Household Portfolios and Volatility: Evidence from Dutch Households over Booms and Busts

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Abstract:
This paper contributes to the rapidly growing body of literature on household portfolios. It links portfolio theory to empirical research in order to investigate the relationship between stock volatility and households’ stock allocation. Several recent studies concerning investment behavior under risk found the separation of up- and downside volatility to make an important difference. Using data from Dutch households, this paper examines whether this pattern is also reflected by microdata from annual surveys. It is the first study exploring households’ risk perceptions and behavior by including financial market data in an analysis of household panel data. The results indicate that both volatility per se, as well as its predominant direction, significantly affect the portfolio shares allocated to stocks, and the subjective aversion against stock investments. There is no clear effect on stockownership.

1 Field of studies: Economics; closing date: July 28, 2011.
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1 Introduction

As in many industrialized countries, the composition of household portfolios in the Netherlands has changed substantially during the last two decades. In the course of decreasing transaction and information costs the fraction of households directly owning stocks doubled from 6% in 1993 to almost 12% in 2009, whereas the conditional portfolio shares of stocks fell from 46% to 15%.

Understanding these trends is crucial, for commercial banks as well as for monetary and fiscal policy makers. As Bertaut and Starr-McCluer (2002) point out, household portfolio decisions play a major role “in determining how changes in macrovariables – interest rates, stock prices, inflation, and unemployment – affect household spending and saving. [...] Portfolio decisions also underlie the effects of fiscal policies [...] on personal and national saving.”

Previous studies on household finance mostly focus on socioeconomic and -demographic characteristics, such as income, education, age and gender, as major determinants of portfolio choice. While also controlling for these characteristics, this study focuses on the effects of stock market performance by including variables on stock returns and volatility.

A critical assumption across virtually all papers on household portfolios is that assets can be classified as “safe”, “fairly safe” and “risky” in a way that corresponds with the households’ perceptions. But what exactly is “risk”? The common approach here is to simply use the variance of returns (or volatility), as proposed by traditional portfolio theory. In contrast, growing evidence in the literature suggests that investors are loss averse rather than risk averse indicating that the direction of deviation from the mean (i.e. upside or downside volatility) is the determinant of perceived risk and, hence, cannot to be neglected. Since (upside and downside) volatility is not constant over time, another question is, if it is reasonable to determine assets’ riskiness statically. Behavioral finance shows that investors tend to evaluate their portfolios frequently. As a consequence, expectation formation and decision-making concerning financial investments largely depend on the performances of specific assets in the recent past, not on long-run trends.

Suppose a household reduces its portfolio share of stocks from one year to another by 20%. If evaluated on the background of the Capital Asset Pricing Model (CAPM) increased risk aversion would explain this retreat from stocks.

2 Conditional on stock market participation; see section 5.1 for further explanation.
3 See section 4.1, figure 1 for a graph on this development.
According to Vayanos (2004), “during volatile times, investors’ effective risk aversion increases” in fact. An alternative explanation, however, is that it is not risk aversion but rather the perceived risk associated with stocks that increases during volatile times. This especially makes sense in consideration of the theory of loss aversion, as volatile times are generally times of highly negative returns and high downside volatility. Using the DHS data Hurd (2009), recently found “a signification negative relationship between the subjective standard deviation of stock returns and ownership” even without distinguishing the direction of deviations.

This paper hypothesizes that households reduce their portfolio allocation to stocks in times of predominant downside volatility, which is perceived as (negative) risk, and increase it (or do not reduce it) in response to higher upside volatility. Volatility per se is thus only in part a bad thing in the investors’ view. If it is mostly driven by upside deviations from the yearly mean, which is usually the case when volatility is relatively low, it might even be considered positively. Therefore, this study includes measures of upside and downside volatility in order to control for changing risk perceptions and expectations.

Section 2 briefly presents the most relevant insights from portfolio theory and behavioral finance. Section 3 gives an overview of the previous evidence on household portfolios from diverse countries, in particular the Netherlands. The focus is on socioeconomic and demographic characteristics, the effects of external factors, and findings on risk aversion. Section 4 describes the data used for this study: the yearly panel data from the DNB Household Survey (DHS) since 1993, and performance data of the Amsterdam Exchange Index (AEX). Section 5 contains the empirical analysis, which is structured into three models (conditional portfolio shares, stock ownership, and stock aversion), each consisting of two main specifications: a basic model including only the variables discussed in section 3 as well as an extended model, which adds the variables on stock returns and volatility.

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4 See section 4.2, figure 2 for a graphical representation of the relationship between yearly stock returns and volatility.
2 Portfolio choice and risk – *theory*

2.1 Modern Portfolio Theory

“The concept of risk has so permeated the financial community that no one needs to be convinced of the necessity of including risk in investment analysis” (Blume 1971). Today, the mid 20th century may be viewed as the florescence of modern portfolio theory. The seminal work has been done by Markowitz (1952). He developed a theory of optimal portfolio selection, the so-called EV rule, solely depending on the expected return (E) and the variance (V) of a portfolio. According to Markowitz, “the investor does (or should) consider expected return a desirable thing and variance of return an undesirable thing”. The term variance, as he remarks immediately afterwards, may be replaced by “risk” without changing the apparent meaning of this rule.

Of course, Markowitz does not intend to advice investors against risk of any kind. As Engle (2004) notes, “there are some risks we choose to take because the benefits from taking them exceed the possible costs. [...] Optimal behavior takes risks that are worthwhile.” Optimal portfolio choice in the sense of Markowitz (1952) relies on diversification: “[...] for a large, presumably representative range of \( \mu, \sigma \) the E-V rule leads to efficient portfolios almost all of which are diversified.” In Markowitz’ model investors choose mean-variance efficient, sometimes called Markowitz efficient, portfolios that either minimize portfolio variance, given expected return, or maximize expected return, given variance.

The CAPM: Assuming that all investors follow this rule with the same set of information, Sharpe (1964), Lintner (1965) and Mossin (1966) developed an equilibrium model based theory called *Capital Asset Pricing Model* (CAPM). Building on the work of Markowitz (1952), it suggests a close positive relation between expected returns and variance. Sharpe (1964) distinguishes two prices that the market offers to investors: “the price of time, or the pure interest rate [...] and the price of risk (or more precisely, as noted by Mossin (1966), the price of risk reduction), the additional expected return per unit of risk borne.” According to the CAPM, every investor holds a portfolio composed of two asset categories: a risk-free one, traditionally represented by government bonds, and a risky mutual fund, the so-called market portfolio. The lower the degree of risk aversion, the higher the proportion of wealth allocated
to the market portfolio. In regard to the market portfolio the model assumes “that if an investor holds any risky assets at all (i.e., if he is not so averse to risk as to place everything in the riskless asset), then he holds some of every asset” (Mossin [1966]). The key feature of the market portfolio is that it minimizes the portfolio variance (for a given expected return) so that there is no diversifiable (or systematic) risk, as opposed to unsystematic (or undiversifiable) risk, left. The systematic risk refers to the market risk, i.e. the risk that is common to all securities; the unsystematic risk is the risk associated with individual assets.  

2.2 Post Modern Portfolio Theory

Traditional portfolio theory suggests that investment decisions should be a function of expected returns, variance and the covariance structure of the returns of all investment opportunities available. Informational constraints and bounded rationality, however, may prevent ordinary investors from actually following that rationale. There is a large body of evidence suggesting that investors diversify their portfolios insufficiently – both in terms of the number of assets held (e.g., investing predominantly in domestic assets) as well as in terms of proportions of these assets within the portfolio (e.g., attaching the same weight 1/n to each of the n available assets). Especially “the very idea that risk is defined at the level of the portfolio – rather than at the level of individual assets – and that risk depends on covariation between returns remains foreign to many investors” (De Bondt [1998]).

**Downside Risk:** Already in 1964 Sharpe pointed out that “under certain conditions the mean-variance approach can be shown to lead to unsatisfactory predictions of behavior.” Markowitz suggests that a model based on the semi-variance (the average of the squared deviations below the mean) would be preferable; in light of the formidable computational problems, however, he bases his analysis on the variance and standard deviation.” As early as Roy [1952], economists as well as researchers in finance and psychology have recognized that investors care differently about their exposure to the risk of

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6 The relationship between the expected return of a particular asset i within the market portfolio m to its unsystematic risk is given by the CAPM pricing formula: $E[R_i] = r_f + \beta_i (E[R_m] - r_f)$, where $\beta_i = \text{Cov}(R_i, R_m)/\text{Var}(R_m)$.

7 The former example refers to what French and Poterba [1991] call home bias; the latter describes an extreme form of naive diversification (Benatzi and Thaler [2001]). Excessive trading (Barber and Odean [2001]) is another phenomenon commonly occurring among both individual and institutional investors.
earning a return below a certain threshold (downside risk), and the chance of making a profit above (upside risk). Kahneman and Tversky (1979) developed a general theory taking into account the asymmetric nature of investors’ risk perception. Their Prospect Theory provides a concept of loss aversion, referring to the tendency of individuals to weigh losses more heavily than gains. As Olsen (1998) notes, investors tend “to focus on negative information when under stress, overweighting the probability of negative events, and becoming more loss averse as downward movements in the value of their portfolios remind them of their incomplete personal control.”

Investors who are sensitive to downside losses, relative to upside gains, require a premium for holding assets that covary strongly with market downturns. Taking this into account, Bawa and Lindenberg (1977) suggest an extension to the traditional CAPM that specifies asymmetric downside betas (if the market returns \( r_m \) is below the average excess return \( \mu_m \)) and upside betas (if \( r_m \) > \( \mu_m \)). The downside beta is given by the cosemivariance between an individual asset’s returns and the market divided by the market’s semivariance of returns. Estrada (2007) provides evidence “supporting the downside beta over beta, and, therefore, the pricing model based on downside risk over the CAPM.” There is a considerable body of evidence (e.g., Harlow (1991) suggesting that the investor’s risk perceptions depend on expected downside volatility rather than on expected volatility per se.

**Myopia:** The Myopic Loss Aversion (MLA) theory by Benatzi and Thaler (1995) combines the concept of loss aversion with another behavioral concept developed by Kahneman and Tversky (1984), called mental accounting. Mental accounting here refers to the process whereby investors evaluate financial outcomes. It assumes that people in general have myopic expectations, meaning that they focus on the recent rather than on the distant past. Many empirical papers, for instance De Bondt (1993), indicate “that non-experts expect the continuation of apparent past ‘trends’ in prices.” The MLA implies that investors tend to underestimate the attractiveness of risky assets due to short-sighted, or too frequent, portfolio evaluations.

An important feature of mental accounting is narrow framing – the tendency to evaluate single investments separately from the other portions of the portfolio, often “simply because information about those gains and losses is more readily available” (Barberis and Huang, 2001). Barberis and Huang (2001)
distinguish two kinds of narrow framing: 1) *portfolio accounting*, which refers to the separate evaluation of a particular sub-portfolio, and 2) – the extreme form of narrow framing – *individual stock accounting*. An investor engaging in individual stock accounting is “loss averse over individual stock fluctuations, [...] (implicitly using) a discount rate [...] that changes as a function of the stock’s past performance. If a stock has had good recent performance, the investor gets utility from this gain, and becomes less concerned about future losses on the stock because any losses will be cushioned by the prior gains. [...] Conversely, if one of his stocks performs dismally, he finds this painful and becomes more sensitive to the possibility of further losses on the stock.” Building on these insights from portfolio theory this paper assumes that...

- investors trade-off returns against risk,
- individuals are averse against losses, i.e. negative (or downside) risk,
- (downside) volatility is an appropriate measure of (downside) risk,
- investors evaluate their portfolios frequently, focusing on performance in the recent past,
- investors tend to evaluate specific assets or sub-portfolios separately.

This leads to the hypothesis that recent stock returns and also volatility – in particular its size and overall direction – affect households’ portfolio choice.

### 3 Previous evidence on household portfolios – literature overview

#### 3.1 Evidence on socioeconomic and -demographic characteristics

**Income and Wealth:** Empirical research on the factors determining the portfolio choice of private households has its beginnings in the early 1970s. **Uhler and Cragg (1971)** were the first to use U.S. household survey data in order to “investigate the effects of income and non-human wealth on the way in which households structure their holdings of financial assets.” Their major result indicating that raising levels of income and wealth come along with a higher degree of diversification has been confirmed by several recent studies covering different industrialized countries. **Bertaut and Starr-McCluer (2002)** and **Börsch-Supan and Eymann (2002)**, for instance, found that ownership as well as portfolio shares of risky assets rise with wealth, while the income effect
is shown to be negative in regard to portfolio shares and positive in regard to ownership of risky assets. Cocco et al. (2005) demonstrate that the level of secure labor income, being a close substitute for risk-free assets, increases stockholdings. Using the DHS data, Alessie et al. (2002) found “a strong positive relation between total net worth and ownership of risky assets” and moreover that “the share of risky assets conditional on ownership also increases with wealth.”

**Age:** A truly classic issue in household portfolio studies is the effect of age. King and Leape (1987) found that age positively affects the probability of owning different assets, even if controlled for wealth. They assign this result to financial knowledge, which is assumed to be increasing with years of age. Paxson (1990) notes that young households, often characterized by confined liquidity that has to be available on demand, tend to hold relatively safe and liquid assets. In contrast, Bodie et al. (1992) predict a decline in holdings of risky assets in old age as younger investors enjoy greater labor supply flexibility and better opportunities to diversify shocks over time. Some more recent studies indicate a hump-shaped age-profile of risky asset ownership. As remarked by Ameriks and Zeldes (2001) the interpretation of “age effects” might be ambiguous since it is difficult to disentangle time and cohort effects from it.

**Education:** Several papers point out the role of education in households’ portfolio decisions, with most of them showing a strong positive education effect on ownership and portfolio shares of risky assets. For example, Haliassos and Bertaut (1995) show that “at all income groups, the incidence of stockholding is substantially larger among more educated groups with higher information-processing capabilities.” Bertaut (1998) introduces the costs of information on stock investing to a consumption-CAPM. The model indicates that investing in stocks depends critically on the households’ ability to process financial information, which is assumed to be positively related to education. Numerous recent studies provide evidence on the positive relationship between

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8 See for instance Guiso and Jappelli (2002), and Campbell (2006).
9 The CCAPM is an intertemporal extension to the CAPM assuming that the representative investor’s utility is a concave function of aggregate consumption. He tries to smooth consumption by demanding assets that are negatively correlated with consumption. Thus, the CCAPM predicts that the premium on a specific asset will be proportional to its consumption $\beta$. 

7
education, financial literacy and risky asset holdings.\textsuperscript{10}

**Employment status:** There is large evidence on the importance of job and income security in determining households’ financial decisions. The majority of studies suggest that households facing lower income risk are less reluctant to undertake additional risks.\textsuperscript{11} For example, Agnew et al. (2003) argue that “job security [...] makes human capital less risky, which makes it optimal to increase financial exposure to the riskier assets.” A number of studies emphasize the differences between particular kinds of employment. For example, Agnew et al. (2003) found that the self-employed are more likely to hold stocks than others. Bertaut and Starr-McCluer (2002), on the other hand, provide contradictory evidence indicating that being employed has a positive effect on diversification in risky assets, being self-employed however a negative one.

**Gender and relationship status:** A widespread view concerning portfolio choice is that women are more conservative and in general more risk averse investors than men.\textsuperscript{12} Barber and Odean (2001), for instance, found that men are more overconfident regarding their knowledge about an asset’s value, making them to trade more excessively and to hold more risky positions in their portfolios. However, there is also a number of papers that cannot support this gender stereotype, suggesting that there are no gender differences in risk propensity (e.g. Brachinger et al. (1999)) or even showing a reverse effect (e.g. Bertaut and Starr-McCluer (2002)).

The empirical findings on the relationship status are less controversial. According to Agnew et al. (2003), married couples trade more actively and have higher stock allocations than their non-married counterparts. A possible explanation is that couples with dual earners enjoy some diversification of labor-income shocks. Sung and Hanna (1998) found a significant spouse effect on households’ portfolio choice, implying that couples make their investment decisions together. Similarly, Barber and Odean (2001) argue that “married couples influence each other’s investment decisions and thereby reduce the

\textsuperscript{10} See for example Campbell (2006), Alessie et al. (2007), Barasinska et al. (2008), and Guiso and Jappelli (2008).

\textsuperscript{11} See for example Haliassos and Bertaut (1995), Guiso and Jappelli (2002), and Agnew et al. (2003).

\textsuperscript{12} See for example Hinz et al. (1997), Barber and Odean (2001), and Alessie et al. (2007).
effects of gender differences in overconfidence.”

Other socio-demographic factors: As early as Uhler and Cragg (1971), household portfolio studies have considered the effect of family size. According to Uhler and Cragg, family size, just like age, can be taken as a proxy for the households’ utility function. They identify a significant negative relationship between family size and the level of portfolio diversification, which has been confirmed by several recent studies. In contrast, Börsch-Supan and Eymann (2002) found that the probability of holding risky assets increases with household size.

Interestingly, there is also evidence that the health status influences households’ portfolio choice. Rosen and Wu (2004) show that healthier investors, all things being equal, are more likely to own risky assets and also allocate higher shares of their total wealth to risky assets.

This study’s empirical results are broadly in line with these previous findings. Except for the relationship status each of the discussed characteristics is shown to be a significant determinant of household portfolio choice in at least one model.

3.2 Evidence on external conditions

Similar to this paper, some previous studies focus on the influence of external factors, such as transaction and information costs, taxes or the overall economic conditions.

There is broad agreement that transaction and information costs involved in buying and holding assets play a major role in investment decisions, in particular for smaller, less wealthy investors. Several household portfolio studies provide evidence on the participation discouraging effect of monetary transaction and information costs.

13 See for example Guiso and Jappelli (2002), and Guiso et al. (2003).

14 Some studies also analyze the effect of race on households’ portfolio choice (e.g. Haliassos and Bertaut 1995, and Bertaut and Starr-McCluer 2002). They usually show that whites are more likely to own risky assets and also allocate higher shares of their wealth to risky assets. However, as the used dataset does not contain information on race, this study cannot control for this aspect.

15 See for example Uhler and Cragg (1971), King and Leape (1987), Alessie et al. (2004), and Bertaut and Starr-McCluer (2002).
The tax system is another factor that is widely assumed to influence portfolio choice. Leape (1987), for instance, found that taxation affects participation decisions if transaction costs are tax deductible. Also Alessie et al. (2002) and Börsch-Supan and Eymann (2002) show that tax incentives have a powerful effect on portfolio decisions.\[16\]

Contrasting to the above evidence on socioeconomic and demographic characteristics, Christelis et al. (2010) have recently shown that differences in these “characteristics often play no role, (while) differences in economic environment are seen to explain most of the observed differences in ownership rates and in amounts held.”\[17\]

3.3 Evidence on risk aversion

As explained in the previous section, portfolio theory assumes the investor’s attitude towards risk to be a crucial factor of portfolio diversification. Accordingly, a higher risk aversion is related to a higher level of portfolio diversification and lower portfolio risk, respectively. While there is hardly any doubt that this should be true, the practical application of this insight is by no means straightforward. If there is no information about individual risk aversion, it has to be inferred from the given data. A household is commonly assumed to be the more risk averse, the less risky assets it holds. In the strict sense of portfolio theory, the opposite should be the case. Yet, in regard of the large evidence indicating that most households do not fully understand the risk-reducing effects of diversification and rather employ portfolio or stock accounting (Barberis and Huang, 2001)\[18\], it seems to be reasonable to take (high) holdings of risky assets as an indicator of (low) risk aversion.

Many contemporary surveys on household finance contain data on subjective risk aversion (i.e. people are asked to state their risk aversion on a scale) that have been analyzed in a number of recent studies. Most of them confirm the above assumption that high risk aversion implies low or no holdings.

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16 This study does not explicitly control for taxes. However, the variable on net income may take account of this issue to some extent.

17 The variable on economic conditions is composed of four indicators: market capitalization to GDP ratio, number of Internet connections, a measure of shareholder rights, and an aggregate index of prevailing trust.

18 See section 2.2.
of risky assets. Surprisingly, Gomes and Michaelides (2005) found that risk-averse investors are more likely to own risky assets, as they accumulate more wealth and, thus, market entry and transaction costs carry less weight.

4 Data

4.1 DNB Household Survey (DHS)

There are three reasons why this study analyzes the portfolios of households in the Netherlands. First and foremost, the Netherlands is a small country, in particular if measured against the size of its economy. Companies such as Unilever, ING, Heineken or Shell belong to the world’s largest listed companies. Just as their products, the stocks of these companies are traded all around the world. This largely prevents endogeneity problems in regard to the stock returns, i.e. that the stock returns are a result of the Dutch households’ trading activity instead of the other way around.

Another major reason to study the Netherlands is the availability of rich and detailed panel data: the DNB Household Survey (DHS)\(^1\) sponsored by the Dutch National Bank (DNB) the panel is carried out by CentERdata, an Internet survey specialized unit of CentER Group, which is closely linked to the University of Tilburg. The survey provides extensive information on various topics, including work, income, mortgages, assets, loans and health, and on all major socioeconomic and demographic household characteristics. While (repeated) cross-section data are available for many countries, household panel data with detailed information on portfolio choice and wealth are still scarce. For example, the German SOEP does not record holdings of particular assets. Instead, it aggregates “safe”, “fairly risky” and “risky” assets. The Europe-wide SHARE panel is more specific on the kinds of assets held. However, stockholdings are still not reported separately but summarized with mutual and real estate funds. Another critical drawback of this panel is that it covers only the period from 2004 up to now. The DHS, on the other hand, allows for distinction between more than 20 different assets, including company share holdings (henceforth “stocks”). Moreover, the panel is conducted since 1993 with only a few small design adjustments.

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\(^{19}\) See for example King and Leape (1998), Campbell (2006), and Barasinska et al. (2008).  
\(^{20}\) Formerly CentER Savings Survey (CSS).
The sample of the DHS is representative of the Dutch population with respect to certain socioeconomic variables (region, degree of urbanization, income, political preference, housing, and age of the head of the household). The initial sampling was conducted using telephone directories as the sampling frame. In order to obtain a sample, which was an appropriate representation of the Dutch population, a four-step stratified sampling procedure was used. Potential participants were phoned, asked for background information and if they would be willing to take part in the panel. Those expressing willingness were then interviewed and introduced to the computer-based interviewing technique used. Households without Internet access are given the use of a so-called Net.Box, allowing them to enter data and submit the filled in questionnaires online. Participants have to agree to answer seven questionnaires on various topics every year. The questionnaires are transmitted to all household members aged 16 or over on a weekly basis. To date, the DHS data set contains 18 yearly waves from 1993 till 2010 with each wave comprising a representative sample of about 2,000 households. The data from 1993 till 1998 also contain an additional sample of about 500 high-income households. For this analysis both samples are combined. In order to keep the results representative a dummy variable (highinc) controls for the sample the household belongs to. Table 1 presents basic descriptive statistics for the full sample, and for the sub-sample of stock market participating individuals.

Alessie et al. (2002) emphasize the institutional setting to be another reason why the analysis of households’ portfolio allocation is interesting particularly with regard to the Netherlands: “Financial markets are well developed compared to, for example, Germany and Italy [...] and the information channels through which the common household can learn about all the existing investment possibilities are quite extensive.” Still, as shown in figure 1, the large majority of households do not (directly) hold any stocks. Very low transition rates (from non stockownership to stockownership and vice versa) moreover indicate that most households either hold stocks in every period or in none. Nonetheless, the (direct) ownership rate of stocks has gradually risen from about 6% in 1992 to around 13% between 2000 and 2003. It is a widely held view that this increase is largely due to fallen transaction and information costs. After the financial crisis 2001/2002, however, the rate fell back to its current level of about 11%. This may be considered as evidence on Christelis et al. (2010) who suggest that it is mostly the overall economic environment what determines households’ portfolio choice. Surprisingly, stockownership has barely changed
Table 1: Socioeconomic profile of the households

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>Stock market participating</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean/Percentage</td>
<td>Mean/Percentage</td>
</tr>
<tr>
<td>Women</td>
<td>46.82%</td>
<td>23.59%</td>
</tr>
<tr>
<td>Age</td>
<td>48.86</td>
<td>54.47</td>
</tr>
<tr>
<td></td>
<td>(14.14)</td>
<td>(13.80)</td>
</tr>
<tr>
<td>No. of children at home</td>
<td>0.81</td>
<td>0.70</td>
</tr>
<tr>
<td></td>
<td>(1.13)</td>
<td>(1.13)</td>
</tr>
<tr>
<td>Net income, in Euro</td>
<td>33085.51</td>
<td>50644.09</td>
</tr>
<tr>
<td></td>
<td>(33719.64)</td>
<td>(41638.60)</td>
</tr>
<tr>
<td>Financial wealth, in Euro</td>
<td>52722.32</td>
<td>256608.10</td>
</tr>
<tr>
<td></td>
<td>(1642838)</td>
<td>(4753016)</td>
</tr>
<tr>
<td>Vocational education</td>
<td>34.02%</td>
<td>28.06%</td>
</tr>
<tr>
<td>Higher education</td>
<td>17.38%</td>
<td>24.04%</td>
</tr>
<tr>
<td>Employed</td>
<td>51.59%</td>
<td>49.11%</td>
</tr>
<tr>
<td>Self-employed</td>
<td>3.43%</td>
<td>4.46%</td>
</tr>
<tr>
<td>Unemployed</td>
<td>2.57%</td>
<td>1.06%</td>
</tr>
<tr>
<td>Retired</td>
<td>15.77%</td>
<td>28.18%</td>
</tr>
<tr>
<td>Number of households</td>
<td>7584</td>
<td>1068</td>
</tr>
<tr>
<td>Number of individuals</td>
<td>12671</td>
<td>1266</td>
</tr>
<tr>
<td>Number of observations</td>
<td>40834</td>
<td>4052</td>
</tr>
</tbody>
</table>

Source: DNB Household Survey, Datastream, own calculations; standard deviations in brackets.

during the boom 2004–2007, and just as little in response to the following financial crisis (2008–2010). The rate stays more or less constant around 11%. Next to the ownership rates, figure 1 also shows the average portfolio shares conditional on stock market participation between 1992 and 2009. While the declines in 1993/1994 and 2002/2003 are certainly related to stock market downturns, an explanation for the sharp fall between 1996 and 1999 may be that investors to some extent replaced stocks by innovative financial products. Furthermore, the charts roughly indicate reverse long-term trends: the average conditional portfolio share of stocks dropped from 46% in 1992 down to 15% in 2009; stockownership, on the other hand, doubled from 6% to almost 12%.

4.2 Amsterdam Exchange Index (AEX)

In order to calculate stock returns and volatility faced by the households, this study uses the Amsterdam Exchange Index (AEX) as a proxy for the households’

21 See section 5.1 for the definition of the conditional portfolio share of stocks.
Figure 1: Stockownership rate and average conditional portfolio share of stocks

stock portfolios. The data are retrieved via *Thomson Reuters Datastream*. The
AEX is composed of the 25 Dutch companies with the highest share turnover
(in Euro), excluding companies with less than 25% of shares considered free
float. Of course, not all stock-owning households hold exclusively shares of
AEX or even Dutch companies. In fact most do not. Yet, the data show
that most stockowners allocate a large proportion of their stock investments
to domestic companies. Besides that, the leading European stock markets are
highly correlated. That means that even in the short run their charts move in
a very similar way. Figure 2 illustrates the yearly returns and volatility of the

Figure 2: AEX stock returns and volatility

The charts clearly show that volatility tends to be low during booms and
high during busts: the lower the stock returns, the higher volatility, and vice
versa. For example, volatility reached all-time highs in the financial crises
2001/2002 and 2007/2008, while it dropped back to its low levels of the early
1990s during the recovery period inbetween.
5 Empirical Analysis

5.1 Methods

“The key feature of panel data that distinguishes them from a pooled cross section is the fact that the same cross-sectional units [...] are followed over a given time period.” This implies two major advantages: first, “having multiple observations on the same units allows us to control for certain unobserved characteristics of individuals [...]. A second advantage of panel data is that they often allow us to study the importance of lags in behavior” (Wooldridge, 2006). The methodological framework underlying the models estimated in this paper will be described below.

Volatility: Since the household data are yearly, the additional variables on volatility have to be calculated on yearly basis, too. Hence, volatility is defined as the variance of the daily returns within a trading year (corresponds roughly to 250 trading days). As the key hypothesis of this paper is that households’ portfolio allocation to stocks depends on upside and downside risk (i.e. upside and downside volatility) rather than on risk per se (i.e. volatility), variables that distinguish the direction of deviation from the yearly mean must be computed as well. For this purpose the returns will be separated into two columns: one for the positive returns (column 1), and another for the negative ones (column 2). If there is a positive return in column 1, the corresponding value in column 2 is set to zero (and vice versa). Thereupon, the variance for both columns is calculated, using the mean of all returns. In this way, the volatility is split into a positive and negative component, whereas the sum of these components (approximately) equals the overall volatility.

Conditionality: In order to analyze portfolio shares in a meaningful way it is crucial to restrict the sample to those individuals who actually participate in the stock markets. Otherwise, the coefficients would be biased by observations of individuals who generally do not take stock investing into consideration. One opportunity is to simply analyze portfolio shares conditional on stockownership, i.e. to exclude all observations where the dummy variable on stockownership equals zero. Yet, this approach also excludes observations of individuals who actually do participate in the stock market but have deliberately chosen a 0% portfolio share in one period, perhaps also on account of their stocks’ (expected) performance. This paper
considers individuals as participating in the stock market even in periods with zero proportions, if they held a positive proportion in the preceding period. In such a case the zero proportion is assumed to be (potentially) related to changes in stock returns and volatility.

**Dependent Variables:** While the primary interest of this paper lies in the analysis of conditional stock portfolio shares, there are two further aspects that are worth considering here: the degree of stock aversion ($stocksav$), as stated by the respondents, as well as stockownership. The former variable is derived from the respondent’s agreement (on a scale from 1 to 7, whereas 7 means “totally agree”) with the statement: “I would never consider investments in shares because I find this too risky”; the latter is a dummy variable ($stocksp$) indicating whether a person holds stocks or not. The definition of the dependent variable for the portfolio share models, on the other hand, is more complex. The problem with simply dividing stockholdings by total assets is that it is impossible to distinguish deliberate trading activities from changes in portfolio shares that are merely due to the yearly stock returns. Naturally, a global stock market crash where stock prices drop severely implies decreasing portfolio shares of stocks. The purpose of this study, however, is not to explain stock market trends but to examine how individuals with certain characteristics act in response to these trends. For this reason, the stockholdings are stock return adjusted by subtracting the product of the stockholdings at the end of the previous year ($stocks_{t-1}$), or at the beginning of this year, and the yearly stock market return in the current year ($return_t$) from the stockholdings at the end of this year ($stocks_t$):

$$stocks_{t}^{adj} = stocks_t - (stocks_{t-1} \cdot return_t) \quad (1)$$

The portfolio ($portf$) applied as denominator is given by the sum of 15 different financial assets (i.e. assets held in order to make profits, excluding real estate). Instead of adjusting each particular asset for its yearly returns, the entire portfolio is adjusted for the inflation rate ($infl$) in the Netherlands, defined as the year-to-year change in the Consumer Price Index (CPI):

$$portf_{t}^{adj} = portf_{t,nostocks} - (portf_{t-1,nostocks} \cdot infl_t) + stocks_{t}^{adj} \quad (2)$$

By implication, the adjusted stock portfolio share of an individual holding a prefect representation of the AEX (i.e. his stock portfolio returns are perfectly
equal to the AEX returns) and a financial portfolio (without stocks) that pays off a return equal to the inflation rate varies only in consequence of trading activities. Hence, the portfolio share of stocks, or more precisely the inflation adjusted financial portfolio share of return adjusted stockholdings, is defined as:

$$\text{stockss}^{adj}_{t} = \frac{\text{stocks}^{adj}_{t}}{\text{portf}^{adj}_{t}}$$

(3)

Thus, the dependent variable $\text{stockss}^{adj}_{t}$ is a proportion \( p = \frac{y}{n} \) with values (usually) between 0 and 1 and a variance given by: \( \sigma(p) = \frac{p(1-p)}{n-1} \). The fact that the variance of \( p \) depends on its particular value, however, violates the general homogeneity of variance assumption across subjects, causing non-normal residual distributions. One approach to deal with this problem is to transform \( p \) with a mathematical function whose variance is independent of the value \( p \). The most commonly used variance stabilizing transformation for proportion variables is the so-called arcsine-root (or angular) transformation (see e.g. Bromiley and Thacker (2002)), which transforms $\text{stockss}^{adj}_{t}$ to

$$t_{\text{stockss}^{adj}_{t}} = \arcsin\sqrt{\text{stockss}^{adj}_{t}}.$$ 

(4)

The arcsine-root transformation is a positive monotonic transformation, so it does not change the rank order of the original set of numbers. It is one of three so-called “first aid transformations” suggested by Mosteller and Tukey (1977) to apply always, unless there are special reasons against. Unlike the logit transformation – another quite common approach to transform proportions – the arcsine-root transformation works well even if there are a high number of observations with zero proportions (Hopkins, 2000). Furthermore, the transformation can be improved by replacing 0 by $\frac{1}{4n}$ and 1 by $(1 - \frac{1}{4n})$ before taking angular values, where \( n \) is the denominator based on which the proportion has been calculated (Bartlett, 1947). The beneficial effects of the transformation on the residual distributions are illustrated in figures 3 - 6.

**Independent Variables:** In order to investigate an unobserved phenomenon by using observed non-laboratory data, it is necessary to separate out the objects of interest from extraneous background factors, i.e. to control the circumstances. This is possible – even though only to a certain extent – by including adequate control variables to the models (Boumans, 2005).

22 The other two are (1) the (natural) logarithmic transformation of non-negative, continuous variables, and (2) the square root transformation of count variables.
Depending on the different dependent variables (i.e. conditional portfolio share of stocks, stockownership, stock aversion) the empirical analysis is structured into three models, each consisting of two main specifications: a basic model including only the variables discussed in section 3 as well as an extended model, which adds the variables on stock returns and volatility. Volatility is incorporated as follows: the variables \( \ln v_{ola} \) (natural log of the volatility) and \( \ln v_{ola}^2 \) (quadratic form of \( \ln v_{ola} \)) capture the effect of volatility per se, whereas the relationship between the dependent variable and volatility is predicted to be concave (convex) if \( \ln v_{ola}^2 \) is significant with a negative (positive) sign; \( \text{diffvola} \) integrates the percentage difference between upside and downside volatility, calculated as the “growth rate” between upside volatility and downside volatility (i.e. \( \frac{\text{uvola} - \text{dvola}}{\text{dvola}} \)). As explained in section 2, investment decisions are generally characterized by the trade-off between risk and return, rather than solely by risk. Hence, the control variable \( \text{return} \) is included in the extended models as well. The inclusion of the stock returns is also useful in regard to time-specific effects (see next paragraph) and the adjustment for changes in wealth and portfolio shares that are not due to trading activity (see preceding paragraph). While differing in the dependent variable and, hence, in the kind of model applied, all models use the same set of explanatory variables:

\[
\text{female, age, age}^2, \ln n_{inc}, \text{highinc}, \ln f_{wealth}, \text{edu}, \text{job}, \text{hhcomp}, \text{partner, health, riskav},
\]

where \( \text{age}^2 \) tests for a non-linear age-profile, \( \ln n_{inc} \) is the natural log of net income (in Euro), \( \text{highinc} \) a dummy variable indicating whether an individual belongs to the representative or the high-income panel, and \( \ln f_{wealth} \) denotes the natural log of the financial wealth (in Euro), calculated as the sum of all financial assets; \( \text{edu} \) indicates the highest level of education completed by incorporating two dummy variables on vocational education (\( \text{edu}_\text{voca} \)) and university education (\( \text{edu}_\text{high} \)), respectively; \( \text{job} \) encompasses six dummy variables specifying the kind of occupation (\( \text{job}_\text{empl} \)

As usual, for reasons of interpretation and multicollinearity the regressors analyzed in regard to a non-linear relationship have been centered at their mean first by subtracting the mean of the entire pooled sample.

Financial wealth consists of Euro amounts held in form of checking accounts, savings accounts, employer-sponsored savings plans, deposit books, savings certificates, insurance policies, mutual funds, bonds, stocks (company shares), and options.

For reasons of little time variance the set of job dummies will be reduced to \( \text{job}_\text{unempl}, \text{job}_\text{self}, \text{job}_\text{disab} \) and the aggregative dummy \( \text{job}_{\text{other}} \) during the empirical analysis (see section 5.2.1 for a detailed explanation).
for employed, \textit{job\_self} for self-employed, \textit{job\_unempl} for unemployed, \textit{job\_home} for housework, \textit{job\_ret} for retired and \textit{job\_disab} for disabled); \textit{hhcomp} indicates the number of persons living in the household, partner if the respondent is living together with a partner, \textit{health} the health status of the respondent (scaled from 1 to 7, whereas 1 is “excellent”), and \textit{riskav} the degree of risk aversion (scaled from 1 to 7, whereas 7 is “totally risk averse”). The last variable is derived from the level of agreement with the statement: “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.” Furthermore, assuming that stock investing takes place within a dynamic rather than a static setting, lags of stockownership/share (\textit{stocksp\_lag}/\textit{stockss\_lag}) and financial wealth (\textit{fwealth\_lag}) are added to the panel models in order to express the relationship between the current outcome and previous financial wealth and stock allocations.

\textbf{Time-specific effects:} Usually, panel studies on household portfolios include a full set of year dummies in order to control for changing macroeconomic conditions, financial innovations and other time-specific effects. This cannot be done within this study, as the key variables on stock returns and volatility (\textit{return}, \textit{ln\_vola}, \textit{diff\_vola}) are invariant across individuals and change only over time, just like time dummies. According to Wooldridge (2006), time panel models “(implemented with a time indicator variable) require regressors’ variation over units within each period.” In view of fixed effects models (see next paragraph) he furthermore notes that “when we include a full set of year dummies – that is, year dummies for all years but the first – we cannot estimate the effect of any variable whose change across time is constant”, such as \textit{age} in the present context. This is also true if the year dummies are replaced by other variables that vary only over time, as done in this study. The inclusion of year dummies only for some specific years is possible but always to some extent arbitrary. This paper approaches the issue of time-specific effects as follows. First, it seems reasonable to assume that the included regressors on stock returns and volatility largely serve as substitutes for the year dummies. As illustrated in figure 2, the overall economic conditions are quite well reflected by the stock markets. Second, the regressors that

\footnote{The implementation of these lags has been done following Alessie et al. (2004), who found “that the dynamics of ownership of either type of risky assets are driven by state dependence [...].” For reasons of plausibility, the lags are not implemented in the analysis of stock aversion.}
(substantially) vary over time and across units (i.e. \( \ln \text{wealth}, \ln \text{ninc} \) and the corresponding lags) are time-demeaned in order to further control for time-specific effects (i.e. these variables are transformed into deviations from the cross-unit mean at time \( t \)). This also decreases possible correlation between the stock market variables and net income.

**Model choice:** As done within most studies on household portfolio stockownership, stock ownership is analyzed using binary choice probit models. Likewise, the determinants of stock aversion are examined by means of ordinal choice probit regressions. The panel probit model is defined as

\[
P(y_{it}|x_{it}, u_i) = \phi(x_{it} \beta + u_i),
\]

where \( \phi \) is the standard cumulative normal probability distribution and \( x_{it} \beta \) the z-score, or probit index. The interpretation of a probit coefficient, \( \beta \), is that a one-unit increase in the predictor leads to increasing the z-score, or the probability that \( y \) takes the highest value (i.e. 1 in the binary choice model), by \( \beta \) standard deviations. \( u_i \) is the unobserved individual-specific random effect, which is assumed to be normally distributed. Once \( u_i \) is conditioned on, only \( x_{it} \) appears in the response probability at time \( t \) (Wooldridge 2002).

In regard to the analysis of portfolio shares, on the other hand, there are far less previous studies. Hence, there is no common practice regarding the model choice this paper could refer to. Instead, different kinds of panel models are taken into consideration. The basic linear panel data model with a continuous dependent variable takes the form

\[
y_{it} = x_{it} \beta + \alpha_i + \varepsilon_{it},
\]

where \( y_{it} \) is the dependent variable and \( x_{it} \) the vector of explanatory variables. \( \alpha_i + \varepsilon_{it} \) is the residual term, whereas \( \alpha_i \) captures the unobserved cross-section unit-level (or individual-specific) effects that differ between individuals but not within. \( \varepsilon_{it} \) denotes the common, strictly exogenous residuals that are independently and identically distributed (\( \text{iid} \)) (i.e. mean 0, homoskedasticity, and no correlation):

\[
E[\varepsilon_{it}| \alpha_i, x_{iT}] = 0
\]

The various panel data models depend on the assumptions made about the unobserved individual-specific effects $\alpha_i$. The simplest way to perform the analysis is to pool the observations for all periods and regress using OLS, i.e. ignoring the panel data structure and treating the unobserved individual-specific residuals $\alpha_i$ as non-existent. Yet, as this is rarely the case when dealing with long-run panel data, the pooled OLS (POL) estimator is likely to be biased and inconsistent in this context.

The fixed effects (FE) model treats $\alpha_i$ as random variables that are (unlike $\varepsilon_{it}$) potentially correlated with the explanatory variables and, thus, not necessarily normally distributed. The FE estimator is a regression of $y_{it} - \bar{y}_i$ on $x_{it} - \bar{x}_i$. This transformation, often called fixed effects or within transformation, implies that all variables that are fixed over time for all $i$, i.e. $\alpha_i$ and female, get swept away (Baltagi, 2005; Wooldridge, 2002). Thus, when using an FE model one has to neglect the variable female, even though there is evidence on its influence on portfolio decisions. As shown by Plümper and Troeger (2007), “a second drawback of the FE model [...] results from its inefficiency in estimating the effect of variables that have very little within variance”, such as relationship status, education or family size.

Another variant of model 6, the random effects (RE) model, assumes $\alpha_i$ (just like $\varepsilon_{it}$) to be random variables that are entirely uncorrelated with the explanatory variables:

$$E[\alpha_i|x_{it}] = 0 \quad (8)$$

The RE estimator is a generalized least squares (GLS) estimator, which uses both within- and between-group variations and weights them according to the relative sizes of $\sigma^2_{\varepsilon} + T_i \sigma^2_{\alpha}$ and $\sigma^2_{\alpha}$. If assumption 8 is met, the RE estimator confers the advantage of greater efficiency over the FE estimator. Otherwise, the RE estimator is biased and inconsistent.

Hausman and Taylor (1981) proposed an estimator (henceforth “HT estimator”), which allows to preserve the advantages of the FE estimator, i.e. correlation between the unobserved individual-specific effects and the independent variables, as well as of the RE estimator, i.e. the identification of effects linked to time-invariant regressors. They consider the following modification of 6:

$$y_{it} = x_{1it}\beta_1 + x_{2it}\beta_2 + w_{1i}\gamma_1 + w_{2i}\gamma_2 + \alpha_1 + \varepsilon_{it}, \quad (9)$$
where $x_{1it}$ and $x_{2it}$ are time varying variables while $w_{1i}$ and $w_{2i}$ are time-invariant variables. $x_{1it}$ and $w_{1i}$ are assumed to be uncorrelated with individual effect $\alpha_i$, whereas $x_{2it}$ and $w_{2i}$ are assumed to be correlated with $\alpha_i$, i.e. endogenous,

$$E[\alpha_i|w_{1i}] = E[\alpha_i|x_{1it}] ,$$

(10)

Under assumptions [7] and [10] the HT estimator consistently and efficiently provides estimates of $\beta$, while the FE estimator consistently estimates $\beta$ under weaker assumptions [7] but less efficiently. The downside of the HT estimator resides in specifying the exogeneity status for the included regressors. As noted by Plümper and Troeger (2007), this is difficult not only because the correlations between the regressors and the unit effects are unobserved. Those variables identified to be exogenous as to the unit effects have to satisfy the second condition of being correlated with the endogenous variables as well.

The most commonly employed procedure to decide whether the estimation of an RE model is a viable alternative to estimating an FE model is the Hausman specification test (Hausman, 1978). In this test, one estimator that is consistent and efficient under the null hypothesis but inconsistent if the null is rejected (the RE estimator) is compared with an estimator that is consistent under both outcomes (the FE estimator). According to Baltagi et al. (2003), the test can also be used to decide between FE and HT. If the null hypothesis is not rejected, the exogeneity restrictions imposed by the choice of exogenous and endogenous regressors are not too restrictive, implying that the HT estimator fits the statistical requirements.

**Further methodological notes:** As noted above it is usually assumed that the residuals $\varepsilon_{it}$ meet condition (2), i.e. they are independently and identically distributed. However, this assumption is often false, especially when panel data with a large number of clusters (i.e. many units for which there are more than two observations) are concerned. A common approach to address potential heteroskedasticity problems arising from groupwise differences is the use of the so-called cluster-robust covariance matrix estimator. It is a generalization of Huber (1967) and White (1980) that allows the error terms to be correlated within clusters, though observations from different clusters are still assumed to be independent. According to Kezdi (2004), these errors converge to accuracy as the number of clusters approaches infinity. He
shows that already 50 clusters\textsuperscript{28} are often enough for accurate inference, and moreover, that a sufficiently large number of clusters allow precise inference even if there is actually no clustering. Unfortunately, it is not possible to apply the cluster-robust covariance matrix estimator, or the conventional Huber-White robust standard errors, to probit or HT models\textsuperscript{29} An applicable alternative method to compute some kind of cluster-robust standard errors is bootstrapping\textsuperscript{30}. The downside of this method is that its random resampling technique leads to highly random estimates of standard errors. Even with 200 bootstrap replications, the results of exactly the same regression vary substantially. Considering the standardized residual diagram (shown in figure\textsuperscript{7}) of the portfolio share model (does not indicate heteroscedasticity problems), it thus seems reasonable not to use bootstrapped standard errors. However, as the portfolio share models comprise 943 clusters, this study generally applies the cluster-robust covariance matrix estimator (with the individual id as the cluster variable) to the linear FE and RE models.

Another problem that can plague the models is the existence of outliers. As yet, there are no standard outlier-robust procedures or numerical methods to detect outliers for panel data. And even if such methods were available, there is still the tough (and sometimes impossible) task of distinguishing extreme observations that are meaningful and cannot be disregarded without distorting reality, and extreme observations that result from some kind of mistake, i.e. outliers. This study approaches the diagnostics for outliers graphically by assessing diagrams of standardized and deviance residuals (for the probit models), respectively (figures\textsuperscript{7} and \textsuperscript{8}). Observations that are clearly separated from the others (marked red) are considered outliers\textsuperscript{31}

The distributions of $\varepsilon_{it}$ in the portfolio share models are also examined with respect to non-normality. Residual histograms and normal QQ-plots are two simple and effective graphical approaches to this issue. Normality is given if the histograms show a normal distribution, and if the QQ-plots display standardized residuals distributed along the straight diagonal line (from the bottom left to the upper right corner). Figures\textsuperscript{3} and \textsuperscript{4} indeed indicate that the residuals $\varepsilon_{it}$ are not normally distributed (heavy-tailed normal QQ-plot). Though, as shown in figures\textsuperscript{5} and \textsuperscript{6}, this problem can be solved to a large extent by transforming the dependent variable as explained above. As for

\textsuperscript{28} In this study there are at least 943 clusters in all regressions.
\textsuperscript{29} In fact, it is possible to compute the cluster-robust covariance estimator from a HT model. However, this option is not available in Stata yet.
\textsuperscript{30} See Efron and Tibshirani\textsuperscript{1994} for a detailed explanation of this procedure
\textsuperscript{31} In doing so, 3 out of 2722 observations in the portfolio share models are identified as outliers and thus excluded. In the probit models no clear outliers can be detected.
panel probit models there are no common procedures for normality testing.

Individuals with the household position “child living at home” are assumed to be not responsible for their investments and are thus generally excluded from the regressions. Finally, the data are also corrected for obvious misentries that could have been detected by transitions in the gender dummy variable (female).

5.2 Results

5.2.1 Conditional portfolio share of stocks

The analysis of portfolio shares is the most difficult not only because the dependent variable and conditionality have to be determined properly, but also due to the choice of an appropriate model, i.e. whether to choose fixed effects (FE), random effects (RE) or something inbetween (HT). Hausman specification tests applied to both the basic FE and RE models as well as the extended versions unambiguously suggest using FE. In both cases the null hypothesis that the RE model is consistent and efficient is rejected with a p-value of zero. This result also does not change if the models are specified in a slightly different way. Thus, a correlation of the individual-specific effect with some regressors cannot be ruled out, and RE estimators are inconsistent. As explained in the previous section, the downside of FE model is that time-invariant (female) or constantly variant variables (age) cannot be included. Moreover, it assumes all regressors to be correlated with the individual-specific effect, which is not plausible for clearly exogenous variables like return, ln_vola, ln_vola2 and diffvola.

The Hausman Taylor (HT) model presented above may provide a solution to these problems, if it can be specified appropriately. As explained, the HT approach requires specifying time-invariant, endogenous (i.e. correlated with the random effect), and exogenous (i.e. not correlated with the random effect, but correlated with the endogenous variables) variables. The only time-invariant variable in this study is female. Variables that are out of the individuals’ control are considered as clearly exogenous (female, age, age2, return, ln_vola, ln_vola2, diffvola). Referring to [Alessie et al. (2004)], it is supposed that financial wealth (ln_fwealth and fwealth_lag) and income (ln_ninc and highinc) might be endogenous. Wealth and income determine the households’ opportunities to diversify in different assets. Also, these variables may include stockholdings and income from stockholdings so that
they are likely to be explained by the same set of independent variables as the
dependent variable. Of course, the same applies for the lagged variable on the
stock portfolio share ($\text{stockss}_\text{lag}$). Based on the Hausman specification test,
the remaining variables on education ($\text{edu}_*$), the job ($\text{job}_*$), the household
composition ($\text{hhcomp}$), relationship status ($\text{partner}$), risk aversion ($\text{riskav}$)
and $\text{health}$ are all specified exogenous, i.e. instruments for the endogenous
variables. The estimators of the HT model specified this way and the FE model
differ only to a very small extend, expect for some of the job dummies (which are
all clearly insignificant). This might be due to the FE model’s “inefficiency in
estimating the effect of variables that have very little within variance” ([Plümper
and Troeger, 2007] – only self-employed, unemployed and disabled individuals
switch to other occupations by more than 10%. Also, the HT and FE estimators
of $\text{job}_\text{self}$, $\text{job}_\text{unempl}$ and $\text{job}_\text{disab}$ differ considerably less than the other job
dummies. Thus, it seems more reasonable to include only $\text{job}_\text{self}$, $\text{job}_\text{unempl}$
and $\text{job}_\text{disab}$ separately and to aggregate the other occupations to the dummy
$\text{job}_\text{other}$, as similarly done by [Alessie et al., 2004]. Yet, the still relatively
small within standard deviations of $\text{job}_\text{self}$ (0.065) and $\text{job}_\text{unempl}$ (0.073)
indicate that the coefficients of these variables may be less well identified than
the others (see [Baum, 2006] for a detailed explanation on this). The p-values of
the corresponding Hausman specification test equal 42.4% (basic models) and
32.1% (extended models), indicating that both the FE and the HT models are
consistent and efficient. The results of these models are presented in Table 2.

**Basic models:** The basic models unanimously indicate that financial
wealth, risk aversion, as well as the lags of financial wealth and stock portfolio
shares significantly affect the portfolio share allocated to stocks. The results
on age, income, and the household composition, on the other hand, are not clear.

The HT model indicates both $\text{age}$ and $\text{age2}$ to be insignificant, whereas
$\text{age2}$ is negative with a p-value only slightly above the 10% significance level.
The $\text{age2}$ coefficient in the FE model, on the other hand, is highly significant
(even if age were included as well), suggesting a small negative effect of the
age particularly at higher ages. However, it is possible that the age coefficients
are to some extent biased by implied cohort effects. In line with [Bertaut
and Starr-McCluer, 2002] the HT model suggests a negative income effect
($\ln \text{ninc}$). On the other hand, the high-income sample dummy ($\text{highinc}$) is
also significant in the HT model – with positive coefficients. As high-income
individuals usually can expect to earn relatively high income for sure, this could
be interpreted according to [Cocco et al., 2005]. They argue that income serves
Table 2: Conditional portfolio share of stocks

<table>
<thead>
<tr>
<th>Variable</th>
<th>Basic models</th>
<th>Extended models</th>
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<tbody>
<tr>
<td></td>
<td>FE</td>
<td>HT</td>
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<tr>
<td>return</td>
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<tr>
<td>ln_vola</td>
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<tr>
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<td>-0.015***</td>
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<td>0.628***</td>
</tr>
</tbody>
</table>

Number of obs. 2722
Number of ind. 943
Hausman test 0.424

Source: DNB Household Survey, Datastream, own calculations; standard errors in brackets;
* p < 0.1, ** p < 0.05, *** p < 0.01; italicized variables are specified endogenous in the HT models.
as some kind of a risk-free asset, making investors more willing to allocate their funds to risky assets. The income coefficients in the FE model show very similar effects of $\ln(nine)$ and $highinc$, however insignificant with p-values between 10% and 20%. Furthermore departing from the FE model, the HT model also shows a significant negative effect of the family size ($hhcomp$).

Not surprisingly, the models provide strong evidence on the positive effect of financial wealth ($ln(fwealth)$), which has been shown within many previous studies. An explanation for this is that wealthier households have more money available to invest, what in turn makes the fixed costs of buying and holding stocks less decisive. Interestingly, the result by Alessie et al. (2004) indicating that “the effect of log financial wealth in the previous year is much smaller and, surprisingly, negative [.]” is confirmed by both models. Their assumption that “the relation between asset ownership and financial wealth probably requires more structure than is incorporated in the current model” seems to be plausible here as well. As expected, both models also suggest a highly significant negative relationship between the stated level of risk aversion ($riskav$) and the portfolio share allocated to stocks. A decrease in risk aversion by 1 adds about 1.5% to the stock portfolio share. This agrees not only with previous evidence suggesting that risk averse investors tend to hold few risky assets (e.g. King and Leape (1998)). It is also in line with portfolio theory, according to which investors should diversify to all assets available, whereas the proportion of wealth allocated to the (risky) market portfolio decreases with the degree of risk aversion.

Finally, the models indicate strong positive state dependence effects: $stockss_{lag}$ is highly significant with a positive coefficient about for times as high as, for example, the effect of financial wealth, which is predicted the second most important determinant. Explanations for this may be transaction costs involved with buying stocks and asset-specific learning, giving stockowners monetary and experiential advantages.

**Extended models:** The extended models indicate that both the size as well as the direction of stock return volatility have a considerable influence on the portfolio allocation to stocks. Stock returns ($return$), on the other hand, do not affect the (adjusted) conditional portfolio shares.

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32 See for example Bertaut and Starr-McCluer (2002), and Alessie et al. (2004).
Both models suggest a significant hump-shaped volatility pattern with a turning point at around 36% (24% in the HT model). This implies that individuals increase their relative stockholdings when volatility increases just slightly (by less than 36%), but reduce them when there is a more severe increase in volatility (by more than 36%). In other words: the individuals are in fact willing to take some risks but only up to a certain threshold. In the HT model the negative coefficient of \( \ln \text{vola}^2 \) is even twice as high as the positive coefficient of \( \ln \text{vola} \), implying that the turning point is reached earlier (24%).

The most striking result is the strong effect of \( \text{diffvola} \), which denotes the percentage by which upside volatility exceeds downside volatility. If upside volatility is twice as high as downside volatility (i.e. \( \text{diffvola} \) is equal to 1 or 100%), the predicted conditional stock portfolio share is about 16% higher than it would be if up- and downside volatility were exactly the same. Of course, a 100% gap is extremely unlikely to occur over periods longer than a few days. The largest positive differences in yearly up- and downside volatility numbers of the AEX (implying positive values of \( \text{diffvola} \)) observed between 1993 and 2009 are 18.1% in 2003 and 16.2% in 2004, during the recovery period after the financial crisis in 2001/2002. On the other hand, \( \text{diffvola} \) was most negative in the crisis years 2001 (-21.4%) and 2008 (-18.7%). While it is hard to estimate the households’ exact reaction to these shocks, the \( \text{diffvola} \) coefficients clearly reveal that individuals in fact distinguish the direction of stock return volatility: the higher the upside volatility relative to the downside volatility, the lower the perceived (negative) risk of stock investing, the higher the portfolio allocation to stocks; vice versa, relatively high downside volatility implies a reduction of stockholdings. As downside volatility is particularly high during bust periods, when volatility is generally high, the results concerning \( \ln \text{vola} \) and \( \ln \text{vola}^2 \) are likely to be to some extent driven by the upside downside volatility trade-off.

It is important to note that the results of the portfolio share models largely depend on their exact specification. First, the models are sensitive to the applied conditionality restriction, i.e. whether all observations, only observations of individuals considered stock market participating – as done in this paper – or, for instance, only observations with time-varying stock portfolio shares are taken into account. Another critical aspect is the definition of the dependent variable. This study applies some kind of stock return and
inflation adjustment and a transformation typical for proportion variables. Especially the latter measure strongly affects the results. Moreover, it makes the interpretation of the effect magnitudes difficult, as the dependent variable does not represent actual stock portfolio shares. Nonetheless, as illustrated in figures 3 - 6, a transformation of the dependent variable is absolutely essential in order to obtain reliable results with linear models. Even though these figures show that the transformation of the dependent variable makes the residual distributions closer to normality, it must be noted that the distributions are still not perfectly normal. In regard to the used models (FE and HT) it is important to note that the specification of HT models is always to some degree discretionary, as correlations between explanatory variables and the individual-specific random effect are unobserved. In case of doubt, the results of the FE models should be given priority. Table 3 presents the most important results of some alternative specifications of the fixed effect portfolio share model. The results of the models conditional on active stock market participation (column 1), and using a reduced portfolio of the most important assets as denominator for stocks’ portfolio share (column 2), respectively, are very similar to those of the original model, indicating a hump-shaped volatility pattern and a strong negative (positive) effect of downside (upside) volatility. Not surprisingly, there is a highly significant positive effect of stock returns if asset holdings are not adjusted for market performance (column 3). Furthermore, the effects of up- and downside volatility vanish. Without transformation of the dependent variable (column 4) the volatility coefficients still have the same signs. However, they are considerably smaller and, most notably, insignificant.

5.2.2 Stockownership

As indicated by the Hausman specification tests in the preceding analysis of conditional portfolio shares, the RE approach might be inconsistent. This is the case if at least one of the independent variables is correlated with the individual-specific random effect. However, the test cannot be applied here, because there is no sufficient probit model allowing fixed effects to be conditioned out of the likelihood yet. While for linear models the Hausman Taylor model provides an opportunity to include both endogenous and exogenous variables, there is no such approach for probit models. All regressors must be specified either as exogenous or as endogenous. In order to reduce the possible bias through neglected endogeneity this paper follows
Table 3: Alternative portfolio share model specifications

<table>
<thead>
<tr>
<th></th>
<th>Only time-varying stock shares</th>
<th>Reduced portfolio †</th>
<th>No return/inflation adjustments</th>
<th>No arcsine transformation</th>
</tr>
</thead>
<tbody>
<tr>
<td>return</td>
<td>-0.012</td>
<td>-0.018</td>
<td>0.096***</td>
<td>-0.020</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.034)</td>
<td>(0.031)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>ln_vola</td>
<td>0.027**</td>
<td>0.024**</td>
<td>0.029**</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.012)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>ln_vola2</td>
<td>-0.035***</td>
<td>-0.040***</td>
<td>-0.035***</td>
<td>-0.017</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.013)</td>
<td>(0.12)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>diffvola</td>
<td>0.169**</td>
<td>0.206**</td>
<td>0.102</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>(0.081)</td>
<td>(0.082)</td>
<td>(0.075)</td>
<td>(0.074)</td>
</tr>
</tbody>
</table>

Number of obs.       2498     2707     2769     2800
Number of ind.        819      941      948      956

Source: DNB Household Survey, Datastream, own calculations; standard errors in brackets;
* p < 0.1, ** p < 0.05, *** p < 0.01; † the reduced portfolio contains only assets with a mean portfolio share (conditional on stock market participation) of at least 5%, namely checking accounts, savings accounts, employer-sponsored savings plans, insurance policies, mutual funds, bonds, and stocks.

by distinguishing model specifications with and without variables on financial wealth (ln_fwealth, fwealth_lag), which is assumed not to be strictly exogenous. Table 4 shows the basic and extended models – each with and without financial wealth – on stockownership.

Basic models: In agreement with Alessie et al. (2004), the model indicates positive effects of net income (ln_ninc) and belonging to the high-income group (highinc) that, however, become clearly insignificant once financial wealth is included. Another factor shown to be a positive determinant of stockownership is age (age): every additional year of age increases the probability of owning stocks by about 1%. In line with most previous papers, the results indicate that women (female) are significantly less likely to hold stocks, by 25%. Barber and Odean (2001), for example, show that men are generally more overconfident regarding their financial knowledge, inducing them to invest less conservatively than women. As expected, the model furthermore suggests negative effects of risk aversion (riskav) and vocational education as highest level of education completed (edu_voca), and a positive influence of higher education (edu_high). University degree holders are 11% more likely to hold stocks.

Departing from Alessie et al. (2004) there is no evidence on a positive
Table 4: Stockownership

<table>
<thead>
<tr>
<th></th>
<th>Basic models</th>
<th></th>
<th>Extended models</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Without</td>
<td>With</td>
<td>Without</td>
<td>With</td>
</tr>
<tr>
<td>return</td>
<td>0.238**</td>
<td>0.245**</td>
<td>(0.106)</td>
<td>(0.114)</td>
</tr>
<tr>
<td>ln_vola</td>
<td>0.081**</td>
<td>0.099***</td>
<td>(0.034)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>ln_vola2</td>
<td>-0.006</td>
<td>-0.016</td>
<td>(0.040)</td>
<td>(0.043)</td>
</tr>
<tr>
<td>diffvola</td>
<td>0.212</td>
<td>0.260</td>
<td>(0.289)</td>
<td>(0.310)</td>
</tr>
<tr>
<td>ln_fwealth</td>
<td>0.360***</td>
<td>0.361***</td>
<td>(0.024)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>fwealth_lag</td>
<td>-0.075***</td>
<td>-0.074***</td>
<td>(0.021)</td>
<td>(0.024)</td>
</tr>
<tr>
<td>ln_ninc</td>
<td>0.100***</td>
<td>-0.040</td>
<td>0.101***</td>
<td>-0.040</td>
</tr>
<tr>
<td>stockss_lag</td>
<td>2.691***</td>
<td>2.570***</td>
<td>2.692***</td>
<td>2.567***</td>
</tr>
<tr>
<td>highinc</td>
<td>0.076*</td>
<td>-0.008</td>
<td>0.117**</td>
<td>0.043</td>
</tr>
<tr>
<td>age</td>
<td>0.011***</td>
<td>0.005**</td>
<td>0.011***</td>
<td>0.005**</td>
</tr>
<tr>
<td>age2/100</td>
<td>-0.015</td>
<td>-0.003</td>
<td>-0.015</td>
<td>-0.021</td>
</tr>
<tr>
<td>edu_voca</td>
<td>-0.130*</td>
<td>-0.090</td>
<td>-0.137**</td>
<td>-0.100</td>
</tr>
<tr>
<td>edu_high</td>
<td>0.107***</td>
<td>0.055</td>
<td>0.109**</td>
<td>0.058</td>
</tr>
<tr>
<td>hhcomp</td>
<td>0.012</td>
<td>0.023</td>
<td>0.012</td>
<td>0.023</td>
</tr>
<tr>
<td>job_unempl</td>
<td>-0.130</td>
<td>0.116</td>
<td>-0.141</td>
<td>0.102</td>
</tr>
<tr>
<td>job_self</td>
<td>-0.156</td>
<td>-0.415***</td>
<td>-0.152</td>
<td>-0.415***</td>
</tr>
<tr>
<td>job_disab</td>
<td>0.128</td>
<td>0.374**</td>
<td>0.124</td>
<td>0.364***</td>
</tr>
<tr>
<td>job_other</td>
<td>-0.023</td>
<td>0.185</td>
<td>-0.024</td>
<td>0.181</td>
</tr>
<tr>
<td>partner</td>
<td>0.042</td>
<td>0.023</td>
<td>0.040</td>
<td>0.027</td>
</tr>
<tr>
<td>riskav</td>
<td>-0.073***</td>
<td>-0.092***</td>
<td>-0.074***</td>
<td>-0.093***</td>
</tr>
<tr>
<td>health</td>
<td>-0.063**</td>
<td>-0.049</td>
<td>-0.065*</td>
<td>-0.050</td>
</tr>
<tr>
<td>female</td>
<td>-0.250***</td>
<td>-0.206***</td>
<td>-0.252***</td>
<td>-0.204***</td>
</tr>
<tr>
<td>constant</td>
<td>-0.777***</td>
<td>-1.204***</td>
<td>-0.791***</td>
<td>-1.213***</td>
</tr>
</tbody>
</table>

Number of obs. 12508 12508 12508 12508
Number of ind. 4599 4599 4599 4599
Pr(X^2) 0.000 0.000 0.000 0.000
Log likelihood -2213.12 -2207.67 -2028.82 -2022.58

Source: DNB Household Survey; Datastream, own calculations; standard errors in brackets;
* p < 0.1, ** p < 0.05, *** p < 0.01.
effect of self-employment (*job_self*). If financial wealth is included, even the opposite effect is shown, whereas being disabled is predicted to increase the probability of holding stocks. Interestingly, the results also indicate that healthier (*health*) individuals are significantly more likely (by about 6%) to own stocks. This supports the findings by Rosen and Wu (2004), who were the first to investigate the influence of health status on household portfolio choice. Again, the strong positive state dependence effect (*stock_{sp, lag}* ) found by Alessie et al. (2004) can be confirmed clearly. Just as argued above regarding portfolio shares, the state dependence is likely to be associated with transaction costs and asset-specific knowledge. The coefficients of *ln_{fwealth}* and *fwealth_{lag}* , which are not included by default, are highly significant, suggesting a similar relationship with stockownership as previously shown in regard to portfolio shares.

**Extended models:** The inclusion of the stock market variables barely affects the other coefficients. The additional coefficients are significantly positive for *return* and *ln_{vola}* but not significant for *ln_{vola2}* and *diffvola*, no matter if financial wealth is included or not.

While the strong positive effect of stock returns, according to which the likelihood of stockownership increases by about 24% if returns double, perfectly fits the common risk-return trade-off, the positive volatility coefficient (*ln_{vola}* coefficient 0.08) does not meet expectations, in particular as *ln_{vola}* stays positive even if its insignificant negative squared term *ln_{vola2}* is omitted. This result implies that the individuals, all else being equal, become more likely to own stocks when volatility goes up, regardless of the deviations’ size and direction. However, it is quite possible that *ln_{vola}* captures other time-specific effects as well, which are hard to disentangle from the mere volatility effect. For example, at the beginning of the 2000s new technologies substantially reduced the transaction and information costs associated with stock investing. As a consequence, more people could afford to buy, and to regularly trade stocks. While in 1993 only 6% of the survey respondents held stocks, the rate more than doubled to about 13% in 2003. At the same time – in part probably also due to these developments – volatility became uncommonly

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34 Note that higher values of *health* imply a worse health status.

35 See section 5.2.1 for a discussion on this result.

36 See section 4.1, figure 1 for a graph on this development.
high, with its all-time-peak in the financial crisis 2001/2002. Sizes and signs of the \textit{diffvola} coefficients are similar to those in the portfolio share models but clearly insignificant. This suggests that the predominant direction of volatility does not affect the decision whether to hold stocks or not.

### 5.2.3 Subjective stock aversion

This section finally examines, which aspects determine the individuals’ self-reported and, thus, \textit{subjective} aversion towards stocks, as opposed to actual stock investment behavior analyzed in the previous models. The analysis is based on panel data RE probit models for ordinal outcomes, as the dependent variable takes integers from 1 to 7.\footnote{See section 5.1 for an explanation of the dependent variable \textit{stocksav}.} The coefficients of the ordered probit model can be interpreted as change in the probability of the highest category in response to an increase of the independent variable by 1 (or 100%). Table 5 gives the results for the two models.

**Basic model:** Both the basic as well as the extended model are largely in line with the evidence from the two previous analyses. Increases in net income (\textit{ln\_ninc}, \textit{highinc}), financial wealth (\textit{ln\_fwealth}), and education (\textit{edu\_high} coefficient negative, \textit{edu\_voca} coefficient positive) have a negative effect on stock aversion, i.e. increase the individuals’ propensity to invest in stocks. In particular, the effect of education was expectable as in the light of portfolio theory, where risk is defined at the portfolio level, an aversion against stocks per se is not rational and thus likely to be due to lacking financial literacy. Furthermore, the health coefficient (\textit{health}) is again significant, suggesting that healthier individuals are likely to be less averse against stocks.\footnote{Note that higher values of \textit{health} imply a worse health status.}

On the other hand, age (\textit{age}), being female (\textit{female}), risk aversion (\textit{riskav}), and being unemployed (\textit{job\_unempl}) are predicted positive determinants of stock aversion. Interpreted in the spirit of King and Leape (1987) and Alessie \textit{et al.} (2007) the 1\% age effect (\textit{age2} omitted due to clear insignificance) may be attributed to relatively low levels of financial literacy in young age. Also in regard to the gender effect (\textit{female}), according to which women are 35\% more likely to be extremely stock averse, Alessie \textit{et al.} (2007) argue in terms of financial knowledge, which is shown to be much lower among women. Interestingly, the positive effect of being unemployed (\textit{job\_unempl}) is even
Table 5: Subjective stock aversion

<table>
<thead>
<tr>
<th>Variable</th>
<th>Basic model</th>
<th>Extended model</th>
</tr>
</thead>
<tbody>
<tr>
<td>return</td>
<td>-0.278*** (0.038)</td>
<td>-</td>
</tr>
<tr>
<td>ln_vola</td>
<td>0.028** (0.013)</td>
<td></td>
</tr>
<tr>
<td>diffvola</td>
<td>-0.292*** (0.097)</td>
<td></td>
</tr>
<tr>
<td>ln_fwealth</td>
<td>-0.125*** (0.007)</td>
<td>-0.124*** (0.007)</td>
</tr>
<tr>
<td>ln_ninc</td>
<td>-0.132*** (0.016)</td>
<td>-0.128*** (0.016)</td>
</tr>
<tr>
<td>highinc</td>
<td>-0.048* (0.027)</td>
<td>-0.019 (0.028)</td>
</tr>
<tr>
<td>age</td>
<td>0.014*** (0.001)</td>
<td>0.014*** (0.001)</td>
</tr>
<tr>
<td>edu_voca</td>
<td>0.219*** (0.010)</td>
<td>0.208*** (0.011)</td>
</tr>
<tr>
<td>edu_high</td>
<td>-0.162*** (0.032)</td>
<td>-0.154*** (0.032)</td>
</tr>
<tr>
<td>hhcomp</td>
<td>0.000 (0.014)</td>
<td>0.003 (0.014)</td>
</tr>
<tr>
<td>job_unempl</td>
<td>0.447*** (0.111)</td>
<td>0.463*** (0.110)</td>
</tr>
<tr>
<td>job_self</td>
<td>0.016 (0.094)</td>
<td>0.010 (0.094)</td>
</tr>
<tr>
<td>job_disab</td>
<td>0.085 (0.084)</td>
<td>0.070 (0.084)</td>
</tr>
<tr>
<td>job_other</td>
<td>0.093 (0.060)</td>
<td>0.093 (0.060)</td>
</tr>
<tr>
<td>partner</td>
<td>-0.063 (0.045)</td>
<td>-0.060 (0.045)</td>
</tr>
<tr>
<td>riskav</td>
<td>0.237*** (0.007)</td>
<td>0.238*** (0.007)</td>
</tr>
<tr>
<td>health</td>
<td>0.035* (0.018)</td>
<td>0.033* (0.018)</td>
</tr>
<tr>
<td>female</td>
<td>0.351*** (0.037)</td>
<td>0.350*** (0.037)</td>
</tr>
</tbody>
</table>

Number of obs. 17399 17399
Number of ind. 6115 6115
Pr(X^2) 0.000 0.000
Log likelihood -29700.02 -29674.80

Source: DNB Household Survey, Datastream, own calculations; standard errors in brackets;
* p < 0.1, ** p < 0.05, *** p < 0.01.

10% higher than the gender effect. This might be due to the lack of income (see income effect above) and (on average) comparatively low levels of financial
wealth and education. As expected, the model indicates a positive correlation between stock and general risk aversion ($riskav$): each additional level of risk aversion increases the probability of being extremely stock averse by about 24%.

**Extended model:** If $return$, $ln_{vola}$ and $diffvola$ are added ($ln_{vola2}$ is omitted due to clear insignificance) the effect of $highinc$ vanishes. Concerning the other variables of the basic model there is no noteworthy change. The results on the additional stock market variables broadly confirm the hypothesis derived from portfolio theory that investors evaluate investment opportunities based on the trade-off between returns and perceived (negative) risk, whereas the latter is measured by the relative downside volatility in the recent past. All things being equal, a household member is almost 28% less likely to state a stock aversion of the highest level if stock returns shoot up by 100%, for example from 6% in one year to 12% in the following year. The ratio of up- and downside volatility ($diffvola$) plays a similarly important role: if upside volatility is twice as high as downside volatility (i.e. $diffvola$ equals 1) the probability of being extremely averse against stocks is by 29% lower, compared to the case of equal up- and downside volatility. A more realistic (but still quite unlikely) example is a change in $diffvola$ from -0.5 to 0.5. Accordingly, an equivalent change in the opposite direction (i.e. downside volatility prevails) increases the probability of extreme stock aversion by 29%. While there is no general negative correlation between $return$ and $diffvola$, downside volatility tends to be dominating (i.e. $diffvola$ is negative) especially during recessions, such as the financial crises 2001/2002 and 2007/2008.

Moreover, volatility per se ($ln_{vola}$) – or the size of volatility, as opposed to the direction of volatility ($diffvola$) – is shown to be a significant stock aversion-increasing factor, too. If volatility increases by 100%, stock aversion increases by 2.8%. At first sight this effect seems very small compared to the effect of $diffvola$. However, one must take into account that such an extreme increase in volatility is perfectly possible, whereas in regard to $diffvola$ this is a highly improbable case. In fact, the magnitudes of both the size and the direction effect of volatility are quite similar. Nonetheless, the strongest determinant of stock aversion among the stock market variables are definitely the stock returns.
6 Conclusion

As stockownership in the Netherlands and in many other western countries has increased considerably over the last two decades, understanding how households make their portfolio decisions over time has wide-ranging implications for financial markets and macro-economic policy. Using a large sample from the Dutch DNB Household Survey (DHS), this paper explores the link between households’ stock investment behavior and the recent stock market performance. The DHS data allow controlling for major socioeconomic and demographic characteristics of the household members, such as income, education, age and gender. Moreover, they provide detailed information on holdings of various financial assets, so that it is possible to investigate a specific type of assets (i.e. stocks) in detail. A major implication of traditional portfolio theory is that investors trade-off returns against risk, whereas risk is defined as the variance of returns, or volatility. More recent portfolio theory refines this relation taking into account that investors are loss rather than risk averse (i.e. averse against downside volatility) and that assets’ risk exposure may vary over time. Moreover, it assumes that investors tend to focus on performances in the recent past (myopic expectation formation). Based on these assumptions this study empirically analyzes if and to what extent stock returns and (upside/downside) volatility affect stock portfolio shares, stockownership and subjective stock aversion among households. The additional explanatory variables are derived from the Amsterdam Exchange Index (AEX), which is taken as a rough proxy of the households’ stock portfolios.

The empirical results show that the recent stock market performance in fact has an influence on households’ financial behavior in regard to stocks. Households reduce their portfolio allocation to stocks if volatility is high, and all the more if it is mostly driven by downside volatility. Low levels of volatility, on the other hand, seem to be considered risk worth to take, as the models suggest a hump-shaped volatility profile with regard to portfolio shares. Also, the stated level of stock aversion becomes considerably higher if volatility and, in particular, the relative size of downside volatility increase. In contrast, stockownership decisions do not seem to be determined by volatility. If anything, the ownership models indicate a positive effect of volatility per se. Stock returns, on the other hand, significantly affect stockownership as well as stock aversion – in the expected directions – but not conditional portfolio shares. However, if the stock portfolio shares are not adjusted for
stock returns in advance, the effect of stock returns concerning portfolio shares becomes significantly positive, too. All in all, the expected (downside) risk-return pattern is largely reflected by the empirical results. In addition, the results confirm previous evidence suggesting socioeconomic and demographic household characteristics, such as financial wealth, income and age, as well as stated levels of risk aversion and state dependence to be powerful predictors of portfolio choice. The models on stockownership and stock aversion also show significant effects of education, bad health and being female.

Finally, there are limitations related to the additional explanatory variables on stock returns and volatility to keep in mind when interpreting the empirical results. Since these variables vary only over time, not across individuals, it is not possible to include a full set of year dummies, as usually done in order to control for time-specific effects. It can be assumed that the stock variables capture those effects to some extent. Besides, the analysis of household financial behavior in response to financial market data would be strongly facilitated if panel data were available on a more regular basis.
References


A Appendix

Figure 3: Residual histogram of the portfolio share model (HT) before transformation of the dependent variable

Figure 4: QQ-plot of the portfolio share model (HT) before transformation of the dependent variable
Figure 5: Residual histogram of the portfolio share model (HT) after transformation of the dependent variable

Figure 6: QQ-plot of the portfolio share model (HT) after transformation of the dependent variable
Figure 7: Standardized residual diagram of the portfolio share model (HT)

Figure 8: Deviance residual diagram of the stockownership model