
The Happy household investor

The impact of happiness on household stock market participation and portfolio risky shares

Ellinor Lindstén*

ABSTRACT

The research on happiness and its impacts on risk-taking in the form of stock market participation has attracted interest in recent years. Yet, what the actual impact is remains unclear. Several studies find statistically significant correlations between happiness and stock market participation as well as the risky share, but the direction of the correlations is sometimes found to be positive, and sometimes negative. Moreover, while some evidence pointing to a causal relationship between short-term happiness and risk-taking has been provided, evidence for such a relationship between long-term happiness and risk-taking remains to be found. In this study, I provide further color on the relationship between happiness and stock market participation as well as the risky share. Firstly, using static OLS regression models, I show that investors that report being either “unhappy” or “very unhappy” are more likely to participate in the stock market, but also have a lower risky share. In the context of happiness and financial investments, this is to the best of my knowledge the first study to show that happiness, or rather unhappiness, has a complex association with risk-taking, neither only encouraging nor only discouraging it. Secondly, using dynamic OLS regression models, I show that experiencing a reduction in long-term happiness is associated with a smaller increase in the risky share, as compared to experiencing an increase or reporting the same level of happiness in two consecutive years. Future research could aim at analyzing whether this is due to decreasing happiness being associated with increased risk aversion, increased passiveness, or something else.

*23530@student.hhs.se

Master Thesis in Finance

Supervisor: Professor Paolo Sodini, Department of Finance, Stockholm School of Economics

Keywords: Stock market participation, Risky share, Happiness, DNB Household survey,

Acknowledgements: I would like to thank my supervisor Professor Paolo Sodini for his support and guidance throughout the process of this thesis.

In this paper, use is made of data of the DNB Household Survey. I would like to thank CentERdata for the provision of the dataset.

Table of Contents

1.	Introduction.....	2
2.	Literature review.....	4
2.1	Economic framework: Classical portfolio choice theory	4
2.2	Household and individual characteristics with an impact on stock market participation and the risky share	6
2.2.1 .	Characteristics related to household sophistication.....	6
2.2.2 .	Characteristics related to background risk or labor risk	7
2.2.3 .	Socio-cultural characteristics.....	8
2.2.4 .	Characteristics related to beliefs, emotions, and moods.....	8
3.	Research question and hypotheses	10
4.	The Dutch National Bank Household Survey	11
4.1	Data	11
4.2	Variable selection and definitions	12
4.2.1 .	Dependent variables	12
4.2.2 .	Independent variables of interest.....	13
4.2.3 .	Other independent variables	14
4.3	Distribution of data, all respondents.....	15
4.4	Variable transformation.....	16
5.	Empirical methodology.....	17
5.1	Testing hypothesis 1	17
5.2	Testing hypothesis 2	18
6.	Results.....	21
6.1	Descriptive statistics.....	21
6.2	Static regression results	25
6.2.1 .	Stock market participation.....	25
6.2.2 .	Risky share	27
6.3	Dynamic regression results.....	29
6.3.1 .	Stock market participation.....	29
6.3.2 .	Risky share	31
7.	Discussion and limitations	34
7.1	Discussion	34
7.2	Limitations.....	35
8.	Conclusions.....	37
9.	References.....	39
	Appendix A.....	42
	Appendix B	44
	Appendix C	45

1. Introduction

Households and individuals have a wide array of choices to make when it comes to asset allocation – now more so than ever. There are an increasing number of financial products and services to choose from, and the decision-making responsibility for financial allocation of e.g. pension savings is shifting from government and employers making most decisions to the individual. With the increased decision-power it is of high importance that individuals understand the choices they have to make and the implications of those choices, as allocating assets in a sub-optimal manner can lead to significant return losses. One of the most common investment mistakes by households is the non-participation in risky financial markets (Campbell, 2006). In the Netherlands less than a quarter of all households participate in risky financial markets through ownership of stocks or mutual funds (Van Rooij et al., 2011), and in some countries including Spain and Italy, less than ten percent of households are participants (Guiso and Sodini, 2013).

The low degree of stock market participation is a true puzzle in standard financial theory with investors exhibiting expected utility preferences. Under such preferences, some stock ownership is always optimal assuming a positive equity premium (Haliassos and Bertaut, 1995), and expected utility preferences further cannot explain the large heterogeneity in the risky share that is observed in the portfolios of households. In the field of household finance, households' asset allocation and the puzzles related to those allocations are investigated, providing further color on the non-participation in risky financial markets and the heterogeneity in portfolio risky shares. It is well-documented that there are both financial, demographic and socio-cultural household characteristics that are associated with higher or lower participation rates and/or higher or lower risky shares. Research on the connection between household asset allocations and beliefs, affects, moods, and emotions has gained popularity in recent years. For example, Delis and Mylonidis (2015) find that happy people are less likely to participate in stock markets after controlling for trust, which has a positive correlation with happiness and a positive impact on participation, and Guven and Hoxha (2015) show that changes to short-term happiness (short-term being happiness today, a relatively fast-moving measurement) impacts risk preferences, with people preferring safer investments when short-term happiness is higher. On the other hand, Kamstra et al. (2003) show that seasonal affective disorder, a depressed mood felt by many when the hours of daylight are few, leads to a lower demand for risky assets. Consistent with this, Rao et al. (2016) find that happy households are more likely to participate in the stock market than unhappy households, and that their risky share conditional on participation tends to be higher. While both Kamstra et al. (2003) and Guven and Hoxha (2015) provide some evidence for a causal link between short-term happiness and risk taking in financial decisions, the evidence points in different directions. Moreover, no causality has to the best of my knowledge been documented for long-term happiness, which is a relatively slow-moving measurement. As mentioned by Lane (2017), neither the consequences nor the effects of short- and long-term happiness are necessarily the same.

In this paper, I use survey data from the Dutch Household Survey (DHS), an extensive panel data set provided by CentERdata, allowing me to analyze asset holdings simultaneously with elicited variables that are observable in a survey setting, such as happiness. In the first part of my analysis, I investigate how a long-term measurement of happiness correlates with stock market participation and the risky share, defined as the share of stocks and mutual funds within a household's liquid financial portfolio, after controlling for a set of financial and demographic characteristics. My findings suggest that it is unhappy investors that differ from others rather than happy investors, with those reporting being "unhappy" or "very unhappy" being more likely to participate in stock markets, while no statistically significant difference for stock market participation is found between those who report being "neither happy nor unhappy", "happy", or "very happy". Similarly, my results suggest that the risky share, conditional on participation, for those that report being "unhappy" or "very unhappy" is lower than the risky share of others with higher levels of happiness. Although recognizing that the results in the first part of my analysis only describe correlations, they indicate that the impact of happiness (or rather, unhappiness) on risk-taking is different for participation than it is for the risky share.

In the second part of my analysis, I investigate whether the investment behavior differs between investors at different happiness levels, which would suggest more than a correlation between happiness and stock market participation and/or the risky share. I use a dynamic regression for the change in stock market participation and the change in the risky share, respectively, between one year and the next, with both the happiness level in the beginning of that period (the former year), and the change in happiness between those years as regressors, and control for both levels and changes in a number of financial and demographic characteristics. I find no statistically significant impact on the change in participation for any level of happiness, and cannot rule out that people at any level of happiness enter and exit the stock market at the same rate. I also do not find any statistically significant impact of the change in happiness on the change in stock market participation. For the change in the risky share, I likewise cannot rule out that people at any level of happiness behave the same. However, my results indicate that those who experience a decrease in their self-reported, long-term measurement of happiness over the year, increase their risky share relatively less, or equivalently decrease their risky share relatively more, than those that experience an increase or report the same level of happiness. This difference in behavior remains statistically significant even after controlling for periods when the stock market performed badly, suggesting that there could be a link stronger than a correlation between the evolution of long-term happiness and how investors update their risky share. However, my analysis does not differentiate between changes in risk preferences and changes in how actively the portfolio is rebalanced, and it remains an open question in this context if a decrease in happiness is associated with a shift to a preference for safer assets, or a shift to a higher degree of

passiveness. I would recommend further research on the topic before drawing any conclusion on the impact of a decrease in happiness on risk preferences.

2. Literature review

2.1 Economic framework: Classical portfolio choice theory

In a simple two-period model of portfolio choice, the household investor maximizes expected utility by selecting a set of risky assets and a set of non-risky assets. The investor's budget constraint can be written:

$$\tilde{W}_i = W_{i0}\{1 + r_f + \alpha_i E[r_m - r_f]\} \quad (1)$$

Where $\tilde{W}_i$ is the end-of-period wealth of investor i , W_{i0} is the initial wealth of investor i , α_i is the share of wealth that the investor invests in risky assets, r_f is the riskfree rate, and r_m is the return of the risky assets in the portfolio. The utility of $\tilde{W}_i$ can equally be expressed as:

$$E[U(\tilde{W}_i)] = U(W_{i0}) + U'(W_{i0})W_{i0}\{r_f + \alpha_i E[r_m - r_f]\} + \frac{1}{2}U''(W_{i0})\alpha_i^2\sigma_m^2 \quad (2)$$

Where σ_m^2 is the variance of the return of investors i 's portfolio of risky assets. Maximizing $U(\tilde{W}_i)$ with respect to α_i yields:

$$U'(W_{i0})W_{i0}E[r_m - r_f] + U''(W_{i0})W_{i0}^2\alpha_i\sigma_m^2 = 0 \quad (3)$$

The Pratt measure of relative risk aversion, here expressed as γ_i , is derived from the utility function, and can be defined as:

$$\gamma_i = W_{i0} \left[-U''(W_{i0}) \frac{1}{U'(W_{i0})} \right] \quad (4)$$

Note that the Pratt measure of risk aversion is different from subjective risk aversion. Plugging (4) into (3) and solving for α_i yields an optimal risky share of:

$$\alpha_i = \frac{1}{\gamma_i} \frac{E[r_m - r_f]}{\sigma_m^2} \quad (5)$$

Thus, the optimal risky share in this simple model is determined only by the investor's risk aversion, the expected excess return of the risky asset, and the volatility of the risky asset. However, this model is too simplistic to capture the reality, being the high rates of non-participation in risky financial markets. As pointed out by Haliassos and Bertaut (1995), it is sufficient that the equity premium is positive for the optimal portfolio to become one with some quantity of risky assets, for investors with any level of risk aversion allowed under expected utility preferences. The only possibility for this model to capture non-participation in stock markets as an optimal outcome is that investors are exposed to risks to income streams which are correlated with stock returns, such as labor and income risk or background risk. As no correlations strong enough to motivate the non-participation are observed (Heaton and Lucas, 2000), the model seemingly lacks important nuances.

Moreover, faced with the same opportunity set, having the same information and rational expectations, and assuming that labor and background risk is uncorrelated with stock returns, at a given point in time investors' risky shares can only be heterogenous due to differences in risk aversion. If risk aversion is the only parameter that can lead to the heterogeneity that is observed, the risk aversion parameter must be able to range from very small to very large values, which are unreasonably high. This is the case even if labor risk and income risk are somewhat correlated with stock returns.

A variety of explanations have been put forward for non-participation and the highly heterogenous risky share, including other utility functions, fixed costs, and individual preferences. For example, if participation in stock markets is associated with a fixed cost (for example for learning how to trade), that could render it sub-optimal for rational investors with low wealth to participate (Vissing-Jorgensen, 2004). But fixed costs cannot explain the non-participation of wealthy households and can thus not be the entire explanation. In household finance the possibility is often explored that individual preferences differ structurally, reflecting socioeconomic characteristics, and that those differences partly account for the heterogenous asset allocation. The case of individual preferences differs from the fixed costs explanation as it does not assume the actual value of net stock returns to be different at different levels of wealth or other characteristics, but rather a bias in the preference for relative risk within the financial portfolio. Naturally, these preferences do not have to be consciously known by the investor; the term preference rather refers to observed outcomes. In order to analyze characteristics which potentially have an impact on stock market participation, the following generic expression is commonly used (see for example van Rooij et al., 2011):

$$P(participation)_{it} = \beta_0 + \beta_1(I_{it}) + \beta_2X_{it} + u_h + v_{it} \quad (6)$$

Where $P(participation)_{it}$ denotes the probability of stock market participation for investor i at time t , and depends on a variable of interest (I), a set of individual or household control characteristics (vector X), time-invariant heterogeneity in preferences which is unobserved (u_h), and a random disturbance term (v_{it}) which should not be correlated with any of the other terms. The equivalent expression for the risky share can be written as:

$$\alpha_{it} = \beta_0 + \beta_1(I_{it}) + \beta_2 X_{it} + u_h + v_{it} \quad (7)$$

The following sections give an overview of household characteristics which have been found to have an impact either on the likelihood of participation in stock markets, or the risky share.

2.2 Household and individual characteristics with an impact on stock market participation and the risky share

2.2.1 Characteristics related to household sophistication

Characteristics related to household sophistication, such as wealth, income, liabilities, or education, are generally found to be positively associated with stock market participation and the risky share. Two potential explanations, fixed costs and individual preferences differing structurally within different characteristics, have been presented in section 2.1 in this paper. In particular, the impact of wealth on participation and the risky share in the cross section is relatively well-known. Households with higher wealth are more likely to participate in stock markets and generally have a higher risky share. For example, Haliassos and Bertaut (1995), Mankiw and Zeldes (1991), Vissing-Jorgensen (2004), Calvet et al. (2007), and van Rooij et al. (2011) find higher wealth to be associated with higher likelihood to participate in stock markets. Higher financial wealth is generally associated also with a substantially higher risky share (Carroll, 2000, Calvet et al., 2007, Calvet and Sodini, 2014, Chiappori and Paiella, 2011). Other than financial wealth, real estate wealth, income, liabilities, and education have been found to be associated with higher participation in risky financial markets (Haliassos and Bertaut, 1995, Calvet et al., 2007). Education has further been found to be positively associated with the risky share of households (Calvet et al., 2007). Van Rooij et al. (2011) find the same relationship with participation for income and education, using Dutch data, and further show that investors with low financial literacy are much less likely to invest in the stock market. The impact of financial literacy on stock market participation is likewise documented by Almenberg and Dreber (2015).

With regards to financial characteristics an important distinguishment needs to be made between static results, and dynamic results. While the impact of financial wealth is well-documented in the cross

section and in static panel data models, it's impact in dynamic panel data models is debated. In other words, it remains unclear whether an increase in financial wealth is associated with increased risk-taking with regards to financial investments, as would be the case under decreasing relative risk aversion, or if such risk-taking is constant within investors at all levels of financial wealth. The former case is documented by for example Calvet et al. (2009) and Calvet and Sodini (2014) and supports the theory of decreasing relative risk aversion. The latter case is documented by for example Brunnermeier and Nagel (2008) and Chiappori and Paiella (2011). The dynamic regression model can be achieved by taking the first difference of equation (7), with wealth being the variable of interest:

$$\Delta\alpha_{it} = \beta_1\Delta(W_{it}) + \beta_2\Delta X_{it} + \Delta v_{it} \quad (8)$$

Where $\Delta\alpha_{it} = \alpha_{it} - \alpha_{it-1}$, $\Delta W_{it} = W_{it} - W_{it-1}$ and so forth.

2.2.2 Characteristics related to background risk or labor risk

Another category of characteristics which has been shown to impact the participation in risky financial markets is background risk or income risk. Background or labor risk can render household income or expenses volatile, in a way that makes the households prefer safe investments over risky investments. In equation 5 labor or background risk can be thought of as a positive variance-covariance matrix if the risk exposes cash inflows with a positive correlation with stock returns, or equivalently cash outflows negatively correlated with stock returns. Alternatively, it can be thought of as households perceiving such correlations, even if they are not actually observed, and that their preference therefore tilts toward less risky assets. Household background risk can be high due to several things. For example, one or several adults in the household may hold high-risk occupations where the risk of losing one's job is relatively high. Haliassos and Bertaut (1995) find that those with high-risk occupations are less likely to participate in stock markets, and Calvet and Sodini (2014) find that income risk has a negative impact on the risky share. Related to income risk, an entrepreneur may be exposed to a higher risk of income loss or may have to cover unexpected expenses, than somebody working on a contractual basis. Heaton and Lucas (2000) find that households with high and variable business income have a lower risky share, potentially due to their higher income risk, and Calvet and Sodini (2014) find the same relationship on the risky share for entrepreneurs. Further, Calvet, et al. (2007) find that increasing household size, unemployment and immigration reduces the likelihood of participation and reduces the risky share, with the latter two characteristics being associated with uncertainty of one's future income streams, and the former with larger and potentially more volatile expenses. The negative effect of household size is also found by Chiappori and Paiella (2011). Higher leverage is associated with a lower risky share (Calvet and Sodini, 2014), potentially due high

leverage leaving less room for negative wealth shocks, which could result from a high degree of risky assets, as interest payments consistently must be made. Age can be thought of as a background risk characteristic, if one assumes that investors prefer to have a secured portfolio of wealth as they are approaching retirement and less time until retirement gives a smaller change of making up for losses from negative wealth shocks (a common recommendation is to reduce the degree of stocks in the portfolio with increasing age for this reason). Ameriks and Zeldes (2004) find some tendency of exits from the stock market for older investors, but no evidence of a reduction in the risky share with age. Van Rooij et al. (2011) find a positive relationship between age and participation, with those aged over 40 owning stocks to a larger extent than younger people. Chiappori and Paiella find that age is positively associated with the risky share.

2.2.3 Socio-cultural characteristics

Yet another category of characteristics with documented impact on risky asset allocation is socio-cultural characteristics. Hong et al. (2004) as well as Brown et al. (2008) find that social interaction has a positive relationship with stock market participation, with people interacting more with neighbors or attending church being significantly more likely to participate. The authors attribute this to peer effects – a social investor whose peers participate in the stock market finds the stock market more attractive for that reason.

Moreover, gender has been found to have an impact financial decision making under risk, by for example Dohmen et al. (2011) (who interestingly also document that height and parents' background has an influence). Consistent with this, women participate less in stock markets, as documented by for example Almenberg and Dreber (2015), who further show that this is largely due to lower financial literacy among women, and Thörnqvist and Vardardottir (2014) who document that women have a preference for less risk in the financial portfolio as compared to men.

2.2.4 Characteristics related to beliefs, emotions, and moods

The above-mentioned characteristics related to sophistication, background risk or labor risk, or socio-cultural demographics, have relatively well-documented impacts on participation in risky financial markets and the risky share. Recently, research on the impact of psychological or emotional characteristics have gained popularity. Several studies find an impact of moods, emotions, affects and beliefs and decisions making under risk, including decisions about financial investments. Van Winden et al. (2011) conduct an experimental study and find anticipating emotions to be important for investment behavior, where positive emotions can encourage investments and negative emotions can discourage them (the positive association with the risky share is well in line with this). Guiso et al. (2008), using both Dutch and Italian data, show that the impact of trust (which can be seen as an emotional belief) on stock market participation, as well as on the risky share, is positive, as lack of trust reduces the investor's expectations on returns. The positive effect of trust on participation is also documented by Delis and Mylonidis (2015), and Georgarakos and

Pasini (2011) who further find that sociability has a positive impact on participation. Another belief which has been shown to have an impact on economic behavior is locus of control (the belief that outcomes are due to one's personal efforts) which Salamanca et al. (2020) document has a positive impact on risky investments. They find that both the probability to participate in stock markets and the risky share are increasing with internal locus of control, controlling for risk aversion and a set of standard characteristics.

The impact of moods on decisions under risk is less straightforward. For example, Isen and Patrick (1983) find that positive moods are associated with more risk averse behavior when stakes are high. This relationship is referred to as the mood maintenance hypothesis, where individuals experiencing a positive mood are reluctant to make decisions which may alter that mood. Ifcher and Zarghamee (2011) likewise find an impact of positive moods on decisions under risk, with the former documenting that positive affect significantly reduces the time preference of money. On the other hand, Forgas (1995) proposes the affect infusion model, where positive moods instead induce more risk-taking behavior, a pattern which was also found by Isen and Patrick (1983), but for only low-stake decisions. Drichoutis and Nayga (2013) find that both positive and negative moods increase risk aversion as well as patience compared to neutral moods.

Happiness, or self-reported well-being, is one of the moods which has been found to impact economic behavior. For example, Guven (2012) find that happy people save more and spend less, and likewise Cryder et al. (2008) show that unhappy people spend more, providing some evidence that time preferences in economic decisions are different for happy people than for less happy people, consistent with Ifcher and Zarghamee (2011). As for the relationship between happiness and risk aversion, or risk tolerance, there is as noted by Lane (2017) a body of research of decent size, but the relationship yet remains unclear. In other words, whether happiness is associated with the mood maintenance hypothesis of the affect infusion model in relation to stock market participation and the risky share, is not established. Delis and Mylonidis (2015) study Dutch data from 2012 and find that long-term happiness is negatively associated with stock market participation, after controlling for trust, optimism, and a set of standard characteristics. Importantly, they find that the large heterogeneity in financial decisions by individuals with the same level of trust, can partly be explained by differences in self-reported happiness. Further, they document that the positive effect of trust fades away as happiness increases. In other words, they find that the impact of happiness on stock market participation is more significant than the impact of trust. Guven and Hoxha (2015) use Dutch and German data on households and investments in combination with weather data, showing that there is a strong association between weather and short-term happiness, and that happier people are more risk averse and less likely to participate in stock markets. In their analysis they control for subjective risk aversion as well as standard characteristics, and further, Guven and Hoxha (2015) let weather changes instrument for changes in short-term happiness, and provide some evidence that there is an impact “stronger than a correlation” of happiness on risk taking in financial matters. Kamstra et al. (2003) use a

similar approach, but on the contrary show that seasonal affective disorder, a depressed mood felt by many when the hours of daylight are few, leads to a lower demand for risky assets. There is thus contradictory evidence on the impacts of short-term happiness on risk-taking in financial decisions. Moreover, as is noted by Lane (2017), the validity of the effects of short-term happiness on economic behavior has not been established for long-term happiness, and while the conclusions of Delis and Mylonidis (2015) and Guven and Hoxha (2015) seem consistent, more research is needed before an impact “stronger than a correlation” can be said to have been found also for long-term happiness. Further, other research shows the opposite impact of happiness on stock market participation. In a study on the impact of happiness on stock market participation and the risky share in China in 2011, Rao et al. (2016) find that happy households are more likely to participate in the stock market than unhappy households, and that their risky asset share (conditional on participation) tends to be higher. In their study they control for standard factors such as wealth, income, age, and education, as well as risk aversion. They find no evidence that the effect of happiness would be driven by risk aversion, but rather trust. They also find that the effect of happiness is stronger on the risky share than on participation.

Optimism is likewise related to economic behavior, with optimistic household investors having been found to save more, being more likely to invest in individual stocks, and holding a larger share of wealth in those individual stocks (Puri and Robinson, 2007). Expectations about future stock market returns are found by Vissing-Jorgensen (2004) to have a positive impact on the risky share, and Bonaparte et al. (2017) similarly document that investors allocate relatively more to risky asset as their optimism towards financial markets increases. However, Puri and Robinson (2007) find no evidence of an increasing risky share as optimism, in their case not specific to financial markets, increases. Delis and Mylonidis (2015) control for optimism in their regression on the impact of happiness on stock market participation, reasoning that as optimistic households have been found to be more likely to hold stocks, a potential positive impact of happiness on stock market participation could in fact reflect optimism. They find no evidence that such is the case.

3. Research question and hypotheses

Based on the ambiguity of the results obtained in previous research on the impact of happiness on stock market participation and the risky share, it is clear that more research is needed to establish the direction of the impact. I similarly to Delis and Mylonidis (2015) recognize that the potential impact of happiness on stock market participation can theoretically be either positive or negative, depending on which psychological framework that resides. This can also be said for the risky share. Furthermore, while the relationship between happiness and trust has frequently been documented in the context of stock market participation and the risky share, the relationship between happiness and optimism can easily be imagined

but has not yet been established, making it an interesting analysis. Moreover, as happiness has been found to have an impact on risk aversion, albeit the direction remains unclear, it is of importance to control for a potential relationship between happiness and subjective risk aversion. Therefore, my first hypothesis can be written as:

Hypothesis 1: Happiness has either a positive or a negative statistically significant impact on the likelihood of stock market participation, as well as on the risky share, after controlling for a set of standard household and individual characteristics, as well as for subjective risk aversion and optimism.

Notably, the happiness coefficients could theoretically have different directions for participation and for the risky share, for example if participation is perceived as a high-stake decision and the level of risky share as a low-stake decision, and results are in line with the findings of Isen and Patrick (1983).

For the second part of the analysis, the dynamic regression, I hypothesize that the happiness assessed at year $t-1$ has an impact on the change in participation between years $t-1$ and t , or the change of the risky share between years $t-1$ and t , with a coefficient which is statistically different from zero. Again, the direction of the coefficient could theoretically be either positive or negative, but it should reflect the direction of the coefficient in the static regression model. Further, my hypothesis is that changes in happiness between years $t-1$ and t likewise have an impact on the change in participation and the risky share, respectively. Hypothesis 2 can thus be written as:

Hypothesis 2: Happiness at year $t-1$ has either a positive or a negative statistically significant impact on the change in participation and the change in the risky share, respectively, between years $t-1$ and t . The change in happiness between years $t-1$ and t also has a statistically significant impact on the change in participation and the change in the risky share between years $t-1$ and t .

4. The Dutch National Bank Household Survey

4.1 Data

I use the 2011 to 2020 waves of the Dutch National Bank Household Survey (DHS), which is a comprehensive annual panel survey run and provided by CentERdata¹ (the survey research institute at Tilburg University). The survey is taken online and includes six detailed questionnaires on the topics of general information about the household, household and work, accommodation and mortgages, health and

¹ CentERdata: Institute for data collection and research: [Centerdata.nl](https://www.centerdata.nl)

income, assets and liabilities, and economic and psychological concepts. The panel includes over 2000 households, representative of the Dutch population, in which each member over the age of 15 is presented with each of the six questionnaires on an annual basis.

Survey data is one of the most common types of datasets used in household finance (see e.g. van Rooij et al., 2011, Rao et al., 2016). The survey format of the data enables the analysis of the impact of strictly subjective characteristics on participation and the risky share. By strictly subjective I mean characteristics which can only be quantitatively captured if the respondent is directly asked about them. Happiness is a good example of such a characteristic; subjective (self-assessed) risk aversion, financial literacy and self-assessed financial literacy, and optimistic mood are other good examples.

It is further worth to note that in the DHS, one member of the household who takes the survey has to report being the head of the household. The head of the household reports assets and liabilities owned individually as well as jointly in the household. Thus, characteristics related to assets, liabilities and mortgages are already reported on the household level, and in my analyses I therefore only study those who report as being heads of households. I limit the sample to respondents who at the time of the survey are over 20 years old, report financial wealth in excess of 100 Euro, cash in excess of 100 Euro, and net income for the current (at the time of the survey) year in excess of 100 Euro.

4.2 Variable selection and definitions

4.2.1 Dependent variables

Participation: A dummy assuming the value one for a household with a positive risky share, and the value zero for a household with a risky share of zero.

The risky share: The sum of the value of investments in stocks and mutual funds, divided by the household's liquid financial portfolio.

The risky share is generally measured as the share within a household's liquid financial portfolio that is allocated to risky financial products, including both stocks and mutual funds. Given that many households own both stocks and mutual funds rather than just one of the two, it is as suggested by Calvet, Campbell and Sodini (2007) of importance to observe stock holdings and mutual fund holdings simultaneously when measuring the risky share. I therefore define the risky share as the sum of the value of investments in stocks and mutual funds, divided by the household's liquid financial portfolio. Thus, it can assume any value between zero and one. Notably, while bonds qualify as risky financial assets, they are excluded from the numerator in my definition. The section about bonds in the questionnaire encompasses both government bonds and company bonds, and the differentiation is made in a question requiring relatively much detail, which could put it at risk for misreporting. Moreover, bond-funds are included in the mutual fund definition. In the risky share regressions, I always refer to the risky share

conditional on participation, meaning that households that do not participate in risky financial markets are excluded from those analyses.

4.2.2 Independent variables of interest

Happiness: There are two separate questions on happiness in the economic and psychological concepts questionnaire of the DHS. One is phrased with a more long-term view on happiness (although this is subject to interpretation by the respondents), while the other asks about happiness in the past month. I use the question on long-term happiness in my analysis, similar to the approach of Delis and Mylonidis (2015). Respondents are posed the question: *All in all, to what extent do you consider yourself a happy person?* Possible answers are categorical, including *very happy, happy, neither happy nor unhappy, unhappy, very unhappy, and don't know*.

Subjective risk aversion: The DHS survey includes six questions about respondents' preferences for risk with regards to investments. These six questions are validated as measures of risk aversion by for example Kapteyn and Teppa (2011). However, note that respondents' answers to these six questions can only measure self-assessed, subjective risk aversion, not the Arrow-Pratt measure of risk aversion which is derived from the utility function. I will throughout my analyses refer to self-assessed subjective risk aversion as simply risk aversion. Respondents are asked to indicate on a scale from 1 to 7 to what extent they agree with the six statements listed below, where 1 indicates "totally disagree" and 7 indicates "totally agree".

- *I think it is more important to have safe investments and guaranteed returns, than to take a risk to have a chance to get the highest possible returns*
- *I do not invest in shares, because I find this too risky*
- *If I think an investment will be profitable, I am prepared to borrow money to make this investment*
- *I want to be certain that my investments are safe*
- *If I want to improve my financial position, I should take financial risks*
- *I am prepared to take the risk to lose money, when there is also a chance to gain money*

Similar to the methodology used by Salamanca et al. (2020), I first reverse the respondents' answers to question 3 (If I think an investment will be profitable, I am prepared to borrow money to make this investment), question 5 (If I want to improve my financial position, I should take financial risks) and question 6 (I am prepared to take the risk to lose money, when there is also a chance to gain money), such that a high score indicates high risk aversion for all six questions. Secondly, I calculate the within-person mean of the six answers by year. This average is used as an indicator of risk aversion in a particular year for each respondent.

Optimism: The survey question about respondents' optimistic mood that I use is phrased: *What is the chance of having a sunny day tomorrow, according to you?* Respondents can give any value between 0 and 100. While this question comes right after the explanation that the section is about estimating chances and therefore could measure relative optimistic mood, it has many flaws for the usage. Firstly, some respondents may interpret from the explanation before the question that the answer should be based on a chance, disregarding potential reliable information, while other respondents may account for information received in weather forecasts. Secondly, respondents may be influenced by the weather in the previous weeks, expecting the weather of say today to prevail also tomorrow. Thirdly, respondents are not located in the same part of the Netherlands, and chances of having a sunny day tomorrow may statistically differ between different regions. Nonetheless, I use this question, referring to it as optimism or optimistic mood, as an extra control, hypothesizing that any potential effect of happiness could be due to its correlation with optimism.

4.2.3 Other independent variables

Financial wealth: I define liquid financial wealth as the sum of the reported amounts of cash, stocks, mutual funds, and bonds, where cash is defined as the respondents' reported amounts on checking accounts, savings or deposit accounts, and deposit books. I exclude from the definition illiquid financial products such as employers sponsored savings plans, savings certificates, single-premium annuity insurance policies and savings or endowment policies, and the amount in savings or investments reported as "not mentioned before". I further exclude financial derivatives, which represent a very small share of total assets (99.5% of respondents report no ownership of derivatives). It should be noted that liquid financial wealth, which in the rest of the report will simply be referred to as financial wealth, is a gross amount with no liabilities deducted.

Real estate wealth: the value of a household's privately owned accommodation and commercial property.

Business wealth: wealth in stocks from substantial holdings, and business equity.

Gross wealth: the sum of liquid financial wealth, the wealth in illiquid financial products which fall outside of my definition of liquid financial wealth, real estate wealth, and business wealth.

Leverage: mortgages and other debts divided by gross wealth. It can technically assume any value greater than or equal to zero.

Net income: Net disposable income which measures the income which is left after mandatory payments such as tax payments, that can be used for consumption and savings. It consists of the sum of labor income, unemployment and disability benefits, social security and pension benefits, and other capital

transfers, deducted for taxes, negative interest and other mandatory payments such as child support. Net disposable income will be referred to as simply net income.

Financial literacy: The survey does not include any questions that enable calculation of the actual level of financial literacy among respondents, but it does include a question about self-assessed knowledge about financial matters. Respondents are asked to answer the question: *How knowledgeable do you consider yourself with respect to financial matters?* with possible answers including “not knowledgeable at all”, “more or less knowledgeable”, “knowledgeable”, and “very knowledgeable”. As van Rooij et al. (2011) find that there is a very strong correlation between objective and subjective financial literacy among Dutch households participating in the 2005 and 2006 waves of the DHS survey, I have included self-assessed financial literacy in my analysis despite it not measuring “real” financial literacy. Self-assessed financial literacy will be referred to as simply financial literacy.

Other variables: I include variables for the age of the respondent, and for the number of children in the household, in my analyses. I further use dummy variables for whether or not the respondent has university or vocational college education, collectively referred to as higher education, for whether the respondent is female, for whether or not there is a partner to the respondent in the household, and for retirement including early retirees (in order to capture a possible decumulation of wealth phase that some may enter upon retirement, which has a separate effect from age). I further use dummies for whether the respondent is a student, is an entrepreneur, defined as a respondent with a positive amount of business wealth, and for whether the respondent is unemployed. I have in this study defined unemployed as a respondent who reports either looking for work for the first time or looking for work after having lost a job.

4.3 Distribution of data, all respondents

While all analyses are made on only the head of the household, summary statistics for *all* respondents are provided in table 1.

Table 1: Summary statistics - all respondents

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Gross wealth	11,929	229,868.50	273,302.20	104	15,675.0	331,525	5,622,900
Financial wealth	11,929	42,905.61	100,159.30	104	4,367	40,250	2,874,771
Stocks	11,929	2,605.88	18,293.77	0	0	0	785,120
Mutual funds	11,929	7,671.06	43,018.98	0	0	0	1,039,500
Risky share	11,929	0.09	0.21	0.00	0.00	0.00	1.00
Real estate wealth	11,929	182,492.10	217,452.60	0	0	280,000	5,500,000
Business wealth	11,929	4,470.77	65,493.90	0	0	0	3,825,000
Net income	11,929	27,288.28	20,407.01	105.00	16,356.47	34,471.05	689,704.10
Leverage	11,929	1.23	13.68	0.00	0.00	0.53	751.83
Age	11,929	56.17	16.20	21	43	69	95
Higher education dummy	11,926	0.44	0.50	0.00	0.00	1.00	1.00
Female dummy	11,929	0.41	0.49	0	0	1	1
Partner in household dummy	11,929	0.70	0.46	0	0	1	1
Retirement dummy	11,929	0.33	0.47	0	0	1	1
Unemployment dummy	11,929	0.02	0.14	0	0	0	1
Student dummy	11,929	0.02	0.14	0	0	0	1
Entrepreneur dummy	11,929	0.04	0.20	0	0	0	1
Number of kids	11,929	0.50	0.93	0	0	1	6
Risk aversion	11,351	5.24	1.03	1.50	4.50	6.00	7.00
Financial literacy	11,919	2.29	0.73	1.00	2.00	3.00	4.00
Optimism	11,920	53.43	26.67	0.00	40.00	75.00	100.00
Happiness	11,875	4.07	0.65	1.00	4.00	4.00	5.00

Table 1 shows summary statistics, including the number of observations, the mean, standard deviation, minimum, 25th percentile, 75th percentile, and maximum of the selected variables for all respondents in the dataset. For the dummy variables, the mean value corresponds to the share of observations assuming a value 1.

4.4 Variable transformation

As can be expected, the distributions of net income, financial wealth, and real estate wealth are highly skewed. In the regressions I therefore use the natural logarithm of these characteristics. For real estate wealth, if the value is zero, I use zero also after the transformation, rather than the natural logarithm. The distribution of leverage is likewise highly skewed, with most observations being between 0 and 1.5, but a small number having much higher leverage, as shown in table 1. Since most banks and lending institutions put leverage requirements on household lending, very high leverage ratios should typically not occur, and there is a risk that the few observations with exceedingly high values contain subcomponents subject to misreporting. Therefore, I cap leverage at 1.5, such that all observations of leverage exceeding the cap are assigned the value 1.5. With regards to happiness, very few respondents report being very unhappy, with only 25 accounts of “very unhappy” (here assuming a value 5) of the almost 12000 observations shown in table 1. This could either reflect that very few in the Dutch population actually are very unhappy, which is a positive result from a well-being perspective, or it could reflect a selection bias, with very unhappy people opting out of these types of surveys. Nonetheless, I deem the “very unhappy” group too small to base any robust conclusions on, and I therefore group it together with the “unhappy” group. In my analysis I thus end up with four groups of observations for happiness, being “very unhappy or unhappy”, “neither happy

nor unhappy”, “happy”, and “very happy”. Since there are only four groups, I treat happiness as a factor variable rather than a continuous variable in the regressions. Distributions of the transformed variables can be found in Appendix A.

5. Empirical methodology

5.1 Testing hypothesis 1

For the first part of the analysis, I regress stock market participation as well as the risky share, conditional on participation, on happiness, and the standard sophistication, background or income risk, and socio-cultural characteristics mentioned in section 4.2. I further include the elicited variables subjective risk aversion, and optimism, which could have an impact on any potential effects found for happiness. Rather than using data from just one year, which is done by both Delis and Mylonidis (2015) and Rao et al. (2016), I use panel data consisting of the 2011 to the 2020 waves of the DHS, thus including ten years of data. The use of panel data in household finance studies has in recent years become more and more common, as the results obtained are more robust in the sense that they naturally have more degrees of freedom compared to a one-year cross sectional analysis, and while results obtained in a one-year cross sectional regressions may suffer from one-time shocks in that particular year, by including several years and time fixed effects, panel data can handle this better. For example, both Guven and Hoxha (2015) and Salamanca et al. (2020) use panel data in their analyses. With an emphasis on my variable of interest and specifically controlling for subjective risk aversion and optimism, equations (6) and (7) can be rewritten as:

$$P(participation)_{it} = \beta_0 + \beta_1(H_{it}) + \beta_2(R_{it}) + \beta_3O_{it} + \beta_4X_{it} + u_h + v_{it} \quad (9)$$

$$\alpha_{it} = \beta_0 + \beta_1(H_{it}) + \beta_2(R_{it}) + \beta_3O_{it} + \beta_4X_{it} + u_h + v_{it} \quad (10)$$

Where H_{it} is the happiness level of investor i at time t , R is the subjective risk aversion, O is optimism, and X is the vector of individual or household control characteristics as mentioned in section 4.2. The participation regression includes all households within the limitations for inclusion as defined in section 4.1, while the risky share regression is subject to participation. Thus, only households that participate in stock markets and have a risky share larger than zero enter the risky share regression. For the participation estimation, I conduct a linear probability estimation model using ordinary least squares (OLS) with time fixed effects. Given that the main purpose of my analysis is to estimate the partial effects of the independent variables, in particular happiness, on the dependent variable, a linear probability model should do well despite the binary outcome, and the method has been used previously by for example van Rooij et al. (2011). For the risky share estimation, I conduct a standard ordinary least squares estimation with time fixed effects.

I report cluster-robust standard errors in all analyses, clustered on the household level, to control for the potential within-household correlation or heteroscedasticity.

5.2 Testing hypothesis 2

The static panel regressions give an indication of the correlation between the independent variables, with a particular emphasis on happiness, and the dependent variables participation and risky share respectively. However, it does not give an indication of causality. Reverse causality problems are particularly prominent for happiness as it may well be that participation in the stock market or a higher risky share leads to a higher level of happiness. An approach to address this problem is to instrument happiness with other, exogenous, variables. With short-term happiness this can be done with instruments, with the approach of Guven and Hoxha (2015) to let weather changes induce changes in short-term happiness some evidence for a causal impact of short-term happiness on investment behavior. With changes in long-term happiness, finding instruments is harder, as it is expected to be very slow-moving. Therefore, instead of using instruments for happiness, I use a dynamic regression approach, similar to the method commonly used in analyses of relative risk (for example Brunnermeier and Nagel, 2008, Calvet et al., 2009, and Chiappori and Paiella, 2011). Commonly in dynamic regressions the first difference of the risky share equation is used, as noted in equation 8. The equation can also contain a set of lagged or non-lagged control variables (see for example Brunnermeier and Nagel, 2008).

The idea of the application of the dynamic regression is that while happiness could result from participation or the risky share rather than the opposite, the change in participation or the risky share between one year and the next should not differ significantly between different levels of happiness at the beginning of that period, if happiness indeed has no causal impact on participation or the risky share. In other words, if happiness correlates with participation but happiness has no causal impact on participation, the investment behavior of investors at different happiness levels should not differ, and those that are more or less happy should enter or exit the stock market at more or less the same rate. Likewise, if happiness correlates with the risky share but happiness has no causal impact on the risky share, the investment behavior of investors at different happiness levels should not differ, and those that are more or less happy should increase or decrease their risky share at more or less the same rate. The dynamic regression with the first difference in participation and the risky share, respectively, thus allows me to analyze the investment behavior over the year given a level of happiness at the beginning of that year, and a set of controls. Note that simply lagging happiness but not taking the first difference of participation and the risky share would not do, as participation or the risky share is likely to be an outcome of the investment behavior over several years.

To get a full picture of the impact of happiness on stock market participation and the risky share, I further include the change in happiness over the year in the dynamic regressions, to account for a potential impact on investment behavior from increasing or decreasing happiness. To provide an illustrative example, an investor who was “neither happy nor unhappy” in the beginning of the year may enter the stock market due to a variety of reasons where one could be that her happiness has increased over the year, but her being “neither happy nor unhappy” in the beginning of the year not being one of the reasons.

For the dynamic regressions, I regress the change in participation between years t and $t - 1$, and the change in risky share between the years t and $t - 1$, respectively, on first only the lagged values of happiness, corresponding to year $t - 1$, and a set of control variables, and then on both the lagged values of happiness and the change in happiness between years t and $t - 1$, and a set of control variables. The set of control variables, including changes in characteristic between year t and year $t - 1$, and lagged values of characteristics, deserves further explanation. When measuring the change in both participation and the risky share, there is reason to suspect that cash inflows and outflows will have an impact (whether that is actually the case is debated, but it is an important suspicion to control for). Therefore, I control for changes in all characteristics that measure cash inflows or outflows, including the change in (the log of) financial wealth and the change in (the log of) net income. The change in (the log of) real estate wealth is a special case, as households that are saving up for buying a house may prefer risk-free assets given their short time horizon (as documented by Calvet et al., 2007), but once they have purchased that house their horizon becomes longer and their preference for risky assets shifts. For this reason I use a dummy for whether a household has shifted from having no real estate wealth to having some positive value of real estate wealth, and another dummy for the opposite shift associated with disposal of real estate (this type of variable is referred to as a preference shifter by Brunnermeier and Nagel, 2008). The dynamic regression also includes lagged characteristic (those measured in year $t - 1$), reflecting the characteristics used in the static regressions in the first part of the analysis. The first difference regression for the change in participation is here estimated with an OLS method and can be written as:

$$\Delta(participation)_{it} = \beta_1(H_{it-1}) + \beta_2(\Delta H_{it}) + \beta_3\Delta X_{it} + \beta_4Y_{it-1} + \Delta v_{it} \quad (11)$$

Where $\Delta(participation)_{it} = (participation)_{it} - (participation)_{it-1}$ is the change in participation between years $t - 1$ and t (in other words exits, entries, stay ins and stay outs of the stock market), (H_{it-1}) is the lagged level of happiness, and $\Delta H_{it} = H_{it} - H_{it-1}$ is the change in happiness between years $t - 1$ and t , which I transform into two dummy variables where one assumes the value one if happiness has increased between years $t - 1$ and t , and one assumes the value one if it has decreased. X is a vector of

control characteristics related to cash inflows or outflows and ΔX_{it} is the change in those characteristics between years $t - 1$ and t . Y is a vector of lagged values of control characteristics.

It is in the regression of the risky share important to take inertia, or the tendency of household investors to rebalance their portfolios slowly, into consideration using the change in the (log of) financial wealth as an explanatory variable. Changes in financial wealth tend to materialize in the riskless category, in the form of cash for example through an inheritance or an unusually large bonus. If inertia is present, such that the household only rebalances its portfolio slowly, an increase in cash will mechanically lead to an increase in financial wealth but a reduction in the risky share, which would yield a negative coefficient for financial wealth in the risky share regression. Indeed, Brunnermeier and Nagel (2008) find a small effect of changes in financial wealth on participation, but an insignificant negative effect on the risky share, which they attribute to inertia. If inertia is present the impact of financial wealth on the risky share could differ in the immediate time from the long-term, which would yield biased results. I will address this problem by instrumenting the change in (the log of) financial wealth with its lagged values, as is done by for example Calvet et al. (2009), who through this method find a positive relationship between the changes in financial wealth and the risky share. Further, note that while the change in financial wealth is not my variable of interest, its coefficient and significance can give an indication for whether relative risk aversion is constant, decreasing, or, potentially, increasing. As is suggested by Arellano and Bond (1991), increasing the number of years increases the number of available instruments as all lags of, in this case the change in (the log of) financial wealth, can be used as instruments. However, given that my dataset is an unbalanced panel with many households not participating all years, increasing the number of lags for the instrumentation will rather dramatically reduce the number of observations that can be used in the estimation. Therefore, while I theoretically could instrument with deeper lags, I only use the second and the third lag for my instrumentation of the change in (the log of) financial wealth. Note that the instrumentation of (the log of) financial wealth is not needed in the participation regression as there is no mechanical relationship between the change in financial wealth and stock market participation. The first difference regression for the change in the risky share is estimated with a two-stage least squares (2SLS) method due to the use of instrument variables, and can be written as:

$$\Delta \alpha_{it} = \beta_1(H_{it-1}) + \beta_2(\Delta H_{it}) + \beta_3\Delta W_{it} + \beta_4\Delta X_{it} + \beta_5Y_{it-1} + \Delta v_{it} \quad (12)$$

Where $\Delta \alpha_{it} = \alpha_{it} - \alpha_{it-1}$ is the change in the risky share, still conditional on participation, between years $t - 1$ and t , (H_{it-1}) is the lagged level of happiness, and $\Delta H_{it} = H_{it} - H_{it-1}$ is the change in happiness between years $t - 1$ and t , which I transform into two dummy variables where one assumes the value one if happiness has increased between years $t - 1$ and t , and one assumes the value one if it has decreased. ΔW_{it}

is an endogenous variable due to its mechanical relationship with $\Delta\alpha_{it}$ and is instrumented with ΔW_{it-2} and ΔW_{it-3} in the two-stage least squares regression. X is a vector of control characteristics related to cash inflows or outflows and ΔX_{it} is the change in those characteristics between years $t - 1$ and t . Y is a vector of lagged values of control characteristics.

Since I use instruments for financial wealth I need to check the validity of these instruments. An instrument has to be correlated with its endogenous explanatory variable after the inclusion of controls, but not have the same endogeneity problem. Weak instruments are weakly correlated with the endogenous explanatory variables, which would yield biased estimates. A regression using instruments should moreover be more consistent than the standard OLS to motivate its use. Further, when using more than one instrument per endogenous explanatory variable, the model might be overidentified. I conduct three validity checks and report the diagnostics.

6. Results

6.1 Descriptive statistics

For all analyses I only use the demographic information which is provided by the head of each household. Tables 2, and 3 show summary statistics for households that participate in risky financial markets, and households that do not participate in risky financial markets, respectively. Corresponding summary statistics for all households, regardless of stock market participation, can be found in Appendix B. Note that for the dummy variables, the mean column signifies the share of observations which assume a value 1. Also, wealth characteristics are reported on the household level while strictly individual characteristics such as age, higher education, gender, risk aversion, financial literacy, optimism and happiness are reported for the head of the household. Across years 2011 to 2020, 24.5% of the observations showed household participation in risky financial markets either directly or indirectly. This is in line with the 23.8% participation documented by van Rooij et al. (2011). 10.0% participated directly through stocks, and 15.7% indirectly through mutual funds, while 4.4% held both mutual funds and stocks. Tables 3 and 4 illustrate that households that participate in risky financial markets have higher net income, higher gross wealth, financial wealth, and real estate wealth than households that do not participate. Leverage is somewhat lower. They are slightly older and a greater proportion have a higher education degree. Their self-assessed financial literacy is somewhat higher, and their risk aversion lower. Their level of happiness is similar to non-participating household.

Table 2: Summary statistics - participating households

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Gross wealth	2,173	400,920.60	346,997.70	1,400	216,340	500,800.0	4,688,500
Financial wealth	2,173	113,185.50	181,609.00	210	24,250	124,253.5	2,777,750
Stocks	2,173	13,196.82	40,317.15	0	0	8,000	785,120
Mutual funds	2,173	38,570.04	92,453.66	0	0	33,808.6	1,039,500
Risky share	2,173	0.40	0.30	0.0002	0.14	0.65	1.00
Real estate wealth	2,173	280,645.90	232,528.70	0	161,243.9	370,000	2,555,000
Business wealth	2,173	7,089.22	73,947.60	0	0	0	1,888,000
Log of financial wealth	2,173	10.91	1.26	5.35	10.10	11.73	14.84
Log of real estate wealth	2,173	10.42	4.78	0.00	11.99	12.82	14.75
Log of net income	2,173	10.34	0.59	4.65	10.09	10.67	12.83
Leverage	2,173	0.26	0.33	0.00	0.00	0.41	1.50
Age	2,173	60.52	14.13	21	51	71	93
Higher education dummy	2,173	0.59	0.49	0	0	1	1
Female dummy	2,173	0.16	0.37	0	0	0	1
Partner in household dummy	2,173	0.66	0.48	0	0	1	1
Retirement dummy	2,173	0.43	0.50	0	0	1	1
Unemployment dummy	2,173	0.02	0.13	0	0	0	1
Student dummy	2,173	0.01	0.07	0	0	0	1
Entrepreneur dummy	2,173	0.04	0.20	0	0	0	1
Number of kids	2,173	0.35	0.80	0	0	0	4
Risk aversion	2,123	4.53	0.97	1.50	3.83	5.17	7.00
Financial literacy	2,172	2.53	0.70	1.00	2.00	3.00	4.00
Optimism	2,172	53.38	26.39	0.00	40.00	75.00	100.00
Happiness	2,170	4.04	0.67	1.00	4.00	4.00	5.00

Table 2 shows summary statistics, including the number of observations, the mean, standard deviation, minimum, 25th percentile, 75th percentile, and maximum of the selected variables for households that participate in the stock market, defined as having some ownership of stocks or mutual funds greater than zero. For the dummy variables, the mean value corresponds to the share of observations assuming a value 1.

Table 3: Summary statistics - non-participating households

Statistic	N	Mean	St. Dev.	Min	Pctl (25)	Pctl (75)	Max
Gross wealth	6,674	228,391.60	237,835.60	104	23,520	321,195	5,622,900
Financial wealth	6,674	26,123.47	46,926.83	104	3,500	28,705	723,987
Stocks	6,674	0.00	0.00	0	0	0	0
Mutual funds	6,674	0.00	0.00	0	0	0	0
Risky share	6,674	0.00	0.00	0	0	0	0
Real estate wealth	6,674	198,926.20	213,095.20	0	0	285,000	5,500,000
Business wealth	6,674	3,341.99	56,259.42	0	0	0	3,825,000
Log of financial wealth	6,674	9.16	1.57	4.65	8.16	10.26	13.49
Log of real estate wealth	6,674	8.56	5.78	0.00	0.00	12.56	15.52
Log of net income	6,674	10.08	0.69	4.94	9.86	10.46	13.44
Leverage	6,674	0.36	0.44	0.00	0.00	0.63	1.50
Age	6,674	57.08	16.34	21	44	70	95
Higher education dummy	6,672	0.42	0.49	0.00	0.00	1.00	1.00
Female dummy	6,674	0.32	0.47	0	0	1	1
Partner in household dummy	6,674	0.61	0.49	0	0	1	1
Retirement dummy	6,674	0.36	0.48	0	0	1	1
Unemployment dummy	6,674	0.02	0.15	0	0	0	1
Student dummy	6,674	0.02	0.14	0	0	0	1
Entrepreneur dummy	6,674	0.03	0.18	0	0	0	1
Number of kids	6,674	0.44	0.88	0	0	0	6
Risk aversion	6,364	5.41	0.97	1.50	4.67	6.00	7.00
Financial literacy	6,670	2.27	0.73	1.00	2.00	3.00	4.00
Optimism	6,671	53.52	26.89	0.00	40.00	75.00	100.00
Happiness	6,648	4.03	0.67	1.00	4.00	4.00	5.00

Table 3 shows summary statistics, including the number of observations, the mean, standard deviation, minimum, 25th percentile, 75th percentile, and maximum of the selected variables for households that do not participate in the stock market. For the dummy variables, the mean value corresponds to the share of observations assuming a value 1.

Figures 1 and 2 show the average participation and the average risky share, conditional on participation, for each category of happiness. Note that the groups of happiness range from 2 ("unhappy" or "very unhappy") to 5 ("very happy").

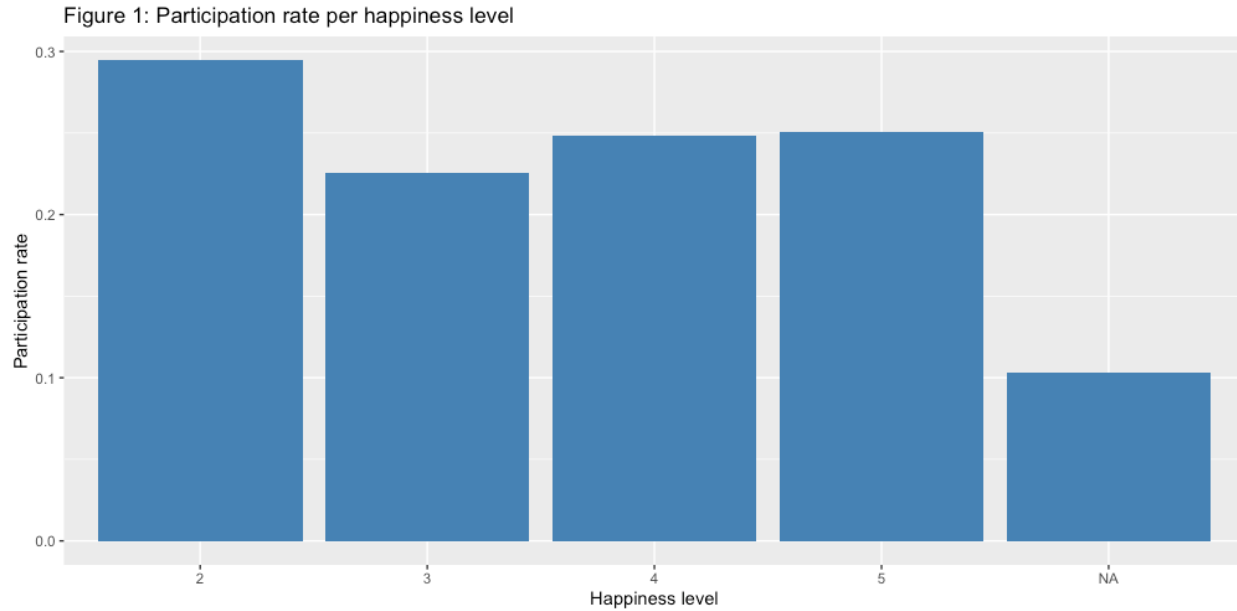


Figure 1 shows the participation rate in the stock market per reported level of happiness, where group 2 is those who report being "unhappy" or "very unhappy", 3 is "neither happy nor unhappy", 4 is "happy", 5 is "very happy", and NA is "don't know" and those who have answered the question on happiness. A participation rate of e.g. 0.3 for a certain level of happiness means that 30% of observations on that happiness level is stock market participants.

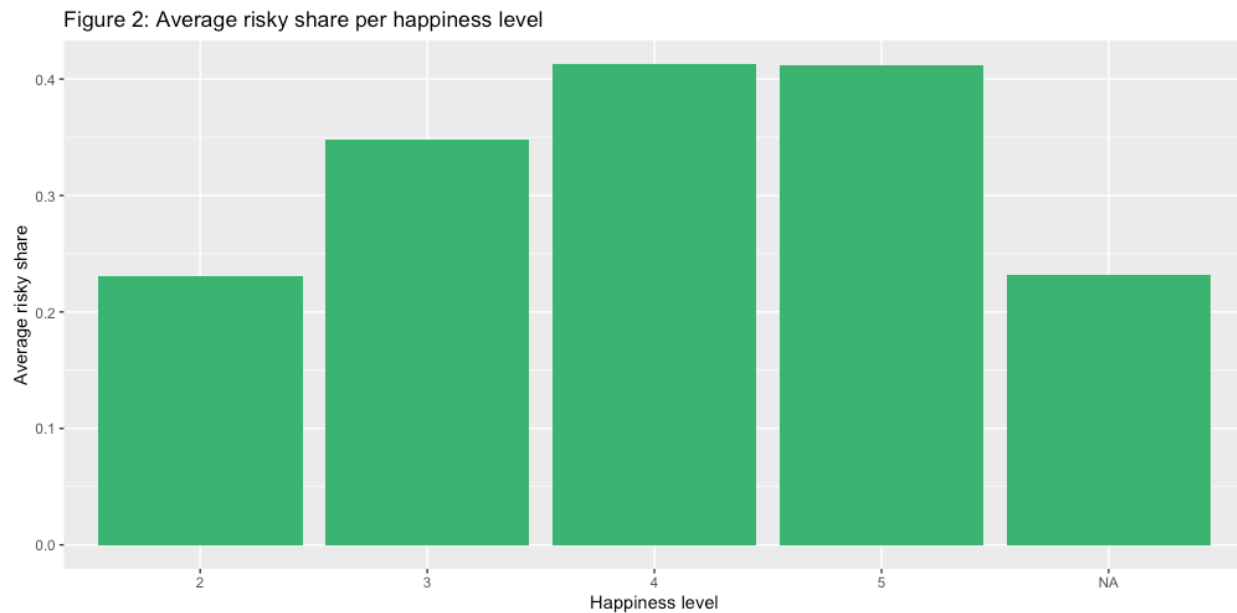


Figure 2 shows the average risky share, conditional on participation, per reported level of happiness, where group 2 is those who report being "unhappy" or "very unhappy", 3 is "neither happy nor unhappy", 4 is "happy", 5 is "very happy", and NA is "don't know" and those who have answered the question on happiness. An average risky share of e.g. 0.3 for a certain level of happiness means that on average, 30% of the liquid financial portfolio is invested in the stock market out of observations with a positive risky share (i.e. stock market participants) at that happiness level.

6.2 Static regression results

6.2.1 Stock market participation

First I regress participation on only happiness. Table 4 shows that the impact on participation of being either neither happy nor unhappy, happy, or very happy, relative to being unhappy which is the base group, is negative but insignificant, controlling for no other independent variables.

Table 4: Static regression results with only happiness: participation

Dependent variable:	
Participation	
Neither happy nor unhappy	-0.071 (0.059)
Happy	-0.047 (0.059)
Very happy	-0.044 (0.061)
Observations	8,818
R2	0.004
Adjusted R2	0.003
Residual Std. Error	0.430 (df = 8805)
Note: *p<0.1; **p<0.05; ***p<0.01	

Table 4 shows the results of a linear probability regression (OLS) with time fixed effects on the dependent binary variable stock market participation, and the independent variable happiness, which is a categorical variable. The categories “neither happy nor unhappy”, “happy”, and “very happy” are shown in the table, the category “unhappy or very unhappy” is the base category. The correlation between the dependent variable and the happiness variable, controlling for no other independent variables, is negative but not statistically significant. Standard errors (in parenthesis) are robust, clustered at the household level.

Secondly, I regress participation on all standard variables, excluding the elicited variables happiness, subjective risk aversion, financial literacy, and optimism. The results are shown in column (1) of table 5. The results are in line with previous findings, with financial wealth and higher education having a statistically significant positive impact on participation, and female gender, being retired, and having a partner in the household having a statistically significant negative impact. The lack of statistical significance for the other characteristics can likely be explained by either noise in the reporting of these characteristics and their sub-components, the lower number of observations in my analysis compared to studies using official registers, or my definition of these characteristics. Note that the relatively low R square in this regression is expected, considering that the dependent variable ultimately reflects a decision made to either participate or not in the stock market. There are inevitably unobserved factors that go into a decision, and these types of regressions in general have low explanatory power. In column (2) of table 5 I have additionally included the elicited variables. The R squared improves substantially after the inclusion of elicited variables. Notably, net income, age, and the number of children in the household are now statistically

significant. Female gender is the only parameter that is no longer statistically significant, most likely due to its correlation with financial literacy and risk aversion. This loss of statistical significance for female gender has been documented by for example Almenberg and Dreber (2015). Interestingly, most variables survive the inclusion of the elicit variables, including subjective risk aversion, giving some support to the argument that financial and demographic characteristics have an impact on their own on stock market participation which is more than just a correlation with risk aversion, with the caveat that there is a risk that subjective risk aversion and a more objective measurement of risk aversion could differ. All elicit variables are statistically significant at the 10% level, including happiness, which was negative but insignificant in itself as shown in table 4. This suggests that happiness does have a negative correlation with stock market participation, similarly to what Delis and Mylonidis (2015) find. However, it is important to note that “happiness” in this context means everyone but “unhappy” or “very unhappy” people. The coefficients on the three groups “Neither happy nor unhappy”, “Happy”, and “Very happy” are very similar. Therefore, my results indicate that it is unhappy people that differ from others by having higher than average stock market participation rates, even after controlling for several standard characteristics shown in column (1). In column (3) of table 5 I also control for optimism, in order to analyze whether my results achieved for happiness rather capture optimism. If that is the case, the statistical significance of the happiness variables would diminish after the inclusion of optimism in the regression. The results demonstrate that they do not. They further demonstrate that the measure of optimism that I am using has no explanatory power in the stock market participation regression.

Table 5: Static regression results: participation

	Dependent variable:		
	Participation		
	(1)	(2)	(3)
Log of net income	0.012 (0.010)	0.019** (0.010)	0.019** (0.010)
Log of financial wealth	0.109*** (0.005)	0.100*** (0.005)	0.100*** (0.005)
Log of real estate wealth	0.001 (0.002)	0.0004 (0.001)	0.0004 (0.001)
Leverage	-0.006 (0.018)	-0.005 (0.017)	-0.005 (0.017)
Age	0.001 (0.001)	0.003*** (0.001)	0.003*** (0.001)
Higher education dummy	0.054*** (0.020)	0.032* (0.018)	0.032* (0.018)
Female dummy	-0.105*** (0.020)	-0.027 (0.019)	-0.027 (0.019)
Unemployment dummy	-0.027 (0.038)	-0.019 (0.040)	-0.019 (0.040)
Retirement dummy	-0.066*** (0.024)	-0.057** (0.023)	-0.057** (0.023)
Entrepreneur dummy	0.024 (0.043)	-0.020 (0.039)	-0.020 (0.039)
Partner in household dummy	-0.062*** (0.020)	-0.035* (0.019)	-0.035* (0.019)
Number of children in household	-0.011 (0.010)	-0.017* (0.009)	-0.017* (0.009)
Riskaversion		-0.136*** (0.007)	-0.136*** (0.007)
Financial literacy		0.023** (0.010)	0.023** (0.010)
Neither happy nor unhappy		-0.091* (0.052)	-0.091* (0.052)
Happy		-0.117** (0.050)	-0.117** (0.050)
Very happy		-0.093* (0.052)	-0.093* (0.052)
Optimism			-0.00001 (0.0002)
Observations	8,845	8,466	8,466
R2	0.221	0.321	0.321
Adjusted R2	0.219	0.319	0.319
Residual Std. Error	0.381 (df = 8823)	0.358 (df = 8439)	0.358 (df = 8438)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5 shows the results of a linear probability regression (OLS) with time fixed effects results on the dependent binary variable stock market participation. Column (1) shows the results of a regression including standard characteristics related to household sophistication and background or labor risk. Column (2) further includes the elicited variables subjective risk aversion, self-assessed financial literacy, and happiness levels, where the latter is a categorical variable, and the group “unhappy or very unhappy” is the base. Column (3) includes also optimism, to control for a potential correlation between happiness and optimism. Standard errors (in parenthesis) are robust, clustered at the household level. All logs are in the natural logarithm form.

A sensitivity analysis of model assumptions, on the impact of using a linear approximation on a binary endpoint, is found in Appendix C, where a probit model has been applied on the panel data. Here I show that the direction of the coefficients and the characters which are statistically significant remain unchanged, while the coefficients naturally are different in the maximum likelihood estimation.

6.2.2 Risky share

I then move on to the analysis of the risky share, conditional on stock market participation (thus only including respondents with a positive risky share). Table 6 shows that the impact on the risky share of being either “neither happy nor unhappy”, “happy”, or “very happy”, relative to being “unhappy” or “very unhappy” which is the base group, is positive and statistically significant, controlling for no other independent variables.

Table 6: Static regression results with only happiness: risky share

Dependent variable:	
Risky share	
Neither happy nor unhappy	0.117** (0.049)
Happy	0.183*** (0.044)
Very happy	0.184*** (0.049)
Observations	2,170
R2	0.021
Adjusted R2	0.016
Residual Std. Error	0.295 (df = 2157)
Note: *p<0.1; **p<0.05; ***p<0.01	

Table 6 shows the results of an OLS regression with time fixed effects on the dependent variable risky share, which is defined as the share within a household's liquid financial portfolio allocated to stock and/or mutual funds, and the independent variable happiness, which is a categorical variable. The categories "neither happy nor unhappy", "happy", and "very happy" are shown in the table, the category "unhappy or very unhappy" is the base category. The correlation between the dependent variable and the happiness variable, controlling for no other independent variables, is positive and statistically significant. Standard errors (in parenthesis) are robust, clustered at the household level.

I also regress the risky share on all standard characteristics, excluding the elicited variables happiness, subjective risk aversion, financial literacy, and optimism. The results are shown in column (1) in table 7. Unsurprisingly, and in line with previous findings, several characteristics that were statistically significant in the participation regressions lack significance in the risky share regressions. However, even financial wealth which has extensive theoretical support for having an impact on the risky share, is insignificant. In this case, the insignificance arises because of its correlation with age and my definition of leverage. Since the direction of the coefficient is in line with previous findings, no further emphasis is put on this insignificance. Notably, the R square in this regression in column (1) of table 7 is very low. Again, unobserved factors going into a decision render the explanatory power of these types of regressions low, and an R squared between 3% and 10% is in line with previous research. While few of the standard variables are statistically significant, column (2) shows that happiness is indeed positive and significant, compared to the comparison group of unhappy respondents, even after controlling for all the standard characteristics shown in column (1). Similarly to the case in the participation regression, it is unhappy people that stand out, this time by having a lower risky share than any other happiness level group. The R square improves substantially from the inclusion of elicited variables, albeit it remains low. In column (3) I also control for optimism. As in the participation regression, my results indicate that the influence of happiness on the dependent variable is not driven by optimism, and optimism in itself has no explanatory power in the stock market participation regression.

The results of the first part of the analysis indicate that there is indeed a negative correlation between happiness and stock market participation, with those that are unhappy standing out as more likely to participate, and a positive correlation between happiness and the risky share conditional on participation, with those that are unhappy standing out as having a lower risky share.

Table 7: Static regression results: risky share

Dependent variable:			
	(1)	Risky share (2)	(3)
Log of net income	-0.020 (0.018)	-0.009 (0.019)	-0.009 (0.019)
Log of financial wealth	0.018 (0.012)	0.013 (0.012)	0.013 (0.012)
Log of real estate wealth	0.002 (0.002)	0.001 (0.002)	0.001 (0.002)
Leverage	0.036 (0.043)	0.014 (0.044)	0.014 (0.044)
Age	0.003** (0.001)	0.005*** (0.001)	0.005*** (0.001)
Higher education dummy	0.052* (0.028)	0.045 (0.028)	0.046 (0.028)
Female dummy	-0.027 (0.034)	0.007 (0.034)	0.007 (0.034)
Unemployment dummy	-0.041 (0.057)	-0.026 (0.060)	-0.026 (0.060)
Retirement dummy	-0.012 (0.034)	-0.029 (0.034)	-0.029 (0.034)
Entrepreneur dummy	0.072 (0.051)	0.054 (0.052)	0.053 (0.052)
Partner in household dummy	-0.015 (0.030)	-0.016 (0.029)	-0.016 (0.029)
Number of children in household	0.005 (0.018)	0.001 (0.019)	0.001 (0.019)
Risk aversion		-0.059*** (0.013)	-0.059*** (0.013)
Financial literacy		0.007 (0.017)	0.007 (0.017)
Neither happy nor unhappy		0.100** (0.049)	0.100** (0.049)
Happy		0.132*** (0.046)	0.131*** (0.046)
Very happy		0.146*** (0.051)	0.145*** (0.051)
Optimism			0.0001 (0.0003)
Observations	2,173	2,122	2,122
R2	0.042	0.086	0.086
Adjusted R2	0.033	0.075	0.074
Residual Std. Error	0.292 (df = 2151)	0.285 (df = 2095)	0.285 (df = 2094)

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 7 shows the results of an OLS regression with time fixed effects on the dependent variable risky share, which is defined as the share within a household's liquid financial portfolio allocated to stock and/or mutual funds, conditional on participation (only including households with a positive risky share). Column (1) shows the results of a regression including standard characteristics related to household sophistication and background or labor risk. Column (2) further includes the elicited variables subjective risk aversion, self-assessed financial literacy, and happiness levels, where the latter is a categorical variable, and the group "unhappy or very unhappy" is the base. Column (3) includes also optimism, to control for a potential correlation between happiness and optimism. Standard errors (in parenthesis) are robust, clustered at the household level. All logs are in the natural logarithm form.

6.3 Dynamic regression results

6.3.1 Stock market participation

In the second part of the analysis, I first regress the change in participation on the lagged value of happiness and a set of control variables. The results of this regression can be found in column (1) of table 8. As can be seen, the coefficients on "neither happy nor unhappy", "happy" and "very happy" are all positive, indicating that these groups could be more likely to enter the stock market and less likely to exit than those

that were "unhappy" or "very unhappy" in the previous year, which is in contrast to the negative correlation found in the static regression shown in table 5. However, as no statistical significance is found there is not necessarily any significant difference between the groups. The change in the log of financial wealth has a positive impact on the change in stock market participation, indicating that a positive change in financial wealth is associated with a larger likelihood to enter the stock market, or a smaller likelihood to exit it. Age has a negative impact – at a higher age investors are less likely to enter the stock market, and more likely to exit it, which seems reasonable. In column (2) of table 8 I additionally include the change in happiness as explanatory variables, but find no statistically significant difference in the investment behavior in terms of changes in stock market participation between those that experience an increase in long-term happiness, those that experience a decrease, and those that report the same level of happiness in two consecutive years.

Table 8: Dynamic regression results: change in participation

Dependent variable:		
	Change in participation	
	(1)	(2)
Change in log of net income	-0.00000 (0.00000)	-0.00000 (0.00000)
Change in log of financial wealth	0.039*** (0.003)	0.039*** (0.003)
Purchase of real estate	-0.008 (0.017)	-0.007 (0.017)
Disposal of real estate	-0.004 (0.017)	-0.005 (0.017)
Lagged: Leverage	0.001 (0.007)	0.001 (0.007)
Age	-0.0004* (0.0003)	-0.0004* (0.0003)
Lagged: Higher education dummy	-0.001 (0.005)	-0.001 (0.005)
Female dummy	-0.006 (0.007)	-0.006 (0.007)
Becoming unemployed	-0.037 (0.026)	-0.039 (0.026)
Finding work	-0.014 (0.026)	-0.014 (0.026)
Lagged: Retirement dummy	0.003 (0.008)	0.004 (0.008)
Lagged: Entrepreneur dummy	-0.011 (0.014)	-0.011 (0.014)
Lagged: Partner in household dummy	-0.010 (0.006)	-0.009 (0.006)
Lagged: Number of children in household	0.001 (0.003)	0.001 (0.003)
Lagged: Riskaversion	0.0005 (0.002)	0.001 (0.002)
Lagged: Financial literacy	0.005 (0.004)	0.005 (0.004)
Lagged: Neither happy nor unhappy	0.002 (0.021)	-0.0004 (0.022)
Lagged: Happy	0.011 (0.021)	0.006 (0.021)
Lagged: Very happy	0.018 (0.021)	0.009 (0.022)
Increase in happiness		-0.010 (0.008)
Decrease in happiness		0.010 (0.008)
Constant	0.003 (0.029)	0.006 (0.030)
Observations	6,059	6,044
R2	0.028	0.028
Adjusted R2	0.025	0.025
Residual Std. Error	0.192 (df = 6039)	0.192 (df = 6022)
F Statistic	9.043*** (df = 19; 6039)	8.349*** (df = 21; 6022)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8 shows the results of a dynamic OLS regression on the dependent variable change in stock market participation, measured over one year. The dependent variable assumes the value 1 for a stock market entry, and -1 for a stock market exit. Column (1) shows the results of a regression including the lagged values of the categorical variable happiness, as well as a set of control variables which measures either changes in cash in- or outflows, or lagged values of household characteristics. Column (2) further includes the change in happiness, measured as two dummies assuming the values 1 if happiness has increased or decreased, respectively. All logs are in the natural logarithm form. Standard errors (in parenthesis) are robust, clustered at the household level.

6.3.2 Risky share

Secondly, I regress the change in the risky share on the lagged value of happiness and a set of control variables. The results are shown in column (1) of table 9, and demonstrate no statistically significant difference in the investment behavior in terms of the change in the risky share for the different happiness levels, although the positive coefficients suggest that those who report being “unhappy” or “very unhappy” could potentially increase their risky share less, or reduce it more, than others. The only variables that are found significant are the indicator for finding a job after having been unemployed, and the change in the log of financial wealth. It is reasonable that finding a job has a positive impact on the change in risky share as the uncertainty associated with having no job disappears. It also seems reasonable that a positive change in financial wealth leads to a larger change in the risky share. This finding is in line with Calvet et al. (2009) and Calvet and Sodini (2014) and the theory of decreasing relative risk aversion. In column (2) of table 9 I also include the changes to happiness as explanatory variables. As can be seen, experiencing a decrease in self-reported long-term happiness is associated with a statistically significant smaller increase, or likewise larger reduction, in the risky share, in comparison to either experiencing an increase in happiness or staying at the same level of happiness. Since I find a statistical significance, in column (3) I also control for bad years in the stock market. A bad year in the stock market, here defined as a year with negative returns on the AEX index between July of the former year and July of the next year, could be mechanically associated with a smaller increase in the risky share or a larger reduction, and I therefore want to control for this effect to make sure that the results found for the decrease in happiness do not simply capture years with negative returns. As can be seen, the statistical significance for the decrease in happiness remains valid. However, my analysis provides no insight on the channel through which the decrease in happiness impacts the change in the risky share. Therefore, I in column (4) include a control for the change in subjective risk aversion, and further interact the change in risk aversion with the change in happiness. Since no statistical significance is found for the interaction variables, nor for the change in risk aversion, it does not seem as if risk aversion is the channel through which the decrease in happiness has an impact. In other words, I find no indication that a decrease in happiness leads to a lower change in the risky share because it increases risk aversion. It could be that the channel through which it has an impact is increased passiveness, leading to a smaller degree of rebalancing of the financial portfolio. On the other hand, the coefficient on the change in risk aversion (without interaction) is positive, which is contrary to what would be expected. This could indicate that there is some noise in the reporting of subjective risk aversion, or at least that subjective risk aversion does not fully reflect a more objective measurement of risk aversion which would describe actual risk-taking behaviors. Therefore, I cannot fully rule out that a decrease in happiness could be associated with an increase in risk aversion.

As for the diagnostics reported at the bottom of table 9, the low p-value for the weak instruments shows that the instruments have a high enough correlation with the instrumented variable, the change in the log of financial wealth. Likewise, the low p-value on the Wu-Hausman statistic shows that the two-stage least squares regression is more consistent than an OLS regression. The null hypothesis of the Sargan test is that the variables that is instrumented is over-identified, so the relatively high p-value of the Sargan statistic implies that all instruments are valid.

Table 9: Dynamic regression results: change in risky share

	Dependent variable:			
	Change in risky share			
	(1)	(2)	(3)	(4)
Change in log of net income	-0.00000* (0.00000)	-0.00000** (0.00000)	-0.00000** (0.00000)	-0.00000** (0.00000)
Change in log of financial wealth (IV)	0.269*** (0.070)	0.276*** (0.071)	0.276*** (0.071)	0.271*** (0.069)
Purchase of real estate	0.074 (0.071)	0.075 (0.071)	0.078 (0.071)	0.075 (0.071)
Disposal of real estate	-0.028 (0.058)	-0.032 (0.059)	-0.035 (0.059)	-0.034 (0.058)
Lagged: Leverage	0.002 (0.033)	0.002 (0.034)	0.002 (0.034)	-0.003 (0.034)
Age	0.0001 (0.001)	0.0002 (0.001)	0.0002 (0.001)	-0.00000 (0.001)
Lagged: Higher education dummy	-0.004 (0.015)	-0.005 (0.015)	-0.006 (0.015)	-0.006 (0.015)
Female dummy	-0.001 (0.025)	-0.002 (0.025)	-0.002 (0.025)	-0.004 (0.025)
Becoming unemployed	-0.141 (0.087)	-0.146* (0.088)	-0.148* (0.088)	-0.171* (0.098)
Finding work	0.170* (0.089)	0.204** (0.100)	0.203** (0.100)	0.203** (0.099)
Lagged: Retirement dummy	0.015 (0.022)	0.013 (0.022)	0.013 (0.022)	0.014 (0.022)
Lagged: Entrepreneur dummy	-0.033 (0.044)	-0.029 (0.045)	-0.030 (0.045)	-0.031 (0.044)
Lagged: Partner in household dummy	0.012 (0.019)	0.012 (0.019)	0.012 (0.019)	0.011 (0.019)
Lagged: Number of children in household	-0.009 (0.011)	-0.008 (0.011)	-0.008 (0.011)	-0.008 (0.011)
Lagged: Riskaversion	-0.004 (0.008)	-0.004 (0.008)	-0.004 (0.008)	-0.001 (0.009)
Lagged: Financial literacy	-0.002 (0.012)	-0.001 (0.012)	-0.001 (0.012)	0.0003 (0.012)
Lagged: Neither happy nor unhappy	0.023 (0.067)	0.019 (0.068)	0.018 (0.068)	0.010 (0.068)
Lagged: Happy	0.048 (0.065)	0.044 (0.067)	0.042 (0.067)	0.040 (0.067)
Lagged: Very happy	0.028 (0.067)	0.038 (0.070)	0.035 (0.070)	0.029 (0.070)
Increase in happiness		-0.017 (0.025)	-0.017 (0.025)	-0.022 (0.025)
Decrease in happiness		-0.055** (0.027)	-0.054** (0.027)	-0.051* (0.027)
Bad year in stockmarket			-0.011 (0.015)	-0.012 (0.015)
Change in risk aversion				0.013 (0.013)
Increase in happiness*Change in risk aversion				-0.017 (0.032)
Decrease in happiness*Change in risk aversion				-0.045 (0.037)
Constant	-0.037 (0.102)	-0.036 (0.104)	-0.030 (0.104)	-0.022 (0.105)
Weak instruments	0	0	0	1e-05
Wu-Hausman	0.00017	0.00014	0.00014	0.00013
Sargan	0.14787	0.14139	0.15774	0.66563
Observations	705	704	704	697
R2	-0.408	-0.431	-0.428	-0.406
Adjusted R2	-0.447	-0.475	-0.475	-0.458
Residual Std. Error	0.190 (df = 685)	0.192 (df = 682)	0.192 (df = 681)	0.190 (df = 671)

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 9 shows the results of a dynamic OLS regression on the dependent variable change in the risky share, measured over one year. Column (1) shows the results of a regression including the lagged values of the categorical variable happiness, as well as a set of control variables which measures either changes in cash in- or outflows, or lagged values of household characteristics. Column (2) further includes the change in happiness, measured as two dummies assuming the values 1 if happiness has increased or decreased, respectively. All logs are in the natural logarithm form. Standard errors (in parenthesis) are robust, clustered at the household level. Note that the change in financial wealth has been instrumented with its lagged values, due to its mechanical relationship with the change in the risky share, rendering the number of observations relatively low. The diagnostics statistics shown at the bottom of the table indicate that the instruments used are valid, that the two-stage least squares estimation is more consistent than an OLS estimation, and that the instrumented variable is not over-identified.

7. Discussion and limitations

7.1 Discussion

My findings from the static regressions in the first part of the analysis suggest that it is unhappy investors that differ from others rather than happy investors, with those reporting being “unhappy” or “very unhappy” being more likely to participate in stock markets, and among those who do participate in stock markets, “unhappy” or “very unhappy” households have a lower risky share. Hypothesis 1, that *happiness has either a positive or a negative statistically significant impact on the likelihood of stock market participation, as well as on the risky share, after controlling for a set of standard household and individual characteristics, as well as for subjective risk aversion and optimism*, is therefore confirmed, again with the caveat that it is the unhappy investors that stand out, not those that are “happy” or “very happy”. Interestingly though, the coefficients in the static participation regression are more negative on “happy” or “very happy” households than on those that are “neither happy nor unhappy”, in line with the findings of Delis and Mylonidis (2015), and more positive in the static risky share regression, in line with the findings of Rao et al. (2016). With a different sample, a significant difference could possibly be found. Although recognizing that the results of the static regressions only describe correlations, they indicate that the impact of happiness (or rather, unhappiness) on risk-taking is different for participation than it is for the risky share. If one takes the view that a decision to participate or not in stock markets is a high-stake decision (although it of course should not be under a simple expected utility framework if one increases the risky share from zero to something very small, it could be perceived by investors as a high-stake decision), while the decision of the level of risky share is seen as a low-stake decision, this is in line with the findings of Isen and Patrick (1983), who document that positive moods are associated with the mood maintenance hypothesis for high-stake decisions, but the affect induced model for low-stake decisions. Importantly though, the dynamic participation regression which investigates how investment behavior differs for levels of happiness find no statistically significant difference between neither levels of happiness nor changes in happiness on stock market entry and exit behavior, and the coefficients on the lagged values of “neither happy nor unhappy”, “happy”, and “very happy”, albeit insignificant, are positive and close to zero. This indicates that investment behaviors do not differ significantly for investors at different levels of happiness. Therefore, it could be that the results found in the static regression are simply correlations, saying nothing about the validity of the mood maintenance hypothesis for a potentially high-stake decision.

As for the risky share, the dynamic regression shows that the coefficients on the lagged values of happiness are not statistically significant. Thus, we cannot conclude that investors at different levels of happiness change their risky share in a significantly different way. However, I find statistical significance for investors experiencing a decrease in long-term happiness over the year increasing their risky share less,

or decreasing it more than others. Taken together, this indicates that it is not the level of happiness relative to others' happiness that matters for investment behavior, it is the level of happiness relative to one own's past level of happiness that does, but only if that level is declining. It should be mentioned that the change in happiness is measured over the same period as the change in the risky share, indicating that endogeneity issues could remain and that this finding does not necessarily indicate more than a correlation. Whether it is likely that investors become less happy because their risky share has increased less than others' risky shares, or even declined, even after controlling for years that are bad or good in the stock market and several other characteristics, is outside the scope of this thesis to answer. However, if one assumes for a moment that that is unlikely (which in my view is not unreasonable), my results would indicate more than a correlation between the decrease in happiness and the change in the risky share, and it would be interesting to see further analyses of this in future research. Future research could also aim at finding the channel through which the decrease in happiness potentially impacts the change in the risky share. I found no indication that a change in risk aversion would be the channel, but as subjective risk preferences which I control for are not necessarily updated at the same speed as more objective measurements, I cannot rule out this channel completely. The channel of increased passiveness as a result from decreased happiness could in the future be analyzed with a data set containing trading data.

Altogether, I cannot completely confirm Hypothesis 2, that *happiness at year $t - 1$ has either a positive or a negative statistically significant impact on the change in participation and the change in the risky share, respectively, and the change in happiness between years $t - 1$ and t also has a statistically significant impact on the change in participation and the change in the risky share*. However, I can confirm that those that become less happy over the year do behave differently in that they increase their risky share less or decrease it more than others. While I cannot rule out that this is simply a correlation, I think it is likely that there is a stronger relationship than that, which would be interesting to investigate in future research. Interestingly then, my dynamic regressions point in the direction of the affect induced model, that positive moods induce risk-taking compared to negative moods. Since I cannot confirm the channel through which the decrease in happiness impacts risk taking, I cannot confirm whether risk preferences are affected by happiness evolvement at all, or if it is passiveness, or something else that is affected.

7.2 Limitations

Naturally, there are drawbacks of the survey format compared to other types of data. For example, data from official registers, such as the data from Statistics Sweden used in Calvet et al. (2007), is of very high quality and relies on for example tax records and systematically compiled bank statements. The risk of misreporting in these datasets is very low compared to the risk in survey datasets. Further, the size of the

official register datasets tends to be very large, while surveys rarely include more than a few thousand households. However, my variable of interest, happiness, is not captured in official registers. A difficulty with surveys is that respondents may misreport to get through the survey quicker. The DHS questionnaires on assets, liabilities, accommodation, mortgages, and income should be taken with bank statements or other relevant information at hand, but there is no guarantee that respondents report exactly in accordance with that information. The risk for misreporting is especially high for very detailed information, such as the value of a certain company stock or the value in bond funds versus stock funds within the mutual fund category.

Another difficulty which applies to the elicit variables is that respondents may interpret questions differently, partly depending on phrasing of the question, partly depending on framing and where in the questionnaire the question is placed. Their answers to the elicit variable questions could thus be biased. For example, there is a risk that the question on long-term happiness which I use in the analyses partly capture short-term happiness, if respondents are influenced by their current mood when answering the question. All this being said, the DHS is a high-quality survey which has been run and developed since 1993, and has been used in research in a wide range of areas including household finance (see for example van Rooij et al., 2011).

When it comes to my method, there are certain limitations that should be noted. Firstly, while the studying of only heads of households in this type of dataset is typical, I recognize that this means that strictly individual characteristics, such as education or happiness are only included for the head of the household and may not be drawn randomly from a population. Rather, it is likely that there are underlying structures impacting who reports as the head of the household. Notably, the share of women in the sample of heads of households is substantially smaller than in the original dataset. The alternative to selecting only heads of households would be to study all adult members of the household, aggregating joint and individually owned assets per household. However, this would put twice the weight on a household with two adult members compared to households with only one adult member, which could create significant biases. Moreover, this alternative approach would require that both adults report in all years, rather than just the head of the household reporting in all years, otherwise significant variations in assets and liabilities could result. Therefore, selecting only heads of households is deemed to be the most straightforward and consistent approach.

Secondly, there are some characteristics which have in earlier research been found to have an impact on either stock market participation or the risky share which are missing from my analysis, two examples being human capital and income risk. This could lead to omitted variable bias. On the other hand, these types of analyses will always suffer to some extent from omitted variable biases, as there will always be unobserved factors going into decisions, and participating or not in the stock market, and how one updates the risky share, are ultimately two complex decisions.

Thirdly, my results indicate that happiness is not driven by optimism, but I am hesitant to draw too much of a conclusion here, given the definition of optimism that I use. The idea was to use a general definition of optimism which is not only related to optimism towards financial markets, but as mentioned previously, a lot of different interpretations can go into the question on the likelihood of a sunny day tomorrow. It is therefore difficult to determine whether the lack of connection between happiness is due to the flaws of the optimism variable, or if general optimism actually does not have an impact on either long-term happiness, stock market participation, or the risky share. The latter would be in line with Delis and Mylonidis (2015), albeit they use a different measurement of optimism, but I am again hesitant to draw any firm conclusion.

Fourthly, the number of observations in the “unhappy” or “very unhappy” group is small relative to the groups of “neither happy nor unhappy”, “happy”, and “very happy”. My idea was to distinguish between those that report being “unhappy” or “very unhappy” and those that report being “neither happy nor unhappy”, rather than grouping them together, with the thought that those that report some level of unhappiness might exhibit a distinguishable behavior, in line with the findings of Kamstra et al. (2003). As I did find a significant difference for the unhappy group in the static regression, this thought was probably right, but the smaller number of observations in this group is of course not ideal. Yet, I deem the approximately 200 respondents in this group to be sufficient.

As for the use of the changes in happiness in the dynamic regressions, it is a limitation that there are only four groups of happiness. Those that report being in the unhappiest group cannot change downwards from one year to the other, and those that report being in the happiest group cannot change upwards, while the reality may look different. Further, in the dynamic regression on the change in the risky share, I instrument for the change in the log of financial wealth through lagging the variable two and three years. This reduces the number of observations substantially. It would be desirable to start with a larger dataset where every household reports every year, in order to have a larger number of observations in this regression.

8. Conclusions

In this study, I have provided color on the relationship between happiness and stock market participation as well as the risky share. Firstly, I show that investors that report being either “unhappy” or “very unhappy” are more likely to participate in the stock market, but also have a lower risky share. In the context of happiness and financial investments, this is to the best of my knowledge the first study to show that happiness, or rather unhappiness, has a complex association with risk-taking, neither only encouraging nor

only discouraging it. Secondly, I show that experiencing a reduction in long-term happiness is associated with a smaller increase in the risky share, as compared to experiencing an increase or reporting the same level of happiness in two consecutive years. Future research could aim at analyzing whether this is due to decreasing happiness being associated with increased risk aversion, increased passiveness, or something else.

9. References

- Almenberg, J., & Dreber, A. (2015). Gender, stock market participation and financial literacy. *Economics Letters* , 137, 140–142.
- Ameriks, J., & Zeldes, S. P. (2004). *How do household portfolio shares vary with age*. Tech. rep., working paper, Columbia University.
- Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of economic studies* , 58, 277–297.
- Bonaparte, Y., Kumar, A., & Page, J. K. (2012). Political climate, optimism, and investment decisions. *AFA 2012 Chicago Meetings Paper*.
- Brown, J. R., Ivković, Z., Smith, P. A., & Weisbenner, S. (2008). Neighbors matter: Causal community effects and stock market participation. *The Journal of Finance* , 63, 1509–1531.
- Brunnermeier, M. K., & Nagel, S. (2008). Do wealth fluctuations generate time-varying risk aversion? Micro-evidence on individuals. *American Economic Review* , 98, 713–36.
- Calvet, L. E., & Sodini, P. (2014). Twin picks: Disentangling the determinants of risk-taking in household portfolios. *The Journal of Finance* , 69, 867–906.
- Calvet, L. E., Campbell, J. Y., & Sodini, P. (2007). Down or out: Assessing the welfare costs of household investment mistakes. *Journal of Political Economy* , 115, 707–747.
- Calvet, L. E., Campbell, J. Y., & Sodini, P. (2009). Fight or flight? Portfolio rebalancing by individual investors. *The Quarterly journal of economics* , 124, 301–348.
- Campbell, J. Y. (2006). Household finance. *The journal of finance* , 61, 1553–1604.
- Carroll, C. D. (2000). *Portfolios of the Rich*. Tech. rep., National bureau of economic research.
- Carroll, C. D., & Samwick, A. A. (1997). The nature of precautionary wealth. *Journal of monetary Economics* , 40, 41–71.
- Chiappori, P.-A., & Paiella, M. (2011). Relative risk aversion is constant: Evidence from panel data. *Journal of the European Economic Association* , 9, 1021–1052.
- Cryder, C. E., Lerner, J. S., Gross, J. J., & Dahl, R. E. (2008). Misery is not miserly: Sad and self-focused individuals spend more. *Psychological science* , 19, 525–530.
- Delis, M. D., & Mylonidis, N. (2015). Trust, happiness, and households' financial decisions. *Journal of financial stability* , 20, 82–92.
- Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., & Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the european economic association* , 9, 522–550.
- Drichoutis, A. C., & Nayga Jr, R. M. (2013). Eliciting risk and time preferences under induced mood states. *The Journal of Socio-Economics* , 45, 18–27.
- Georgarakos, D., & Pasini, G. (2011). Trust, sociability, and stock market participation. *Review of Finance* , 15, 693–725.

- Guiso, L., Sapienza, P., & Zingales, L. (2008). Trusting the stock market. *the Journal of Finance* , 63, 2557–2600.
- Guiso, L., & Sodini, P. (2013). Household Finance: An Emerging Field. In: G. M. Constantinides, M. Harris, R. M. Stulz (Eds.), *Handbook of the Economics of Finance* (pp. 1397–1532), North-Holland, Amsterdam.
- Güven, C. (2012). Reversing the question: Does happiness affect consumption and savings behavior? *Journal of Economic Psychology* , 33, 701–717.
- Güven, C., & Hoxha, I. (2015). Rain or shine: Happiness and risk-taking. *The Quarterly Review of Economics and Finance* , 57, 1–10.
- Habimana, O. (2017). Do flexible exchange rates facilitate external adjustment? A dynamic approach with time-varying and asymmetric volatility. *International Economics and Economic Policy* , 14, 625–642.
- Haliassos, M., & Bertaut, C. C. (1995). Why do so few hold stocks? *the economic Journal* , 105, 1110–1129.
- Hlavac, M. (2018). Stargazer: Well-Formatted Regression and Summary Statistics Tables. R package version 5.2.2. <https://CRAN.R-project.org/package=stargazer>
- Heaton, J., & Lucas, D. (2000). Portfolio choice and asset prices: The importance of entrepreneurial risk. *The journal of finance* , 55, 1163–1198.
- Hong, H., Kubik, J. D., & Stein, J. C. (2004). Social interaction and stock-market participation. *The journal of finance* , 59, 137–163.
- Ifcher, J., & Zarghamee, H. (2011). Happiness and time preference: The effect of positive affect in a random-assignment experiment. *American Economic Review* , 101, 3109–29.
- Isen, A. M., & Patrick, R. (1983). The effect of positive feelings on risk taking: When the chips are down. *Organizational behavior and human performance* , 31, 194–202.
- Kamstra, M.J., Kramer, L.A., & Levi, M.D. (2003). Winter blues: a SAD stock market cycle. *American Economic Review*, 93(1), 324–343.
- Kapteyn, A., & Teppa, F. (2011). Subjective measures of risk aversion, fixed costs, and portfolio choice. *Journal of Economic Psychology* , 32, 564–580.
- Lane, T. (2017). How does happiness relate to economic behaviour? A review of the literature. *Journal of behavioral and experimental economics* , 68, 62–78.
- Mankiw, N. G., & Zeldes, S. P. (1991). The consumption of stockholders and nonstockholders. *Journal of financial Economics* , 29, 97–112.
- Puri, M., & Robinson, D. T. (2007). Optimism and economic choice. *Journal of financial economics* , 86, 71–99.
- Rao, Y., Mei, L., & Zhu, R. (2016). Happiness and stock-market participation: Empirical evidence from China. *Journal of Happiness Studies* , 17, 271–293.
- Salamanca, N., de Grip, A., Fouarge, D., & Montizaan, R. M. (2016). Locus of control and investment in risky assets.

Thörnqvist, T., & Vardardottir, A. (2014). Bargaining over risk: The impact of decision power on household portfolios.

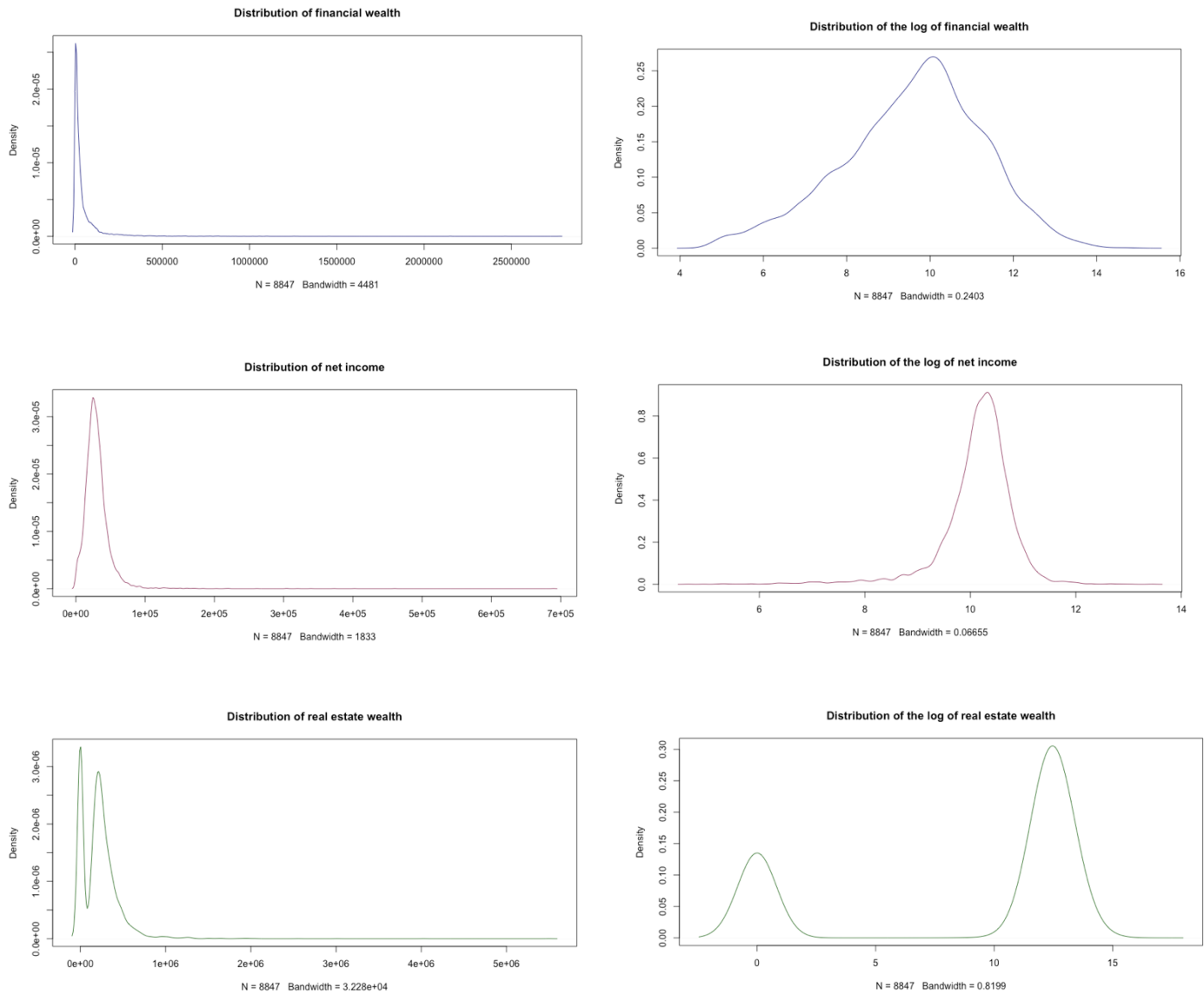
Van Rooij, M., Lusardi, A., & Alessie, R. (2011). Financial literacy and stock market participation. *Journal of Financial Economics* , 101, 449–472.

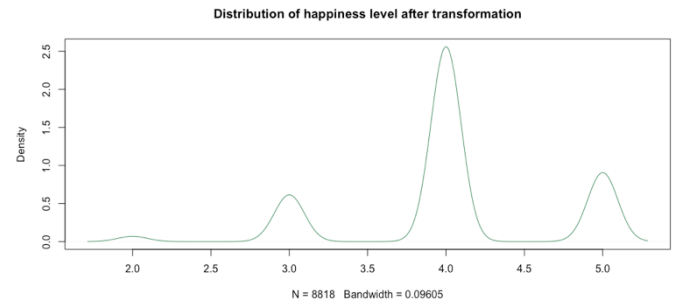
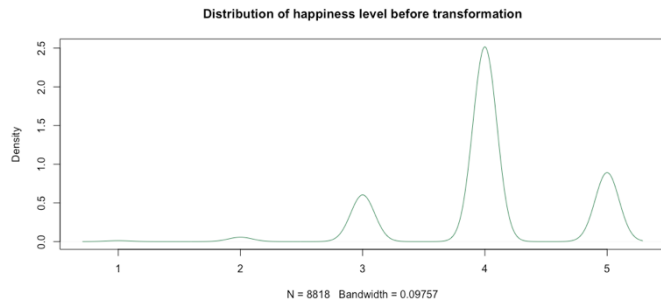
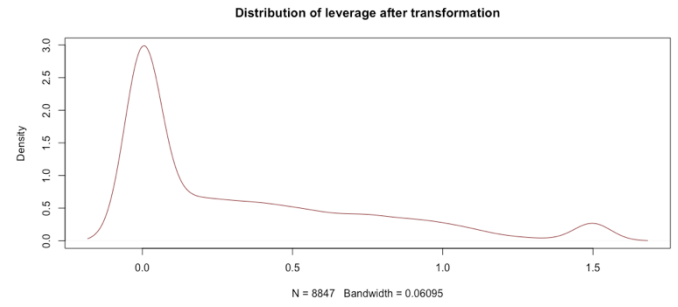
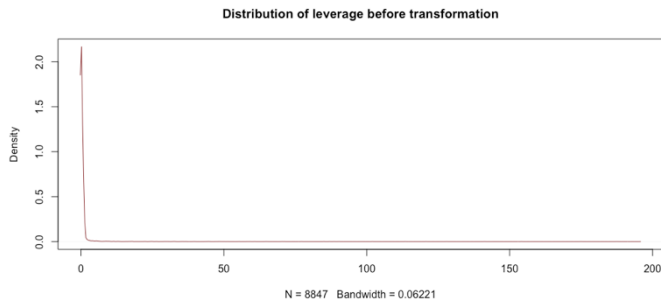
Van Winden, F., Krawczyk, M., & Hopfensitz, A. (2011). Investment, resolution of risk, and the role of affect. *Journal of Economic Psychology* , 32, 918–939.

Vissing-Jorgensen, A. (2003). Perspectives on behavioral finance: Does" irrationality" disappear with wealth? Evidence from expectations and actions. *NBER macroeconomics annual* , 18, 139–194.

Appendix A

Distribution of variables before and after transformation. For financial wealth and net income the transformation is done by taking the natural logarithm of the reported values. For real estate wealth, the the natural logarithm of the reported values is taken, unless real estate is reported as zero, when the transformed value is also zero. For leverage the transformation is done by capping at 1.5, such that all observations with leverage exceeding 1.5 receive the value 1.5. For happiness, the groups “very unhappy”, shown in the image as “1”, and “unhappy”, shown in the image as “2” are merged together.





Appendix B

Summary statistics for all households included in the dataset, after limitations. The table shows the number of observations, the mean, standard deviation, minimum, 25th percentile, 75th percentile, and maximum of the selected variables for all households, whether they participate in the stock market or not. For the dummy variables, the mean value corresponds to the share of observations assuming a value 1.

Summary statistics - all households

Statistic	N	Mean	St. Dev.	Min	Pctl (25)	Pctl (75)	Max
Gross wealth	8,847	270,768.20	278,838.20	104	62,679	362,400	5,622,900
Financial wealth	8,847	47,507.64	105,659.80	104	5,100	46,175.5	2,777,750
Stocks	8,847	3,241.40	20,769.76	0	0	0	785,120
Mutual funds	8,847	9,473.57	48,728.13	0	0	0	1,039,500
Risky share	8,847	0.10	0.23	0.00	0.00	0.00	1.00
Real estate wealth	8,847	218,998.20	220,835.40	0	0	300,000	5,500,000
Business wealth	8,847	4,262.39	61,097.16	0	0	0	3,825,000
Log of financial wealth	8,847	9.59	1.67	4.65	8.54	10.74	14.84
Log of real estate wealth	8,847	9.02	5.61	0.00	0.00	12.61	15.52
Log of net income	8,847	10.15	0.68	4.65	9.90	10.51	13.44
Leverage	8,847	0.33	0.42	0.00	0.00	0.57	1.50
Age	8,847	57.92	15.89	21	46	70	95
Higher education dummy	8,845	0.47	0.50	0.00	0.00	1.00	1.00
Female dummy	8,847	0.28	0.45	0	0	1	1
Partner in household dummy	8,847	0.62	0.48	0	0	1	1
Retirement dummy	8,847	0.38	0.48	0	0	1	1
Unemployment dummy	8,847	0.02	0.14	0	0	0	1
Student dummy	8,847	0.02	0.13	0	0	0	1
Entrepreneur dummy	8,847	0.04	0.19	0	0	0	1
Number of kids	8,847	0.41	0.87	0	0	0	6
Risk aversion	8,487	5.19	1.04	1.50	4.50	6.00	7.00
Financial literacy	8,842	2.34	0.73	1.00	2.00	3.00	4.00
Optimism	8,843	53.48	26.77	0.00	40.00	75.00	100.00
Happiness	8,818	4.03	0.67	1.00	4.00	4.00	5.00

Appendix C

Static probit regression on the binary dependent variable stock market participation. Note that the coefficients are not comparable to the linear probability model with results shown in table 5, as the probit regression uses a maximum likelihood estimation. The variables for which a statistical significance is found in the linear probability estimation remain the same in the probit regression, and the direction of the coefficients is the same.

Probit regression results - participation

	Estimate	Std. error	z value	Pr(> z)
Log of net income	0.089	0.034	2.602	0.009
Log of financial wealth	0.508	0.016	31.272	0
Log of real estate wealth	0.004	0.004	1.134	0.257
Leverage	-0.037	0.061	-0.609	0.542
Age	0.009	0.002	4.570	0.00000
Higher education dummy	0.094	0.039	2.420	0.016
Female	-0.153	0.050	-3.064	0.002
Unemployment dummy	-0.130	0.137	-0.946	0.344
Retirement dummy	-0.234	0.056	-4.147	0.00003
Entrepreneur	-0.087	0.096	-0.905	0.366
Partner in household dummy	-0.117	0.046	-2.571	0.010
Number of children	-0.084	0.024	-3.457	0.001
Risk aversion	-0.583	0.020	-29.251	0
Financial literacy	0.073	0.026	2.754	0.006
Neither happy nor unhappy	-0.245	0.148	-1.660	0.097
Happy	-0.389	0.143	-2.729	0.006
Very happy	-0.283	0.147	-1.926	0.054
Optimism	-0.00001	0.001	-0.009	0.993