks then he has to fill in the tax statement - including

[3] Some exit from the stock market after retirement may occur even without a per period participation cost if households are heavily invested in stocks and liquidate stocks to finance consumptions following retirement, that is if stock is the prominent form of liquid wealth (Alan 2006). In general, however, absent participation costs, one should see a decumulation of both stocks and bonds and very little exit.

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

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

calculations of capital gains/losses and deduction claims. The statement is sent back to the tax authority which, as in the previous case receives all the basic information from employers and intermediaries and can thus check its truthfulness and correctness.[5] Stockholders are treated differentially only because the government wants to save on the time necessary to fill in more complex tax statements and to reduce the risk of controversy due to miscalculated deductions on capital losses and taxes on capital gains. Since the early 2000's all this is done electronically, prior to 2000 tax reports were done on paper forms. This procedure and the fact that the tax authority always receives directly from the intermediaries the information on asset holdings and relative yields, makes tax evasion very difficult and thus very likely negligible.

During the sample time period, asset markets worldwide and in Norway experienced both booms and busts, and the mutual fund industry expanded significantly making it easier for many households to participate in the risky asset market, e.g. by lowering participation costs, offering cheaper diversification opportunities and spreading information about mutual fund investments. The administrative data contains information about all individuals and their demographics. The quality of this data is similar to that in the Swedish data studied by Calvet, Campbell, and Sodini (2007). Until 2007, Sweden like Norway collected taxes on both individual income and wealth. In 2007, however, Sweden abandoned the wealth tax, leaving Norway as the only Scandinavian country with this arrangement. Tax reports on both labor income and asset holdings are filed by each individual even for married couples. Data on asset holdings are reported as of December 31 of the previous year. We focus on the financial portfolio and distinguish between bank deposits, bonds, stocks (of listed and non-listed companies), mutual funds, money market funds.[6] Following the literature, we consider a two asset-portfolio and define risky financial assets as the sum of stock mutual funds and directly held stocks; the rest - the sum of bank deposits, money market funds and bonds - is classified as risk-free (or safe) assets. A financial market participant is one that holds some positive amount in either risky or risk-free assets at the end of the year. Since some households report very few financial assets, we set a minimum of 3000NOK (approx. 480 USD (1995)). A risky asset market participant is defined as a household holding a positive amount (minimum 1000NOK - approx. 160 USD (1995)) of either stocks or stock mutual fund at the end of the year.[7]

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

[6]Some households also hold more sophisticated financial instruments, like forward contracts and options. These households are very few and do not affect the results of the analysis.

[7]About the use of selection requirements, see Calvet, Campbell, and Sodini (2007) and Brunnermeier and Nagel (2008).

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

Table 1.1: Descriptive Statistics - 1995

	Full Sample				Balanced Panel Sample			
	Obs	Mean	Std Dev	Median	Obs	Mean	Std Dev	Median
Demographics:								
Age Husband	74,711	51.26	14.15	50	48,928	47.96	11.73	47
Age Wife	74,711	48.54	14.02	47	48,928	45.33	11.48	45
Share Less High School Education	73,345	0.23			48,158	0.18		
Share High School Education	73,345	0.51			48,158	0.53		
Share College Education	73,345	0.27			48,158	0.29		
Household Size	74,628	3.22	1.17	3	48,888	3.42	1.17	3
Asset Holdings in USD:								
Financial Wealth	74,711	41,923	112,291	14,232	48,928	41,079	114,751	13,287
Stocks	74,711	14,029	96,685	0	48,928	15,210	99,654	0
Mutual Funds	74,711	1,284	4,056	0	48,928	1,350	4,106	0
Safe Assets	74,711	26,610	38,776	11,597	48,928	24,519	36,710	10,580
Net worth	74,711	120,354	143,051	97,543	48,928	122,045	145,279	99,174
Participant share:								
Risky Assets	74,711	0.40	0.49	0	48,928	0.42	0.49	0
Stocks	74,711	0.29	0.45	0	48,928	0.31	0.46	0
Mutual Funds	74,711	0.24	0.43	0	48,928	0.25	0.43	0
Risky Asset (min 160$)	74,711	0.36	0.48	0	48,928	0.39	0.49	0
Mean share participants:								
Risky Assets	30,036	0.29	0.30	0.16	20,784	0.30	0.31	0.18
Stocks	30,036	0.21	0.33	0.13	20,784	0.22	0.31	0.04
Mutual Funds	30,036	0.08	0.16	0.08	20,784	0.09	0.14	0.03
Attrition:	26,253							
Share Death		0.62						
Share Migration		0.13						
Share Divorce/Separation		0.25						
Mean yearly attrition rate:		0.029	0.001					
Age at Exit		65.51	16.57					

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

In what follows, a household is defined as a married couple, and the age reported is that of the husband; we refer to this as the age of the household. The term ”cohort” refers to the year of birth of the husband. In order to have the largest possible sample that is computationally manageable, we randomly draw a sample of about 75,000 households from the 1995 population of tax reports, and follow these households over the following 15 years, until 2009. There is a certain attrition as individuals die, migrate and divorce. These households are left out and are not replaced. Further details regarding our wealth data are provided in Halvorsen (2011).

Table 1.1 provides summary statistics for the household sample in 1995. The average age of households is 51 years. Education attainment measured in 1995 is available for almost all the households. The most common educational attainment level is a high school diploma, which is obtained by 51% of the sample, while 26.5% hold a college degree.[8] Although there is attrition in the sample at an average annual rate of 2.9%, we can track 2/3 of the households sampled in 1995 all the way until 2009. The main reason for exiting the sample is death of a spouse (62%), as suggests households' average age of 65 years when they exit from the sample. The average Norwegian household holds around 42,000 USD (1995) in financial assets. Net worth, comprising financial assets and real estate net of debt amounts to 120,000 USD (1995), of which about 2/3 is real estate.[9] The financial portfolio of the average household is mostly composed of safe assets which account for 63% of the total average financial assets. Around 40% of the Norwegian population participates in risky asset markets. If we define as participant only a household with at least 160 USD (1995) of risky assets, the participation rate amounts to 36%. A closer look at the data, reveals that 29% of the population hold stocks directly, while 23% percent participate via mutual funds. Hence, back in 1995 mutual funds were not as widespread as direct stock-holding amongst Norwegian households. Among participants, the average of the portfolio share in risky assets is 29% while mutual funds account for 8% - a similar figure prevails in other European countries, as documented in Haliassos, Guiso, and Jappelli (2001). The right part of Table 1.1 displays summary statistics for the majority of households that do not drop out of our 15 year panel. The selection of the households present in all years have a lower average age back in 1995. Further, this group contains a lower fraction of households with less than high school education. The levels of asset holdings are similar across the two groups, although the balanced panel displays slightly higher holdings of risky assets. For the asset market participants of the two groups, the mean shares in risky asset classes differ only by 1 percentage point when it comes to stocks and mutual funds.

[8]These numbers are in line with official numbers from Statistics Norway. For 2010 data, see e.g `http://www.ssb.no/English/subjects/04/01/utniv_en/tab-2011-06-09-03-en.html`.

[9]The real estate value is a proxy based on the reported tax values of Norwegian households, and is not updated every year. For our measure here, we use the reported tax value of real estate and divide by 0.25 to get an approximation, following the guidelines of the Norwegian Tax Authorities, stating that the tax value of real estate shall not exceed 30% of market value.

Fagereng, Andreas (2012), Three Essays in Household Finance
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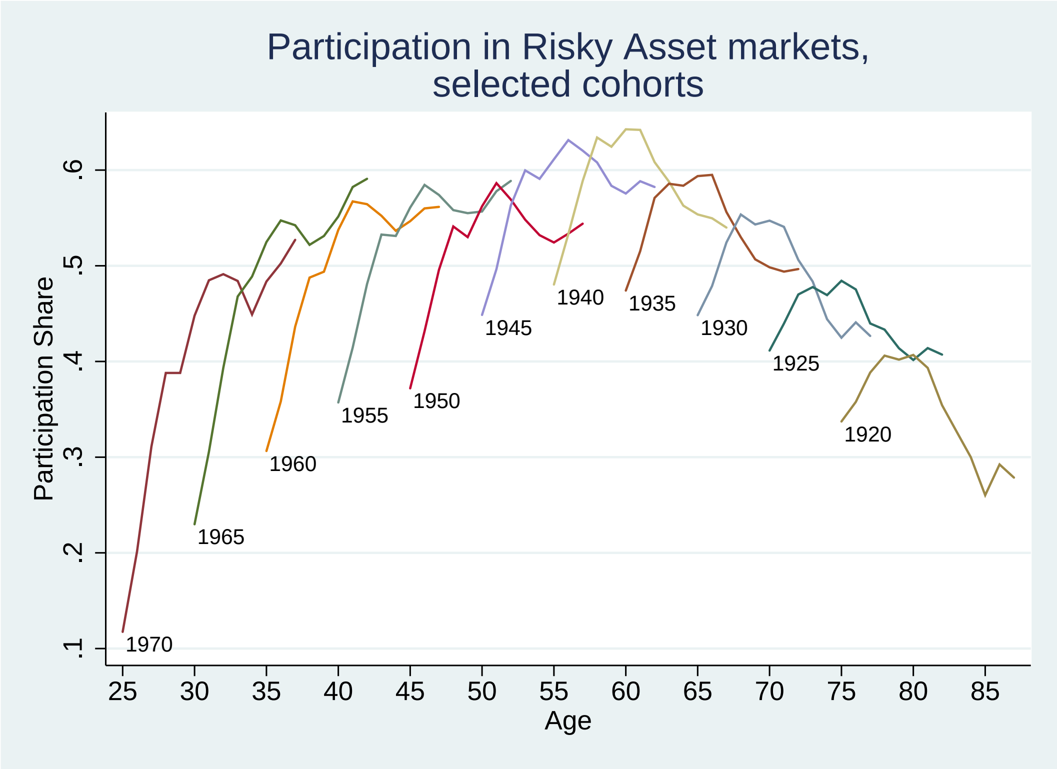

Figure 1.1: **Participation shares in Risky Asset markets by Cohort**.
Note: This Figure plots the mean participation rates in Risky Asset markets at observed age for selected cohorts.

1.3.2 Portfolio Life Cycle Patterns by Cohort: Descriptive Evidence

Figure 1.1 plots the age participation profile in the risky asset markets for selected cohorts with intervals of 5 years, beginning with the cohort born in 1970 who are aged 25 in 1995, the first sample year. Since we are able to follow each cohort for 15 years, we are able to provide a good picture of the life cycle portfolio pattern by just plotting the raw data.

Consider the first cohort born in 1970. In 1995, they were 25 years old and only slightly more than 10% of them were participating in risky asset markets. However, in the following years the share of participants in this cohort increased significantly, and when this cohort reached the age of 30, more than 40% of the households held risky assets in their portfolio. Clearly, this pattern is consistent with a marked age effect (an increase in participation with age), with strong time effects (an increase in participation due to favourable market conditions, e.g. the boom of the mutual funds industry), as well as with a cohort specific

Table 1.2: Entry and Exit Definitions

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

pattern. If this were the only cohort observed, these effects would be hard to disentangle as time and age evolve in parallel and we only observe one cohort; we could not make any claim on whether the increase in participation rate is cohort-specific, a pure age effect, or if it reflects a common time trend that affects all cohorts in the years 1995-1999.

The next plotted cohort - that of the households born in 1965 - shows also for these households a steep increase in the average participation during the first years of our sample. This suggests that the increase in participation is unlikely to be cohort specific. Yet it is still unclear whether this surge in participation rates is due to an age-effect, or to a common time trend. Comparing the evolution of participation across cohorts suggests that time effects are likely to be important; for instance, all cohorts experience a marked increase in participation during the first years of our sample, even those born in 1920 - who are 75 in 1995 - and thus typically exit risky asset markets. The graphical evidence given by Figure 1.1 suggests that cohort effects play an important role. In Section 1.4, we describe our empirical strategy to separate these effects and to test for the presence of cohort effects.

As a next step in the descriptive analysis of the life cycle patterns of participation, we consider two measures of entry into and exit from the stock market, as defined in Table 1.2. These two measures are plotted in Figure 1.2 for the same selected cohorts. The first measure refers to entry (exit) in a given year, regardless of the household's past (future) participation pattern. The second, reports entry (exit) that was not preceded (followed) by a previous entry (a subsequent exit). In other words, the second measure captures first-time entry and permanent exit.

First-time entry is very high at the beginning of the life cycle, with a peak at 13%, and drops steadily thereafter. Instead permanent exit is low at the beginning of the life

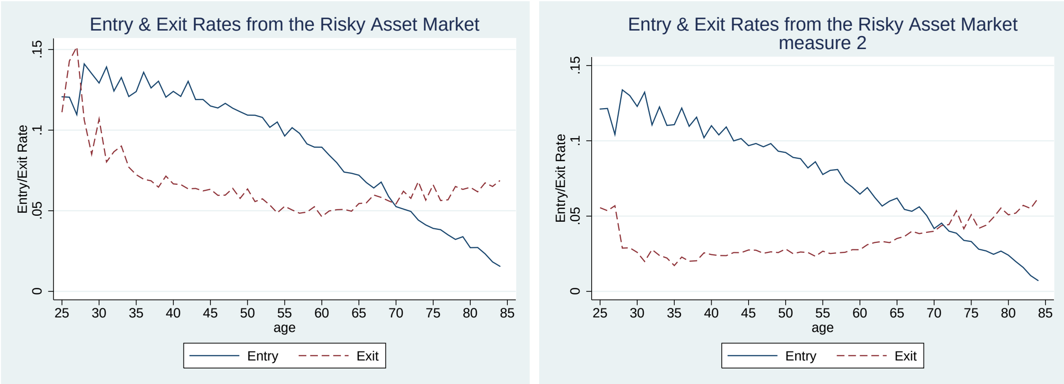

Figure 1.2: **Entry and Exit rates from Risky Asset Markets**.
Note: This Figure plots entry and exit rates into the risky asset markets. The left graph depicts entry and exit frequencies, allowing for re-entry/exits. In the right graph, entry and exit frequencies of first time entry and once for all exit are plotted.

cycle and increases sharply after retirement. By reporting the two measures, Figure 1.2 highlights that early in life temporary entry and exit are very common phenomena. Among households in their early 30s, 30% enter the stock market but only half of them enter for the first time. Similarly, the fraction of young households that sell all risky financial assets to return to the stock market later in life is almost five times the fraction of households that exit permanently. These figures suggest important learning effects of early stock market experiences. Some households decide to hold stocks when young, and to exit the market permanently, after that early experience.[10]

For the same cohorts selected for Figure 1.1, we plot in Figure 1.3 the risky financial share for households who participate in the stock market - that is the portfolio share conditional on participation. In what follows, we refer to it as the conditional share. To obtain a smoother picture, we have plotted centred average shares around the current age using the two adjacent years. Overall, the picture suggests that once people enter, they invest a relatively large share in risky assets and reduce it as they age. A comparison across cohorts suggests less pronounced cohort effects than the ones we observed for participation. On the other hand, comparing the pattern of the conditional share over time across cohorts reveals strong time effects. This may reflect variation in stock prices coupled with active rebalancing in response to changes in the share induced by stock price movements, as suggested by Calvet, Campbell, and Sodini (2007). Although the graphic does not give an unambiguous

[10]Note that at low and high ages, the number of observations is limited because fewer households and of more limited stock market participation at those ages. Both in this graph and in the Figure 1.3 this explains the higher variability at these ages.

picture, just plotting the raw data of risky shares is quite informative in suggesting that there is substantial rebalancing over the life cycle, in particular when households approach retirement.

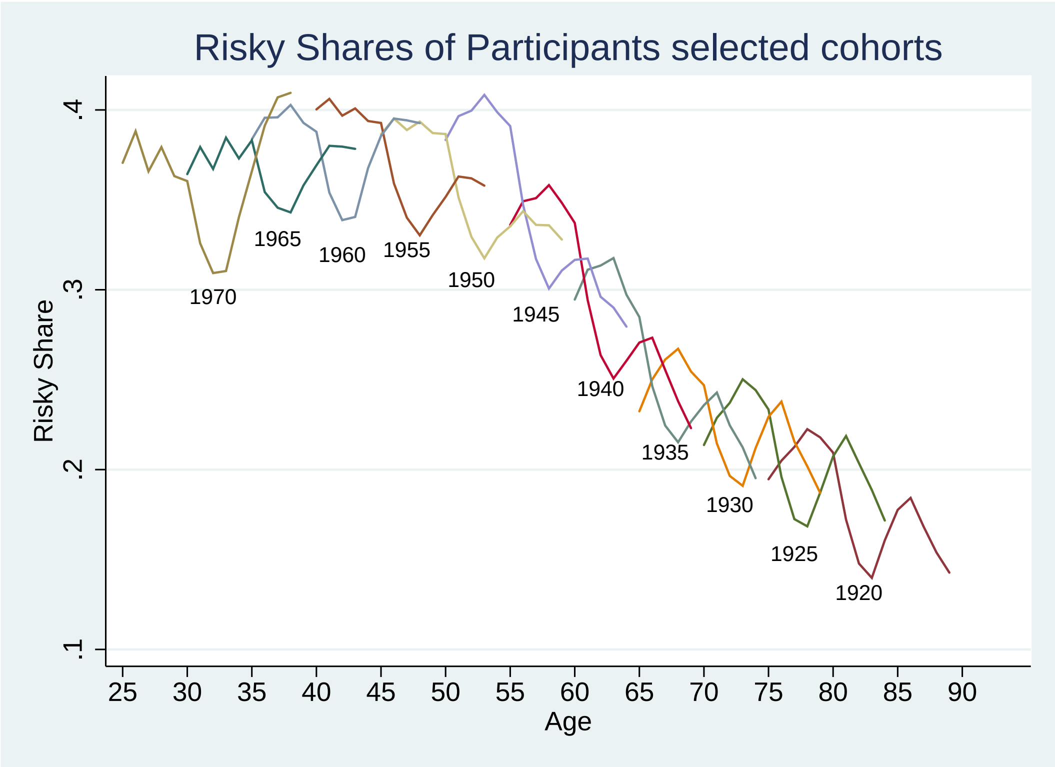

Figure 1.3: **Risky Share of Financial Wealth by Cohort**.

Note: This Figure plots the average risky shares of households' financial portfolios conditional on participation, for selected cohorts at each age they are observed. In order to smooth large market movements out of the graphs, we plot 3 years averages.

1.4 Estimation

The descriptive evidence presented so far suggests the existence of a life cycle pattern both for the participation decision, and the risky share of household's portfolio conditional on participation. Although informative for descriptive matters, we have not yet addressed the problems tied to limited stock market participation and the identification problem of age, time and cohort effects properly. In this Section, we discuss these issues, and propose a way to address them, allowing us to pin down these patterns accurately.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

1.4.1 Methodology: Limited Asset Market Participation

It is a well established 'puzzle' that not all households participate in risky asset markets. Previous empirical analysis of the life cycle profile of household portfolios have ignored this issue (Ameriks and Zeldes 2002). Also theoretical models have until recently assumed that all households participate in risky asset markets. What may cause households that "should" be in the risky asset market not to participate? Under the assumptions that households have a constant relative risk aversion (CRRA) and face some fixed cost to participate in risky asset markets, not everyone will find it worthwhile to participate.

Our empirical strategy consists in addressing this issue in a Heckman type selection model: we use a probit selection model to estimate whether or not a household participates in risky asset markets, and subsequently estimate the risky share conditional on the selection equation. We follow Vissing-Jorgensen (2002) and apply a commonly used exclusion restriction, namely households lagged net-wealth. Given CRRA preferences, higher wealth will *ceteris paribus* make a household more likely to participate in risky asset markets, as it is more likely that he can afford the participation cost, without affecting the risk aversion, thereby allowing us to observe the risky share.[11]

1.4.2 Methodology: Proxy for cohort effects

The issue of identification of age, time and cohort effects is extensively covered in Ameriks and Zeldes (2002), but not appropriately addressed, as we argue herein. Campbell (2006) asserts that even with the perfect data set, where the researcher observes a panel of households over their entire life span, it is not possible to identify cohort, time and age effects simultaneously without further restrictions. In fact as discussed in Section 1.3, one cannot distinguish between age and cohort effects. If older people hold more stocks, it is either an age effect, or it can be due to the fact that they grew up in different times, such that they have developed different attitudes towards risk-taking (cohort effect). Given that we can observe the same household over time in a panel data setting, we can partially address this issue, but as much as it helps identifying one extra dimension, it also adds one more dimension to identify.

Berndt and Griliches (1995) solve the problem of identification in the unbreakable relationship $cohort_i = time + age_{it}$ in a non-parametric fashion, by restricting some of the age coefficients to be constant (e.g. that there is no age effect between for example age 30 to

[11] If q is the fixed cost of participation in risky asset markets, W is a households' wealth, α is the risky share derived from the households preferences, and R^e are the excess returns of the stock market the relation $F \lesseqgtr W * \alpha * R^e$ will decide if a household that period decides to participate in risky asset markets or not.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

35). In their analysis of price indexes for personal computers, this allows them to identify age, time and cohort effects separately. We build on recent research in the field of household finance which indicates that cohort effects affect individual risk taking substantially. Giuliano and Spilimbergo (2009) show that generations growing up during recessions have different socio-economic beliefs relative to generations growing up during booms. In addition, Malmendier and Nagel (2011) show that households who have experienced higher stock market returns throughout their life time are more likely to participate in the stock market and, that conditional on participation, these households will invest a higher fraction of their wealth in risky assets. This evidence supports their use of the returns of S&P 500 as a proxy for cohort effects. For the purpose of our estimation, we will use stock market returns experienced during the household heads' youth as a proxy for cohort effects. In particular, we use a weighted index of the Norwegian stock market and the S&P 500 as a proxy. As we will demonstrate, these returns significantly affect both the decision to enter risky asset markets and the risky conditional share.

1.4.3 Results from estimating Life Cycle patterns

Table 1.3 reports the estimates of the selection model and shows that experienced asset market returns affect positively both the participation decision and the risky share conditioned on participation.[12] The coefficients for the age dummies of this regression are plotted in Figure 1.4. First, we note that these Figures represent refined versions of the raw plots of the data presented in Figures 1.1 and 1.3, and document a distinct hump-shaped pattern of asset market participation over the life cycle. Younger households enter risky asset markets steadily until the age of approximately 41, age at which the level of participation is stable until the age of approximately 55. From age 55 onwards, the participation rate drops almost linearly until the age of 80. The pattern for the conditional risky share is remarkably different: until age 47 the conditional risky share is stable around 39%, it then declines steadily until retirement, time at which the risky share stabilizes around 30%.

[12]In order to enable Stata to find feasible initial values, we have made a draw of 50% from our household sample to estimate the Heckman selection procedure with Maximum Likelihood. The results displayed here are those from a Heckman two-step procedure, but results are identical for both procedures.

 DOI: 10.2870/403

Table 1.3: Heckman Selection Model

Risky Share (Outcome Eq):	
Youth Stock Returns	0.004
	(0.002)**
Participation (Selection Eq):	
Youth Stock Returns	0.041
	(0.003)***
Lag Financial Wealth	0.256
	(0.006)***
Observations	418,163

Note: This table displays the estimated Heckman selection equation for asset market participation and the conditional risky share. Lagged Financial Wealth is in 100.000 USD (1995). Coefficients in the Selection Equation are calculated marginal effects from the underlying probit regression. Omitted are calendar year fixed effects, age coefficients and marginal effects in Figure 1.4. Standard errors are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

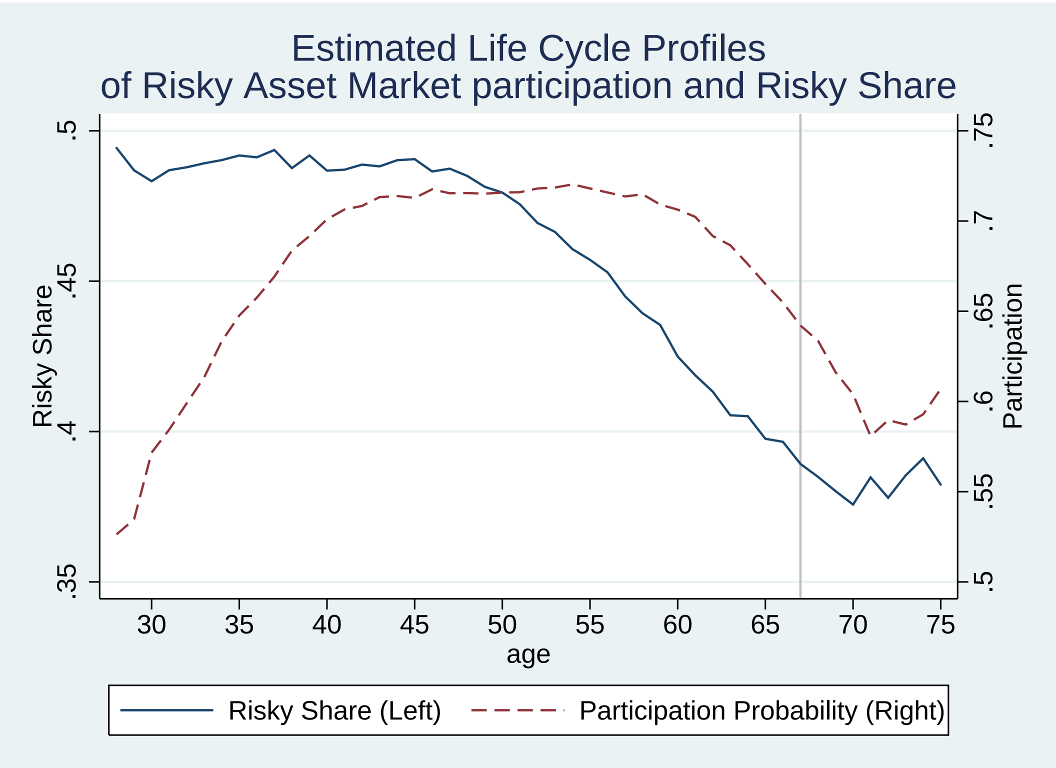

Figure 1.4: **Estimation: Risky Asset Market Participation & Risky Shares**.

Note: This Figure plots the life cycle patterns for both the **Risky Asset Market Participation** and the **Conditional Risky Share** of Financial Wealth coming from the Heckman selection equation reported in Table 1.3. For the Selection/Participation Equation, we plot the marginal values of the estimated underlying probit equation, and for the risky share, the age coefficients of the Outcome equation in the Heckman model.

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Table 1.4: Heckman Selection Model by Educational Attainment

	Less High School	High School	College
Risky Share (Outcome Eq):			
Youth Stock Returns	0.017	-0.003	0.019
	(0.006)***	(0.003)	(0.004)***
Participation (Selection Eq):			
Youth Stock Returns	0.011	0.057	0.071
	(0.005)***	(0.004)***	(0.005)***
Lag Financial Wealth	0.182	0.273	0.280
	(0.002)***	(0.002)***	(0.003)***
athrho			
Constant	-0.346	-0.500	-0.557
	(0.014)***	(0.007)***	(0.010)***
lnsigma			
Constant	-1.397	-1.280	-1.253
	(0.005)***	(0.003)***	(0.004)***
Observations	90,654	222,904	102,471

Note: The table displays the estimated Heckman selection equation for asset market participation and the conditional risky share for three levels of educational attainment. Lag Financial Wealth is in 100.000 USD (1995). Coefficients in the Selection Equation are calculated marginal effects from the underlying probit regression. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

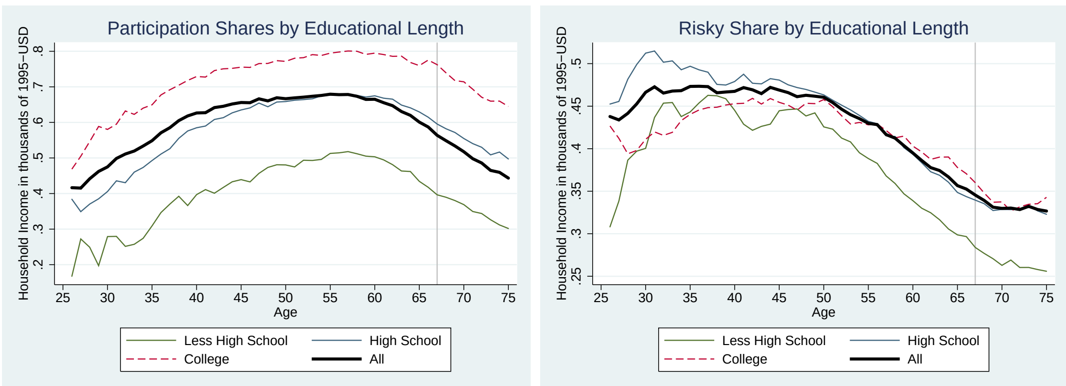

Figure 1.5: **Participation and Risky Shares by Educational Achievement.**

Note: These Figures plot the life cycle patterns of **Risky Asset Market Participation** and **Conditional Risky Share** of Financial Wealth by educational achievement level coming from the Heckman selection equations reported in Table 1.4. The participation graphs plot the marginal values of the estimated underlying probit equations, and for the risky share it plots the age coefficients of the Outcome equation in the Heckman model.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute
DOI: 10.2870/403

Table 1.5: Entry and Exit Regressions

	Entry (all)	Exit (all)	Entry (first time)	Exit (forever)
Youth Stock Returns	0.009***	-0.005***	0.005**	0.001
	(0.002)	(0.001)	(0.002)	(0.001)
Constant	0.035	0.071	0.104	0.039
	(536.209)	(518.577)	(0.086)	(384.926)
R^2	0.026	0.006	0.034	0.008
Observations	404,268	437,132	317,994	437,132

Note: This Table reports the estimates obtained from regressing the different entry and exit patters on a set of age dummies, year dummies and a cohort proxy. Year dummies are omitted from the table, where as the age dummies plotted in Figure 1.6. Standard error in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

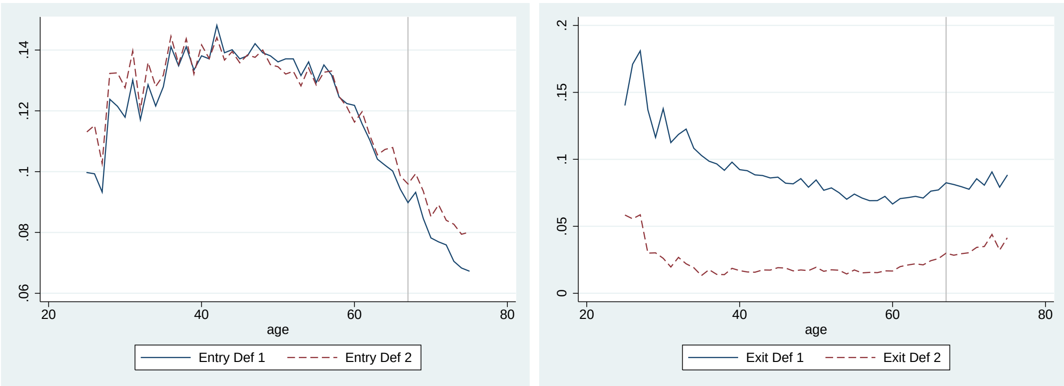

Figure 1.6: **Life Cycle Patterns of Entry and Exit from Risky Asset Markets**.

Note: These Figures plot the life cycle patterns of Entry and Exit, defined by two different measures in Table 1.2 used in the regressions reported in Table 1.5.

Figure 1.4 highlights two regimes for the age pattern of the conditional risky share. First, participating households aged between 27 and 45 hold around 40% of their financial portfolio in stocks. Second, from 64 onwards households participating in asset markets invest around 30% of their wealth in risky assets. Between the age of 45 and 64, households reduce their risky shares by about half a percentage point per year. For a matter of reference, one should bear in mind that the advice of professionals from the financial service industry to households is to reduce their exposure to risky assets by one percentage point every year. These empirical patterns are the targets of the overlapping generations model developed in Section 1.5.

In Table 1.4, we re-ran the regression for the sample split by educational attainment,

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

and plotted the corresponding age patterns in Figure 1.5. We note a differences in the participation probabilities, which fits well the literature on financial literacy, according to which more educated households are likely to possess also more information on risky asset markets, which will effectively reduce their cost of participation (Van Rooij, Lusardi, and Alessie 2007). However, conditional on participation, households with medium or high educational attainment have fairly similar profiles of risky asset holdings as a share of total financial wealth.

Next, we apply the same methodology to clean out year and cohort effects from the entry and exit patterns in Figure 1.2. We regress the two different measures of entry and exit of the risky asset market on age dummies, calendar year fixed effects and a proxy for cohort effects, the stock market return at ages 15-25. These regressions are reported in Table 1.5 and Figure 1.6. Due to the very limited sample of households participating early in life, we see that, already early in the life cycle, the exit rates (especially of the first definition) are high. Entry into the risky asset market picks up just after the age of 30, and the inflow rate remains constant up until mid life.

1.4.4 Validation of strategy

Following Berndt and Griliches (1995), we check our identification strategy of age, time and cohort effects. Studying the age profiles in Figure 1.4 more closely, we note that both curves have distinct plateaus. Specifically, the risky share is fairly stable around 48% until the age of 50, whereas the participation rate is stable from the age of approximately 45 to 55. We impose testable restrictions on the age effects over these periods which then enables us to replace the cohort proxy (stock market life time gains) with the original cohort dummies. One restriction is that the age patterns are stable from age 30 to 40 for the conditional risky share, and from the age 45 to 55 for the participation rate. These hypotheses cannot be rejected at the 10% level (p-value of 0.55). Using the imposed restrictions on age, we estimate the selection model including all three age, time and cohort effects, offering a candidate for resolving the issue of identification in this framework. Having inserted the restricted age patterns into the Heckman selection model, we now re-run the analysis using instead of the cohort proxies (stock market returns) the cohort dummies. Table 1.6 displays the correlation between these estimated cohort dummies and the proxies. As noted earlier for the regression including the cohort proxies, the cohort effects seem to matter more for the decision of participation than for the risky share. This is indeed confirmed here as we see that for the participation decision the estimated cohort effects are highly correlated with the cohort proxies, whereas it is not the case for the risky share. One way to interpret this is that there are cohort components in a once and for all participation costs (which would come in addition to the per period participation cost), hence cohort proxies would affect participation but not the conditional share.

In Table 1.7 the same correlations are reported for the regressions split by education reported in Table 1.4 after imposing restrictions to the age patters of participation and risky shares. As we see, this effect disappears for lower education groups, whereas we find it significant for households with high school or college education.

Table 1.6: Cohort Effect Correlation

	Share	Participation
Youth Stock Returns	-0.006	0.172 ***
	(0.012)	(0.034)
Constant	0.021	-1.048 ***
	(0.012)	(0.033)
Observations	61	61
R^2	0.004	0.304

Note: The table displays the correlation between estimated cohort proxies and the estimated cohort effects when restricting the age pattern of the model estimated in table 1.3 and figure 1.4. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 1.7: Cohort Effect Correlation, by Education

	Less High School		High School		College	
	Part	Share	Part	Share	Part	Share
Youth Stock	-0.009	-0.096	-0.008	0.236***	0.087 ***	0.023
Returns	(0.013)	(0.067)	(0.013)	(0.086)	(0.021)	(0.091)
Constant	0.298 ***	5.786 ***	-0.016	-1.649 ***	-0.088 ***	5.852 ***
	(0.012)	(0.061)	(0.013)	(0.085)	(0.020)	(0.087)
Observations	57	57	60	60	58	58
R^2	0.009	0.036	0.007	0.115	0.233	0.001

Note: The table displays the correlation between estimated cohort proxies and the estimated cohort effects when restricting the age pattern of the models estimated by educational attainment in Table 1.4 and Figure 1.5. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Fagereng, Andreas (2012), Three Essays in Household Finance
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1.5 Model

Having shown evidence on the life cycle portfolio profile of Norwegian households asset market participation and conditional portfolio share, we present in this section a life cycle model that can account for the life cycle portfolio profile along both margins. In a nutshell, we use a version of the workhorse portfolio choice model of Cocco, Gomes, and Maenhout (2005) and extend it in two ways: first, we allow for a fixed per-period stock market participation cost. This is meant to provide a motive for exiting the stock market as people age. Second, we allow for a limited trust element as in Guiso, Sapienza, and Zingales (2008) in order to avoid the "too" high conditional shares in risky assets at young and middle ages that these models typically generate. Over the recent years, several claims of accused fraud against the biggest financial advisor firms in Norway for selling dubious products with high leverage are ongoing, see for example the ongoing case against Norway's biggest commercial bank, DNB. [13]

1.5.1 Model Specification

Preferences

We assume that households leave no bequests and let t denote the age of the household head. Households work from age T^b until age T^w, after which households retire. Households face uncertainty in the amount of period they live (T). We model this component as Hubbard, Skinner, and Zeldes (1995) and denote p_t the probability that the household is still alive at age $t+1$ conditional on being alive at t. Household preferences are described as follows:

$$E\sum_{t=1}^{T}\underbrace{\delta^t(\prod_{j=0}^{t-2}p_j)}_{=\beta_t}U(c_{i,t}) \tag{1.1}$$

where $c_{i,t}$ is the consumption of household i at age t and δ the discount factor, and β_t the age-dependent effective discount factor that takes into account the probability of death.

Market Structure

In the model economy, markets are incomplete. Households smooth consumption over the life cycle by holding a riskless asset and possibly a risky asset. The riskless asset can be

[13] http://www.reuters.com/article/2009/04/24/dnbnor-lawsuit-idUSL013864720090424 and http://www.risk.net/structured-products/news/1512563/norwegian-watchdog-rules-dnb-nor

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thought of as a real bond and has a time-invariant return r_f. We denote the amount of wealth the household i in bonds at age t with $B_{i,t}$. Whereas the riskless asset can be purchased and sold at no cost, we impose a fixed per-period participation cost q to hold risky assets. The risky asset has a time-dependent real return $\tilde{r}_t$, and a risk premium denoted r_p.

$$\tilde{r}_t = r_f + r_p + \nu_t, \quad \nu \sim \mathcal{N}(0, \sigma_r^2). \tag{1.2}$$

where ν_t is the period t innovation to stock market returns drawn from a normal distribution. The amount of risky asset held by household i at age t is denoted by $A_{i,t}$. Furthermore, we assume that households can't borrow against future labor income and that the quantities of the two assets held are positive.

$$A_{i,t} \geq 0, \quad B_{i,t} \geq 0. \tag{1.3}$$

These constraints ensure that the share $\alpha_{i,t}$ of financial wealth invested in risky assets at age t, is non-negative and $\alpha_{i,t} \in [0,1]$. Finally, we incorporate trust as defined by Guiso, Sapienza, and Zingales (2008) into the model. Trust is defined as the probability a household attributes to the possibility of being cheated. In deciding whether to hold shares a household assesses the probability that the company is just a scam, or that the manager steals proceeds. We denote with p_{cheat} the probability that such scam occurs and that the household's investment in shares is fully lost. The complementary probability $(1 - p_{cheat})$ identifies the degree of trust an investor has in the stock market and the probability of recovering his investment with the accrued return.

1.5.2 Household Problem

Households start a period with a certain amount of cash-on-hand which is the sum of their labor income and financial wealth. Then households decide how much to consume and to save in bonds if they don't participate in the stock market, and how much to consume and save in bonds and equity, if they choose to participate in the stock market. Finally, they compare their utility in both scenarios (participation vs. non-participation) and decide whether to enter or exit the stock market.

The budget constraint of a working age household reads as follows:

$$c_{i,t} + \mathbf{1}_{i,t+1}(a_{i,t+1} + q) + b_{i,t+1} = w_t z_{i,t} + (1 + \tilde{r}_t)\mathbf{1}_{i,t}a_{i,t} + (1 + r_f)b_{i,t}, \quad t = 1, ..., T^w \tag{1.4}$$

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

where $\mathbf{1}$ is an indicator function taking value 1 if the household participates in the stock market at age t and 0 if not; $w_t z_{i,t}$ stands for the age-dependent labor income which is composed of a deterministic component of age w_t and a random walk component $z_{i,t}$ as shown in equation (1.13).

The retired households' budget constraint is as follows.

$$c_{i,t}+\mathbf{1}_{i,t+1}(a_{i,t+1}+q)+b_{i,t+1}=\phi_{ret}w_{T^w}+(1+\tilde{r}_t)\mathbf{1}_{i,t}a_{i,t}+(1+r_f)b_{i,t}, \quad t=T^w+1,...,T \quad (1.5)$$

Equation (1.5) is isomorphic to (1.4) with the only difference that labor income is time-invariant and not subject to uncertainty. Retirement income is a fixed share ϕ_{ret} of the last working-age labor income of the household.

The problem of a household is to maximize equation (1.1) subject to the above constraints (1.2)-(1.5). In the following subsection, we formulate this problem recursively .

1.5.3 Recursive Formulation

The household problem has a set of control variables $\{c_{i,t}, a_{i,t}, b_{i,t}, \mathbf{1}_{i,t}\}_{t=1}^{T}$ and a set of state variables $\{t, x_{i,t}, z_{i,t}\}_{t=1}^{T}$, where $x_{i,t}$ denotes financial wealth and $z_{i,t}$ labor income. Let $V_t^{in}(x,z)$ be the value of the objective function of a t-year old household who participates in the stock market, has labor productivity z and financial wealth amounting to x.[14]

$$V_t^{in}(x,z)=\max_{c,a',b'}U(c)+\beta_{t+1}E_{z',\tilde{r}'}((1-p_{cheat})V_{t+1}(x',z')+p_{cheat}V_{t+1}((1+r_f)b',z')) \quad (1.6)$$

where

$$x'=(1+r_f)b'+(1+\tilde{r})a' \quad (1.7)$$

Households participating in the stock market have with probability $(1-p_{cheat})$ the law of motion given by equation (1.7).

The Bellman equation below describes the value of the objective function of a working age household who does not bear the fixed participation cost and invests only in risk-free assets.

$$V_t^{out}(x,z)=\max_{c,b'}\{U(c)+\beta_{t+1}E_{z'}V_{t+1}(x',z')\} \quad (1.8)$$

[14]We drop the indices i and t, to keep the notation light. Also x' denotes x_{t+1}.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

where

$$x' = (1 + r_f)b' \tag{1.9}$$

The budget constraint of the household problem reads as follows:

$$c + \mathbf{1}'(a' + q) + b' = wz + x, \tag{1.10}$$

The Bellman equation for the household problem pins down the participation decision of the household problem.

$$V_t(x, z) = \max_{\mathbf{1}'=\{1,0\}} (V_t^{in}(x, z); V_t^{out}(x, z)) \tag{1.11}$$

The optimal policy correspondence P for the participation decision can be derived as follows.

$$\mathbf{1}' = \begin{cases} 1, & \text{if } \overline{x} \in X_p, \\ 0, & \text{otherwise.} \end{cases} \quad \text{where} X_p \equiv \{\overline{x} : V_t^{in}(x, z) > V_t^{out}(x, z)\}. \tag{1.12}$$

The maximization problem of the retired households is analogous to the above formulation with the only difference that the uncertainty with regard to the realization of the income shocks is shut down and replaced with a deterministic income that is equal to a fraction ϕ_{ret} of the last working age period labor income.

1.5.4 Parametrization

As emphasized in Section 1.2, the value of a workers' human capital (the discounted sum of future income streams) makes up a dominant part of a workers overall portfolio, and is according to the literature a key rationale for portfolio rebalancing over the life cycle. Therefore an accurate quantitative analysis of the risk structure of a workers human capital is essential for a thorough analysis of the life cycle pattern of portfolio allocation. At the onset of a career, a household has relatively low holdings of financial wealth. The human wealth is correspondingly higher, as the worker has a full career in front of him/her. To account for this, we gather income data for our sample of households over the same time span to pin down a measure of their life long labor income and of the risk related to a workers labor income. We use a broad measure of labor income: the sum of pre-tax pensionable earnings at the household level. In addition to labor income, this measure also contains sickness money, maternity leave, and benefits paid during unemployment spells. Similar to Carroll (1997), we also include all income that counts towards retirement and individuals retirement savings base. The measure is summed up for both husband and wife in the household, and we also add pension payments to pin down the within-household replacement rate.[15] The official retirement age in Norway is 67 years of age, in practice however, there exists a number of arrangements for workers to retire at earlier ages.[16] Our measure is then deflated using the growth in the National Insurance Scheme basic amount, which is used to adjust payments of unemployment insurance and pensions.[17]

For the matter of the estimation of the life cycle profile of labor income, we follow closely Carroll (1997) and Cocco, Gomes, and Maenhout (2005). The analysis of the income variance is highly dependent on low income realizations of few households. Contrary to these previous contributions, we have highly reliable data reported for tax calculations and whereas they exclude any household that has one or more observations below 80% of the within household sample mean during the observation period (after having deflated the data with the consumer price index), we use the same sample as for the portfolio analysis.[18]

We estimate the life cycle income profiles using the following equation:

$$log(Y_{i,t}) = \alpha + \beta(X_{i,t}) + \gamma_t + \varepsilon_{i,t}, \tag{1.13}$$

where α is the constant, $X_{i,t}$ includes the age dummies and household size, β the corresponding vector of coefficients, γ_t the calendar year fixed effects and $\varepsilon_{i,t}$ the error term. The estimation is done for 3 different levels of educational attainment in addition to year fixed effects, in addition to the whole sample. The educational level associated with a particular household is determined by the highest achieved educational level of the husband.

The life cycle income profiles are obtained from the estimation of equation 1.7 on the full data sample from age 25 to 80 years. The age coefficients are plotted in Figure 1.7, where the solid lines represent the estimated pattern of age dummies. Table 1.8 displays the estimated 5th order polynomials that fits the income profiles best. The income profiles by educational attainment deliver evidence for the existence of an education premium for households where the husband has a college education. Furthermore, we see a drop in income prior to the official retirement age as some income earners retire prior to the age of 67, as some households retire prior to the official retirement age.

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[15] Values are in 1995 US$ - converted using the 1995 NOK/USD exchange rate.

[16] See e.g.`http://ec.europa.eu/economy_finance/publications/publication14992_en.pdf`, where the average actual retirement age in Norway is reported closer to 64.

[17] See NAV `http://www.nav.no/English/Membership+in+The+National+Insurance+Scheme` for more information on Basic Amount

[18] We also experimented with a few exclusion thresholds as in Carroll and Samwick (1997). Results show that estimated variances vary significantly with such thresholds. We chose to use the full sample, as our data are unlikely to suffer from measurement errors as in the PSID.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

Table 1.8: Age polynomials for labor income process

	Less High School	High School	College	All
Age	0.0563	0.0236	0.172	0.0769
	(6.58)	(2.99)	(11.74)	(10.09)
Age2	-0.00344	-0.000761	-0.0121	-0.00501
	(-3.71)	(-0.89)	(-7.63)	(-6.08)
Age3	0.000118	0.0000423	0.000433	0.000192
	(2.85)	(1.10)	(6.07)	(5.21)
Age4	-0.00000238	-0.00000158	-0.00000772	-0.00000408
	(-2.93)	(-2.10)	(-5.53)	(-5.62)
Age5	1.86e-08	1.66e-08	5.28e-08	3.24e-08
	(3.22)	(3.11)	(5.32)	(6.30)
Constant	3.653	3.851	3.397	3.678
	(149.03)	(170.05)	(80.78)	(168.57)
Observations	55	55	55	55
r2	0.976	0.978	0.954	0.986

Note: The table shows the coefficients of a 5th order polynomial describing labor income as a function of age. *t* statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

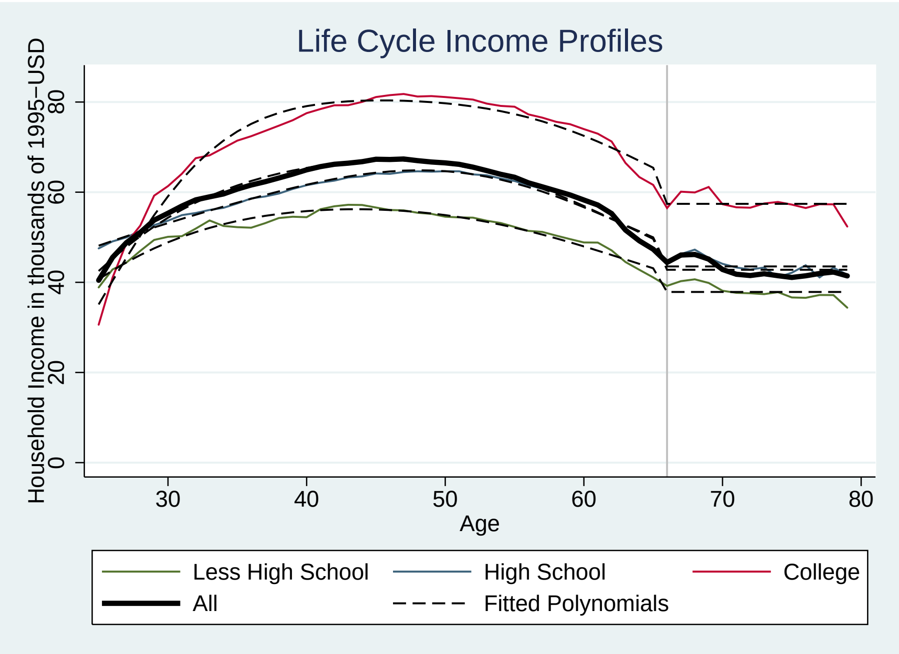

Figure 1.7: **Life Cycle Income Profiles**

Note: This Figure plots the estimated labor income processes by educational level for the full sample, coming from equation 1.13 estimated on the different sub-samples.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute
DOI: 10.2870/403

To estimate the variance components of the income process, we follow the procedure in Carroll and Samwick (1997) and Cocco, Gomes, and Maenhout (2005). We re-run the regressions from above, but deviate from the literature and cut the sample prior to retirement. As retirement income is essentially considered to be riskless and constant, including these observations will bias down our estimates of income variance.[19] Based on the labor income polynomials, we obtain prediction errors for each observation, which allow us to calculate the variance of the d-th period income deviation from the base year (1995). We then estimate the variance using the distance from the base year as the right hand side variable.

The results of the decomposition are displayed in Table 1.9. We see that the variance of both the permanent and transitory income shocks are considerably smaller for the group of households with High school education or College relative to the ones with education less than high school. Relative to the findings in Cocco, Gomes, and Maenhout (2005), we find lower estimates of the transitory components (they find 7.38 % for High school graduates, we find 4.7%). Considering the social insurance scheme in Norway, this number is not implausible. There are however limits to how much of a comparison one can make, as the result from Cocco, Gomes, and Maenhout (2005) build on PSID surveys, and one would expect our analysis to be less prone to measurement errors.

Finally, we also computed the correlation between labor income and stock market returns on the Norwegian stock market. A correlation here would represent a hedging opportunity for the households, as argued in Bodie, Merton, and Samuelson (1992a). Table 1.9 shows that the correlation indeed tends to be negative but that it is not significant at the 10% level. This confirms the results in Cocco, Gomes, and Maenhout (2005) for the United States.[20]

Table 1.10 reports the benchmark parameter values. The retirement age is set to 67 for all households in accordance with Norwegian law. The discount factor is set to 0.96 as we aim at matching yearly data, and the coefficient of relative risk aversion is set at 6. As in the literature on the equity premium puzzle, we set the risk free rate at 2% and the equity premium at 4%. The standard deviation of the innovation to the risky return is set to 0.231, the standard deviation of returns on the Oslo Stock Exchange. The conditional survival probabilities are taken from the population tables of Statistics Norway. We used the survival estimates for both sexes to calculate the conditional survival probabilities p_j for $j = 1, ...T$.[21] For the simulations, we draw households' initial financial wealth from a Pareto distribution that is fitted to the initial wealth of households with age 25 from our sample.

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

[20]The same holds for a combined measure of returns from the S& P 500 and the Oslo stock exchange.

[21]Table 5 - Life tables `http://www.ssb.no/english/subjects/02/02/10/dode_en/tab-2011-04-14-05-en.html`

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

Table 1.9: Income variance decomposition and correlation with stock return

	Less High School	t	High School	t	College	t	All	t
Transitory	0.079	13.3	0.047	17.4	0.028	10.7	0.049	27.4
Permanent	0.048	24.94	0.027	32.8	0.024	30.5	0.031	57.5
Stock Market	0.017	0.48	0.045	0.34	0.005	0.75	0.008	0.50

Note: The table reports estimates of the variance of permanent and transitory labor income shocks. The estimation is based on the error terms from estimating the labor income process in Figure 1.7. The procedure is based on the method in Carroll and Samwick (1997), which is also used in Cocco, Gomes, and Maenhout (2005).

Table 1.10: Parameter choice

Variable Name	Variable	Value	Source
Discount factor	δ	.96	yearly data
Risk aversion (CRRA)	γ	6	
Participation Cost (1995 US$)	q	500	
Probability of scam	p_{cheat}	0.0175	
Retirement age	T^r	67	Norwegian Law
Variance of transitory shocks		0.047	Data - table 1.9
Variance of persistent shocks		0.027	Data - table 1.9
Risk free return	r_f	.02	Literature
Risk premium	r_p	.04	Literature
Std deviation stock return	σ_r	0.231	Data - Oslo Stock Exchange
Income share of retired HH	ϕ_{ret}	.9058	Data - Table 1.8
Shape of Pareto Distribution for x_0	μ	0.4521	Data
Scale of Pareto Distribution for x_0	σ	5711.7	Data

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

1.5.5 Solution Method

The problem is solved by backward induction. Given the terminal condition, the policy functions are trivial: households consume all their wealth, and the value function equals to the utility function. We substitute this value function in the bellman equation and compute the policy functions one period backward. We do this for 75 periods, from $T = 100$ to age $T_b = 25$. We discretize the state space for cash-on-hand state variable and iterate on the value function. The density function for the labor income process as well as for the risky return is approximated using Gaussian quadrature. Finally, we simulate 10,000 agents. In the next section, we present and discuss the policy functions and the simulation results of the model.[22]

1.6 Results

1.6.1 Model Solution

The upper panel of Figure 1.8 plots the optimal portfolio share invested in risky assets conditional on participating as a function of cash-on-hand at a given age. The optimal portfolio rule is decreasing with both cash on hand, and age, a pattern that is consistent with Cocco, Gomes, and Maenhout (2005). The inclusion of a per-period participation cost and limited trust have two distinct effects on the policy functions. The participation cost introduces an age and wealth dependent entry threshold, and lowers the risky share conditional on participating. The trust friction further reduces the conditional risky share as emphasized in the stylized model presented in Guiso, Sapienza, and Zingales (2008).

Also in a model with incomplete markets and uninsurable labor income risk, the optimal share invested in risky assets is decreasing with cash on hand because it is driven by the importance of human capital relative to accumulated wealth, as in for example Merton (1971). During working age, since shocks to labor income are uncorrelated with stock market returns, the deterministic component of labor income mimics the pay-off of a risk free asset. Therefore, for a given level of human capital, households with low levels of financial wealth have a relatively large amount of future income from risk free assets (relative to their financial wealth) and thus invest more aggressively in stocks than wealthier households. A higher level of financial wealth reduces the relative importance of the safe human capital and leads households to rebalance their portfolio by investing less in stocks relative to their wealth level. A similar logic applies after retirement. As for the negative correlation with age, this

[22]For comparison with the data, we cut the simulation results at age 75.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

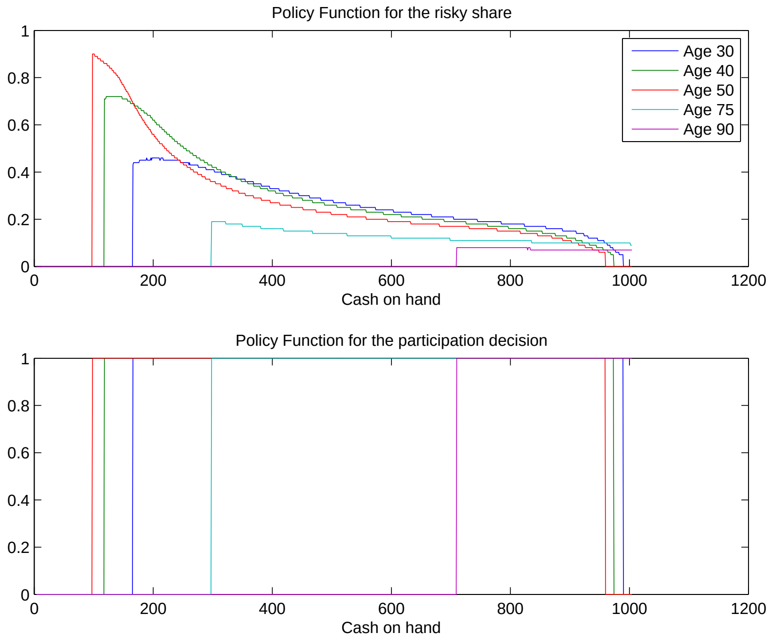

Figure 1.8: **Policy Functions**

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

The lower panel of Figure 1.8 plots the cash-on-hand thresholds beyond which households find it optimal to participate in the stock market at a given age. The wealth threshold of risky asset market participation is decreasing with age until age 50, age at which average labor income peaks. Prior to age 50, the participation cost is, relative to average labor income, getting smaller with increased working age. However, above age 50, when households are approaching retirement the trajectory of their labor income profile is declining, and the participation threshold shifts rightward with increased age. From then onwards, household seek to diversify away from stocks, and shift towards risk free assets in order to compensate for the reduction of risk free labor income.

It is also important to notice that the model delivers a counter-factual behaviour, in the sense that it is optimal for some working age household with very high levels of cash on hand to exit risky asset markets. This is a by-product of the downward sloping optimal portfolio rule; above a certain wealth threshold, it is optimal for household to hold a very low share of equity. However, the low-level of the optimal share does not justify incurring the fixed cost, thereby making the outside option of not participating more worthwhile, even for wealthy

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

households.

1.6.2 Simulations

The upper panel of Figure 1.9 plots the mean of the simulated panel of labor income, wealth and consumption. The profile of the mean consumption follows closely the income level, suggesting that a fair share of households are borrowing constrained. With increasing age, the average wealth increases so that households can smooth consumption over the life-cycle. This behaviour persists until around age 60, age at which survival probabilities are substantially lower and reduce the effective discount factor. The lower discount factor and the drop in labor income incites household to reduce their investments. While wealth decumulates rapidly, the consumption path remains contained and the standard hump-shaped consumption profile of life cycle model comes forth.

The lower panel of Figure 1.9 depicts the mean of the simulated panel of stock and bond holdings. Three phases emerge. At first, household hold only risk free portfolios until age 35 and build a stock of financial wealth so that they can privately insure against labor income risk and smooth consumption. After age 35, they start accumulating assets beyond the precautionary motive and can afford the participation cost and they invest in the risky asset. Interestingly, while households continue to accumulate stocks up until retirement they start decumulating stocks much earlier. This decrease in the average level of risky asset coincides with the peak of the average labor income. From then onwards, households prepare for retirement and shift their allocation towards risk-free asset, once again to compensate for the reduction of their risk-free labor income. Finally, at age 70 the average portfolio consists only of bonds, which is imputable to the consumption smoothing motive, and the low effective discount factor.

Figure 1.10 plots the mean stock market participation rate. Households start participating in the equity market at age 31. The participation rate increases rapidly when young and peaks at age 54; at the peak 88% of the households hold stocks. After the peak households exit the risky asset market, initially gradually and more rapidly after retirement. At age 80 all households have exited the stock market.

1.6.3 Model performance relative to data

Figure 1.11 compares the simulated portfolio conditional share in our model with the conditional share from Cocco, Gomes, and Maenhout (2005) (which for them is also the unconditional share as no participation cost is allowed for). In our model the conditional share in

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

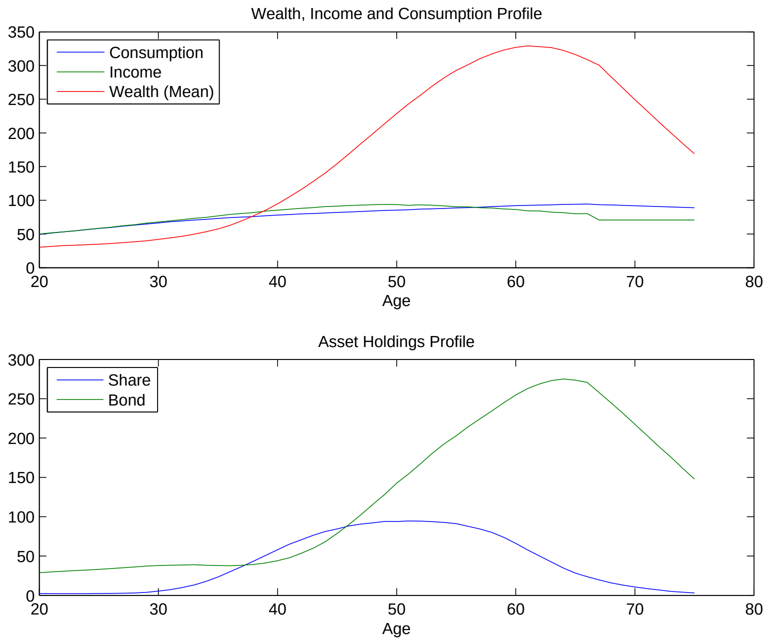

Figure 1.9: **Wealth, Income and Consumption**

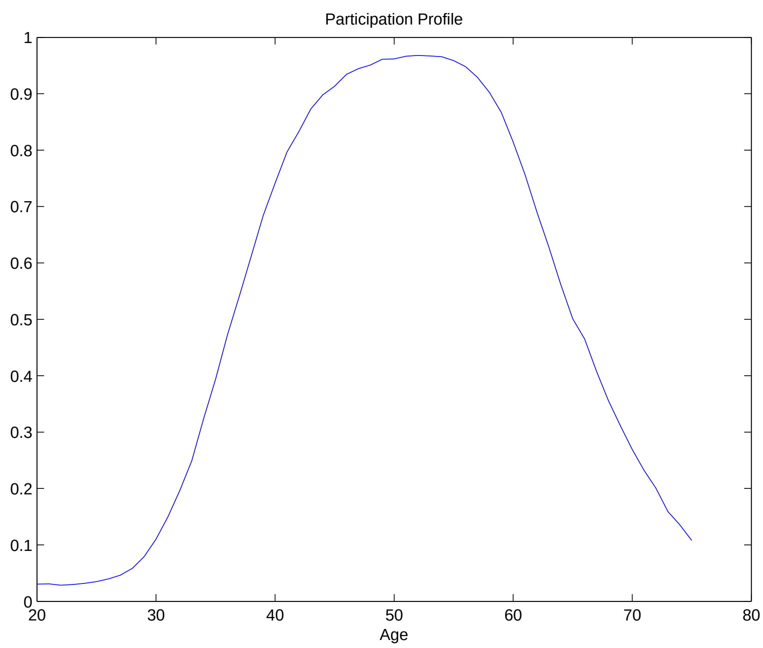

Figure 1.10: **Participation Decision**

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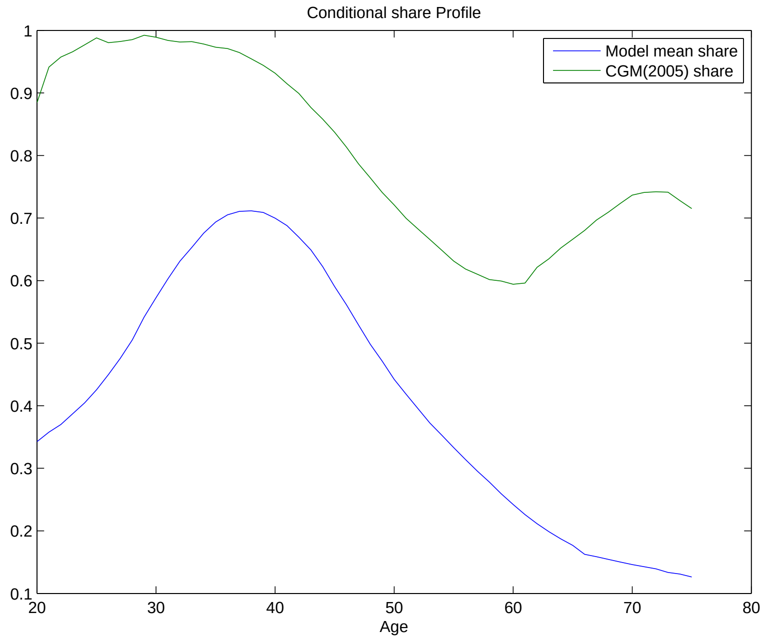

Figure 1.11: **Conditional share profile - Our model vs CGM (2005)**

stocks is substantially lower than in Cocco, Gomes, and Maenhout (2005). This is mostly due to the presence of limited trust in our model. Imposing full trust would produce a profile for the conditional share that is very similar to Cocco, Gomes, and Maenhout (2005), that is a financial portfolio share in stocks very close to 1: this is one of the puzzling features of calibrated life cycle portfolio models (see Guiso and Sodini (Forthcoming 2012) for a review). The introduction of a (very low) probability that an investments in stocks is a scam substantially reduces the mean conditional share to levels that are much closer to those observed in the data (see Figure 1.12). Risk averse households are very concerned with the possibility for extreme losses even though this is a very unlikely event, as emphasized in Jagannathan and Kocherlakota (1996) and more recently by Barro (2006) in relation to the equity premium debate.

The ability of our model to match the empirical estimates from Section 1.4 can be best appreciated in Figure 1.12. One feature that our model replicates well is the joint pattern of life cycle rebalancing and exit. A key finding in the Norwegian data is that households *first* start reducing the conditional share starting from age 45 onwards, and *later* they begin exiting the stock market (from age 57 onwards). Our model replicates this pattern well: the reduction of the conditional share begins at around age 45 and households start to exit the stock market around age 55. This qualitative ability of the model to reproduce the empirical

Fagereng, Andreas (2012), Three Essays in Household Finance
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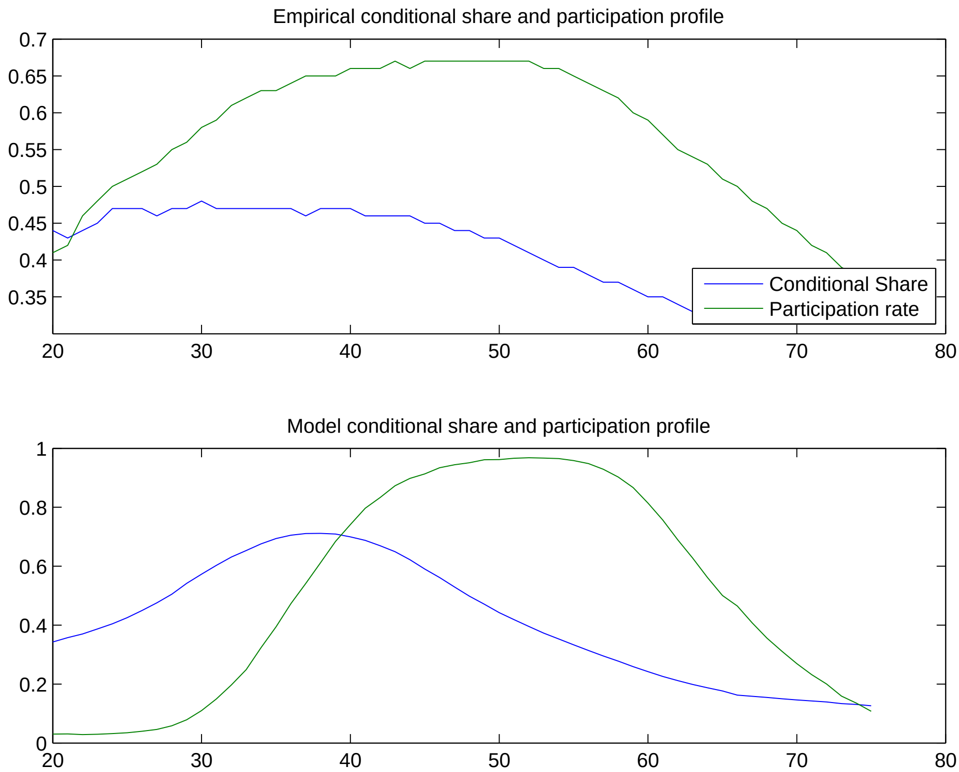

Figure 1.12: **Model vs Data: Participation and Risky Share**

Note: Upper Panel - Empirical conditional share and participation profile ; Lower Panel - Conditional share and participation profile of model.

timing of the double adjustment is the main contribution of this Section of the paper.

In quantitative terms the model performance has potential for improvement. Households exit the stock market too rapidly compared to the empirical evidence. With regard to the entry pattern the model performance is also unsatisfactory. Households enter stock market too late compared to the empirical evidence. However, in terms of quantitative performance of the conditional share at entry the model is close to the the observed share at entry (around 40%-50%).

Finally, we evaluate the model's ability to match the pattern of entry and exit over the life-cycle. In Figure 1.13, we document households' entry and exit profiles according to the definition of entry and exit presented in Table 1.2, but note that the entry and exit rates are regressed on time and cohort effects. Comparing this entry and exit rates to those generated by our model shows that the model is not yet able to generate the diversity of entry and exit patterns observed in the data. For instance, we are not able to explain first time entries at

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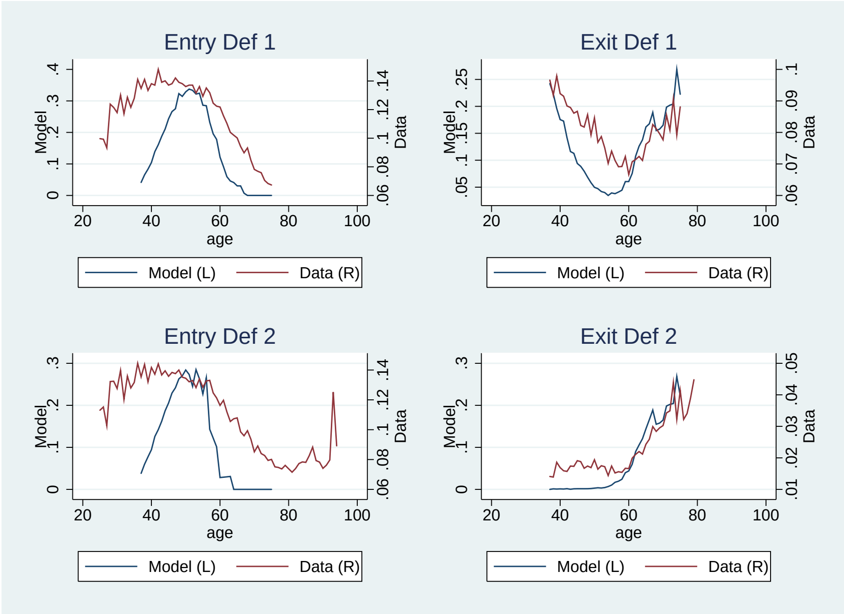

Figure 1.13: **Model vs Data: Entry and Exit**

late age as can be seen in the upper left panel of Figure 1.13. We also fail to explain the intensity of early entry pattern as measured by both definitions. However, qualitatively our model is relatively close to the data, in particular when looking at the exit pattern given by both definitions.

1.7 Conclusion

Over the past decade many scholars have used calibrated models to study life cycle portfolio allocations, departing from the simplifying assumptions of early generations models and adding realistic features of households environments. Among them, uninsurable income risk, non-tradeable human capital and imperfect borrowing markets. Despite these (and other) complications, these models uniformly predict that households should at a certain point before retirement start lowering exposure to the stock market in order to compensate for the decline in the stock of human wealth as people age, which in this models acts mostly as a risk-free asset. Finding empirical evidence in support, however, has been hard. We argue that this is likely to be due to data limitations, both because a proper treatment of the issue requires long longitudinal data and because the information on assets needs to be exhaustive, free of measurement error. Combining administrative and tax registry data from Norway we

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute
DOI: 10.2870/403

are fulfilling these requirements and find that households do indeed manage their portfolio over the life cycle in a way that is consistent with models predictions. We find that they adjust their financial portfolios along two margins: the share invested if they participate in the stock market and the decision whether to stay or leave the market altogether. They tend to enter the stock market early in life as they accumulate assets and tend to invest a relatively large share of financial wealth in stocks. As they start foreseeing retirement, they rebalance their portfolio share, reducing it gradually. Around retirement they start adjusting on the other margin, exiting the stock market. Extending that this double adjustment pattern along the intensive and extensive margin with its clear timing cannot be explained by none of the available life-cycle portfolio models; but a simple extension of these models to allow for a per period participation cost, and a trust friction, is able to qualitatively reproduce the data.

Our next step will be to try estimate the key parameters of the model - the households discount factor, the risk aversion parameter, the per-period participation cost and the probability of being cheated so as to best match model and data life cycle patterns of the conditional share and the participation rate as well as well as the entry and exit patterns.

Fagereng, Andreas (2012), Three Essays in Household Finance
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Chapter 2

Saving and Portfolio Allocation Before and After Job Loss

With Christoph Basten and Kjetil Telle

2.1 Introduction

The financial crisis and the resulting recession have significantly increased the number of unemployed in most OECD economies, with associated increase in governments' spending on unemployment insurance (UI) benefits. The US spending on out-of-work income maintenance amounted in 2009 to 1% of GDP, a marked increase from 0.24 % in 2005 according to OECD data. The OECD average also amounted to 1% in 2009 (Adema, Fron, and Ladaique (2011)). With strained public finances and concerns about moral hazard – under which UI can prolong unemployment by "subsidizing" it – the question is whether insurance mechanisms other than UI can smooth consumption for those hit by unemployment. In this paper we investigate the extent to which workers in wealthy welfare states, such as Norway, are able to smooth consumption by foreseeing an upcoming unemployment spell and react to it by increasing their savings. In particular, we estimate the development of households' labor income, financial wealth and asset holdings four years before and after job displacement.

In the optimal UI literature, coined by Baily (1978) and further developed by e.g. Chetty (2006), the main substitute for publicly provided UI is private savings.[1] In the extreme case, unprepared "hand-to-mouth consumers" would have to reduce their consumption in line with the unemployment-induced reduction in their income, strengthening the case for UI. By

[1] Relatedly, Crossley and Low (2011) show how the optimal UI replacement rate depends on, among other things, the cost of self-insurance.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

contrast, households with sufficient savings might not need UI at all to maintain consumption levels.[2] Indeed, Browning and Crossley (2001) show that households in Canada, particularly those with insufficient prior wealth, have to cut their consumption during unemployment spells when UI benefits are cut. Bloemen and Stancanelli (2005) present similar findings for food consumption in the UK.[3] Finally, results in Card, Chetty, and Weber (2007a) and Basten, Fagereng, and Telle (2012a) provide further indication of liquidity constraints among unemployed in Austria and Norway, respectively.

Despite the theoretical recognition of private wealth as insurance against unemployment, there is limited evidence on the extent to which households are able to accumulate wealth before and decumulate it after job loss, chiefly because of the limited availability of adequate data. A notable exception is Gruber (2001) who uses the US Survey of Income and Program Participation (SIPP) to analyze prior holdings and wealth depletion during unemployment. He observes household wealth at two points in time, enabling him to take out household fixed effects in estimating wealth depletion during unemployment.[4] In addition to investigating wealth depletion during unemployment, we investigate the extent of additional saving and of portfolio reallocation in the years leading up to the unemployment spell. This has previously been addressed in the literature on precautionary saving, which recognizes that household saving may be motivated not only by the "life-cycle" purpose of smoothing consumption and preparing for retirement, but also by a desire for "precautionary" or "buffer-stock" saving at shorter horizons, to prepare for events such as unemployment (Deaton (1991) and Carroll (1997)).[5] Furthermore, some studies investigate the extent to which households' investment in risky assets is negatively affected by labor income risk (see e.g. Guiso, Jappelli, and Terlizzese (1996) using survey data on Italian households, or Betermier, Jansson, Parlour, and Walden (Forthcoming 2012) for a study of the portfolios of Swedish job and industry switchers).

[2]Note that the availability of alternative insurance mechanisms captures only the benefit side of the optimal UI framework. To determine whether the current level of UI is optimal, one also needs to know its moral hazard cost, as shown in Chetty (2008). This paper focuses on the benefits of UI; see Roed and Zhang (2003) for a paper addressing the costs for Norway.

[3]This is all the more striking in the light of arguments and findings in Browning and Crossley (2009), whereby households can first, with smaller effects on utility, cut spending on durables, and only thereafter need to cut food expenditures.

[4]Having only two points in time has the disadvantage that the depletion will be underestimated to the extent that some of it takes place before the first or after the second point of observation. While two observations per household do allow to control for household fixed effects in the *level* of wealth, they do not suffice to control for household trends in wealth over time. In this paper we are able to address these shortcomings through the use of a 13-year annual panel on households' income, wealth and asset holdings - for households experiencing and not experiencing an unemployment spell.

[5]For a summary of the different models of precautionary saving, see also Carroll (2001)

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

The major challenge for such empirical studies is that job loss risk can be endogenous. Households that have chosen riskier jobs may in fact be less risk-averse than others and hence engage in less precautionary saving or be less cautious about holding risky assets at all times, biasing downward any estimates of the effect of unemployment risk on saving or portfolio reshuffling. The precautionary saving literature in particular has tried to address such endogeneity concerns by instrumenting unemployment risk with variables thought to influence this risk but not to otherwise affect saving (for examples, see Carroll, Dynan, and Krane (2003), Fuchs-Schuendeln and Schuendeln (2005) or Barceló and Villanueva (2010)). In addition to the possible endogeneity of job loss risk, there is the problem that households' behavior will necessarily depend not on actual unemployment probabilities (which econometricians can predict with some measurement error and can then instrument), but rather on households' subjective expectations thereof. That is, households can prepare for upcoming unemployment only to the extent to which they are actually aware of it. In this paper we focus on cases of actual unemployment and test the hypothesis of no behavioral response against the joint hypothesis that households can to some extent foresee their job loss and are motivated and able to respond to it.[6]

This paper thus contributes to the literature in three ways. First, we investigate to what extent households prepare for an unemployment spell with additional saving in the years preceding the spell. Second, we examine to what extent they reallocate their savings toward safer and more liquid assets in the same period. Finally, we explore whether they draw on prior savings during the unemployment spell. To do so, we employ a panel of annual administrative data from Norway in which we observe labor income, financial wealth and the holdings in different asset classes for each household for 13 consecutive calendar years, 1995-2007.[7] Based on these administrative data, we construct a sample comprising households where the man experiences his first unemployment spell in one of the years 1999-2003, and complement this with a placebo sample of comparable households that do not experience an unemployment spell in this period (similar to the approach in Jacobson, LaLonde, and Sullivan (1993)). The panel structure of our data allows us to control for any unobserved household characteristics that are time-invariant, as well as for any calendar-year fixed-effects

[6]Stephens Jr (2004), using the US Health and Retirement Study, finds households to have some sense of upcoming job losses and income drops, but whether this is also the case in Norway must of course still be tested, as the extent to which job losses are foreseeable for employees is likely to vary across national labor markets.

[7]To strike a balance between tracing households for as many "relative years" around job loss (where the year of job loss is year 0) as possible, while also having enough observations for each relative year, using all households that experienced a job loss in 1999-2003 we estimate the coefficients of being in relative year -4 through +4.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

that are household-invariant, such as the effects of being in different phases of the business cycle. In an attempt to explore some sources of selection bias, we also analyze a subsample of individuals whose job loss occurred as part of a mass layoff.

The remainder of this paper is structured as follows. Section 2.2 presents a theoretical model with predictions about how upcoming, current or recent unemployment should affect saving and portfolio choices. Section 2.3 explains our empirical strategy, Section 2.4 the data, and Section 2.5 presents the main results. Section 2.6 concludes.

2.2 Theoretical Framework

To illustrate the role of saving and portfolio allocation in response to upcoming, current and recent job loss, we set up a simple but illustrative two-period model in which households earn labor and capital income, get utility from consumption, and decide in one period how much to save for next-period consumption and how to invest their savings from one period to the next. These theoretical considerations are essentially a simplified version of those in some of the studies cited above (see e.g. Baily (1978), Carroll (2001), Chetty (2006), Bodie, Merton, and Samuelson (1992b)). Detailed derivations are provided in the Appendix.

2.2.1 Wealth Depletion during Unemployment

We start by considering a household that is suffering unemployment and faces uncertainty about the next period's labor income. Unemployment benefits amount to y_l, which is the household's sole income in period 0.[8] In addition, the household has financial wealth holdings of w. Income y in the following period 1 is uncertain: with probability p_1 the household remains unemployed and thus income remains at the unemployment benefit level y_l, and with probability $(1-p_1)$ the household becomes reemployed and receives the higher income, y_h.[9]

The household derives utility from consumption (c) only, and the utility function $u(c)$ is assumed to be strictly increasing and concave in c. Let β denote the discount factor between

[8] For the majority of households in Norway, this corresponds to 62.4% of the earnings in the previous year.

[9] To illustrate what we consider the main links between unemployment and saving behavior, we make two simplifying assumptions here. First, we take the risk of job loss as exogenous. Second, we assume that being unemployed is synonymous with receiving lower income, but does not affect utility through any other channel. In Section 2.3 (Empirical Strategy), we discuss how our analysis changes when some job losses are potentially endogenous.

 DOI: 10.2870/403

the two periods, R the risk-free return on savings and s the saving rate. Then the household solves the following maximization problem:

$$\underset{s}{Max} \qquad u(c_0) + \beta E[u(c_1)], \tag{2.1}$$

subject to:

$$0 \leq s \leq 1 \tag{2.2}$$

$$c_0 = (w + y_l)(1 - s) \tag{2.3}$$

$$c_1 = y_1 + (w + y_l)sR \tag{2.4}$$

This maximization problem yields a simple Euler equation for savings, which tells us that – given an expectation p_1 for the probability of continued unemployment next period – the household will choose its rate of (dis-) saving such that its expectation of the marginal utility of consumption across both periods is equalized:

$$\frac{\delta EU}{\delta s} : u'(c_0) = R\beta \left[(1 - p_1)u'(c_1^E) + p_1 u'(c_1^U)\right], \tag{2.5}$$

where c_1^E and c_1^U denote consumption in period 1 in the case where the household is employed (E) and unemployed (U), respectively. As we show in the Appendix, differentiating this equation with respect to p_1 tells us that there will be less saving, or equivalently more depletion, the more likely the household expects to be back in a regular job next period.

Proposition 2.1. $\frac{\delta s}{\delta p_1} > 0$. *The less likely an unemployed household expects to remain unemployed (with UI below the income of a regular job) in the next period, the more it will now deplete savings to cushion the temporarily lower labor income.*

2.2.2 Extra Saving before Unemployment

Given this motivation for spending additional resources during unemployment, we consider what a household would do upon realizing an increased risk of unemployment. The central intuition behind this consideration can be illustrated using the same kind of parsimonious two-period model with time set back one period. Now we consider behavior in the pre-unemployment *period -1*, in which income is at the higher level $y_{-1} = y_h$, given that the household expects to be unemployed and hence be earning only UI benefits $y_l < y_h$ in the following period 0. In this situation the same relationship of $\frac{\delta s_{-1}}{\delta p_0} > 0$ holds and can now be

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

interpreted as precautionary saving:[10]

Proposition 2.2. $\frac{\delta s_{-1}}{\delta p_0} > 0$. *If in period -1 the household realizes the risk of being unemployed in period 0, then the household will increase its saving rate* s_{-1}.

2.2.3 Portfolio Reallocation before Unemployment

When making its financial choices in response to unemployment risk, the household may also want to optimize the risk structure of its savings, given that asset classes other than the risk-free one are available. To illustrate the mechanism that might be at play here, we add to our illustrative model a second, risky asset yielding the uncertain return of R^r. With probability $(1-q)$ this risky asset yields a high return, $R^r = R_h$; and with probability q a low return, $R^r = R_l$. To motivate risk-averse households to invest any fraction of their financial wealth in the risky asset, its expected return needs to exceed that of the safe asset: $E(R^r) > R^s$. As before, the household chooses its optimal saving rate from period -1 to 0, s_{-1}, to depend positively on the perceived probability of being unemployed next period, p_0. In addition to the previous case, the household now chooses which fraction α of its savings it wishes to invest in the risky asset. The optimization problem with two choice variables becomes:

$$\underset{s_{-1},\alpha}{Max} \qquad u(c_{-1}) + \beta E[u(c_0)], \tag{2.6}$$

subject to:

$$0 \leqslant s_{-1}, \alpha \leqslant 1 \tag{2.7}$$

$$c_{-1} = (y_{-1})(1 - s_{-1}) \tag{2.8}$$

$$E[c_0] = E[y_0] + s_{-1}y_{-1}(\alpha R^r + (1-\alpha)R^s) \tag{2.9}$$

where $E[y_0]$ now depends on the perceived probability p_0 of being unemployed in period 0. For a given level of savings, an increase in the probability of unemployment in period 0 will lower the expected level of consumption in period 0. As the concave utility function is steeper at lower levels of consumption, any absolute variation in consumption at low levels will result in larger fluctuations in utility compared with the case when consumption is higher. Hence, a utility-maximizing household will shift from risky assets to safe assets

[10]Since the period with labor market uncertainty lies in the future, the saving serves at the same time to smooth consumption across states of the world (employed vs. unemployed) and across periods.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

to lower this dispersion accordingly. This can be shown formally from the two first order conditions of the maximization problem in Equation (2.6):[11]

Proposition 2.3. $\frac{\delta\alpha}{\delta p_0} < 0$. *An increase in the probability p_0 of being unemployed next period will induce the household to reduce the share of savings α that is invested in risky assets.*

To sum up, an increase in the perceived likelihood of experiencing unemployment induces households to save more, as well as to reshuffle toward less risky assets. We now explain our strategy for exploring these predictions empirically.

2.3 Empirical Strategy

Cross-sectional regressions of portfolio changes on employment changes using observational data will typically fail to identify the relationship of interest because households that experience unemployment will differ from those not experiencing unemployment. At the same time, there is the risk of confounding general changes in asset markets with developments because of job loss, seeing that the majority of job losses occur during economic downturns. Many previous studies could not solve these issues because they had access to cross-sectional data only. Gruber (2001), in his investigation of wealth depletion after job loss, was able to go a step further, by observing households in the SIPP once before and once after job loss. Although having two observations per household allows him to focus on wealth changes, he cannot compare changes in wealth before or after job loss with those that the same household experiences in normal times. Furthermore, to the extent to which households keep depleting wealth after his second point of observation, or have already started to rebuild some of their wealth, estimates of the full extent of dissaving will be biased downward.

Our panel, in which we observe households annually for 13 years, 1995-2007, gives us a distinct advantage, as we can trace our outcomes of interest for many years.[12] At the same time we can control for both household fixed effects and calendar-year fixed effects. Specifically, our empirical strategy is illustrated by the following model estimated on a panel of households experiencing unemployment:

[11]For simplicity, equation (9) assumes no correlation between the uncertain labor income and the return to the risky asset. This is vindicated by findings in Fagereng, Gottlieb, and Guiso (2012) based on a very similar sample of Norwegian households in 1995-2007. If instead labor income and risky asset returns were negatively correlated, some of the motivation to reduce the risk exposition of the financial wealth would be cancelled out, whereas if they were positively correlated that motivation would be amplified.

[12]Annual observations prevent us from analysing developments that occur and are partly or fully reversed within a calendar year, so our estimates of saving and dissaving are still lower bounds. Nevertheless, they can be expected to be more accurate than estimates based on only two observations per household.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

$$Y_{i,t} = \alpha_i + \beta(RY_{i,t}) + \gamma_t + \varepsilon_{it}, \tag{2.10}$$

where $Y_{i,t}$ denotes different outcome variables (e.g. saving; see Section 2.4) for household i in calendar year t, α_i is a vector of household fixed effects , γ_t is a vector of calendar-year dummies, $RY_{i,t}$ is a vector of dummies for nine relative years around the year of job loss (the relative year zero is the year of job loss) and $\varepsilon_{i,t}$ is an error term with mean zero. Because we use job losses from different calendar years, we are able to separately identify the calendar-year and the relative-year fixed effects. For each outcome variable of interest, we can thus estimate this equation and thereby obtain the respective variable's time path (given by the betas) for relative years before, during and after the year of job loss (see e.g. Jacobson, LaLonde, and Sullivan (1993)).[13] Moreover, controlling for age is potentially important to ensure that the counterfactual time paths without job loss are not biased by life-cycle-related changes over time. Following Jacobson, LaLonde, and Sullivan (1993), both calendar-year fixed effects and age effects are estimated using a larger sample also including individuals who do not become unemployed and who are thus randomly allocated an artificial job loss year. All the regressions are performed on this larger sample. [14]

This empirical strategy identifies the causal effect of an anticipated[15] unemployment event on saving or portfolio reshuffling - or of an actual unemployment event on subsequent depletion of savings - if the timing of the event is uncorrelated with unobserved determinants of the outcome variable. Although unobservable differences in households that are time-invariant or aggregate calendar-year variation - both potential sources of bias in previous studies - are not a threat to our identification strategy, several legitimate concerns remain that our main identifying assumption does not hold. It is possible, for example, that there exist unobserved "third factors" (confounders) that cause both changes in saving behavior and in the employment situation. Individuals going through some kind of personal crisis

[13]The "reference relative year" here is in effect a weighted average of the omitted relative years prior to or after the window of four years prior to and after the job loss. A household with job loss in 1999 will have omitted relative years 5 to 8, whereas a household with job loss in 2003 will have omitted relative years -8 to -5.

[14]Results from regressions on the smaller dataset (households experiencing unemployment only) are, however, very similar to those reported below.

[15]Some workers will be aware of the upcoming unemployment spell with certainty, others may only fear it with low probability. At the end of the current section, we elaborate on how this affects the interpretation of our results. In the next section we also define a placebo sample of households not suffering unemployment spells. Some workers in the placebo sample may still have expected to suffer unemployment, potentially resulting in, for example, precautionary saving. Given our random assignment of the imaginary displacement year for the placebo sample, and our control for household fixed effects, cf. below, expected unemployment spells in the placebo sample that do not occur should not seriously bias our main results.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

might become less disciplined in their saving and investment behavior and might for the same underlying reasons lose their job soon after. If so, effect estimates of the upcoming unemployment would be biased downward. By contrast, households that recently managed to put an above-average amount of money on the side might be more eager to become unemployed (given that some individuals have some leeway on when or whether they are laid off), biasing the effect estimate upward. Indeed, we may even imagine that a worker could be saving *because* he is planning to make himself become unemployed, in which case, it is not the anticipation of (involuntary) unemployment that causes saving, but the saving that causes the unemployment. We attempt to shed some light on the empirical relevance of such endogeneity issues by repeating our analyses for a subsample of households whose job loss occurs in association with a major plant downsizing event. As mass layoffs from bigger plants are unlikely to be influenced by any individual worker's health or intention to become unemployed, several individual-level endogeneity concerns are largely alleviated (Jacobson, LaLonde, and Sullivan (1993), Huttunen, Møen, and Salvanes (2011), Rege, Telle, and Votruba (2009), Wachter, Song, and Manchester (2009)). Relying on job loss in association with mass layoffs will not, however, remove selection issues at the plant level. Workers selected into plants that undertake mass layoffs, may, for example, be less risk-averse than other workers, or they may hold different expectations about future employment opportunities. Therefore, although endogeneity concerns may be somewhat smaller for workers becoming unemployed in association with plant mass-layoffs, it is not clear whether effect estimates for such workers should be interpreted as less biased than effect estimates for all unemployed workers, or simply as indication that different types of workers are heterogeneously affected by (anticipated) unemployment events. It is also possible that the ability to foresee an upcoming unemployment spell differs for workers laid off in association with mass layoffs compared with other workers; cf. next paragraph. Furthermore, it is worth highlighting again that we can expect households to prepare for unemployment only if they can see it coming, which in turn we do not observe. Stephens Jr (2004), using the US Health and Retirement Study, finds that households have some sense of upcoming job losses and income drops, but the strength of such expectations depend on the specifics of each national labor market. Thus our tests for behavioral responses to upcoming unemployment spells are essentially testing the joint hypothesis that households can *sense* the job loss and that they possess the financial ability to *respond* to the upcoming event by saving more.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

2.4 Data

2.4.1 Data Sources

We use administrative data from Norwegian tax registers that cover the every Norwegian resident throughout the period 1995-2007. Three features make these data ideal for our purposes. First, register data are likely to be more reliable than survey data, an aspect that has previously been found to be of particular importance for data on income and financial wealth, as well as for data on unemployment spells, both of which are frequently recalled imperfectly or misreported.[16] Second, observing households in a panel format for a total of 13 years allows us to distinguish household and calendar year fixed effects from what happens in the different years around job loss. Finally, and importantly, we are able to merge information on employment status and labor income with information on household financial wealth, as well as – for the subsample analysis with those losing their job in the course of mass layoffs – with information on employment at the plant level.

Households are identified as couples who are married or who live together with common children (data to identify unmarried but cohabiting couples without children are not available). We focus on cases of male unemployment, as this will have a more significant impact on the household's financial situation. It also makes the sample more homogeneous, as most men return to a job at some point, whereas many women who lose their job tend to remain out of the labor force. A household is defined as unemployed in a year if the man receives unemployment benefits. Throughout the analysis, income is defined as the man's labor-related income.[17]

We follow Gruber (2001) in focusing on the household's financial wealth and disregard real estate. Chetty and Szeidl (2007) argue that it is likely that fixed transaction costs will make it not worthwhile to liquidate a house to pay for an unemployment spell.[18] Household financial wealth and the holdings of different types of assets are used at the household level, i.e., we use the sum of the husband's and the wife's assets. This makes sense conceptually as we would expect most of our households to live on a shared budget. Furthermore, financial

[16]For an example of the effects of misreporting in household surveys, see Meyer, Mok, and Sullivan (2009). For more information on the Norwegian administrative data see Røed and Raaum (2003), and on the wealth data in particular see e.g. Halvorsen (2011) and Fagereng, Gottlieb, and Guiso (2012).

[17]This includes wage income as well as work-related transfers, such as unemployment benefits, sickness benefits and parental leave benefits.

[18]We cannot observe real estate values reliably in our data sources. However, we have information on whether households enter or exit the status of home owner. An analysis of this variable reveals that a few households in our sample go from being to not being home-owner before the unemployment spell. Moreover, there is some indication of a decline in gross debt in the years leading up to the unemployment spell. In an attempt to explore whether these small changes may affect our main results, we restricted our sample to the households that did not change home-owner status in the observation period. Our main results remained virtually identical in this sample.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

variables are more reliable at the household level: while the two spouses do report their wealth separately, they are jointly taxed and they do not have any incentive to ensure that the one who reports holding the wealth is the one who does in fact own it. The category of safe assets is defined to include bank deposits and bonds, whereas risky assets are defined to include direct and indirect (mutual fund) holdings of stocks.[19]

To identify the subset of households becoming unemployed in association with a mass layoff, we count the number of employees and define as mass layoff those cases in which the number of employees decreases by 50% or more from one calendar year to the next. As this would not have much meaning in the case of two-person plants or in plants that experience significant employment differences between any pair of years, we follow previous studies (see for instance Jacobson, LaLonde, and Sullivan (1993), Wachter, Song, and Manchester (2009), Huttunen, Møen, and Salvanes (2011), Rege, Telle, and Votruba (2009)) in imposing some additional requirements. First, we require that plants have employed at least 10 employees in one of the years 1999-2003. We also require that the plant has existed for at least four years and has not already experienced a mass lay-off in the above sense in one of the past three years. Finally, because it is rather common for Norwegian firms to move workers from one of its plants to another (Huttunen, Møen, and Salvanes (2011)), we compute this downsizing rate without counting employees who leave a plant merely to continue working at another plant of the same firm. In the summary statistics we also report the husband's highest educational achievement and industry. The latter follows the standard NACE classification system.[20]

2.4.2 Sample Definitions

Using the above data sources, our main sample is defined as follows. To exclude households still in full-time education or with access to early-retirement schemes, we require the man to be from 30 to 58 (inclusive) years old in the year of job loss. We also require that in the year before the job loss the man had sufficient income to be eligible for the publicly provided and universally utilized unemployment benefits.[21] Households with business income, whose

[19]To ensure that our analyses of the impact of unemployment on labor income and wealth are not just driven by outliers in the far right tail of the distribution, we top-code both variables at the 99th percentile for each year. Furthermore, we consistently use 2004 as the omitted calendar year category, and convert NOK values into US dollars at 2004 exchange rates, with 1 USD corresponding to about NOK 6.7, so that all monetary variables are displayed in 2004 US dollars.

[20]See Eurostat (2011) for definitions. In cases where there are few observations within one industry, we merge industries to obtain adequately sized categories.

[21]This minimum income level necessary to be eligible is updated every year by the Norwegian Parliament in accordance with the general growth in prices and wages. The amount is low by Norwegian standards, and in practice employees with a non-minor position throughout a calendar year will meet the requirements. For 2010, for instance, the amount was about NOK 165,000, or USD 26,000. To ensure that the man's labor market attachment is not too loose, we impose a somewhat stronger restriction (equivalent to about NOK

 DOI: 10.2870/403

unemployment benefits are calculated under different rules, are also excluded. Moreover, we require that households have not experienced any unemployment in the four years leading up to the unemployment spell. To ensure that our comparison of income and wealth across the different relative years is not biased by differences in the sample composition, we require our panel to be fully balanced both across the nine relative years and across the 13 calendar years. We also follow Chetty (2008) in excluding workers who return to the same plant after their unemployment spell, as these are likely to know already at the time of layoff that they will be able to return to their previous plant at a specific time. These requirements leave us with our main analytic sample, comprising two disjoint subsamples. The first subsample includes the households that were in fact unemployed at some point during 1999-2003. This subsample comprises 5,513 households or 71,669 household-year observations, and is labelled *Unemployed*. The second subsample includes the households that were never unemployed in our data sample, and it is labelled *Placebo*. They are randomly assigned an *artificial* year of job loss in the years 1999-2003 to match the other subsample of households that did lose their job in the data window. The union of these two subsamples constitutes our main analytic sample of 57,389 households or 746,057 household-year observations, and the regression results reported below are based on our main analytic sample.[22] In this dataset we can track all households for at least four years before and after the year of job loss.

In addition to the main analytic sample, we also split the *Unemployed* sample in two. The first is the subsample of 1,075 households losing their jobs in relation to a major plant downsizing (labelled *ML*), and the second is the remaining 4,438 (of the 5,513) whose job loss did not occur in association with a mass layoff (*NonML*).

2.4.3 Summary Statistics

Table 2.1 displays summary statistics for the *Unemployed* sample of households actually experiencing unemployment. As we consider men who are married or cohabiting with their spouse and common children, the mean age of the man is relatively high. Close to 35% of the household men have less than a high school education. We see that male labor income is more than twice as high as female income, in terms of both the mean and the median. We also note significant dispersions in financial wealth: whereas the mean holdings in the sample amount to more than USD 14,000, the median is about USD 4,500. We also see that the median household does not participate in risky asset markets. In Table 2.2 we display summary statistics for our *Placebo* sample together with the *Unemployed* sample, the latter split into the *ML* and *NonML* subsamples. As might be expected, mass layoffs occur mainly in the manufacturing and construction sectors. Those affected are on average slightly older

220,000 in 2010). For more information on UI and these amounts; see www.nav.no/english.

[22]Results from regressions on *Unemployed* only, are very similar to those reported.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

with annual income about USD 5,000 higher; otherwise, the samples are relatively similar, with average wealth differences being statistically but arguably not economically important. Nonetheless, the differences here need to be kept in mind below when we interpret the differences in the results for these two subsamples. Those in the *Placebo* sample, by contrast, are on average about four years older and 4 percentage points more likely to have a college degree. Correspondingly they are more likely to be found in sectors such as education. Not surprisingly then their annual income is about USD 5,000 higher and their financial wealth almost USD 7,000 higher. [23]

Table 2.1: Summary Statistics Main Sample

	Mean	Std Dev	Median
Demographics:			
Age Husband	40.72	5.488	41
Job loss year	2001	1.464	2001
Share Low Education	0.37		
Share High School Education	0.39		
Share College Education	0.24		
Income (2004 USD):			
Male Income	55,196	28,762	53,325
Female Income	25,092	20,394	26,930
Household Income	80,288	39,070	81,928
Asset Holdings (2004 USD):			
Risky Assets	7,424	31,469	0
Safe Assets	13,820	24,103	5,556
Financial Wealth	21,245	43,638	6,858
Industry decomposition:			
Manufacturing	0.32		
Construction	0.09		
Wholesale retail	0.17		
Transport / communication	0.07		
Real estate.	0.10		
Education	0.03		

Note: Based on the Unemployed sample of 5,513 households four years prior to the year of job loss (cf. Section 2.4.2), all occurring in the period 1999-2003. Where applicable, values are in 2004 USD. Minor industry categories are omitted from the table. Shares of educational achievements are calculated with about 1% of sample missing an observation for this variable.

[23] To explore whether the differences on observables between the *Placebo* sample and the *Unemployed* sample are affecting our main results, we did two things. First, we used matching on observables to create a smaller placebo sample (which was similar to our *Unemployed* sample on observables). Using this sample instead did not significantly change our main results. Second, we estimated results using the *Unemployed* sample only. Again, and as is evident from Figure 2.4, our main results remained unchanged in this subsample.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

Table 2.2: Summary Statistics for the Subsamples of Employees Displaced in Association with Mass Layoffs (ML), Displaced Not in Association with Mass Layoffs (NonML) and Never Displaced (Placebo)

	1. NonML (N=4,438)			2. ML (N=1,075)			3. Placebo (N=51,876)				
	Mean	Std Dev	Median	Mean	Std Dev	Median	Mean	Std Dev	Median	T(1-2)	T(1-3)
Demographics:											
Age Husband	40.56	5.51	41	41.37	5.33	42	44.69	5.01	45	-4.42	-48.22
Job loss year	2001	1.48	2001	2001	1.35	2002	2001	1.41	2001	-7.39	0.22
Share Low Educ.	0.37			0.35			0.35				
Share High School	0.38			0.45			0.36				
Share College Educ.	0.25			0.20			0.29				
Income (2004 USD):											
Male Income	54,206	29,911	52,657	59,285	22,995	55,192	65,390	22,816	59,499	-6,10	-24,31
Female Income	24,607	20,656	26,358	27,096	19,159	29,578	29,126	19,310	31,351	-3.76	-14.06
Household Income	78,812	40,444	80,672	86,381	32,100	86,718	94,516	30,373	91,826	-6.57	-25.26
Asset Holdings (2004 USD):											
Risky Assets	7,790	31,908	0	5,919	29,557	0	14,118	46,126	0	1.83	-12.17
Safe Assets	13,705	24,447	5,305	14,299	22,637	6,598	20,745	31,968	9,779	-0.76	-17.92
Financial Wealth	21,495	44,541	6,586	20,218	39,701	7,995	34,862	62,737	13,310	0.92	-18.49
Industry decomposition:											
Manufacturing	0.29			0.44			0.31				
Construction	0.08			0.15			0.10				
Wholesale / retail	0.19			0.12			0.16				
Transport /com.	0.08			0.07			0.05				
Real estate.	0.11			0.08			0.07				
Education	0.03			0.02			0.08				

Note: Based on the Placebo sample (51,876 households) and the Unemployed sample (5,513 households), where the latter is split into the NonML (4,438 households) and ML (1,075 households) subsamples (cf. Section 2.4.2). The summary statistics are calculated for the households four years prior to job loss. The two subcolumns on the right indicate the T-values for testing the difference in means between the samples. Minor industry categories are omitted from the table. Shares of educational achievements are calculated with about 1% of sample missing an observation for this variable.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute

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2.5 Results

We now turn to our findings on households' inclination to save and shift assets toward less risky assets before an upcoming job loss, as well as the depletion of savings during unemployment. For our main results, we have estimated the model in Equation (2.10). Regression results are reported in Table 2.3, and Figures 2.1, 2.2 and 2.3 plot the predicted paths of labor income, wealth and its components over time, obtained by adding to the estimate of the constant those of the respective relative-year coefficients. We are interested in the significance of the accumulation of wealth between our first observation in -4 and the last prelayoff observation in -1, in the changes in respectively safe and risky assets between the same pair of years, and finally in the significance of wealth decumulation between the last prelayoff year and the last point before households start to re-save, which for the average household turns out to be relative year 2.

We start our discussion with the results for labor-related income, the variable that is directly affected by job loss even without any active responses. From Figure 2.1, we see that this income path is flat until relative year -1 (recall that our calendar-year fixed effects take out average income growth), but then the average household income drops significantly[24] from about USD 51,000 in the last year before job loss to USD 45,000 in the year of job loss.[25] Income then remains low in relative year +1 before it gradually starts increasing again, as more and more households move back into regular employment. By relative year +4 the difference has shrunk to about USD 1,000, which can be partly because of some households still being unemployed and partly due to lower average income in the new job.[26]

Figure 2.2 reports the predicted time path of financial wealth. We find that the average household starts out with financial wealth of about USD 34,500 in relative year -4 and increases this by more than USD 1,000 by the end of the last calendar year before job loss. As mentioned, this may be considered a conservative estimate because we only observe households per calendar year and we may therefore be mixing some additional saving and some dissaving within year 0 for households experiencing job loss within the calendar year. Furthermore, this is the average across all households, presumably including both households aware of an impending job loss that respond by saving more and households not aware of the

[24]We refer to a difference with a p-value of less than 0.05 as statistically significant; see relevant figures and tables for details.

[25]The drop in relative year 0 here amounts to about 12%. Since we know that all of our households are eligible for UI benefits, which for most of them amount to 62.4% of prior income and thus imply an annualized drop of 37.6%, this tells us that the average household in this sample is unemployed for about one-third of its relative year 0.

[26]This differs from the findings made for instance by Wachter, Song, and Manchester (2009), where workers displaced during the 1982 US recession are permanently worse off in terms of income. Presumably, this difference reflects the general strength of the Norwegian labor market with low unemployment rates during the period under consideration.

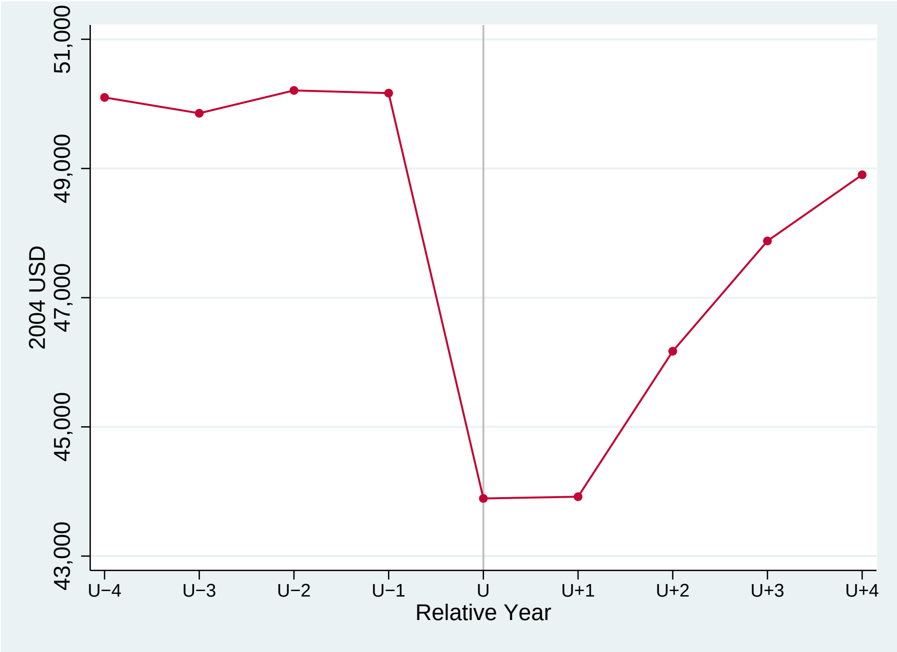

Figure 2.1: **Labor Income around Unemployment**

Note: The graph shows the predicted time path of household financial wealth from four years before to four years after the year of job loss, based on the estimates reported in Table 2.3.

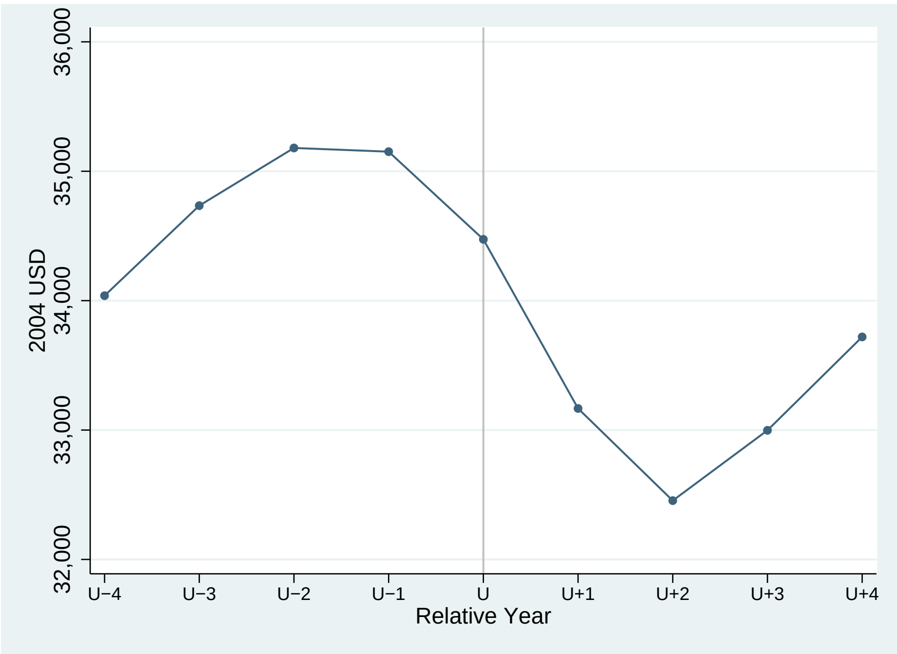

Figure 2.2: **Financial Wealth around Unemployment**

Note: The graph shows the predicted time path of household financial wealth from four years before to four years after the year of job loss, based on the estimates reported in Table 2.3.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute
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upcoming job loss that are thus unable to take any measures to save before the job loss.[27] Despite these factors, however, we do find precautionary saving that is both statistically and economically significant, suggesting that the average household is aware of the upcoming job loss and does prepare for it. Moreover, the subsequent wealth depletion of on average about USD 3,000 between relative years -1 and 2 is statistically significant, and also in line with our theoretical prediction. This depletion of savings does not seem very large, however, significant relative to the income shortfall of more than USD 6,000 in years 0 and 1. Since by the time of job loss the average household would have enough resources for greater wealth depletion, this suggests that the average household can do the remaining adjustment along other margins, such as spousal labor supply (a slight increase in spousal labor income/supply is indeed found in complementary analyses not reported here), temporarily lower spending on durables (as in Browning and Crossley (2009)) or substituting some home production for market consumption. To pursue the predictions for portfolio reshuffling, we turn to Figure 2.3, which plots separately the predicted time paths of risky assets (stocks and mutual funds) and safe assets (bonds and cash). The average household does significantly shift wealth from risky assets toward safe assets. As the household reaches the year of job loss we also note that it draws on both sources of assets. As we reach year +4, the levels of safe and risky assets are pretty much back at their -4 levels. Of course, one should note that the risky assets are held by a smaller share of the households, so the issue of reshuffling does not equally apply to each household in our sample. Nonetheless, these time patterns are in line with our theoretical predictions.[28] In Section 2 we discussed how our household fixed effects take out unobserved time-invariant household characteristics, such as the degree of risk-aversion, and how our calendar-year fixed effects take out the impacts of, for instance, inflation and the business cycle. However, are these two sets of fixed effects sufficient? One way of getting an impression of this is to test whether the same time paths are flat for the *Placebo* sample of households who never experience unemployment and where the year of (artificial) job loss is

[27] Although the pattern of more saving before the job loss is as we expect, the financial wealth in -4 is not statistically significantly different from the wealth in -1. However, the build-up is not far from statistically significant, and it becomes clearly significant when we exclude the 5% richest households or when we exclude households that participate in the stock and bond markets. Those participating in the stock and bond markets, by contrast, respond more strongly in terms of reshuffling their portfolio structure, as we discuss below.

[28] Regressions on asset levels may be very sensitive to outliers, even after winsorizing at the 99th percentile. A possible alternative therefore is to use instead log asset holdings on the left-hand side, although this makes regressions more sensitive to households with very low initial holdings and for whom small dollar accumulations can therefore show up as huge relative changes in wealth. While we rely on levels for the results presented here, the corresponding log specifications confirm the same hypotheses, suggesting that our results are not driven by outliers at either the top or the bottom of the wealth distribution. The same applies when we use as dependent variables the first differences or their logs, although this reduces by one year the length of time for which we can make predictions.

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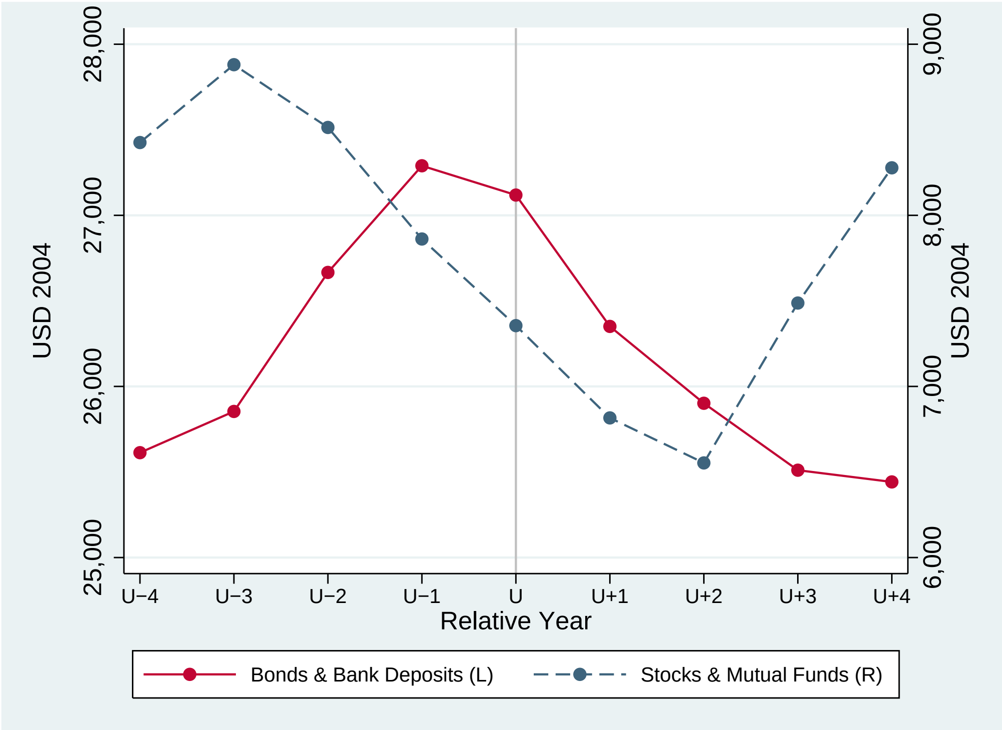

Figure 2.3: **Safe and Risky Assets around Unemployment**

Note: The graph shows the predicted time paths of the holdings of safe assets (bonds and deposits) and risky assets (stocks and mutual funds) from four years before to four years after the year of job loss, based on the estimates reported in Table 2.3.

randomly assigned. In Figure 2.4 we plot the estimates for the RYs in Equation (2.10) - as provided by the regression reported in Table 2.3 - for the *Placebo* sample and the *Unemployed* sample separately. Indeed, we find that for *Placebo* the predicted time paths are flat. This supports the validity of our specification.

In Section 2.3 we also discussed how we can get additional, suggestive evidence on the relevance of remaining individual-level selection issues, by focusing on the subsample of individuals affected by mass layoffs. Figures 2.5 through 2.8 display the predicted time paths of our outcome variables of interest separately for those affected by mass layoffs and the other unemployed, and the underlying coefficient estimates are given in Tables 2.4 and 2.5. We see that the time paths of income, risky and safe assets are all similar across the two subsamples. Looking at financial wealth, displayed in Figure 2.6, wealth depletion during unemployment is also similar for both subsamples. Where the two subsamples differ somewhat is in terms of prior wealth accumulation, of which the ML subsample displays only very slight evidence. As discussed in Section 2.3, it is not straightforward to interpret

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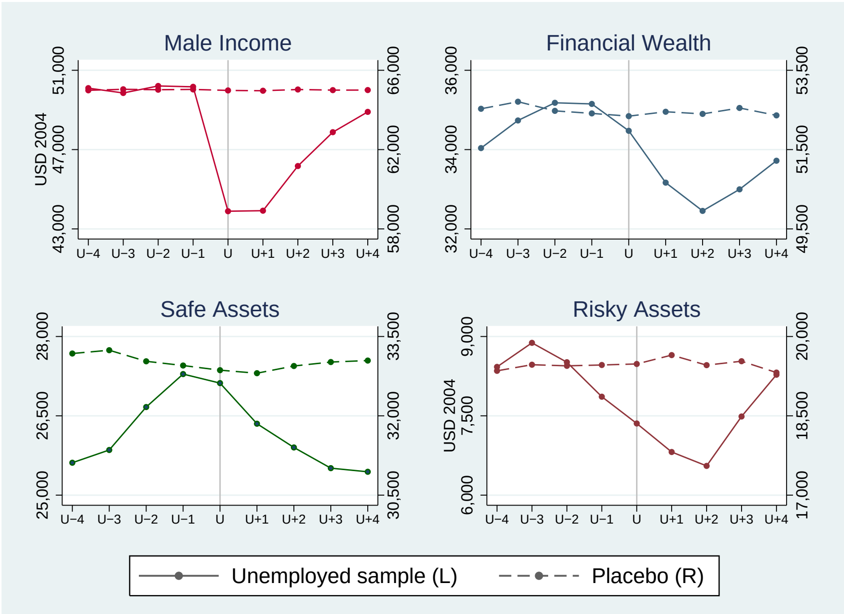

Figure 2.4: **Unemployed vs. Placebo**

Note: The figure displays the predicted time paths of male income, household financial wealth, safe assets, and risky assets for households in the Placebo and the Unemployed sub samples in the years around job loss. Results from the four underlying regressions are reported in Table 2.3. As those in the affected sample have on average lower income and lower wealth, we use different vertical intercepts, but the scaling is the same. The main point in this graph is that for households in the Placebo sample the time paths of all variables of interest are basically flat, confirming the validity of our fixed-effects methodology.

these differences in effect estimates for the households experiencing unemployment in and not in association with mass layoffs. On the one hand, we have seen that the households experiencing job loss in association with mass layoffs have substantially higher income and lower financial wealth throughout our data window, cf. Table 2.2 and Figures 2.5 and 2.6, which may indicate that the samples are different and that we therefore may expect effects of anticipated unemployment to be heterogeneous across the two samples. Moreover, there may be some weak indications that the *ML* households react to the upcoming job loss at a somewhat later stage than the *NonML* households, cf. Figures 2.6 and 2.7, which may indicate differences in the subjectively perceived likelihoods of unemployment. On the other hand, we might take the finding that most of the patterns for the *ML* households by and large line up with our theoretical predictions, as a sign that our main effect estimates are not seriously biased by selection on household characteristics. Nonetheless, we must caution that possible precautionary saving in the *nonML* subsample may be hidden by remaining unobserved sample heterogeneity, and recall that the *ML* sample is relatively small.

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Table 2.3: Main Regression Results

	Male Inc	Fin Wealth	Safe Assets	Risky Assets
U-4	-463.3	1,426.2	682.4	743.8
	(215.9)**	(465.3)***	(306.7)**	(304.8)**
U-3	-707.8	2,122.1	923.4	1,198.8
	(288.0)**	(607.9)***	(412.2)**	(403.3)***
U-2	-354.6	2,567.8	1,735.8	831.9
	(348.1)	(707.9)***	(504.4)***	(470.3)*
U-1	-396.2	2,539.2	2,359.2	180.0
	(400.8)	(811.5)***	(592.4)***	(540.5)
U	-6,670.6	1,861.8	2,188.1	-326.3
	(434.8)***	(893.8)**	(648.3)***	(600.1)
U+1	-6,643.6	554.9	1,420.4	-865.5
	(425.5)***	(902.8)	(647.6)**	(618.2)
U+2	-4,391.9	-157.4	971.3	-1,128.7
	(395.2)***	(843.1)	(597.4)	(563.8)**
U+3	-2,684.9	385.8	580.1	-194.3
	(351.4)***	(801.4)	(567.8)	(548.1)
U+4	-1,660.5	1,107.5	511.5	596.1
	(287.5)***	(755.0)	(512.9)	(527.7)
Constant	50,562.9	32,612.0	24,930.4	7,681.6
	(416.3)***	(908.2)***	(640.6)***	(538.9)***
Observations:				
Unique Households	57,389	57,389	57,389	57,389
Household*Year	746,057	746,057	746,057	746,057

Note: The table displays the estimates for the relative-year dummies (U denotes year of job loss) of the four dependent variables from OLS regressions on our main samples (union of Unemployed and Placebo, cf. Section 2.4.2) of 57,389 households in total. Regressions include household and calendar-year fixed effects, as well as a fourth-order polynomial in age, but these estimates are not reported in the table. The regressions also include relative-year fixed effects interacted with a dummy indicating that the household belongs to the Placebo sample, but these estimates are not reported in the table (they are, however, plotted in Figure 2.4). Values are in 2004 USD and clustered standard errors (on household) are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. P-values from F-tests for equality between coefficients of different relative years: Male Income: p(U-1=U)=0.000, p(U=U+4)=0.000, p(U-1=U+4)=0.000. Financial Wealth: p(U-4=U-1)=0.057, p(U-1=U+2)=0.000, p(U+2=U+4)=0.029. Safe Assets: p(U-3=U-1)=0.000, p(U-1=U+2)=0.001. Risky Assets: p(U-3=U-1)=0.012, p(U-1=U+2)=0.000.

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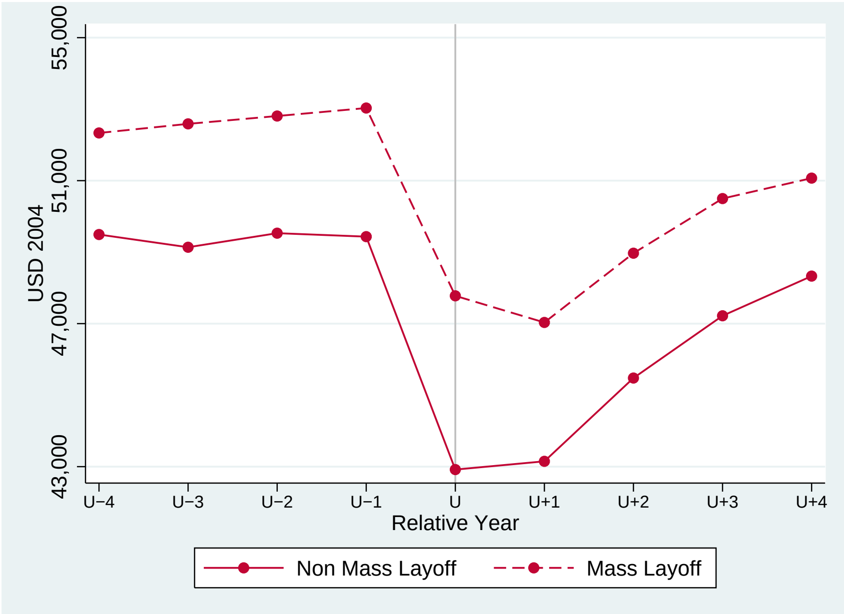

Figure 2.5: **Labor Income Paths: Mass Layoff vs. Non Mass Layoff**

Note: The graph shows the predicted time paths of labor income of the household male from four years before to four years after the year of job loss, based on the estimates reported in Table 2.4 – separately for those losing their jobs in the course of mass layoffs (ML) and for the other job losers (NonML).

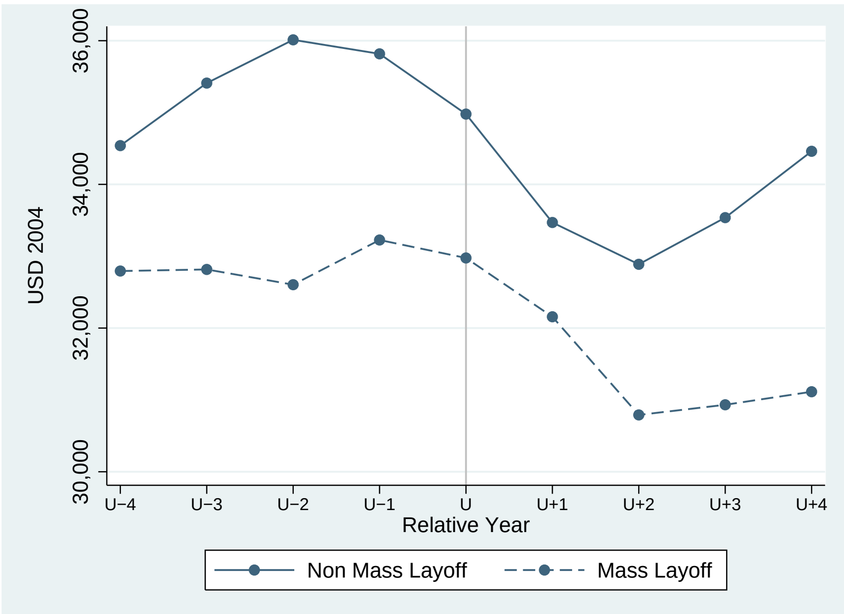

Figure 2.6: **Financial Wealth Paths: Mass Layoff vs. Non Mass Layoff**

Note: The graph shows the predicted time paths of household financial wealth from four years before to four years after the year of job loss, based on the estimates reported in Table 2.4 – separately for those losing their jobs in the course of mass layoffs (ML) and for the other job losers (NonML).

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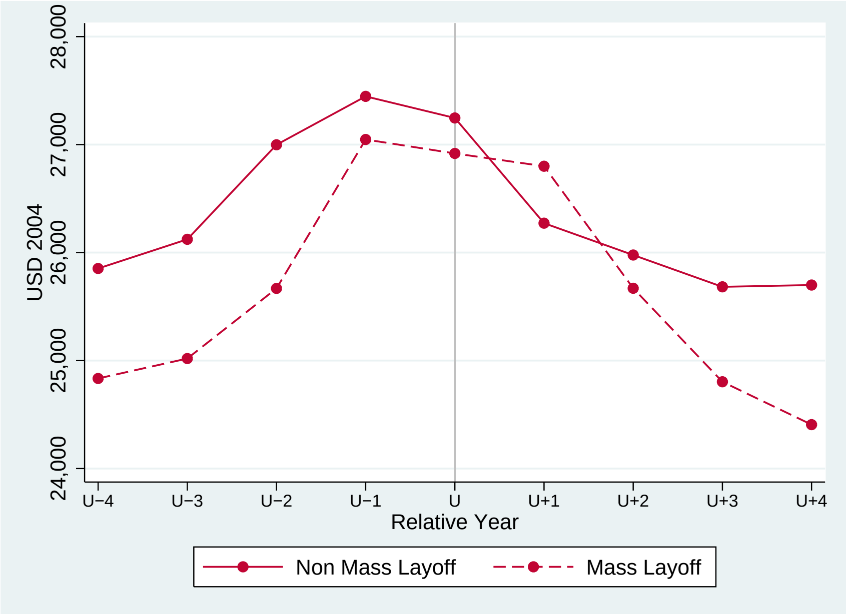

Figure 2.7: **Safe Asset Holdings: Mass Layoff vs. Non Mass Layoff**

Note: The graph shows the predicted time paths of the holdings of safe assets from four years before to four years after the year of job loss, based on the estimates reported in Table 2.5 – separately for those losing their jobs in the course of mass layoffs (ML) and for the other job losers (NonML).

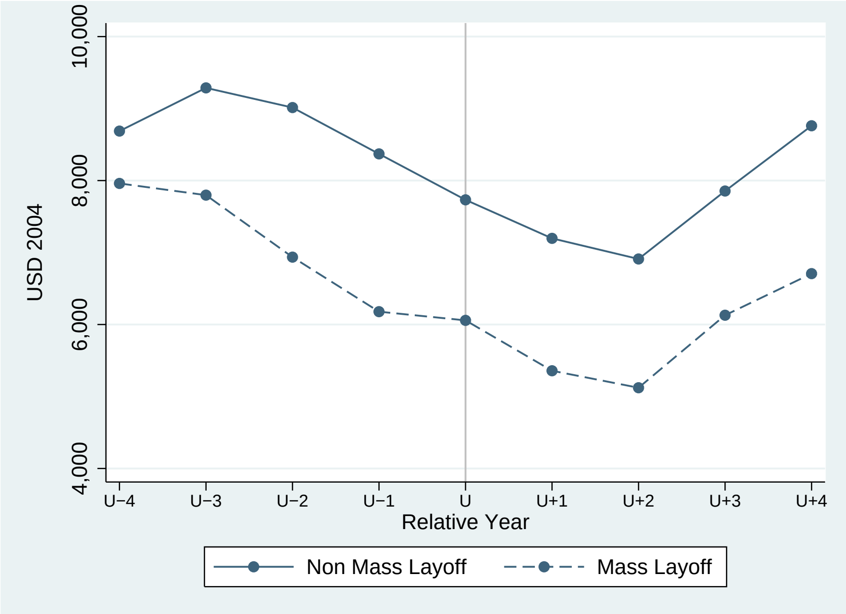

Figure 2.8: **Risky Asset Holdings: Mass Layoff vs. Non Mass Layoff**

Note: The graph shows the predicted time paths of the holdings of risky assets from four years before to four years after the year of job loss, based on the estimates reported in Table 2.5 – separately for those losing their jobs in the course of mass layoffs (ML) and for the other job losers (NonML).

DOI: 10.2870/403

Table 2.4: Regression Results for Displacement and Mass Layoffs: Income and Financial Wealth

	Male Income		Financial Wealth	
	NonML	ML	NonML	ML
U-4	-609.3	659.0	2,243.0	-4,053.5
	(247.4)**	(482.8)	(541.6)***	(1,002.5)***
U-3	-965.5	1,269.6	3,113.3	-4,901.8
	(329.6)***	(646.5)**	(706.0)***	(1,366.2)***
U-2	-572.0	1,095.3	3,715.4	-5,715.9
	(397.6)	(793.8)	(806.2)***	(1,735.6)***
U-1	-668.9	1,415.8	3,520.6	-4,899.2
	(457.2)	(926.7)	(917.3)***	(2,020.5)**
U	-7,184.4	2,678.2	2,681.9	-4,310.4
	(495.6)***	(1,014.5)***	(1,005.6)***	(2,270.7)*
U+1	-6,953.7	1,703.1	1,172.8	-3,619.9
	(486.0)***	(989.3)*	(1,020.0)	(2,252.5)
U+2	-4,624.0	1,309.8	591.1	-4,404.3
	(454.0)***	(906.2)	(951.9)	(2,144.7)**
U+3	-2,882.6	1,097.2	1,240.6	-4,912.5
	(404.0)***	(813.9)	(904.5)	(2,049.1)**
U+4	-1,772.7	559.1	2,164.0	-5,654.7
	(331.4)***	(658.5)	(868.9)**	(1,770.5)***
Constant	50,102.4	2,181.8	32,296.6	2,307.7
	(468.3)***	(996.6)**	(1,007.0)***	(2,348.9)
Observations:				
Unique Households	57,389		57,389	
Household*Year	746,057		746,057	

Note: The table displays the estimates for the relative-year dummies (U denotes year of job loss) of the given dependent variables from OLS regressions on our main sample (union of Unemployed and Placebo, cf. Section 2.4.2), but the relative-year dummies are interacted with the dummy for household belonging to the ML subsample (in addition to the interactions of the Placebo sample dummies as in Table 2.3). Dummies for the Placebo sample (including interactions with relative years), together with calendar-year fixed effects and a fourth-order polynomial in age are included in the regressions but not reported in the table. Values are in 2004 USD, and clustered standard errors (on household) reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. P-values from F-tests for equality between coefficients of different relative years: Male Income NonML: p(U-1=U)=0.000, p(U=U+4)=0.000, p(U-1=U+4)=0.003. Male Income ML: p(U-1=U)=0.000, p(U=U+4)=0.000, p(U-1=U+4)=0.005. Financial Wealth NonML: p(U-4=U-1)=0.048, p(U-1=U+2)=0.000, p(U+2=U+4)=0.018. Financial Wealth ML: p(U-4=U-1)=0.752, p(U-1=U+2)=0.030, p(U+2=U+4)=0.784.

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Table 2.5: Regression Results for Displacement and Mass Layoffs: Safe And Risky Assets

	Safe Assets		Risky Assets	
	NonML	ML	NonML	ML
U-4	1,079.5	-1,985.7	1,163.4	-2,067.7
	(350.4)***	(707.9)***	(354.0)***	(678.7)***
U-3	1,349.9	-2,071.3	1,763.4	-2,830.4
	(470.5)***	(969.1)**	(472.1)***	(904.6)***
U-2	2,225.4	-2,297.8	1,490.1	-3,418.0
	(572.4)***	(1,219.4)*	(531.4)***	(1,220.6)***
U-1	2,673.8	-1,366.7	846.8	-3,532.5
	(669.1)***	(1,453.7)	(605.3)	(1,445.8)**
U	2,473.7	-1,295.9	208.1	-3,014.5
	(735.7)***	(1,569.1)	(669.8)	(1,614.1)*
U+1	1,499.4	-439.9	-326.6	-3,179.9
	(732.7)**	(1,574.7)	(698.7)	(1,595.8)**
U+2	1,204.5	-1,275.5	-613.4	-3,128.8
	(680.9)*	(1,441.0)	(637.3)	(1,489.1)**
U+3	909.8	-1,846.6	330.8	-3,065.9
	(643.2)	(1,403.0)	(627.7)	(1,392.4)**
U+4	926.5	-2,260.3	1,237.5	-3394.4
	(582.2)	(1,244.5)*	(619.7)**	(1,169.3)***
Constant	24,772.9	967.3	7,523.7	1,340.4
	(714.8)***	(1,593.0)	(579.2)***	(1,593.2)
Observations:				
Unique Households	57,389		57,389	
Household*Year	746,057		746,057	

Note: The table displays the estimates for the relative-year dummies (U denotes year of job loss) of the given dependent variables from OLS regressions on our main sample (union of Unemployed and Placebo, cf. Section 2.4.2), but the relative-year dummies are interacted with dummy for household belonging to the ML subsample (in addition to the Placebo sample dummy as in Table 2.3). Dummies for the Placebo sample (including interactions with relative years), together with calendar-year fixed effects and a fourth-order polynomial in age are included in the regression but not reported in the table. Values are in 2004 USD, and clustered standard errors (on household) reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. P-values from F-tests for equality between coefficients of different relative years: Safe Assets NonML: p(U-4=U-1)=0.000, p(U-1=U+2)=0.001. Safe Assets ML: p(U-4=U-1)=0.021, p(U-1=U+2)=0.131. Risky Assets NonML: p(U-3=U-1)=0.051, p(U-1=U+2)=0.001. Risky Assets ML: p(U-3=U-1)=0.034, p(U-1=U+2)=0.157.

Fagereng, Andreas (2012), Three Essays in Household Finance
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2.6 Conclusion

We have empirically investigated saving patterns and portfolio reshuffling toward safer assets before unemployment, as well as depletion of wealth after job loss. Consistent with the predictions of our simple theoretical model, we find, first, that the average household does deplete about USD 2,500 of financial wealth during an unemployment spell. More strikingly, almost all of this is made up for by additional saving in the three years before job loss as well as in years 3 and 4 after job loss. Furthermore, we also find evidence of portfolio reshuffling in the years before job loss. The latter two results suggest that the average household is indeed able to foresee the upcoming unemployment spell, and is then both able and willing to prepare for those rainy days. In countries with high participation in the risky asset markets among the labor force, uncertainty in the labor market may affect financial markets through this reallocation mechanism. This would be interesting to consider further in future research. The results have been obtained using an empirical strategy that allows us to trace the time paths of income, financial wealth and its components, while fully controlling for household and calendar-year fixed effects. Previous studies on wealth depletion, precautionary saving or household portfolios have not been able to include such controls because of due to lack of adequate panel data. The presence of precautionary saving behaviour indicates that at least some workers in our sample are able to foresee and prepare for the upcoming unemployment spell, which indicates that they are partly able to smooth consumption by drawing on their prior savings. While the estimated size of this wealth depletion may be thought to be relatively small compared with the drop in income associated with the job loss, its existence does nonetheless confirm that, to some extent, private savings can serve as a substitute for publicly provided unemployment insurance. At least four things should be noted, however. First, the UI benefits in Norway are very generous by international standards: they typically replace more than 60% of earnings in the calendar year before job loss; at the same time most households are eligible to receive UI for up to 2 years. Second, in our period of observation the Norwegian labor market is characterized by very low unemployment rates, implying relatively easy access to new employment for most of the job losers concerned. Both we and others have found income to recover more rapidly after job loss than is the case in many other countries, with correspondingly modest impacts on the reduction of private financial savings from efforts to smooth consumption through spells of unemployment. In line with this, the households in our sample tend to not end up with permanently lower holdings of financial wealth as a consequence of their unemployment spell, presumably because of the relatively generous UI system and the largely temporary nature of their unemployment spells. Third,

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

the households in our sample do not only enjoy a generous welfare system, but they also hold substantial financial wealth at the outset. On average, they hold assets worth more than a fourth of their annual labor income. Finally, we need to caution that our findings are all based on sample averages and thus do not rule out the possibility that some of the poorest households suffer considerably during unemployment or do end up with permanently lower wealth afterwards.

2.7 Appendix: Analytical Solution of the Model

Complementing the parsimonious model in Section 2.3 this appendix provides the formal derivations behind our propositions.

In the maximization problem from Equation (2.1) we replace c_1 with the two different states that consumption may take in period 1, depending on the employment status (Employed (E) or Unemployed (U)):

$$\underset{s}{Max} \qquad EU = u(c_0) + \beta[(1-p_1)u(c_1^E) + p_1 u(c_1^U)], \tag{2.11}$$

subject to:

$$0 \leqslant s \leqslant 1 \tag{2.12}$$

$$c_0 = (w + y_l)(1-s) \tag{2.13}$$

$$c_1^U = y_l + s(w + y_l\ )R \tag{2.14}$$

$$c_1^E = y_h + s(w + y_l\ )R \tag{2.15}$$

The first order condition (FOC) for s then yields an Euler equation relating the marginal utility of consumption in period 0 to that in period 1.

$$\frac{\delta EU}{\delta s} : u'(c_0) = R\beta\left[(1-p_1)u'(c_1^E) + p_1 u'(c_1^U)\right] \tag{2.16}$$

Taking the total differential with respect to p_1 and assuming, for simplicity and without

DOI: 10.2870/403

loss of generality, a return $R = 1$, gives:

$$\begin{aligned}
&- u''(c_0)(w + y_l)\frac{\delta s}{\delta p_1} \\
&= \beta \left[-u'(c_1^E) + u'(c_1^U) + \left\{(1 - p_1)u''(c_1^E)(w + y_l) + p_1 u''(c_1^U)(w + y_l)\right\} \frac{\delta s}{\delta p_1} \right]
\end{aligned} \tag{2.17}$$

Hence,

$$\begin{aligned}
&\frac{\delta s}{\delta p_1} \\
&= \frac{-u'(c_1^E) + u'(c_1^U)}{-u''(c)(w + y_l) - \beta \left\{(1 - p_1)u''(c_1^E)(w + y_l) + p_1 u''(c_1^U)(w + y_l)\right\}} > 0
\end{aligned} \tag{2.18}$$

Both numerator and denominator are positive because of the concavity of the utility function ($u''(c) < 0$), and the saving rate is increasing in the probability of remaining unemployed. Hence we have proven Proposition 1.

Now we move the timing back one period, considering the household in period -1 before the job loss occurred. Rewriting the maximization problem from Equation (2.6) by substituting for the four different consumption states that the household may face in the next period depending on high (H) vs. low (L) risky asset return and the employment (U or E) status, we get:

$$\begin{aligned}
&\underset{s_{-1},\alpha}{Max} u((y_{-1}(1 - s_{-1}))+ \\
&\beta[(1 - p_0)(1 - q)u(c_1^{EH}) + (1 - p_0)q \cdot u(c_1^{EL}) + p_0(1 - q) \cdot u(c_1^{UH}) + p_0 q \cdot u(c_1^{UL})]
\end{aligned} \tag{2.19}$$

subject to

$$0 \leqslant s, \alpha \leqslant 1 \tag{2.20}$$

where c_1^{EH} denotes consumption in period 1, given that the household is employed and risky asset returns turned out to be high. By contrast, c_1^{UL} denotes the other extreme case where the household is unemployed and risky asset returns turned out to be low.

The FOCs are:

DOI: 10.2870/403

$\frac{\delta EU}{\delta s_{-1}}$:

$$u'(y_{-1}(1-s_{-1})) = \beta \left\{ \begin{array}{c} (1-q)(\alpha R_h + (1-\alpha)R)[(1-p_0)\cdot u'(c_1^{EH}) + p_0 \cdot u'(c_1^{UH})] \\ +q(\alpha R_l + (1-\alpha)R)[(1-p_0)\cdot u'(c_1^{EL}) + p_0 \cdot u'(c_1^{UL})] \end{array} \right\} \quad (2.21)$$

$\frac{\delta EU}{\delta \alpha}$:

$$\frac{R_h - R}{R - R_l} = \frac{q}{1-q} \frac{(1-p_0)\cdot u'(c_1^{EL}) + p_0 \cdot u'(c_1^{UL})}{(1-p_0)\cdot u'(c_1^{EH}) + p_0 \cdot u'(c_1^{UH})} \quad (2.22)$$

For notational convenience, we define the following terms, where the subscripts for p and s are omitted:

$$\Omega_L(p, s, \alpha) = (1-p)\cdot u'(c_1^{EL}) + p \cdot u'(c_1^{UL}) \quad (2.23)$$

$$\Omega_H(p, s, \alpha) = (1-p)\cdot u'(c_1^{EH}) + p \cdot u'(c_1^{UH}) \quad (2.24)$$

$$R_H = (1-q)(\alpha R_h + (1-\alpha)R) \quad (2.25)$$

$$R_L = q(\alpha R_l + (1-\alpha)R) \quad (2.26)$$

$$C = \frac{R_h - R}{R - R_l}\frac{1-q}{q} \quad (2.27)$$

Then we can rewrite the FOCs into

$$\Omega_H \frac{R_h - R}{R - R_l}\frac{1-q}{q} = \Omega_L = \Omega_H \cdot C \quad (2.28)$$

and

$$u'(1-s) = \beta \left\{ R_H \cdot \Omega_H + R_L \cdot \Omega_L \right\} \quad (2.29)$$

Inserting into the other, and setting $\beta = 1$ and $y_{-1} = 1$, we get:

$$u'(1-s) = R_H \cdot \Omega_H + R_L \cdot \Omega_H \cdot C = \Omega_H \left[R_H \cdot + R_L \cdot C \right] = B \cdot \Omega_H$$

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

where $B = (1-q)\frac{R(R_h - R_l)}{R - R_l} > 0$.

In compact notation, the two FOCs are as follows:

$$u'(1-s) = B \cdot \Omega_H \tag{2.30}$$

$$\Omega_L = \Omega_H \cdot C \tag{2.31}$$

$$B \cdot \Omega_H(p, s, \alpha) - u'(1-s) = 0 \tag{2.32}$$

$$C \cdot \Omega_H(p, s, \alpha) - \Omega_L(p, s, \alpha) = 0 \tag{2.33}$$

Taking the total differential wrt. to p of the first:

$$B \cdot \left[\frac{\delta \Omega_H}{\delta p} + \frac{\delta \Omega_H}{\delta s}\frac{\delta s}{\delta p} + \frac{\delta \Omega_H}{\delta \alpha}\frac{\delta \alpha}{\delta p}\right] = -u''(1-s)\frac{\delta s}{\delta p} \tag{2.34}$$

This can be written as:

$$B\frac{\delta \Omega_H}{\delta \alpha}\frac{\delta \alpha}{\delta p} = -u''(1-s)\frac{\delta s}{\delta p} - B\frac{\delta \Omega_H}{\delta p} - B\frac{\delta \Omega_H}{\delta s}\frac{\delta s}{\delta p} \tag{2.35}$$

The total differential of the second FOC is as follows:

$$C \cdot \left[\frac{\delta \Omega_H}{\delta p} + \frac{\delta \Omega_H}{\delta s}\frac{\delta s}{\delta p} + \frac{\delta \Omega_H}{\delta \alpha}\frac{\delta \alpha}{\delta p}\right] = \frac{\delta \Omega_L}{\delta p} + \frac{\delta \Omega_L}{\delta s}\frac{\delta s}{\delta p} + \frac{\delta \Omega_L}{\delta \alpha}\frac{\delta \alpha}{\delta p} \tag{2.36}$$

Solving for $\frac{\delta \alpha}{\delta p}$:

$$\frac{\delta \alpha}{\delta p} = \frac{C\frac{\delta \Omega_H}{\delta p} + C\frac{\delta \Omega_H}{\delta s}\frac{\delta s}{\delta p} - \frac{\delta \Omega_L}{\delta p} - \frac{\delta \Omega_L}{\delta s}\frac{\delta s}{\delta p}}{\left(\frac{\delta \Omega_L}{\delta \alpha} - C\frac{\delta \Omega_H}{\delta \alpha}\right)} \tag{2.37}$$

and inserting $\frac{\delta \alpha}{\delta p}$, the first FOC gives:

 DOI: 10.2870/403

$$B\frac{\delta\Omega_H}{\delta\alpha}\left(\frac{C\frac{\delta\Omega_H}{\delta p}+C\frac{\delta\Omega_H}{\delta s}\frac{\delta s}{\delta p}-\frac{\delta\Omega_L}{\delta p}-\frac{\delta\Omega_L}{\delta s}\frac{\delta s}{\delta p}}{\left(\frac{\delta\Omega_L}{\delta\alpha}-C\frac{\delta\Omega_H}{\delta\alpha}\right)}\right) \tag{2.38}$$
$$=-u''(1-s)\frac{\delta s}{\delta p}-B\frac{\delta\Omega_H}{\delta p}-B\frac{\delta\Omega_H}{\delta s}\frac{\delta s}{\delta p}$$

Multiplying both sides by $\left(\frac{\delta\Omega_L}{\delta\alpha}-C\frac{\delta\Omega_H}{\delta\alpha}\right)$ and rearranging gives:

$$B\frac{\delta\Omega_H}{\delta\alpha}\left(C\frac{\delta\Omega_H}{\delta p}+C\frac{\delta\Omega_H}{\delta s}\frac{\delta s}{\delta p}-\frac{\delta\Omega_L}{\delta p}-\frac{\delta\Omega_L}{\delta s}\frac{\delta s}{\delta p}\right)$$
$$=\left(-u''(1-s)\frac{\delta s}{\delta p}-B\frac{\delta\Omega_H}{\delta p}-B\frac{\delta\Omega_H}{\delta s}\frac{\delta s}{\delta p}\right)\left(\left(\frac{\delta\Omega_L}{\delta\alpha}-C\frac{\delta\Omega_H}{\delta\alpha}\right)\right) \tag{2.39}$$

We can now solve for $\frac{\delta s}{\delta p}$:

$$\frac{\delta s}{\delta p}=\frac{B\left(\frac{\delta\Omega_L}{\delta p}\frac{\delta\Omega_H}{\delta\alpha}-\frac{\delta\Omega_H}{\delta p}\frac{\delta\Omega_L}{\delta\alpha}\right)}{u''(1-s)\left(\frac{\delta\Omega_L}{\delta\alpha}-C\frac{\delta\Omega_H}{\delta\alpha}\right)+B\left(\frac{\delta\Omega_H}{\delta s}\frac{\delta\Omega_L}{\delta\alpha}-\frac{\delta\Omega_H}{\delta\alpha}\frac{\delta\Omega_L}{\delta s}\right)}>0 \tag{2.40}$$

We can verify that $\frac{\delta\Omega_L}{\delta p}$, $\frac{\delta\Omega_H}{\delta p}, \frac{\delta\Omega_L}{\delta\alpha}, B$, $C>0$ and $\frac{\delta\Omega_H}{\delta\alpha}, u''(1-s), \frac{\delta\Omega_H}{\delta s}, \frac{\delta\Omega_L}{\delta s}<0$, given $R_h>R_s>R_l$. Hence, both numerator and denominator are negative and $\frac{\delta s}{\delta p}>0$, which proves Proposition 2.

A higher probability of low income in the second period increases the saving rate out of period-one income and solving this for the first FOC for $\frac{\delta s}{\delta p}$ we obtain:

$$B\cdot\left[\frac{\delta\Omega_H}{\delta p}+\frac{\delta\Omega_H}{\delta s}\frac{\delta s}{\delta p}+\frac{\delta\Omega_H}{\delta\alpha}\frac{\delta\alpha}{\delta p}\right]=-u''(1-s)\frac{\delta s}{\delta p} \tag{2.41}$$

$$\frac{\delta s}{\delta p}=\frac{B\cdot\left[\frac{\delta\Omega_H}{\delta p}+\frac{\delta\Omega_H}{\delta\alpha}\frac{\delta\alpha}{\delta p}\right]}{\left(-u''(1-s)-B\frac{\delta\Omega_H}{\delta s}\right)}$$

and rearranging the other FOC we obtain:

$$\left(C\frac{\delta\Omega_H}{\delta s}-\frac{\delta\Omega_L}{\delta s}\right)\frac{\delta s}{\delta p}=\frac{\delta\Omega_L}{\delta p}-C\frac{\delta\Omega_H}{\delta p}+\left(\frac{\delta\Omega_L}{\delta\alpha}-C\frac{\delta\Omega_H}{\delta\alpha}\right)\frac{\delta\alpha}{\delta p} \tag{2.42}$$

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

Substituting the first FOC and multiplying by$\left(-u''(1-s) - B\frac{\delta\Omega_H}{\delta s}\right)$ we obtain:

$$
\begin{aligned}
&\left(C\frac{\delta\Omega_H}{\delta s} - \frac{\delta\Omega_L}{\delta s}\right)\left(B\cdot\frac{\delta\Omega_H}{\delta p} + B\frac{\delta\Omega_H}{\delta\alpha}\frac{\delta\alpha}{\delta p}\right)\\
&= \left[\frac{\delta\Omega_L}{\delta p} - C\frac{\delta\Omega_H}{\delta p} + \left(\frac{\delta\Omega_L}{\delta\alpha} - C\frac{\delta\Omega_H}{\delta\alpha}\right)\frac{\delta\alpha}{\delta p}\right]\left(-u''(1-s) - B\frac{\delta\Omega_H}{\delta s}\right)
\end{aligned}
\tag{2.43}
$$

Rearranging terms gives:

$$
\begin{aligned}
&B\left(\frac{\delta\Omega_H}{\delta s}\frac{\delta\Omega_L}{\delta p}\right) + u''(1-s)\left(\frac{\delta\Omega_L}{\delta p} - C\frac{\delta\Omega_H}{\delta p}\right)\\
&= \frac{\delta\alpha}{\delta p}\left[u''(1-s)\left(C\frac{\delta\Omega_H}{\delta\alpha} - \frac{\delta\Omega_L}{\delta\alpha}\right) + B\left(\frac{\delta\Omega_L}{\delta s}\frac{\delta\Omega_H}{\delta\alpha} - \frac{\delta\Omega_H}{\delta s}\frac{\delta\Omega_L}{\delta\alpha}\right)\right]
\end{aligned}
\tag{2.44}
$$

Hence,

$$
\frac{B\left(\frac{\delta\Omega_H}{\delta s}\frac{\delta\Omega_L}{\delta p} - \frac{\delta\Omega_H}{\delta p}\frac{\delta\Omega_L}{\delta s}\right) + u''(1-s)\left(\frac{\delta\Omega_L}{\delta p} - C\frac{\delta\Omega_H}{\delta p}\right)}{\left[\underbrace{u''(1-s)\left(C\frac{\delta\Omega_H}{\delta\alpha} - \frac{\delta\Omega_L}{\delta\alpha}\right)}_{+} + \underbrace{B\left(\frac{\delta\Omega_L}{\delta s}\frac{\delta\Omega_H}{\delta\alpha} - \frac{\delta\Omega_H}{\delta s}\frac{\delta\Omega_L}{\delta\alpha}\right)}_{+}\right]} = \frac{\delta\alpha}{\delta p}
\tag{2.45}
$$

At the optimum we know that $\frac{\delta\Omega_L}{\delta p} = C\frac{\delta\Omega_H}{\delta p}$, and we are left to evaluate $\frac{\delta\Omega_H}{\delta s}\frac{\delta\Omega_L}{\delta p} - \frac{\delta\Omega_H}{\delta p}\frac{\delta\Omega_L}{\delta s}$,

Inserting into the expression we have:

$$
\begin{aligned}
&\frac{\delta\Omega_H}{\delta s}\frac{\delta\Omega_L}{\delta p} - \frac{\delta\Omega_H}{\delta p}\frac{\delta\Omega_L}{\delta s}\\
&= \left[(1-p)\cdot u''(c_1^{EH}) + p\cdot u''(c_1^{UH})\right]\cdot(\alpha R_h + (1-\alpha)R)\cdot\left[u'(c_1^{UL}) - u'(c_1^{EL})\right] -\\
&\left[(1-p)\cdot u''(c_1^{EL}) + p\cdot u''(c_1^{UL})\right]\cdot(\alpha R_l + (1-\alpha)R)\cdot\left[u'(c_1^{UH}) - u'(c_1^{EH})\right]
\end{aligned}
\tag{2.46}
$$

We see that both parts of the expression are negative,

$u'(c_1^{UL}) - u'(c_1^{EL}) > u'(c_1^{UH}) - u'(c_1^{EH})$, because of the concavity of the utility function, and the way the consumption states are built up. $(\alpha R_h + (1-\alpha)R) > (\alpha R_l + (1-\alpha)R)$ by definition. Further $0 > (1-p)\cdot u''(c_1^{EH}) + p\cdot u''(c_1^{UH}) > (1-p)\cdot u''(c_1^{EL}) + p\cdot u''(c_1^{UL})$.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

Hence, we have shown that $\frac{\delta\alpha}{\delta p} < 0$, which is Proposition 3. The higher the risk of low income in the next period, the smaller the share of risky financial assets.

Fagereng, Andreas (2012), Three Essays in Household Finance
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Chapter 3

Cash-On-Hand and the Duration of Job Search

With Christoph Basten and Kjetil Telle

3.1 Introduction

Are unemployed households liquidity-constrained, so that they have to accept a job offer earlier than would be optimal? This is the argument implied by Card, Chetty, and Weber (2007a), based on evidence that Austrian job losers eligible for lump-sum severance payments take more time until their next job than do their non-eligible counterparts. Together with Chetty (2008), which shows theoretically how liquidity constraints can affect job search duration and finds longer durations for those with (possibly endogenously) greater financial resources in the United States, this has transformed the unemployment duration literature, which hitherto had assumed that unemployment insurance (UI) prolonged search duration exclusively by distorting the relative price of being unemployed rather than employed ("moral hazard").[1]

Yet two questions remain: First, how generalizable are these findings from Austria and the United States to other countries? The question arises because both countries grant UI only for a relatively short period, maximally 6 months in normal times,[2] and because especially the United States has a more unequal wealth distribution than the majority of OECD economies. Hence, one might think that smaller or no liquidity constraints will

[1] For examples, see Katz and Meyer (1990) or Lalive, Ours, and Zweimueller (2006).

[2] After that period, households can still receive "unemployment assistance", which is however lower and means-tested.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

exist in most other OECD economies. Second, does the reduced-form effect of severance payments indeed reflect liquidity constraints in the sense that households are unable to spend more resources while out of work, or is some alternative mechanism at play? As a possible alternative we suggest *mental accounting*, whereby households do have enough resources of their own, or could borrow them from financial institutions, but after job loss are less willing to spend prior savings than to spend severance pay money.

The present paper addresses both of these questions. First, we investigate whether severance payments prolong job search in Norway, which has one of the world's most generous UI systems, replacing 62% of prior income for up to 2 years, and also has one of the rich world's most equitable wealth distributions. Despite these circumstances, which may be thought to render liquidity constraints less likely, we find clear evidence of a causal severance pay effect. The severance pay amounts to about 1.2 months of net-of-tax median earnings, which allow the job-seeker to "top up" from the 62% replacement rate provided by the UI system to 100% of his prior income for about 3.2 months. These payments are found to increase average non-employment duration by just below a month, and to reduce the fractions re-employed after 12 months by 6 percentage points, which corresponds to a relative reduction of about 10 percent. Thus, severance pay effects do not seem to be specific to countries with relatively short maximum UI durations.

Second, we investigate whether this effect does indeed reflect liquidity constraints, as put forward in Card, Chetty, and Weber (2007a) and Chetty (2008). In particular, we discuss the alternative interpretation of mental accounting in the spirit of Shefrin and Thaler (1988). In this scenario, even households with enough other financial resources prolong their job search only if they receive severance payments, because they hesitate to tap the other resources for the purpose of longer job search. Under the assumption that the strength of potential mental accounting is invariant to prior wealth we can discriminate between the two scenarios, because in a world of liquidity constraints the severance pay effect will clearly be decreasing in prior (liquid) wealth.[3] Since, in contrast to Card, Chetty, and Weber (2007a), we are able to observe various measures of household wealth, we can test this, and we find that the effect is indeed clearly decreasing in prior wealth. In fact, no statistically significant effect is found for those with above-median wealth. This evidence favors an interpretation of the severance pay effect as reflecting liquidity constraints rather than mental accounting.

Our identification exploits the fact that in severance pay agreements concluded between the Confederation of Norwegian Enterprise and the Norwegian Confederation of Trade Unions, only those aged above 50 on the day of their job separation are eligible for payments.

[3] We return to the credibility of this assumption in Section 3.5.

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This allows us to implement a regression discontinuity design (RDD), comparing those aged just above 50 to those aged just below. A number of tests verify that the two groups are statistically identical along the relevant dimensions. Furthermore, the mechanism of the pay-outs, which are made by a joint fund financed by firms in a not experience-rated way, ensures that, as we verify in the data, there is no selective lay-off behavior.

The remainder of the paper is structured as follows: Section 3.2 outlines the Norwegian severance pay program and discusses our empirical strategy. Section 3.3 introduces the data. Section 3.4 presents the general results on the effect of lump-sum severance payments on job search duration, and Section 3.5 addresses theoretically and empirically the possibility of mental accounting behavior. Section 3.6 concludes.

3.2 Empirical Strategy

The challenge in identifying the causal effect of severance payments in most empirical setups is that eligibility or amounts typically depend on factors like age, tenure or prior earnings, which however are likely to be correlated with non-employment duration also through other channels. To address this problem, we exploit a rule under which employees separated from their job just before the age of 50 are not eligible for severance pay, whereas those aged just above 50 are. In the immediate neighborhood of the discontinuity all other factors that might influence our outcomes of interest can be expected to be statistically identical, so that any discontinuity in outcomes can be attributed credibly to the discontinuity in severance pay.

While many firms in Norway have heterogeneous severance pay rules at the firm level, those who are members of Norway's Confederation of Trade Unions, "Landsorganisasjonen i Norge" (LO) and the Confederation of Norwegian Enterprise, "Næringslivets Hovedorganisasjon" (NHO), have agreed on common rules about eligibility and amounts of severance pay ("Sluttvederlag", SLV) paid to employees who are involuntarily separated from their jobs. The LO is Norway's largest and most influential workers' organization, covering about 850,000 Norwegian employees, or one-third of the Norwegian labor force. A key advantage of the LO-NHO agreement for our identification is that actual payments are made not by firms, but by a fund to which firms contribute each month according to their number of full-time employees, and not according to past layoffs. As our sensitivity tests verify, this ensures that there is no manipulation of the threshold in the sense of firms trying to systematically lay off workers just below or just above age 50.[4]

[4]For further information on LO, NHO, and their joint scheme, see http://www.lo-nho-ordningene.no/

Fagereng, Andreas (2012), Three Essays in Household Finance
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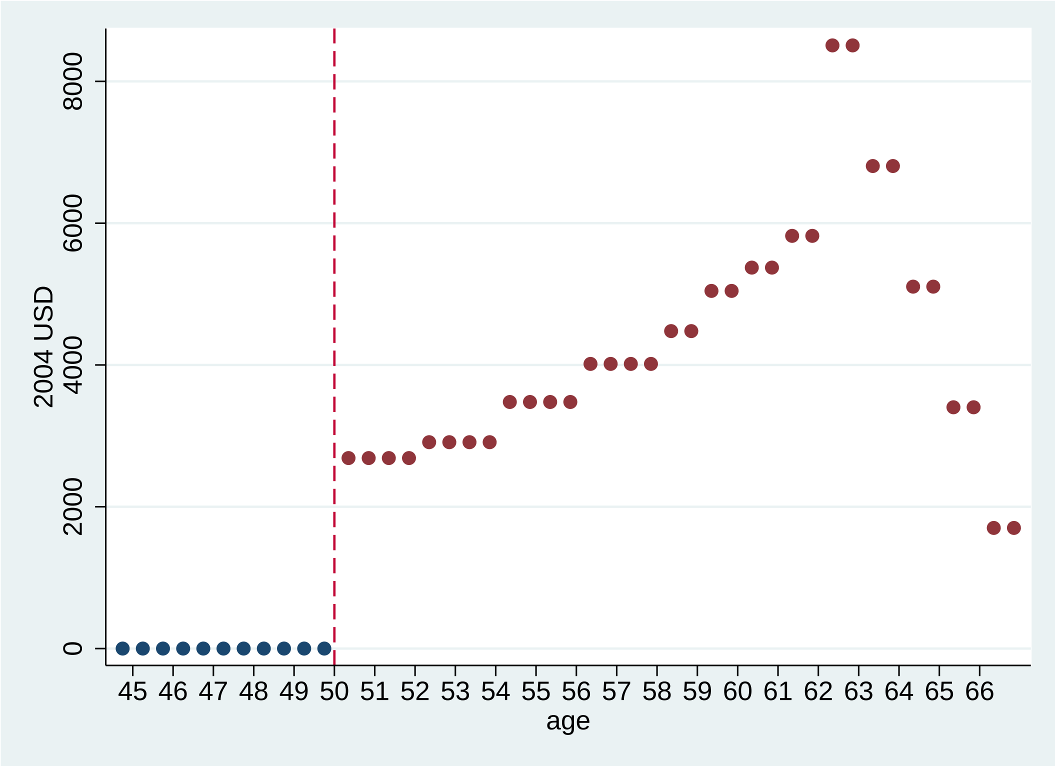

Figure 3.1: **Severance Pay Amounts 2002-2009 In 2004 USD**

For the 15 years for which we have data, 1995-2010, the assigned amount of severance pay varied along three dimensions: By job tenure, by age, and across 4 periods. Firstly individuals were required to have at least 10 years of tenure in their current plant or at least 15 years of tenure in a combination of participating plants. In our data we observe any job start date after 1992. Therefore we know exact tenure for those who started their last job in or after 1992. By contrast for someone who started his last job in, say, 1990 and quit in 1998, we will only know that he must have started before 1992 and hence have at least 8 years of tenure, but we do then not know whether or not his tenure does also exceed the 10 years required for severance pay eligibility. Therefore we are not able to exploit tenure as a RDD assignment variable, and we restrict our sample to those *known* to have had at least 10 years of tenure, so that everyone in our sample did satisfy the tenure requirement for severance pay.

The second dimension and the one we exploit is age. As Figure 3.1 shows, severance pay amounts increased from zero to NOK 18,000 at age 50.[5] This provides a setup for RDD analysis. There are also further increases at ages 52, 54, 56, 58, 59 and 60, as well

[5]At the 2004 exchange rate of 6.7 NOK per USD, this corresponds to about $2,700.

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as annual decreases after age 60. However the other increases until and including the one at age 59 are rather small, and at and above 60 other simultaneous discontinuities apply, in particular in access to early retirement, thus violating the exclusion restriction required for identification. Therefore we restrict our sample to those aged between 48 and 52 on the day of their job separation. Our main estimates do then fully exploit this bandwidth of 2 years per side. Subsequent sensitivity checks show that the results remain robust to using alternative bandwidths, including those declared optimal by the Imbens and Kalyanaraman (2009) algorithm.

Finally, within our period of observation the precise amount paid out at age 50 was adjusted twice. It amounted to NOK 12,000 until September 1995, NOK 14,400 until July 2002, and NOK 18,000 thereafter. Most of our observations come from the last period, and so the average amount individuals in our sample were eligible for if aged above 50 is NOK 16,924 or \$2,500 at 2004 exchange rates.[6]

It is worth noting that these amounts do not depend on prior earnings, so we may expect the same amount to have a larger effect on those with lower previous incomes than on those with higher incomes. Median monthly earnings after taxes (the relevant point of reference, since severance payments are not being taxed) amounted to \$ 2,158 (see Table 3.2), so the payments amounted to about 1.2 monthly after-tax incomes for the median earner. It would thus have allowed him to "top up" from the 62% UI replacement rate to 100% of his former income for about 3 months, and top up to lower replacement rates correspondingly longer.

On those aged between 48 and 52, and known to have had 10 or more years of tenure, we estimate the following equation for different outcome measures y:

$$y_i = \alpha + \beta T_i + \gamma z_i + \delta T_i z_i + \varepsilon_i \tag{3.1}$$

Here T is an indicator for being aged above 50, z is the forcing variable (age-50), and ε is a mean-zero error term. So essentially we estimate the effect of being aged above 50, while controlling for the effect of age *per se*. Since we can make the interval small, we rely on a linear control for age,[7]and we allow the effect of age to differ on the two sides of the discontinuity. The specification does also allow us to add an interaction of T with different measures of wealth when we investigate how the severance pay effect varies with prior wealth. To maximize transparency and facilitate interaction of the treatment indicator

[6]For an overview of the exact severance pay amounts by period and age, see Table 3.1.

[7]Our point estimates change very little if we instead control for age using a second order polynomial.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

with further covariates, our baseline specification uses a rectangular kernel, thus weighting each observation equally. This can be implemented by simply estimating Equation 3.1 by Ordinary Least Squares. The sensitivity checks reveal that our results are robust to the alternative use of a triangular kernel, which assigns greater weight to observations closer to the threshold and which Fan and Gijbels (1996) showed in general to be preferable for RDD purposes.[8]

Table 3.1: Severance Pay Amounts In NOK By Age And Period

Age	Oct 1993-	Oct 1995-	Mar 1998-	Aug 2002-
$\leqslant$ 49	0	0	0	0
50	12,000	14,400	14,400	18,000
51	12,000	14,400	14,400	18,000
52	13,000	15,600	15,600	19,500
53	13,000	15,600	15,600	19,500
54	15,500	18,600	18,600	23,300
55	15,500	18,600	18,600	23,300
56	18,000	21,500	21,500	26,900
57	18,000	21,500	21,500	26,900
58	20,000	24,000	24,000	30,000
59	22,500	27,000	27,000	33,800
60	24,000	28,800	28,800	36,000
61	26,000	31,200	31,200	39,000
62	28,500	34,200	57,000	57,000
63	28,500	34,200	45,600	45,600
64	34,200	34,200	34,200	34,200
65	22,800	22,800	22,800	22,800
66	11,400	11,400	11,400	11,400

Note: The table displays predicted Severance Pay in NOK by age and period, according to the Severance Pay agreements between the Confederation of Norwegian Enterprise (NHO) and the Norwegian Confederation of Trade Unions (LO). For details, see `http://www.sluttvederlag.no/`. For a plot of predicted amounts (in the last period) in 2004 USD, see Figure 3.1.

[8]For background papers on the RDD approach, see Trochim (1984), Lee and Lemieux (2009), Imbens and Lemieux (2008).

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

3.3 Data

We use administrative data from the *FD-Trygd* events database of Statistics Norway, covering the universe of Norwegian residents. We start with information on all job separations by male employees occurring between 1995 and 2010.[9] We then merge in information obtained from the LO-NHO office on which plants were participating in the agreement and restrict to those that were.[10] Furthermore, we add information from *FD-trygd* on exact age at the day of the job separation, and we restrict the main sample to those aged between 48 (inclusive) and 52 (exclusive) on the day of their job separation.

Since we do not explicitly observe which of the job separations are involuntary (another requirement for receiving severance pay), we exclude cases (using information from *FD-Trygd*) in which the job separation is likely to occur because of some other event, after which individuals are likely not to be searching for a new job. These are, first, separators receiving disability pension in the year of their job separation, second, those on parental leave(given the age range of the sample, there are very few), and third, those who start a new job just the day after the separation or return to the same firm within 3 months. All these restrictions will reduce the fraction of voluntary quitters, but they may also introduce bias due to endogenous sample selection. Luckily, however, we find that our point estimates change very little when we lift any or all of these restrictions.

Since severance pay eligibility requires at least 10 years of plant tenure, we restrict the sample accordingly. We drop individuals who started their last job before 1992 (for whom we cannot observe the exact start date) *and* who are separated from it before 2002 since we are unable to know whether their full tenure was above or below 10 years. This reduces the sample size significantly, but it guarantees that everyone in our sample does satisfy the tenure requirement for severance pay, so that the discontinuity at the age threshold reflects as closely as possible the full treatment effect of the payment.

A last restriction from our data is that we do not observe the amounts actually received, as would be necessary to compute the Wald estimate of the effect of actual severance pay on job search duration. Instead, like Card, Chetty, and Weber (2007a), we can only estimate the reduced-form or intention-to-treat (ITT) effect of severance pay eligibility, which constitutes a lower bound on the effect of actual severance pay. But with the other sample restrictions in place, as explained above, and since the claim forms are sent to the LO-NHO office by

[9] We focus on males as even in Norway females earn significantly less than their husbands and they typically work part time.

[10] General employment information is available from 1992 onward, but it is only from 1995 onward that we know plant identifiers.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

the employer together with the layoff notification, we can expect compliance to be rather high, and so our ITT estimates are expected to be not much below the corresponding Wald estimates.

We follow Card, Chetty, and Weber (2007a) in using as outcome variable "non-employment duration", defined as the number of days from layoff until the start of a new job, as opposed to the duration of registered unemployment. Their argument, based on the findings in Card, Chetty, and Weber (2007b), is that people may cease to register as unemployed once their benefit eligibility runs out.[11]

Our first and most natural outcome measure then is the completed duration of job search. One drawback of this measure is that we observe it only for those who start a new job by December 2010. Furthermore, this measure is somewhat sensitive to the choice of the duration after which we censor. Card, Chetty, and Weber (2007a) censor after 6 months, on the grounds that this is the maximum UI duration in their sample. In our case the same argument speaks for censoring after 2 years. However, for someone who has not returned to work after 18 months we do not know whether his complete non-employment duration is 19 months or 24 or 40, yet we *do* know that he was not back in work after 12 months. Therefore, in addition to duration, we also look at three other outcome variables, i.e. the fraction reemployed after 12, 15, and 18 months.[12]

A final data issue to be discussed is the measure of wealth. In view of the previous literature on liquidity constraints of households (Gruber (2001), Chetty and Szeidl (2007)), the most suitable definition of wealth should be financial wealth – including deposits, bonds, stocks and mutual funds, but not real estate – and measured at the household rather than the individual level, i.e. adding in also the wealth, if any, of the spouse. Nonetheless it is conceivable that transaction costs for stocks and bonds are so high that households use only deposits, or that transaction costs for real estate are so low that they can also use their real estate, or that many married individuals keep their budgets sufficiently separate that individual holdings matter more than a household's total holdings. Fortunately, our data set is comprehensive enough that we can use total wealth, financial wealth and deposits alone,

[11]An additional reason in our case is that, as maintained for instance by Bratsberg, Fevang, and Roed (2010), many individuals who would be labelled as unemployed in other countries draw on disability insurance instead of unemployment insurance in Norway. Similar considerations about moral hazard vs. liquidity constraints apply to those on disability pension as to those on regular unemployment insurance (see for instance Autor and Duggan (2007)). In any case, when we perform the analyses excluding any household ever receiving disability pension in our observation window, our main results remain unchanged.

[12]We have also looked at shorter and longer horizons. Effects there go in the same direction, but tend to be smaller. Likely this is the case because at shorter horizons constraints are not yet binding, whereas at longer horizons only a smaller and more selected sample of individuals are still without a job.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

Table 3.2: Summary Statistics, Estimation And Placebo Samples, Age 48-52

	Estimation (N=2,882)			Placebo (N=11,065)		
	Mean	Std Dev	Median	Mean	Std Dev	Median
Year	2,004	4.25	2,005	2,004	4.37	2,004
Age	50.02	1.17	50.02	50.00	1.16	50.00
Tenure (in years)	15.90	5.48	14.20	16.06	5.49	14.52
Dur NonEmpl (in days)	273.77	473.33	63.00	318.09	537.13	95.00
Fraction Re-Employed After (in %):						
12 Months	56.94			53.66		
15 Months	59.92			57.13		
18 Months	62.87			59.99		
Education (in %)						
Less than Highschool	39.3			46.0		
High School	25.2			30.7		
College	35.4			23.3		
Education Main Field (in %)						
General	28.3			33.2		
Humanities	4.4			1.7		
Teaching	5.7			1.3		
Econ/Adm	12.5			9.3		
Science/Eng	33.9			45.4		
Health/Sports	4.2			1.0		
Services	6.1			3.7		
Industry (in %)						
Manufacturing	14.0			32.9		
Construction	8.7			7.9		
Wholesale / Retail	14.8			19.8		
Transport / Communication	10.4			9.8		
Real estate	8.5			10.9		
Public adm / Defense	12.6			0.2		
Education	8.4			1.0		
Health / Social work	6.1			2.4		
Financial Variables (in 2004 USD):						
Annual Earnings	42,671	22,098	37,001	43,109	23,368	37,965
Monthly Earnings After Tax	2,489	1,289	2,158	2,515	1,363	2,215
HH Annual Earnings	56,933	29,282	52,342	58,360	31,274	52,936
Deposits	12,924	28,210	3,349	14,600	30,780	3,611
HH Deposits	17,461	34,343	5,591	19,530	36,489	6,386
Financial Wealth	31,475	90,124	4,686	32,878	83,586	5,869
HH Financial Wealth	39,446	103,107	8,095	41,053	96,484	10,231
Wealth	72,151	117,529	41,962	76,259	113,280	44,633
HH Wealth	88,287	133,935	54,462	93,457	129,952	56,979

Note: This table displays in the left panel summary statistics for the estimation sample of 2,882 households, aged between 48 and 52 and satisfying all the criteria described in Section 3. Additionally, summary statistics for the placebo sample of 11,065 households (satisfying all the same criteria except that the plant of separation was not participating in the severance pay agreements) are displayed in the right panel. For the duration of non-employment, summary statistics are reported for households who have found jobs within the sample window (before 31 Dec 2010). Education Fields and Industries with shares less than 4% are omitted. Financial variables and income are measured two years before the year of job separation and the values are denoted in 2004 USD.

and each of these both at the individual and at the household level, thus allowing us to see how robust findings are to the use of different measures. [13]

Of course how long someone can sustain the household with a given amount of savings will depend on the monthly expenditures such as monthly rent, insurance payments etc, which in turn will largely depend on prior income. On these grounds we have also repeated our analyses using, not absolute wealth, but wealth relative to average income (across 3 years) before the job separation. This yields results similar to those based on absolute wealth.

Table 3.2 shows in the left panel the summary statistics for the sample on which our main results are based, and in the right panel those for a placebo sample – used for some of the sensitivity checks below – subject to all the same constraints but coming from plants not participating in the severance pay agreement. Both samples have mean and median ages of about 50, and tenure of about 16 years at the mean and 14 at the median. Uncensored non-employment duration among those for whom the next job-start is observed in the sample (corresponding figure for the placebo sample in parentheses) is about 9 (10.5) months at the mean and 2 (3) at the median. About 40 (46) percent have less than high-school education, 25 (30) percent have a high school degree, and 35 (23) percent have a college degree. Average annual income before taxes is about US$ 43,000 and household financial wealth about US$ 40,000 at the mean.

3.4 Results

3.4.1 Main Results

Our main results are displayed in Table 3.3. The table reports the coefficients from estimating Equation 3.1 with our baseline bandwidth of 2 years on each side and a simple rectangular kernel, implemented by estimating Equation 3.1 by Ordinary Least Squares. T denotes the indicator for being aged above 50, while z and Tz are the controls for a linear effect of (age-50), allowing it to differ on the left and right side of the discontinuity. To illustrate these regressions graphically, Figure 3.2 plots the average re-employment fraction for each 6-month bin of age against each bin's midpoint, ranging from the age 45 until age 55. We also plot the two separate fitted lines (as provided in Table 3.3) for the sample within 2 years of the threshold at age 50 (along with 90% confidence intervals around this curve).

[13] All wealth measures are recorded at the end of the last calendar year before the one of the job separation. The quality of the real estate values in the data set is highly questionable, and it is thus reassuring that our results do not depend on one particular measure of wealth.

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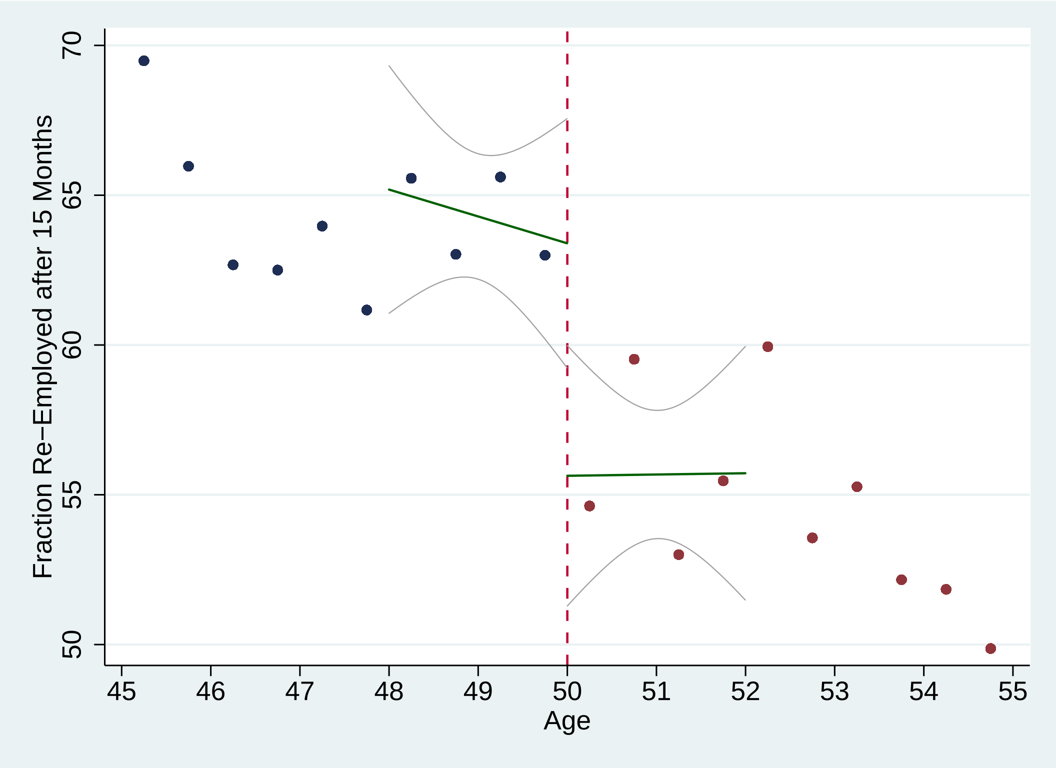

Figure 3.2: **Fraction Re-Employed 15 Months After Job Loss**
Note: The figure plots the fraction re-employed after 15 months by age, in bins averaging over 6 months. In addition fitted linear curves (corresponding to the the estimation of Equation 3.1 as reported in Table 3.3 plus 90% confidence intervals are included for the bandwidth of 2 years around the threshold at age 50.

Looking at the plot for the wider age range (45 to 55) clearly shows the fractions re-employed after different periods are decreasing in age – this confirms the need for a quasi-experiment. Although a lot of noise remains given the limited final sample size, the discontinuity at age 50 is clearly visible. Looking at the estimation results reported in Table 2.3, we find an effect on duration of 28 days or about 1 month, and an effect on the fractions re-employed after 12, 15 and 18 months of respectively 6, 8 and 7 percentage points. The effect on duration is not statistically significant at conventional levels, but those on the different fractions are.

How does the size of the effect compare to the one Card, Chetty, and Weber (2007a) found for Austria? In their case a payment worth 2 months' wages lowered the re-employment probability by 8-12 percent on average over the first 20 weeks after job loss. In our case, a payment worth 1.2 months' wages at the median lowers the re-employment probability by on average 7 percentage points or. This corresponds to a relative decline of about 12%, as the average fraction reemployed after 12 to 18 months is about 0.6 (see Table 3.2). Hence relative

Table 3.3: Baseline Specification, Main Outcomes

	Completed Duration	Fraction Re-Employed After: 12 Months	15 Months	18 Months
T	28.45	-6.20*	-7.76**	-7.06**
	(22.50)	(3.56)	(3.54)	(3.55)
z	14.37	-1.41	-0.90	-2.44
	(13.62)	(2.17)	(2.15)	(2.11)
Tz	-6.06	0.64	0.94	3.31
	(19.69)	(3.16)	(3.12)	(3.07)
Cons	336.24***	59.78***	63.39***	64.80***
	(16.26)	(2.60)	(2.55)	(2.53)
N	2,882	2,882	2,882	2,882

Note: The table provides the regression discontinuity estimates based on Equation 3.1 and using our baseline bandwidth of 2 years on each side. T is the indicator for being aged above 50 and hence eligible for severance pay, z is the age control (age-50) on the left side and Tz allows another age control on the right side of the threshold. The effect on non-employment duration in days is estimated with durations censored after 2 years. Standard errors, clustered by plant, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

to the size of the payment our effects appear somewhat larger. One likely reason for this is the fact that we measure the effect at later points in the spell, where many of the Austrian job losers are presumably already back in a new job. Another is the more generous UI: If households are willing to remain unemployed as long as they can maintain consumption at say 80% of previous income (or any other percentage above the UI replacement rate), then any given severance pay amount will "last longer" the greater the fraction already covered by UI.[14]

3.4.2 Sensitivity Checks

The first possible concern that may arise about the credibility of our estimates is that our controls for the effect of age may not suffice. After all, such an effect is apparent from all

[14]By the Paradigm of Revealed Preferences, the fact that households choose to use some of the severance pay money for longer search durations implies that the availability of the payment makes them better off. To see if the severance pay results in a better subsequent job, we have followed Card, Chetty, and Weber (2007a) and performed the analysis on wage growth from previous to new job. Like them, however, we find no significant effects. Unfortunately, we are not able to analyze duration on the next job (a common measure of non-monetary job satisfaction) as most of the subsequent jobs have only just started by the end of our panel.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

Table 3.4: Placebo Thresholds, Ages 47-51, Employment Fraction Outcomes

	T=47	T=47.5	T=48	T=48.5	T=49	T=49.5	**T=50**	T=50.5	T=51
Completed	-3.04	13.47	-31.42	-0.16	-21.36	32.02	28.45	7.55	9.98
Duration	(22.85)	(21.33)	(22.14)	(22.67)	(23.02)	(22.88)	(22.50)	(23.37)	(22.69)
Fraction Re-Employed	1.47	-2.94	4.59	2.98	1.03	-4.79	-6.20*	-0.56	-3.27
After 12 Months	(3.64)	(3.41)	(3.55)	(3.62)	(3.67)	(3.66)	(3.56)	(3.78)	(3.59)
Fraction Re-Employed	2.69	-1.35	2.67	1.80	1.73	-4.68	-7.76**	-1.06	-1.75
After 15 Months	(3.61)	(3.32)	(3.53)	(3.53)	(3.61)	(3.61)	(3.54)	(3.77)	(3.61)
Fraction Re-Employed	1.99	-2.68	4.26	0.52	0.44	-5.24	-7.06**	-1.35	-0.69
After 18 Months	(3.50)	(3.32)	(3.47)	(3.50)	(3.61)	(3.55)	(3.55)	(3.67)	(3.59)
N	3,019	2,975	2,900	2,876	2,910	2,910	2,882	2,876	2,870

Note: The table provides the regression discontinuity estimates of Equation 3.1 around the true Threshold (T) at age 50, as well as around 8 other placebo thresholds above and below 50. Above we go until age 51, because at 52 there is the next true discontinuity (see Table 3.1). The forcing variable z is defined as 'z = age - placebo threshold', and the baseline bandwidth is 2 years. Standard errors, clustered by plant, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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of the figures and is also reflected in the coefficients on z and Tz in Table 3.3. To test this, Table 3.4 displays the discontinuities in our outcomes of interest for different placebo age thresholds, going in half-year intervals from age 47 all the way until age 51, after which the small discontinuity at 52 will come into play. The table shows that indeed the only age threshold at which we observe significant discontinuities in our outcomes of interest is that at age 50.

Table 3.5: Placebo Plants: Baseline Specification, Main Outcomes

	Completed	Fraction Re-Employed After:		
	Duration	12 Months	15 Months	18 Months
T	-0.11	-0.46	-0.75	-0.80
	(18.16)	(1.89)	(1.86)	(1.86)
z	17.12	-1.39	-1.17	-0.94
	(11.377)	(1.173)	(1.158)	(1.144)
Tz	-9.82	0.39	0.71	0.55
	(16.06)	(1.65)	(1.64)	(1.62)
Constant	479.12***	53.70***	57.15***	60.12***
	(16.11)	(1.54)	(1.51)	(1.48)
N	11,065	11,065	11,065	11,065

Note: This table repeats the main regressions from Table 3.3 for our placebo sample of individuals separated from plants that were not affiliated with LO-NHO and hence did not participate in the severance pay agreements (see Section 3 for details). As before, we estimate Equation 3.1, using our baseline bandwidth of 2 years on each side. T is the indicator for being aged above 50 and hence eligible for severance pay, z is the control for (age-50) on the left side, and Tz allows for another age control on the right side of the threshold. The effect on non-employment duration in days is estimated with durations censored after 2 years. Standard errors, clustered by plant, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The exclusion restriction represents another possible concern. What if other policies that are correlated with non-employment duration do also change at age 50? While there are discontinuities in early retirement access at ages 60 and 62, we are not aware of other policy discontinuities at age 50. One may worry that some policy discontinuities do nonetheless exist. To explore this, we repeat our analysis on a placebo sample of individuals who satisfy all the same requirements as those in our main sample, except that they are separated from plants which were not affiliated with LO-NHO and hence did not participate in the

 DOI: 10.2870/403

severance pay agreements. The results of this test are displayed in Table 3.5. Indeed, no significant effect of being aged above 50 is found here, supporting our findings that the exclusion restriction is satisfied.

Table 3.6: Placebo Outcome Variables, Baseline Specification

	Income HH	Wealth HH	Fin Wealth HH	Deposits HH	Second. Edu.
T	-9,945	-39,459	-28,811	-3,745	0.032
	(6,501)	(55,769)	(71,124)	(3,928)	(0.038)
z	4,574	26,319	36,890	1,121	-0.052**
	(4,715)	(23,632)	(26,166)	(2,490)	(0.023)
Tz	-2,629	-20,840	-51,951	2,056	0.014
	(4,920)	(37,716)	(41,778)	(3,422)	(0.033)
Constant	65,799***	155,278***	123,604***	20,529***	0.516***
	(6,323)	(36,100)	(41,607)	(3,155)	(0.028)
N	2,692	2,692	2,692	2,692	2,701

Note: This table repeats the main regressions from Table 3.3 for a set of outcomes that should not exhibit discontinuities at age 50. Displayed are annual income, total wealth, financial wealth and deposits, all at the household level, as well as an indicator for whether the household has completed high school or a higher degree. Results for financial variables at the individual level or other education categories are not displayed, but do not show discontinuities either. As before, we estimate Equation 3.1, using our baseline bandwidth of 2 years on each side. T is the indicator for being aged above 50 and hence eligible for severance pay, z is the control for (age-50) on the left side, and Tz allows for another age control on the right side of the threshold. The effect on non-employment duration in days is estimated with durations censored after 2 years. Standard errors, clustered by plant, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. An estimation of the density of observations, following McCrary (2008), yields a coefficient of -0.018 and a standard error of 0.134, thus failing to reject the null hypothesis of no difference in densities.

As in any RDD, we need to explore whether there could have been selection around the threshold. As mentioned above, severance payments under the LO-NHO agreement are made by a joint fund and financed in a not experience-related way, thus alleviating concerns that firms might choose to lay off (a selected group of) individuals just before they turn 50. By contrast the fund has an incentive to ensure that firms and employees do not collude to systematically postpone layoffs until after age 50, but how well does it enforce this in practice? A first check is to test for discontinuities at the threshold in the density of observations, following McCrary (2008). In the present case, this test yields a coefficient for the log difference in density of -0.018, with a standard error of .134, so we fail to reject the null hypothesis of no difference. While this suggest that there is no systematic selection of the number of individuals to either side of the threshold, one may still worry that the individuals on each side differ in type. To check this, Table 3.6 reports the results of repeating

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

our main regressions on a set of variables of which the values should be predetermined at the time of the job separation. Here we look in particular at the financial variables also used to investigate the plausibility of the liquidity constraints explanation, as well as an indicator for secondary or higher education (other education categories were also tried and yielded similar results). These analyses, using the exact same methodology as for our main outcome variables, does not reveal any discontinuities at the age 50 threshold. They thus lend further support to the view that our main findings can be given a causal interpretation.

Table 3.7: Alternative Optimal Bandwidths: Main Outcomes

	Completed	Fraction Re-Employed After		
Rectangular Kernel:	Duration	12 Months	15 Months	18 Months
Optimal Bandwidth	37.09**	-7.06**	-8.48***	-7.72***
	(18.65)	(2.99)	(3.02)	(2.78)
N	4,391	4,367	4,352	4,796
0.5*Opt Bw	40.58	-7.17*	-7.83*	-5.71
	(26.51)	(4.19)	(4.20)	(4.01)
N	2,172	2,153	2,146	2,363
Optimal Bandwidth	3.02	3.00	2.99	3.32
Triangular Kernel:				
Optimal Bandwidth	39.12**	-7.56***	-8.50***	-7.65***
	(18.05)	(2.88)	(2.88)	(2.70)
N	5,594	5,530	5,456	6,184
0.5* Opt Bw	29.27	-6.53	-7.43*	-6.37*
	(25.62)	(4.06)	(4.09)	(3.84)
N	2747	2725	2,684	3037
Optimal Bandwidth	3.85	3.81	3.76	4.23

Note: This table displays only the coefficients, and in parentheses the standard errors clustered by plant, on being aged above 50, now for different bandwidths and kernels. The top panel follows our main estimates in using a rectangular kernel, with equal weighting of observations. The bottom panel uses a triangular kernel, putting greater weight on observations closer to the threshold. Within each panel, we display first the estimates based on the Imbens and Kalyanaraman (2009) optimal bandwidth and then those based on half the optimal bandwidth. The respective optimum bandwidth itself is displayed at the bottom of each panel. Stars denote statistical significance as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Another concern that always arises in a RDD is how sensitive the results are to the choice of different bandwidths or kernels. In general the trade-off is between limited precision at

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very narrow bandwidths and potential bias at too wide bandwidths. Our default choice of 2 years on each side has been motivated by choosing the widest-possible bandwidth under which our estimates do not get biased by effects of the next, albeit small, discontinuity in severance pay amounts at age 52 (cf. Figure 3.1). This choice yields a relatively narrow range (and correspondingly limited precision) compared to previous papers in the literature. Card, Chetty, and Weber (2007a), for instance, choose a bandwidth of 3 years per side. This said, Table 3.7 displays the results of varying the bandwidth. The four columns show these for the same four outcomes (completed duration, and fractions re-employed after 12, 15 and 18 months). The top panel provides the results from varying the bandwidth but keeping the rectangular kernel. The bottom panel provides results using a triangular kernel. In both panels we show first the results obtained under the Imbens and Kalyanaraman (2009) "optimal bandwidth", which varies a bit across outcome variables, but is around 3 years in the top and around 4 years in the bottom panel. Then we show results obtained when using half the optimal bandwidth. The point estimates are slightly larger than with our conservative 2-year bandwidth choice and are also somewhat more significant (this added significance might be related to the small next policy discontinuity at age 52). We see these results as confirming our main results.

3.5 Liquidity Constraints vs. Mental Accounting

In the previous section we have shown that the causal effect of lump-sum severance payments on job search duration which Card, Chetty, and Weber (2007a) found for Austria is also present in Norway, making it plausible that the finding applies also to other OECD economies. But given that Norway has both a more egalitarian wealth distribution and a more generous welfare state than for instance Austria or the United States, the question arises whether the severance pay effect does indeed reflect liquidity constraints, or whether it could reflect another mechanism. In particular, it is conceivable that households who could financially afford longer search durations also absent the severance payments would nonetheless be unwilling to do so (and hence respond to severance payments) because they have "earmarked" their savings for other purposes.[15]

Such behavior could be interpreted as an instance of mental accounting in the spirit of Shefrin and Thaler (1988). There individuals behave *as if* there coexisted two selves: A

[15] Furthermore, Basten, Fagereng, and Telle (2012b) find that some Norwegian households do indeed prepare for unemployment by increasing their savings rate in the years before job loss, although the use of these savings after job loss is rather limited.

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myopic "doer self" concerned only with the current period, and a "planner self" concerned with maximizing a function of lifetime doer utilities. If the choices of consumption each period were left to the "doer self", too much would be consumed in early periods, leading to a sub-optimal lifetime path of consumption. Restricting current consumption to a level below what is available in any given period however costs willpower. To address this problem, the "planner self" is then assumed to place constraints on future consumption choices already in advance, either through external commitment devices like pension plans or internal ones like rules-of-thumb. One such rule is mental accounting: Rather than considering all money as fungible, households mentally assign all funds to different "Mental Accounts". The simplest version contains one account for "Current Income" (C), one for "Current Assets" (A) and one for "Future Income" (F). The rule-of-thumb then has the marginal propensity to consume (MPC) – the fraction of each additional dollar consumed right away – be highest for money classified as "Current Income", lower for "Assets", and lowest for "Future Income".[16] In the words of Shefrin and Thaler (1988), "households treat components of their wealth as non-fungible, even in the absence of credit rationing" (p. 609). There are important parallels between mental accounting and standard liquidity constraints. In both cases households would have the necessary (lifetime) wealth to increase spending now, yet cannot do so because the wealth is not available at that specific point in time or for that specific purpose. The difference is first, that mental accounting arises through constraints that are internal rather than external, and second, that – given the individual's temptation to spend excessively absent any commitment devices – the internal constraints can be optimal as a second-best solution. Such mental accounting could be relevant also in the present context of job loss and severance payments, because such payments, received when households lose their jobs and see regular income drop, would likely be classified as "Current Income" and thus attract a higher marginal propensity to consume than prior savings.

So if the severance pay effect identified above could also reflect mental accounting rather than liquidity constraints, it is worthwhile to investigate which interpretation finds greater support in the data. To do so, we make use of our information on prior wealth. Clearly, if the correct interpretation is one of liquidity constraints, then the same payment should have a smaller effect on those with higher prior wealth than on those with lower prior wealth. We can exploit this fact to discriminate between liquidity constraints and mental accounting

[16] In practice, households are likely to have more than just those three accounts, and different households will have different accounts. Furthermore, exactly which consumption choices this classification results in will depend on the exact "framing", i.e. on which categories each account is defined to include and over which horizon each account is to be balanced. This categorization into three main accounts however is thought to be a good first approximation for the average household.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

if and only if plausibly the degree of mental accounting does not covary with wealth. It is however conceivable that education or some personality trait correlated with education, such as discipline, will affect both the degree of mental accounting and the amount of prior wealth held on the day of the job separation. However, none of our results do significantly change when we control for different measures of education.[17] This suggests that plausibly the severance pay effect should be invariant to prior wealth under mental accounting, and that hence any such variation would speak in favor of liquidity constraints.

Table 3.8: Stratifying By Continuous Wealth Measures (W)

		Income	Wealth	Fin Wealth	Deposits
Completed	T	38.84	41.69	43.12	39.39
Duration		(34.06)	(34.13)	(34.02)	(34.05)
	T*W	-80.18	-53.81	-40.94	44.20
		(52.90)	(93.96)	(95.83)	(33.85)
Re-Employed After	T	-5.96	-6.04*	-5.96	-5.84
12 Months:		(3.63)	(3.62)	(3.62)	(3.63)
	T*W	2.90	6.56**	11.89***	-3.65
		(5.06)	(2.68)	(3.60)	(3.29)
Re-Employed After	T	-7.38**	-7.53**	-7.47**	-7.32**
15 Months:		(3.66)	(3.65)	(3.65)	(3.66)
	T*W	4.97	7.16***	11.56***	-2.68
		(5.29)	(2.52)	(3.87)	(3.31)
Re-Employed After	T	-7.07*	-7.24**	-7.17**	-7.03*
18 Months:		(3.62)	(3.60)	(3.60)	(3.61)
	T*W	6.69	7.37***	12.39***	-1.85
		(5.07)	(2.54)	(3.88)	(3.40)
N		2,692	2,692	2,692	2,692

Note: This table provides the regression discontinuity estimates of Equation 3.1, augmented by continuous measures of wealth and income (deflated to 2004 values), as well as their interaction with each of the other regressors. Each column uses a different income or wealth measure as indicated. The top panel uses as outcome variable non-employment duration in days, the following ones use the fraction re-employed after respectively 12, 15 and 18 months. Standard errors, clustered by plant, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[17] Moreover, further results suggest that the size of the severance pay effect does not vary across individuals holding and not holding a university degree.

Fagereng, Andreas (2012), Three Essays in Household Finance
European University Institute DOI: 10.2870/403

Table 3.9: Stratifying By Wealth Measures: Above Median (D)

		Income	Wealth	Fin Wealth	Deposits
Completed Duration	T	78.15	58.48	115.09**	125.46**
		(47.54)	(47.28)	(49.41)	(49.60)
	T*D	-79.78	-38.19	-146.10**	-164.79**
		(69.50)	(68.49)	(72.55)	(71.78)
	T + T*D	-1.64	20.28	-31.01	-39.33
	Prob > F(1,2684)	0.97	0.68	0.53	0.42
Re-Employed After 12 Months:	T	-9.71*	-8.25	-14.95***	-15.87***
		(5.40)	(5.45)	(5.39)	(5.41)
	T*D	7.87	4.95	18.04**	19.84***
		(7.64)	(7.65)	(7.63)	(7.63)
	T + T*D	-1.83	-3.29	3.09	3.98
	Prob > F(1,2684)	0.73	0.54	0.57	0.46
Re-Employed After 15 Months:	T	-12.20**	-9.35*	-15.09***	-16.41***
		(5.34)	(5.40)	(5.36)	(5.38)
	T*D	9.85	4.16	15.50**	17.88**
		(7.56)	(7.57)	(7.56)	(7.55)
	T + T*D	-2.34	-5.19	0.41	1.46
	Prob > F(1,2684)	0.66	0.33	0.94	0.78
Re-Employed After 18 Months:	T	-12.73**	-9.95*	-15.40***	-16.51***
		(5.26)	(5.32)	(5.30)	(5.32)
	T*D	11.50	5.95	16.64**	18.58**
		(7.46)	(7.48)	(7.47)	(7.46)
	T + T*D	-1.22	-4.01	1.23	2.07
	Prob > F(1,2684)	0.82	0.45	0.81	0.69
	N	2,692	2,692	2,692	2,692

Note: This table provides the regression discontinuity estimates of Equation 3.1, augmented by an indicator variable for whether the value of different income and wealth measures (all deflated to 2004 values) exceeds the sample median, as well as interactions between that indicator and the other regressors. Standard errors, clustered by plant, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table does also provide the sum of the coefficient on being above the threshold and the coefficient on the interaction of the threshold dummy with the dummy for income or wealth above the median. The p-value for the F-test with the null hypothesis that this sum is zero is reported in the line below. None of these 16 tests rejects this Null at the 10% level.

To proceed with our test, Table 3.8 augments the baseline regressions from Table 3.1 with continuous measures of income (column 1), total wealth (financial wealth plus real estate;

 DOI: 10.2870/403

column 2), financial wealth (column 3) and deposits (column 4) – all measured prior to the job separation. We find that the effect on all 3 re-employment fractions is clearly decreasing in both total and financial wealth, whereas the interaction with deposits is not statistically significant.[18] In Table 3.9 we interact instead with indicators for whether someone's value of the different wealth measures exceeds the respective sample median. The table displays for each outcome variable and each interaction variable the main effect, T, which is now the effect for only those below the median, then the coefficient on the interaction between T and the dummy for being above the median, and finally the sum of those two. Consistent with the results from the interactions with the continuous measures, we find that the effect is always smaller for those above than for those below the median and in fact we always fail to reject at the 90% confidence level the hypothesis that the effect is zero for those above the median. These results do lend additional support to the view expressed in Card, Chetty, and Weber (2007a) that the severance pay effect should indeed be interpreted as evidence of liquidity constraints.

3.6 Conclusion

We have documented a causal effect of lump-sum severance payments on the duration of job search in Norway. To our knowledge, this is only the second paper in the literature to find such an effect (after Card, Chetty, and Weber (2007a)), and the first to find it in a Scandinavian-type welfare state. This makes it likely that such effects hold also in other OECD economies. But given that Norway has both a more egalitarian wealth distribution and a more generous welfare state than for instance Austria or the United States, the question arises whether the severance pay effect does indeed reflect liquidity constraints, or whether it could reflect another mechanism. In particular, it is conceivable that households who could financially afford longer search durations also absent the severance payments would nonetheless be unwilling to do so (and hence respond to severance payments) because they have "earmarked" their savings for other purposes. We have therefore proceeded to discuss whether the severance pay effect should indeed be interpreted as evidence of liquidity constraints, as in the previous literature, or alternatively as evidence of mental accounting behavior. To discriminate empirically between the two scenarios, we have investigated how the size of the severance pay effect varies with prior wealth and find it to be decreasing

[18] The fact that we find significant interaction effects for total and financial wealth, but not for deposits (which account for only a limited fraction of households' assets) suggests that assets other than deposits either are not as illiquid for our sample as one might have thought, or that those households who do have them are able to borrow against them.

 DOI: 10.2870/403

therein. This lends additional support to the view expressed by Card, Chetty, and Weber (2007a) that the observed severance pay effect does indeed reflect liquidity constraints. The implication of this finding is that in most OECD economies there exists a subset of job losers who, with no or insufficiently generous unemployment insurance, have to accept a new job offer earlier than would be optimal. An efficient way to improve their situation would be to lend them additional resources, as this policy response would not come at the cost of increased moral hazard. Where such lending is not possible, for instance for political reasons, the choice of the optimal generosity of unemployment insurance must still weigh the effects of the liquidity constraints against those of potential moral hazard.

Fagereng, Andreas (2012), Three Essays in Household Finance
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