Do stock market returns affect risk attitudes?

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Abstract:

Investigating attitudes towards risk is intimately linked to the goal of understanding and predicting economic behaviour. This paper examines the relationship between financial risk attitudes and past stock market returns. Using panel data from the CentER DNB Household surveys between 1994 and 2008, it finds that past returns are positively and significantly related to an individual's willingness to take risks. These findings are relatively robust across all models and specifications. Owning stocks or mutual funds increased the strength of the relationship; however the relationship is also significant – albeit smaller – for non-stock holders. No robust evidence was found of the presence of asymmetric effects or non-linearities. Inflation was consistently found to have a strong and negative relationship with the willingness to take risks.

1) Introduction

Attitudes towards risk play a pervasive role in almost all important economic decisions. Choices of wealth accumulation, human capital investment, employment, portfolio allocation as well insurance all depend fundamentally on an individual's risk tolerance. Therefore understanding risk attitudes is in intimately linked to the goal of understanding and predicting economic behaviour (Dohmen *et al*, 2005). This paper aims to add the growing amount of literature on risk attitudes by investigating if and how individual financial risks attitudes[1] are affected by past stock market returns. The hypothesis builds on Thaler and Johnson (1990) who found that previous gains and losses impacted on risk taking behaviour. This paper empirically examines whether the findings of Thaler and Johnson (1990) also applies to previous gains and losses in the form of stock market returns.

Standard expected utility models typically assume that individuals are endowed with stable risk preferences, varying only with wealth. These preferences are based on logic and laws of probability and are unaltered by changes in individual characteristics or recent economic experiences. A common assumption is that individual's exhibit constant relative risk aversion, for example in the asset allocation model of Campbell and Viciera (2002). However, there is a growing amount of evidence against many of the assumptions of expected utility, such that risk preferences are stable (see for example Hirshleifer, 2001). Instead many author's use prospect theory, as developed by Kahneman and Tversky (1979), to explain the behaviour of individuals. This paper is only able to provide illustrative evidence to the ongoing debate since a rigorous link between the theoretical concept of risk tolerance and the measure of willingness to take risks used here has not (yet) been established.

To investigate whether a relationship between previous stock market returns and risk attitudes exist a large panel dataset is used; the CentER DNB Household survey (DHS). The sample used in this paper consists of approximately 18,000 observations from yearly survey waves between 1994 and 2008. This contrasts with several datasets that have been used in the relevant literature, which generally used small samples. The main advantage of this dataset is that it contains information of a broad set of economic, demographic and psychological characteristics. Furthermore the dataset was found to be broadly representative of the Dutch population (Alessie *et al,* 2002).

In order to test whether there is a relationship between the elicited willingness to take risks and past stock returns several different models are used, namely: linear fixed and random effects models, a random effects ordered probit model and a fixed effect logit model. Each model has its own particular advantages and disadvantages, therefore it is instructive to estimate these four models and compare the results. Along with a baseline model three alternative specifications are included – each testing a different aspect of the possible relationship of past stock returns with willingness to take risks. These specifications test whether the impacts of past stock returns are different for owners of risky assets, whether the effects of positive and negative returns are symmetric and whether the size of the return

[1] This paper deals exclusively with financial issues, therefore any reference to risk will denote financial risk (unless explicitly stated otherwise).

matters. This issue of the manner in which previous stock market returns and risk attitudes are related has been largely ignored in the literature. To identify the effect of recent stock market returns several variables are included to control for factors which could influence a respondent's to willingness to take risks. In order to avoid an omitted variable bias it is also necessary to include other macroeconomic factors which may be correlated with stock returns and willingness to take risks. Inflation and the unemployment rate are therefore included in each model. This forms secondary hypothesis; do macroeconomic factors in the form of inflation and unemployment rate influence an individual's willingness to take risks?

Past stock returns are found to be strongly related to willingness to take risks. Positive stock returns are associated with an increase in willingness to take risks, whilst negative stock returns are associated with a decrease. These findings are relatively robust across all models and specifications. The relationship between past stock returns and willingness to take risks was significantly stronger for individuals who owned stocks or mutual funds. However, the relationship was also found to be present in the sample which did not own any risky assets. No robust evidence was found of the existence of asymmetric effects or that the size of the returns is related to willingness to take risks in a non-linear way. Inflation was consistently found to be negatively correlated with the willingness to take risks whilst the unemployment rate did not provided any robust results.

The rest of the paper is organised as follows: Section 2 gives a summary of the relevant literature. Section 3 and 4 provides an overview of the data and methodology respectively. The results are presented in Section 5 and Section 6 concludes.

2) Literature Review

2.1) Experimental Evidence: Do previous results matter?

Thaler and Johnson (1990) investigated the effect of prior gains or losses on risk taking behaviour. They conducted a number of experiments on students by asking them to make several choices relating to gambles. In this experiment some individuals were presented with a one-off gamble, whilst other groups were given two stage gambles. The second stage gamble was the same as the one-off gamble; the only difference being that it was preceded by a gain or loss in the first round. The gains or losses in the first round were set to be much larger than those of the second and one-off rounds. They found that prior gains or losses had a significant impact on risk taking behaviour. The number of individuals who were risk seeking decreased by 30 percent if a previous loss had occurred. Prior losses thus caused a decrease in risk tolerance. These findings were reversed when operating in the realm of gains; in the two stage version 77 percent of the group which experienced a previous gain were risk seeking whilst only 44 percent of the individuals were risk seeking in the one-off gamble. Thus small losses following an initial large gain are integrated with the original gain. This lessens the influence of loss aversion and results in increased risk seeking. Thaler and Johnson (1990) called this the "house money effect." This term, often used by gamblers, captures the notion that losing the "house's money" is less painful that losing one's own money. This result is also different to the one-stage prediction of prospect theory, namely that individuals are risk averse in the realm of gains. In a final experiment Thaler and Johnson (1990) made the loss in the first round a similar size to the possible gain in the second round. They found evidence of the break-even effect: in the presence of prior losses individuals became more willing to take on risk if there was a possibility to win their money back.

The impact of previous gains or losses on risk taking behaviour has also been studied using data from television game shows. Post *et al* (2008) analyzed the behaviour of contestants on the popular game show "Deal or No Deal." Their dataset consisted of 84 contestants from Australia and The Netherlands during 2002 – 2005. They found that previous losses were able to explain a large part of the cross-sectional differences. Relative Risk Aversion decreased after initial losses, implying that individuals became more risk tolerant. Furthermore the size of the estimated coefficient implies that subsequent to a large initial loss contestants would become risk seeking. They argued that this is consistent with the break even effect. However, it not clear that the findings by Post *et al* (2008) do provide evidence of increased risk taking after initial losses, nor the break even effect, since contestants on "Deal or No Deal" cannot lose money. This complicates any interpretation of the effect of previous gains and losses since it depends crucially on the reference point of the individual. Furthermore partaking in a game show might alter the behaviour of the contestants. For example contestants may care about the entertainment they provide and therefore may be willing to take on more risk. If this is the case then the results will be biased upwards, towards greater risk taking.

The findings by Thaler and Johnson (1990) and Post *et al* (2008) clearly show that previous gains or losses impact on risk taking behaviour. However, both papers deal with gains or losses in an explicit setting. This does not necessarily imply that stock market returns will have a similar effect. The example used by Thaler and Johnson (1990) highlights this problem: Imagine that you are attending a convention in Las Vegas. Whilst walking past the slot machine you put a quarter into the machine and win $100. Suppose instead that on the way to the convention your wallet, containing $100, is stolen. Will these events change your gambling behaviour? Their findings suggest so. However, what if upon entering the casino you are told that a stock, of which you own 100 shares, has gone up (or down) by one point? Will this change your behaviour in the same way? This effect is likely to be much more subtle and complex.

2.2) The impact of stock market returns on the willingness to take risk

Yao *et al* (2004) investigated changes in financial risk tolerance over time. Using six cross sectional waves collected during 1983 – 2001 by the Survey of Consumer Finances (SCF) they found that the changes in elicited risk tolerance followed the fluctuations of stock market returns. However, Yao *et al* (2004) relied on time dummies variables which were compared to observed stock market returns, thus the causal link remains a hypothesis.

Grable *et al* (2004) included stock returns into their study of financial risk attitudes, using data from an internet survey of 421 respondents. Their results of indicated that previous stock market returns matter, varying positively with the risk attitudes. This is consistent with the experimental findings of Thaler and Johnson (1990). Grable *et al* (2004) argued that individuals exhibit projection bias when dealing with stock markets; they expect the current trend to continue and adapt their willingness to take risks accordingly. Evidence of the existence of projection bias in stock market investing was also found by Clarke and Statman

(1998), and De Bondt (1991) found that investors surveyed by the American Association of Individual Investors forecasted future stock returns as though they expected continuations of past returns.

Grable *et al* (2004) acknowledged that their sample was not randomly distributed. This is likely to bias the results, for example the relative young sample (average age of 32) might explain why they found no significant age effect. Furthermore, they implicitly assumed that stock market returns only have a linear effect on risk attitudes; this may not be the case as large movements may have a greater impact. Grable *et al* (2004) also left several interesting questions unanswered. For example, are the effects are symmetric around positive and negative returns? And how long does the effect of previous stock returns last?

Malmendier and Nagel (2009) investigated whether experiences of stock or inflation shocks affect long term risk attitudes, also using data from SCF, but utilize a much longer data set (1964 – 2004) than Yao *et al* (2004). Their results were consistent with those of Thaler and Johnson (1990) and Grable *et al* (2004). They found that stock market returns experienced in the past have a significant and positive effect on risk attitudes. These effects are long lasting; returns experienced early in life still affects risk attitudes several decades later, but they do fade away as time progresses. This means that the most recent returns have the stronger effect on risk attitudes.

Sahm (2007) used panel data on hypothetical gambles from the US Health and Retirement Study from 1992 – 2002 to investigate if and how risk tolerance changes over time. Major life events, such as job displacement or the onset of serious health condition were not found to permanently alter the individual's risk tolerance. However, improvements in Index of Consumer Sentiment were associated with an increase in risk tolerance. She highlighted that the Index of Consumer Sentiment is strongly correlated with the S&P 500 Total Stock Return Index.

2.3) Measures of willingness to take risks

Willingness to take risks is measured in several different ways – as is already evident from some of the literature mentioned above. This includes obtaining the measure from actual observed behaviour, from lotteries or direct survey questions.

Using actual behaviour to obtain the willingness to take risks of an individual has the advantage that these measures are necessarily relevant and valid since it deals with real-life choices. Examples include Post *et al* (2008) (see above), Gertner (2003) and Hartley *et al,* (2005) all analysing risks based on responses in various game shows. However, partaking in a game show might alter the behaviour of the contestant which means that the choices made on the game show might not be correlated with choices made in other financial decisions.

A substantial amount of literature uses observations from lotteries. These can either be in the form of experimental or hypothetical lotteries. Experimental lotteries often have small stakes since the respondents play out the lotteries and are rewarded according to their choices (for example Thaler and Johnson, 1990). Hypothetical lotteries are often included in surveys and generally deal with larger amounts (see for example Sahm, 2007). Experimental lotteries (due to the costs involved) are generally done on a small scale, usually with students.

von Gaudecker *et al* (2008) compared results from a large scale experimental lottery (using respondents from the internet survey of CentERpanel) with an experiment lottery performed in a laboratory setting using students. They found that there were large differences between experimental choices of students and the general population, for example the student sample was found to have higher risk tolerance.

It is also possible to use survey questions to ascertain risk attitudes. These questions can either ask respondents to choose an option that they most agree with (as is case in the SCF question) or to evaluate how much they agree with a certain statement on a Likert scale. The main advantage of using the survey question is that it is a direct measure of a respondent's willingness to take risks, avoiding the need to recover behavioural parameters by making restrictive assumptions (Dohmen *et al,* 2005). A common criticism against using survey questions is that it is not always clear what is being measured by the survey questions and therefore they may not predict actual behaviour (Dohmen *et al,* 2005). This issue is dealt with more extensively in the next section.

2.4) Validity and relevance of survey questions on risk attitudes

Melmendier and Nagel (2009) argued that the SCF variable is an imperfect measure of risk tolerance as it depends on the individual's interpretation of "substantial risk" and "above average risk." They argued that this measure is likely to represent a combined effect of the theoretical (Arrow Pratt) risk aversion and beliefs. Yao *et al* (2004) also argued the SCF question measures 'willingness to take risk' rather than theoretical risk tolerance.

Dohmen *et al* (2005) used field experiments to validate the risk measures captured by a large survey of the German population in 2004, the German Socio-economic Panel (GSOEP). They tested whether survey data could predict actual risk taking behaviour in a lottery experiment. The survey sample was roughly 22,000 individuals whilst the experiment used a representative sample of 450 individuals. They found that subjects who indicated a greater willingness to take risks[2] did show a greater willingness to take risks in the lottery experiment. They therefore reject the null hypothesis that the survey measure is behaviourally irrelevant.

2.5) Summary

This section has examined some of the literature on the effect of past returns on risk tolerance. Experimental evidence shows that prior gains and losses impact on risk taking behaviour. This result also applies to previous stock market returns; willingness to take risks tends to increase following positive returns and decreases following negative returns. This is based on a type of herding behaviour, a result of projection bias, where individuals "follow the market" as they overestimate the probability of the current trend continuing. The impact of stock returns is long lasting; however the most recent stock market returns have the biggest impact on the willingness to take risk.

[2] Individuals were asked to rank their willingness to risk on an 11 point scale

3) Data

The data used in this paper is from the CentER DNB Household survey (DHS), a household survey conducted by CentER at Tilburg University in The Netherlands. The DHS contains information on work, pensions, housing income, assets, economic and psychological concepts and personal characteristics for approximately 2000 Dutch households in each wave. To account for possible panel attrition biases new households are included to replace households that have dropped out of the survey. Alessie *et al* (2002) compared the DHS results to national accounts and data on household wealth and found that the survey is broadly representative of the Dutch population. The survey questions are answered via the Internet and participants who do not have Internet access are provided with a device that allows them to access the Internet through their televisions. This has the advantage that respondents fill in the questionnaire in their own time and it removes any possibility of the interviewer effect (Christensen *et al,* 2006). Another benefit of this dataset is that Das *et al* (2007) found that the problem of panel conditioning does not play a role in questions on attitudes, actual behaviour or expectations concerning the future.

This paper uses data from the 1994 – 2008 waves. The sample is restricted to heads of households and spouses or permanent partners. Overall the sample consists of 8,662 households and 15,296 individuals. Across all waves there are a total of 53,575 observations, however only 18,219 are included in the baseline estimation. The missing observations are mainly due to non response to the willingness to take risks questions which are missing 25,114 observations. The distribution of the non response and missing values is biased towards individuals with low income. It is unfortunately not possible impute any willingness to take risk measures from any of the other risk related questions that are included in the survey. However the number of income observations that are excluded due to the missing 'Spaar6' variable is relatively low (3,223 of 25,114), thus the sample bias is likely to be relatively small. The dataset also somewhat under-samples females; only 42 percent of respondents are female. The distribution of missing values is fairly randomly distributed for the other important characteristics such as education, employment and age. The rest of the missing observations come from the following variables: marital status (5,366), future income expectations (1,840), subjective well being (1,389), health (1,046), education (511), income (86) and employed (4). This leaves 6,862 individuals in the sample, each participating in approximately 2.7 surveys. The average individual observation over time is unfortunately quite low and is likely to lead to large standard errors, especially for the fixed effects estimation - which exploits variation over time for each individual rather than cross-sectional variation between individuals. The variables used in this study are discussed in more detail below.

3.1) The dependent variable

The willingness to take risks variable used in this paper is based on responses to the following question, called Spaar6: *"I am prepared to take the risk to lose money, when there is also a chance to gain money."* The answers are given on a scale of 1 (strongly disagree) to 7 (strongly agree). This question is preferred over other possible risk related measures that are available in the DHS. Alessie *et al* (2004) created their elicited risk tolerance variable from responses to the statement (called Spaar1): "*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."* Again respondents answered on a seven point scale from strongly disagree to strongly agree. This is a feasible alternative. In order to examine the relevance of the Spaar1 and Spaar6 measures correlations with actual risky behaviour is calculated. Owning risky assets (stocks or mutual funds) and being self employed are used as risky behaviour. The results are presented in Table 1 below.

Table 1: Correlation of Spaar6 and Spaar1 with risky behaviour, 1994 - 2008

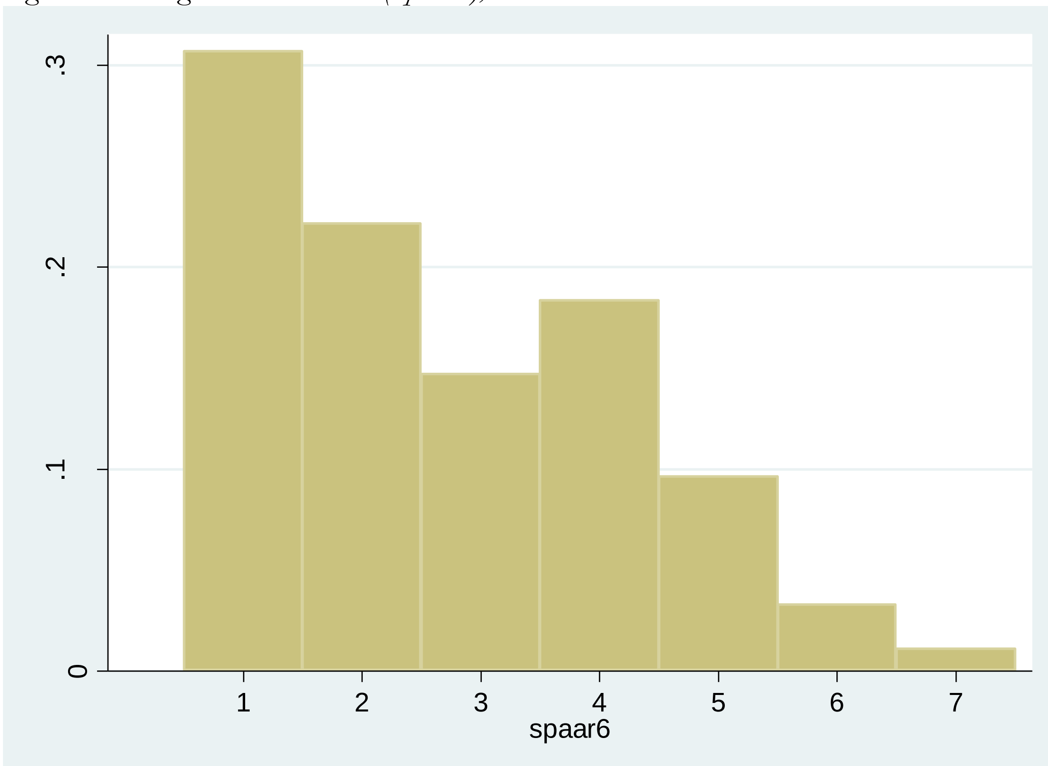
	Spaar1	Spaar6
Spaar1	1	
Spaar6	-0.247	1
Risky asset ownership	-0.067	0.268
Self Employed	-0.010	0.058

Note: Risky assets are defined as stocks or mutual funds

Spaar6 is positively correlated with ownership of risky assets and being self employed, whilst the Spaar1 measure is negatively correlated with both measures of risky behaviour. These are the expected signs as a high value for Spaar1 corresponds to low willingness to take risks, but corresponds to a high willingness to take risks in the Spaar6 measure. This shows that answers to both Spaar1 and Spaar6 are relevant as both measures are correlated with actual risky behaviour. From Table 1 it is also clear that the Spaar6 variable has a significantly stronger relationship with actual behaviour. Therefore the Spaar6 question is the preferred measure of an individual's willingness to take risks.

Figure 1 presents the distribution of the willingness to take risks measure. The distribution is positively skewed. The lowest willingness to take risks category has the most observations whilst the highest willingness to take risk category has the fewest observations. A dummy variable is constructed from these observations, taking on a value of one if the respondent has a high willingness to take risks (if the response to the Spaar6 question is 4 or higher) and zero otherwise. The majority of individuals thus fall into the baseline category, only 32 percent of the respondents fall in the high willingness to take risks category.

Figure 1: Willingness to take risks (Spaar6), 1994 - 2008



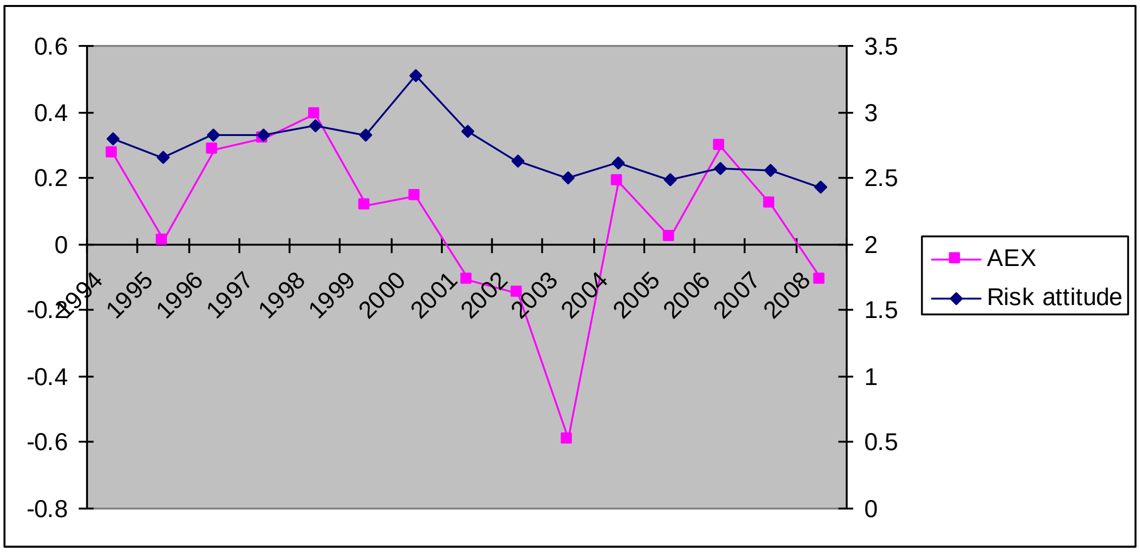
3.2) Independent variables

The main independent variables of interest are those of past stock returns. The Amsterdam Exchange Index (AEX), a stock market index of companies that trade on Euronext Amsterdam, is used. This is arguably the most relevant stock market for the Dutch population. Although The Netherlands has one of the lowest home biases in equity ownership, it is still substantial; in 2001 42 percent of Dutch portfolios consisted of stocks listed on Euronext Amsterdam which has only 1.65 percent of the global market share (Sorensen *et al*, 2005). Yearly return data were obtained from Datastream. Lagged yearly returns are used rather than current returns for two reasons: Firstly, this avoids a problem of endogeneity as aggregate movements in risk attitudes may affect stock market returns. Secondly, including present returns (for example including the returns achieved in 1997 for the survey completed in 1997) means that returns which have not yet occurred at the time of the survey are included. The use of other possible specifications (for example using the most recent monthly or quarterly data) is limited by the fact that the month of the completion of the survey is only known between 1994 and 2000.

The stock return variable is lagged several times as the duration of the effect may be long lasting. Six return variables are included are included in every model and specification, ranging from one year lagged returns to six year lagged returns. The choice of six return variables is a trade-off between keeping the model parsimonious and showing the duration effect. Estimations were run with more than six return variables, but the results did not differ substantially from the estimations with only six return variables. It is however, worth noting that in some cases the lagged returns beyond six years were still significant – thus the duration of the stock return movements is longer lasting than what is captured in this paper.

The AEX provided an average return of 0.08 between 1994 and 2008, with a standard deviation as large as 0.25. Figure 2 shows the changes in willingness to take risks and returns over time. This graph is encouraging since the data seem to follow a roughly follow a similar pattern. The drop in willingness to take risks between 2000 and 2003, following a series of poor returns, stands out in particular. It is also interesting to note that willingness to take risks peaked in 2000, at the height of the dotcom bubble. Willingness to take risks also began to decrease again after 2007, corresponding with the onset of the current financial crisis.

Figure 2: AEX Returns and risk attitdues, 1994 – 2008

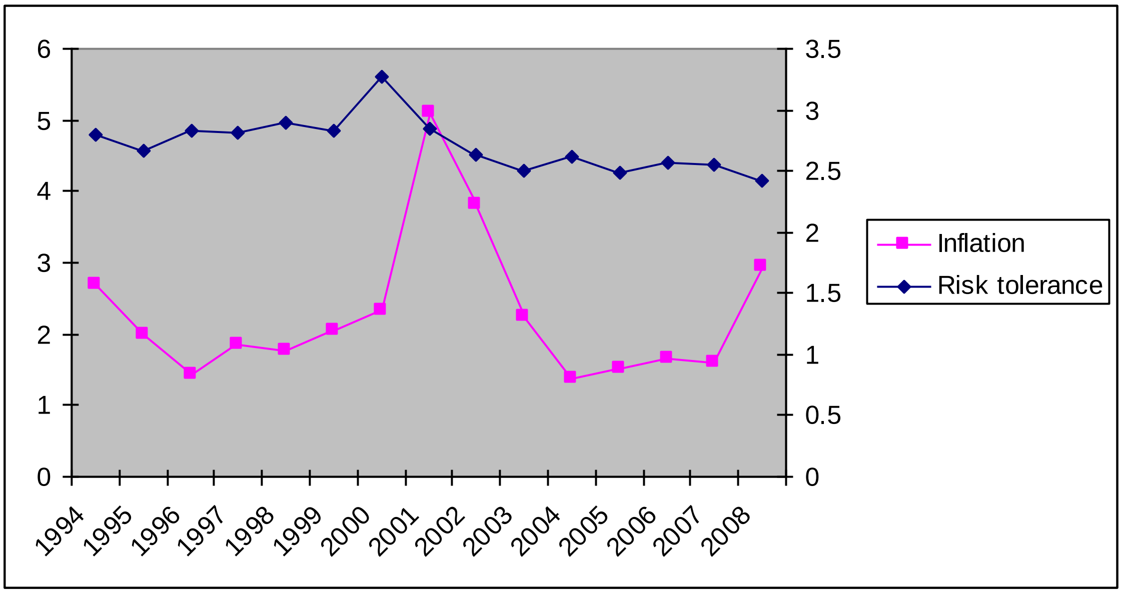


Note: Left Y axis corresponds to AEX returns and right Y axis corresponds to risk attitudes

As argued in Section 2 in order to identify the effect of stock returns on risk attitudes macroeconomic factors should be controlled for. Data on inflation and unemployment rate are therefore included, obtained from the IMF's World Economic Outlook. Christensen *et al* (2006) investigated the qualitative and quantitative perceptions and expectations of past, current and future macroeconomic developments using the DHS. They concluded that economic growth is a more abstract notion for the general Dutch population than inflation. Individuals are faced with price and price developments on a regular basis and thus arguably have a better understanding of inflation. Furthermore they found evidence of a high level of inflation aversion in the general public. For this reason inflation rates are included rather than GDP growth. Unemployment rate is also included since an increase in the probability of joblessness may impact on risk attitudes. This is also argued to be somewhat less abstract than GDP growth. However all of these measures are strongly correlated. Similar to the stock return variables, lagged yearly inflation and unemployment values are used.

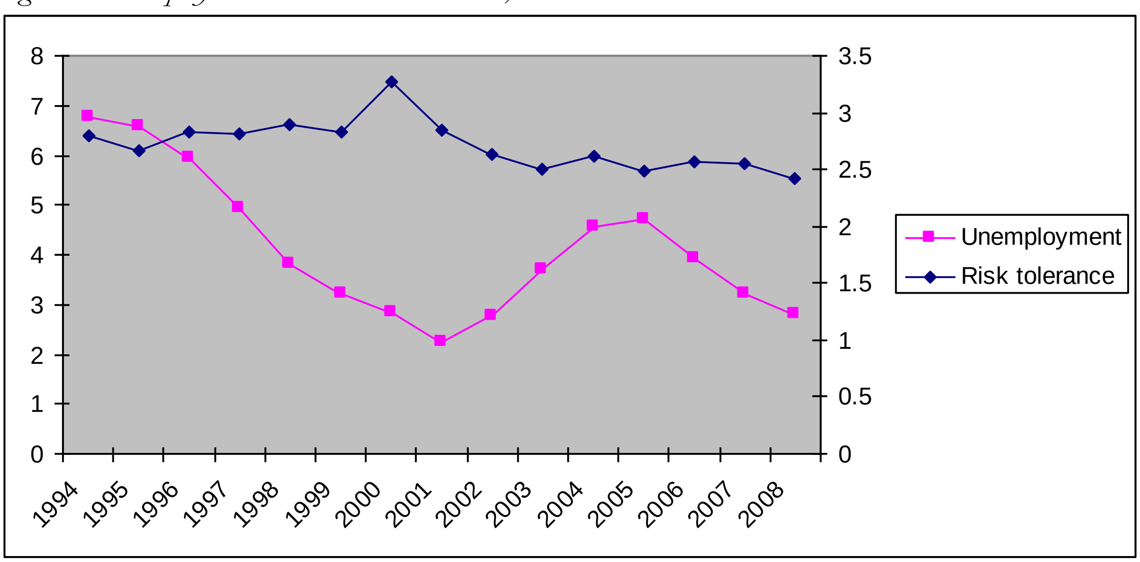
Figure 3 and 4 shows the movements of inflation and unemployment against willingness to take risks for the sample period. Average year on year inflation between 1994 and 2008 was 2.29 percent, but there was quite a lot of variation, seen especially during 2000 and 2004 where inflation spiked dramatically. Overall the standard deviation was 1.02 percent. The unemployment rate also showed some variation, decreasing from nearly 7 percent in 1994 to 2.5 percent in 2003 before increasing again in 2004 and 2005. The average unemployment rate over the sample was 4.13 percent. An interesting observation is that inflation seems to have a positive correlation with risk attitudes, whilst unemployment and risk attitudes appear to be (somewhat) negatively correlated.

Figure 3: Yearly inflation and risk attitudes, 1994 – 2008



Note: The Y axis on the left corresponds to inflation and the Y axis on the right corresponds to risk attitudes

Figure 4: Unemployment rate and risk tolerance, 1994 - 2008



Note: The left Y axis corresponds to the unemployment rate and the right Y axis corresponds to risk attitudes

Variables for current financial situation and expected future income are included in order to control for possible attitudes or beliefs that may influence the responses to the Spaar6 question. The respondent's current financial situation and expectation of income over the next five years are likely to influence how she interprets the phrase "*I am prepared to take the* *risk to lose money."* Accounting for the current financial situation is particularly important since an indebted respondent may indicate that she is not willing to take a risk and potentially lose money, simply because she is in a poor financial situation. Only controlling for income is not enough in this case since high income individuals could also be in poor financial situations. These controls are include in the form of dummy variables, depicting five possible current financial situations (debt, drawing on savings, just managing, saving some, substantial saving) and three possible income expectations over the next five years (worse, the same, better). These variables (along with income) are also used as proxies for wealth, which is not measured in the DHS. Furthermore to account for the mood of the respondents dummy variables are included for happiness (taking on the value of 1 if the respondent is happy and 0 otherwise) and health (taking on a value of 1 if the respondent is in good health and 0 otherwise). These are admittedly very crude proxies for the mood of the respondent.

The following demographic and socio-economic variables are also included, based on previous research: gender, income, education, marital status, age, employment and smoking (see Dohmen *et al,* 2005, and Grable *et al*, 2004). Most of these variables are included in the form of dummy variables, for example employment status (contractual, self employed, student, retired, disabled, and unemployed), education (low, intermediate and high) and income (low, intermediate, high). Unfortunately the DHS contains no measure on wealth. These variables are summarised below in Table 2.

Table 2: Summary statistics, 1994 - 2008

	Variable	**Description**	Mean	Std. Dev.	Min	Max
Current financial situation	Debt	1 if currently in debt, 0 otherwise	0.03	0.17	0	1
	Depleting Savings	1 if depleting savings, 0 otherwise	0.11	0.31	0	1
	Just Managing	1 if just managing, 0 otherwise	0.22	0.41	0	1
	Saving	1 if saving somewhat, 0 otherwise	0.52	0.50	0	1
	Substantial Saving	1 if saving a lot 0 otherwise	0.13	0.33	0	1
Demographics	Female	1 if female, 0 if male	0.42	0.49	0	1
	Age	1 if married or lifelong partner, 0 otherwise	50.00	13.96	18	94
	Married	Age of respondent	0.74	0.44	0	1
Education	Low	High school or lower	0.36	0.48	0	1
	Intermediate	Vocational training	0.51	0.50	0	1
	High	University or Vocational College	0.12	0.32	0	1
Employment	Employed	1 if contractually employed, 0 otherwise	0.53	0.50	0	1
	Unemployed	1 if unemployed, 0 otherwise	0.01	0.12	0	1
	Self employed	1 if self employed, 0 otherwise	0.03	0.17	0	1
	Other	1 if other form of employment, 0 otherwise	0.20	0.40	0	1
	Retired	1 if retired, 0 otherwise	0.18	0.39	0	1
	Disabled	1 if (partly) disabled, 0 otherwise	0.04	0.20	0	1
	Student	1 if student, 0 otherwise	0.00	0.06	0	1
Future income expectations	Lower	1 if expect decrease in income over 5 years, 0 otherwise	0.16	0.37	0	1
	Same	1 if expect no change in income over 5 years, 0 otherwise	0.53	0.50	0	1
	Higher	1 if expect increase in income over 5 years, 0 otherwise	0.31	0.46	0	1
Health & happiness	Good Health	1 if in good health, 0 otherwise	0.80	0.40	0	1
	Happy	1 if happy, 0 otherwise	0.86	0.35	0	1
	Smoker	1 if smoker, 0 otherwise	0.27	0.44	0	1
Income	Low	Less than €14000	0.19	0.39	0	1
	Intermediate	€14000 - €40000	0.37	0.48	0	1
	High	Over €40000	0.44	0.50	0	1

From the summary statistics several interesting patterns emerge. Individuals in the sample generally have medium to high income and 30 percent of respondents expect income to improve over the next 5 years. Only 16 percent of respondents expect their income to fall over the next 5 years. Furthermore only 3 percent of the respondents are in debt, whilst 52 percent claim to be able to save some money. As mentioned above females are somewhat under-sampled. The average age is 50 and majority of respondents are married or have permanent partners. The high number of married individuals means that it will be necessary to correct the standard errors in the estimation for possible correlation within households, since answers are likely to be correlated amongst spouses or partners. The majority of respondents are in good health (despite 27 percent of the sample being smokers) and consider themselves as being happy. The majority of the respondents received vocational training (51 percent), whilst 12 percent have a university degree.

4) Methodology

This paper makes use of four different models: linear fixed and random effects models, an ordered probit model and a fixed effects logit model. Each model has its own advantages and disadvantages. Including four different models forms a test of robustness; by comparing the results across the models it can be established whether the results are dependent on a particular assumption or model. The models are explained in more detail below. The following notation is used (unless stated otherwise):

y_{it} represents the dependent variable, willingness to take risks. This variable takes on integers values from 1 to 7 (increasing in willingness to take risks), except for the fixed effects logit model where it is binary ($y_{it} = 1$ if the individual is risk averse and $y_{it} = 0$ otherwise).

x_{it} is a vector of independent variables. For the baseline estimation these variables are: age, current financial situation, education, employment, future income expectations, gender, happiness, health, inflation, income and martial status, past stock market returns and unemployment rate.

α_i represents the individual specific effect. This captures all individual characteristics not controlled for in x_{it}. Note that there is no time component in α_i as the individual characteristics are assumed to be time-invariant.

ε_{it} denotes the error term. The error term is assumed to be identically and independently distributed (IID) with a zero mean; $\varepsilon_{it} \sim IID(0, \sigma_\varepsilon^2)$.

4.1) Linear fixed effects model

The use of a linear model requires the assumption that the willingness to take risks values are cardinal. This is somewhat unrealistic as it means that an individual with a score of 6 is exactly twice as willing to take risks as an individual with a score of 3. However, the use of a linear model for ordinal data is well established, especially in literature on subjective well-being (see for example Clarke, 2007 and Headey *et al*, 2004). Ferrer-i-Carbonell and Fritjers (2004) investigated the effect of assuming the data to be cardinal or ordinal on the estimation results in a subjective well-being setting. They found that the assumption of cardinality makes little difference to the final results. Therefore a linear estimation is included as an estimation method for its familiarity and ease of interpretation of the coefficients. The advantage of the linear model is that a coefficient represents the marginal effect, meaning that the coefficients have a straightforward interpretation.

The model is estimated with fixed effects. This method of estimation ignores any variations between individuals and concentrates solely on differences 'within' individuals. By focussing only on the within dimension of the data fixed effects estimation controls for possible unobserved heterogeneity that could be correlated with the explanatory variables (Verbeek, 2004).

4.2) Linear random effects model

This model provides an alternative method to deal with the individual specific effects. However, this requires the additional assumption that all α_i are independent of the vector of explanatory variables, x_{it}. On the basis of this assumption α_i can now be modelled as forming part of the error term.

Using random effects estimation has several advantages over fixed effects. Maddala (1987) argued that α_i measures individual specific effects which are unknown to the researcher in the same way the she is ignorant about the error term ε_{it} (which measures the effects of individual *i* in period *t* that she is ignorant about). Thus if ε_{it} is treated as a random variable, then there is no reason why α_i should not also be treated as random. Another advantage of the random effects model is able to take time-invariant observations (such as gender) into account. The lack of within variation of such variables (for each individual) means that these observations cannot be included in a fixed effects model. These characteristics are often important to the study (for example most literature find that women have lower risk tolerance).

4.3) Random effects ordered probit model

This model takes the ordered structure of the risk tolerance question into account. y_{it} can take on any integer values, *j*, from one to seven. The model is constructed in terms of a latent underlying variable:

$$y_{it}^{*} = \alpha_i + x_{it}^{'}\beta + \varepsilon_{it} \qquad (1)$$

with $y_{it} = j$ if $m_{j-1} < y_{it}^{*} \leq m_j$

where m_j are the unobserved thresholds.

The model is estimated with random effects, therefore α_i is assumed to be independent of all x_{it} and ε_{it} and is included in the error term; $u_{it} = \alpha_i + \varepsilon_{it}$. u_{it} is assumed to follow a multivariate normal distribution. Maddala (1987) argued that a probit model (which assumes multivariate normal errors) should be used when estimating with random effects. The random effects produce correlations among the errors and multivariate logistic distribution constrains all these correlations to be a $1/2$. He argued that this is too restrictive, and proposed using a random effects probit model instead, as the multivariate normal distribution is more flexible. The model is estimated using maximum likelihood.

4.4) Fixed effects logit model

Estimating a fixed effects model that exploits the discrete nature of the data presents some potential problems as this requires maximum likelihood estimation. This is problematic since the justification for maximum likelihood estimators is usually asymptotic. The validity of this justification depends on the assumption that the number of parameters remains constant if the sample gets larger (Allison, 2005). This is not the case when using fixed effects since treating α_i as a fixed effect is essentially the same as including a dummy variable for every individual (N). The estimation is consistent if the number of time periods (T) goes to infinity, but for a fixed time period the parameters grow with sample size (as new dummies are added for new individuals in the sample). In this case the estimated coefficients are increasing in N and are therefore biased (Allison, 2005). This referred to as the 'incidental parameter' problem (Verbeek, 2004). This can be overcome using a conditional maximum likelihood for the logit model, which as shown in the Appendix, will result in a consistent estimate of β. This means two of the models used in this paper rely different distributional assumptions on the error terms. There is a trade-off between keeping the distributional assumptions consistent throughout all models (that the error terms always follow a logistic or normal distribution) and using the methodologically correct models (which in this case would mean using the fixed effects logit model and the random effects probit model). This paper opts to use the methodologically correct models.

The logit model is also formulated in terms of an underlying latent model:

$$y_{it}^{*} = \alpha_i + x_{it}^{'}\beta + \varepsilon_{it} \tag{9}$$

with $y_{it} = 1 \text{ if } y_{it}^{*} > 0$

$y_{it} = 0 \text{ if } y_{it}^{*} \leq 0$

However, in this case the individual *i* is only included if $\bar{y}_i \neq 0$ and $\bar{y}_i \neq 1$. The set of errors are assumed to follow a logistic distribution. Once the sample has been restricted the parameters β can be estimated consistently using maximum likelihood, conditional on the restricted sample.

4.5) Specifications

This paper uses four different specification for the different models described above. The first specification simply includes all the relevant variables and controls and serves as a baseline model. The remaining three specifications each investigate a specific trait of stock market returns and act as robustness tests. The second specification separates the sample into those who own risky assets (stocks or mutual funds) and those who do not. The third specification tests for possible asymmetries in the effect of stock market returns. This is done by including a dummy variable for negative returns (equal to one if the return is negative and zero otherwise). The final specification investigates whether the size of the deviation matters. The returns are split into quartiles and dummy variables are created for each quartile and included in the estimation.

No time dummies are included in any of the estimations, since these dummies will be perfectly correlated with the past stock returns and macroeconomic factors. Since the stock market variables always have the same observation for each year it will have an exact linear relationship with a time dummy for that year. Thus all the time dummy variables will be perfectly correlated with the past stock returns variables. Furthermore there is the usual problem of simultaneously estimating time, age and cohort effects. Time, age and cohort effects are linear combinations of each other and cannot be identified without theoretical restrictions (Campbell, 2001). In this case time and stock returns are linear combinations of each other and thus stock returns, age and cohort effects are linear combinations. In order to estimate these effects it is necessary to assume that either the cohort or the age effect is zero. This is a restricting assumption regardless of which variable is chosen since both have been found to have a significant impact on risk tolerance in the relevant literature. This paper assumes cohort effect to be zero.

5) Results

5.1) Baseline Estimation

The results of the baseline estimation are presented below in Table 3. The coefficients of the lagged returns are positive and, for the most part, significant. An increase in past returns, conditional on the control variables, therefore increases an individual's willingness to take risks. The positive signs of the coefficients are consistent with the findings of Thaler and Johnson (1990) and Grable *et al* (2004). It is also consistent with evidence of projection bias. Individuals expect the current trend of stock market returns to continue and, based on this belief, adjust their willingness to take risks. Similar to Malenmedier and Nagel (2009) past stock returns have a long lasting effect, as the coefficients of returns remain significant despite being lagged several times. However, the sizes of the coefficients are somewhat surprising. In contrast to Malemendier and Nagel (2009) the impact of stock returns does not seem to fade away in a clear and neat manner. The coefficients of the twice lagged returns are substantially larger than the coefficients of the most recent returns. Similarly the coefficients of returns five years past are larger than the coefficients of returns three or four years past. It is unclear why this should be the case.

Unfortunately it is not possible to directly compare the coefficients with those of Grable *et al* (2004) or Malmendier and Nagel (2009) since the estimation techniques and variables used differ so much. As mentioned above the benefit of the linear specifications is that the coefficients represent the marginal effects. From the linear fixed effects estimation (column 1) an upward movement the size of one standard deviation, 0.23, of the previous year's return increases the willingness to take risks by 0.03 points (conditional on the control variables). However, the effect is long lasting, for example the increase raises the willingness to take risk by 0.14 points in the following year. Interpretations of the size of the coefficients from the non-linear models are somewhat more complicated as the coefficient cannot be interpreted as the marginal effect. The individual marginal effect for these models is both a function of the parameters and the independent variables. This means that the marginal effect of a change in a variable, say one year lagged returns, depends on the actual value of the lagged return.

The coefficient of inflation is negative and significant in all four models. The sign of the coefficient is somewhat surprising given that the relationship appeared to be positive in Figure 3. An increase in inflation, conditional on the control variables, leads to a lower willingness to take risks. A possible explanation for this finding is that inflation erodes real wealth. Higher levels of wealth are associated with greater willingness to take risk since it cushions the impact of bad outcomes (Dohmen *et al*, 2005). Therefore higher inflation reduces the willingness to take risks through reducing real wealth. Projection bias is also likely to play a role here as people expect the current inflation situation or trend to continue in the future and alter their wealth expectations accordingly. This is also consistent with the finding that inflation expectations are generally slow to adapt to actual changes in inflation (see for example Heinemann and Ullrich, 2006). The coefficient of unemployment rate is generally small and positive and is not consistently significant. The positive sign is somewhat surprising since this indicates that higher unemployment rates are correlated with higher willingness to take risks. If income becomes more variable due to a higher unemployment rate one would expect individuals to become less willing to take risks - as they place greater focus on savings in order to smooth future consumption. This finding also contrasts Guiso and Paiella (2008) who found that individuals who faced high exogenous income risk were less willing to take on any financial risk. Overall these results show that willingness to take risks is correlated with macroeconomic factors. This means that studies such as Grable *et al* (2004) and Malmendier and Nagel (2009) who do not account for these factors are likely to suffer from an omitted variable bias. Furthermore, the results have potentially important policy implications as it highlights another danger of high or variable inflation. The extent to which inflation affects the real economy through this channel is an interesting avenue of future research.

Table 3: Relationship between willingness to take risks and past stock returns, baseline estimation

Variable	Description	Linear Fixed Effects	Linear Random Effects	Conditional Logit Fixed Effects	Ordered Probit Random Effects
AEX Returns	1 year lagged	0.1208*	0.0826*	0.2680*	0.0567
		0.0621	0.0469	0.1592	0.0387
	2 years lagged	0.6149***	0.5223***	1.1158***	0.4092***
		0.1379	0.0496	0.3286	0.0426
	3 years lagged	0.2547	0.1627***	0.4901	0.1855***
		0.1759	0.0495	0.3925	0.0402
	4 years lagged	0.203	0.0849*	0.6819*	0.0703*
		0.1556	0.0502	0.3578	0.041
	5 years lagged	0.6602***	0.4672***	1.3915***	0.3656***
		0.2069	0.0556	0.4875	0.0463
	6 years lagged	0.2451**	0.1700**	0.406	0.1394**
		0.121	0.07	0.274	0.0554
Inflation	1 year lagged	-0.0906***	-0.1045***	-0.1761***	-0.0820***
		0.0184	0.0155	0.0487	0.0125
Unemployment Rate	1 year lagged	0.0925	0.0351***	0.237	0.0377***
		0.0786	0.011	0.1805	0.0093
Future income expectations	Higher	0.0736*	0.1193***	-0.0131	0.1179***
		0.0441	0.0365	0.1083	0.035
	The same	0.0596*	0.0502*	0.0198	0.0266
		0.0337	0.0295	0.0835	0.0306
Current financial situation	Debt	0.0476	0.0453	0.0008	0.0154
		0.0889	0.0685	0.2024	0.0597
	Depleting Savings	-0.0316	-0.0112	-0.038	0.0068
		0.0443	0.0381	0.1155	0.0362
	Saving	0.0786**	0.0821***	0.1930**	0.0709***
		0.0341	0.0279	0.087	0.0261
	Substantial Saving	0.1083*	0.1531***	0.192	0.1496***
		0.056	0.0449	0.1371	0.0431
Education	Intermediate	-0.0344	-0.0224	0.036	-0.0076
		0.0623	0.0316	0.1446	0.0285
	High	-0.0483	0.2145***	0.2984	0.1728***
		0.1571	0.055	0.4007	0.0453
Employment	Self Employed	0.0291	0.3668***	-0.0293	0.3444***
		0.1488	0.0871	0.2991	0.0638
	Unemployed	0.0333	0.1958*	-0.0177	0.1613*
		0.118	0.1005	0.3219	0.089
	Retired	-0.068	-0.0697	-0.3157*	-0.0286
		0.0713	0.0483	0.1788	0.0438
	Disabled	-0.0399	-0.0557	-0.042	-0.039
		0.094	0.0647	0.2484	0.0589
	Student	0.4138	0.3615**	2.2325***	0.3018**
		0.2898	0.1717	0.5897	0.1328
	Other	0.0565	0.0374	0.0421	0.031
		0.0761	0.04	0.1917	0.0343
Income	Intermediate	0.0783*	0.1601***	0.1419	0.1482***
		0.0428	0.033	0.1129	0.0297
	High	0.0855	0.2721***	0.1543	0.2953***
		0.0525	0.0389	0.1374	0.0363
Demographics	Age	0.0203	-0.0115***	0.0896	-0.0079***
		0.0304	0.0015	0.0697	0.0013
	Smoking	-0.0909	-0.036	0.0092	-0.0500*
		0.0629	0.0324	0.1418	0.029
	Happy	0.0104	-0.0318	-0.001	-0.045
		0.0465	0.0362	0.1143	0.0334
	Good health	0.0374	0.0345	0.0428	0.0319
		0.0381	0.03	0.1004	0.0294
	Married	0.0774	-0.0620*	0.0991	-0.0715**
		0.0873	0.0375	0.1791	0.0318
	Female	--	-0.6515***	--	-0.4571***
			0.0315		0.0257
Constant	_cons	1.1527	3.3873***	--	--
		1.959	0.1227		
Statistics	Rho	0.6438	0.4751	--	--
	(Pseudo) R2	0.0188	0.0832	0.0176	0.0273
	N	18219	18219	7681	18219

Note: Robust standard errors (clustered on households) are used in all four models. These are presented below the coefficients

***, **, * represent significance at the 1, 5 and 10 percent level

A strong financial situation generally has a positive relationship with willingness to take risks. This effect is similar to the income or wealth effect; being in a better financial situation allows one to take on more risk. This is also the case with expected future income; higher expected income is positively and significantly correlated with the willingness to take risks (except for the fixed effects logit model where the coefficients are not significant). The rest of the control variables generally have the expected signs. On average females and married individuals are less willing to take risk. Willingness to take risks also decreases with age and being retired. Individuals who are self-employed are generally more risk tolerant and so are individuals with a high education or income. However, many of these coefficients are only significant in the random effects estimations. This due to two possible reasons: Firstly, the effects may only be significant across individuals. For example self-employed individuals may be more risk tolerant than individuals who are contractually employed, but it is possible that changing from being contractually employed to being self-employed does not substantially alter one's risk attitudes. Secondly, there may not be enough variation within each individual to accurately identify the effect of several variables in the fixed effect models. A few respondents' marital status may change during the survey period, but for the majority it is likely to stay the same. This leads to large standard errors - the standard deviation of demographic and socio-economic control variables are much larger in the fixed effects models than in the random effects models (for example the standard deviation of marital status in the linear fixed effect model is approximately twice as large as the standard deviation in the linear random effects model).

The (pseudo) R-squared value in all the models are quite low. However, this is to be expected; when dealing with individual attitudes and beliefs the portion of variance that models are able to explain is generally quite low. This is because there is much heterogeneity across individuals (unobserved heterogeneity explains 47 percent of the total unobserved variation in the linear random effects model). Furthermore the formation of attitudes or beliefs is intrinsically difficult to capture in survey questions. The fit of the model is lower than Grable *et al* (2004) (0.1), Malmendier and Nagel (2009) (0.6) and Dohmen *et al* (2005) (0.1). However, Dohmen *et al* (2005) included approximately 80 variables in their estimation, which inflates the R-squared value. Studies of attitudes using the DHS data do however have similarly low R-square values (see for example Christensen *et al* (2006) and van Rooij *et al* (2004)).

In order to test which specification, fixed or random effects, is more suitable a Hausman test is used. The Hausman test effectively acts as a test of the validity of the extra assumption of the random effects model. The Chi-squared test statistic is 108.4, which has a p-value of 0.00. Thus the Hausman test rejects the null hypothesis that the random effects estimation is consistent and efficient. This means that the individual specific effects are not independent of the vector of explanatory variables, thus the random effect estimates are biased. This bias is therefore also likely to be present in the random effects ordered probit model, although it is not directly tested for.

5.2) Risky asset ownership

In this specification the sample is separated into those who own risky assets (stocks or mutual funds) and those who do not. This tests the robustness of the results as the *a priori* expectation is that stock returns have a much bigger impact on actual risky asset owners. The results are presented in Table 4 below. The same demographic and socio-economic controls as the baseline estimations are used in the estimation, but are not shown in Table 4 since they are not the main focus of this paper.

Overall the results are encouraging. The coefficients of past returns are generally much larger for the sample of risky asset owners. The sizes of the coefficients from the sample of risky asset owners are also larger than those from the baseline estimation (Table 3), whilst those from the no ownership sample are generally smaller. Furthermore in both fixed effects models (columns 1 and 4) the coefficients of several of the lagged returns are significant for the sample of risky assets owners, but are not significant for the sample with no ownership. From these results it is therefore clear that stock market returns have a much stronger relationship with the willingness to take risks of risky asset owners.

These findings potentially indicate that the results in the baseline estimation were driven mainly by the asset owners who actually form quite a small part of the sample (approximately 20 percent). However, the coefficients of the twice and five year lagged returns are also significant for the sample with no risky asset ownership in all the models. Thus the stock market also has an impact on individuals who do not own risky assets. Stock market movements may impact on the willingness to take risks of individuals who do not own assets through news and other forms media, which arguably impacts on these individuals' general outlook for the economy.

Table 4: Effect of past stock returns on risky asset owners versus non risky asset owners

		Linear Fixed Effects		Linear Random Effects		Fixed Effects Logit		Random Effects Ordered Probit	
Variable	Description	Risky Assets	No Risky Assets	Risky Assets	No Risky Assets	Risky Assets	No Risky Assets	Risky Assets	No Risky Assets
AEX Returns	1 year lagged	0.3701***	0.0543	0.1281	0.0128	0.6365*	0.2396	0.0464	-0.0047
		0.1405	0.0734	0.0996	0.0544	0.3537	0.195	0.0768	0.0475
	2 years lagged	1.0753***	0.5262***	0.4522***	0.4890***	2.2693***	0.9951**	0.3211***	0.4022***
		0.3282	0.1604	0.1054	0.0576	0.7401	0.3934	0.0825	0.0516
	3 years lagged	0.9058**	0.1457	0.1824	0.1480**	1.7439*	0.3285	0.2011**	0.1839***
		0.4249	0.2069	0.1145	0.0576	0.9423	0.4668	0.0865	0.0493
	4 years lagged	0.8418**	0.0861	0.1407	0.0356	1.5908*	0.5572	0.1199	0.0168
		0.3629	0.1837	0.1061	0.0576	0.8196	0.4244	0.0816	0.0508
	5 years lagged	1.2922***	0.5707**	0.2474**	0.4562***	2.2520**	1.4125**	0.1572*	0.3555***
		0.4911	0.2417	0.1211	0.0618	1.0943	0.583	0.089	0.0547
	6 years lagged	0.6733**	0.1562	0.1777	0.1157	1.7794***	0.2404	0.1555	0.1101*
		0.2927	0.1394	0.1489	0.0813	0.6677	0.3198	0.1149	0.0658
Inflation	1 year lagged	-0.1127***	-0.0708***	-0.1445***	-0.0831***	-0.2842***	-0.1011	-0.1005***	-0.0718***
		0.0385	0.0226	0.0316	0.0183	0.0986	0.0637	0.024	0.0157
Unemployment Rate	1 year lagged	0.3297*	0.0809	-0.0293	0.0638***	0.5713	0.2649	-0.0126	0.0633***
		0.1841	0.0926	0.024	0.0119	0.4139	0.2129	0.0175	0.0104
Demographic Controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Statistics	Rho	0.8652	0.6143	0.5195	0.4531	--	--	--	--
	(Pseudo) R2	0.0369	0.0192	0.0996	0.0694	0.0527	0.0177	0.0304	0.0244
	N	3901	13424	3901	13424	1633	4912	3901	13424

Note: Robust standard errors (clustered on households) are used in all four models. These are presented below the coefficients
***, **, * represent significance at the 1, 5 and 10 percent level
Risky asset ownership is the ownership of stocks or mutual funds

It is interesting to note that the coefficients of inflation are also larger for the estimation with risky asset owners. This is somewhat unexpected as inflation is expected to have the same impact for all individuals. However, this result may reflect that owners of risky assets generally have better financial knowledge (see for example van Rooij *et al*, 2007). Greater financial knowledge also means a better understanding of inflation, which might make owners of risky assets more sensitive to movements in inflation. The coefficient of the unemployment rate is insignificant for the majority of the estimations. However, where the coefficients are significant (columns 4 and 8) the coefficient once again has the opposite sign. The overall results for the unemployment rate are not clear.

5.3) Asymmetry

The impact of stock returns may not be symmetric between gains and losses. There is no *a priori* expectation on the shape of the asymmetry of stock returns. Negative movements may have a larger impact on the willingness to take risks due to loss aversion or positive movements may have a greater effect by imparting overconfidence. In order to investigate whether returns are asymmetric a dummy variables for negative returns are included (taking on the value of 1 if the lagged return was negative, zero otherwise). The results are presented in Table 5 below.

Table 5: Asymmetric effects of past stock returns on risk attitudes

Variable	Description	Linear Fixed Effects	Linear Random Effects	Conditional Logit Fixed Effects	Ordered Probit Random Effects
Negative Return Dummy	1 year lagged	-0.3663	0.3167***	-1.0122	0.2202***
		0.3453	0.1084	0.7415	0.0851
	2 years lagged	-0.4225	-0.8093***	-0.5752	-0.5427***
		0.3311	0.1607	0.4847	0.124
	3 years lagged	0.5738*	0.4203***	-1.1589*	0.2523**
		0.3222	0.15	0.7043	0.117
	4 years lagged	-0.1702*	-0.1074	-0.4852**	-0.1022*
		0.1013	0.0695	0.2263	0.054
	5 years lagged	-0.6585	--	--	--
		0.5401			
	6 years lagged	-0.3344*	-0.2855**	0.139	-0.1780*
		0.177	0.128	0.559	0.0985
AEX Returns	1 year lagged	--	0.5504***	-2.1517*	0.3788**
			0.2088	1.2394	0.1722
	2 years lagged	0.295	-0.2725	-2.1531*	-0.1619
		0.7242	0.1691	1.1828	0.1289
	3 years lagged	1.3599	0.9556***	-2.9824	0.6642***
		0.833	0.2515	2.2187	0.196
	4 years lagged	0.0602	0.1431	-1.8338	0.0699
		0.3035	0.1124	1.4869	0.087
	5 years lagged	-0.0234	-0.2043	-0.6923	-0.0757
		0.3739	0.162	1.2123	0.1277
	6 years lagged	0.9970***	1.4031***	-0.7158	0.9632***
		0.2101	0.2687	1.0917	0.2183
Inflation	1 year lagged	0.1415	-0.1564***	-0.1946***	-0.1148***
		0.2239	0.0225	0.0629	0.0182
Unemployment Rate	1 year lagged	0.3192	0.1259***	-0.6783	0.1026***
		0.2895	0.036	0.6856	0.028
Demographic Controls		Yes	Yes	Yes	Yes
Statistics	Rho	0.6504	0.4755	--	--
	(Pseudo) R2	0.0214	0.0845	0.0201	0.0277
	N	18219	18219	7681	18219

Note: Robust standard errors (clustered on households) are used in all four models. These are presented below the coefficients

***, **, * represent significance at the 1, 5 and 10 percent level

The results do not provide clear evidence of any asymmetry. The coefficients of the negative return dummies are neither consistently negative nor significant. Only the dummies for the two and four year lagged returns are negative across all four specifications, but are not always significant. Furthermore only the fixed effects logit model (column 3) has no dummy coefficients that are both positive and significant. In contrast there are significant coefficients with positive and negative signs in all the other estimations. These are clearly conflicting results. It is not clear why the results vary so drastically within and between the models, but it is possible that the dummy variables are also capturing the effect of some unknown variable. The lack of time series observations is also likely to play a role. This is likely to lead to large standard errors and means that the relationship cannot be properly identified.

The inclusion of the dummy variables also impacted on the coefficients of the lagged returns. The coefficients in the linear fixed effects model (column 1) become mostly insignificant and the coefficients in the fixed effects logit model (column 3) switch signs and become negative (and in some cases significant). This is a puzzling result and questions the robustness of the earlier specifications. The impact of the additional dummy variables is not so drastic on the two random effect models (columns 2 and 4). Although some of the coefficients are negative, they are never significantly different from zero. Furthermore the coefficients of the first, third and sixth lagged returns remain positive and significant. Inflation coefficients remain negative and significant (except for the linear fixed effects model), whilst the coefficients of unemployment rate remain positive and significant for the random effects models.

Overall the test for asymmetry was not conclusive. The fixed effects model preformed poorly with the inclusion of the dummy variables whilst the random effects models did not provide convincing evidence of the existence of asymmetric effects.

5.4) Size effect

This specification investigates whether the size of the return matters. It may be the case that the results in the baseline estimation were driven by only the large movements and that smaller returns do not significantly impact on the willingness to take risks. To test whether there is a size effect the past returns are split into quartiles and a dummy variable is created for each quartile. Including quartile dummies for all the lagged returns will mean that 18 dummy variables will have to be added. In order to keep the model as parsimonious as possible the quartile dummies are only included for the one year lagged returns. The results are shown in Table 6.

Again the results are inconclusive. Only the coefficients of quartile dummies in the fixed effects logit model (column 3) are all positive and significant. This indicates that the top three quartiles all differ significantly from the baseline variable, the lowest quartile. This is evidence that the size of the return does matter. The size of the dummy coefficients increases for the higher quartiles, moving from 0.64 for the second quartile to 1.17 for the fourth quartile. The coefficients of the second and third quartile do not differ significantly according to a Wald test, but the coefficients of the third and fourth quartile do differ significantly. This indicates that the higher return has a much larger impact than the returns which are closer to the mean and is evidence of a size effect. The results from the other three estimations do not support these findings. In the random effects models (columns 2 and 4) none of the coefficients are significantly different from zero and several have negative signs. The linear fixed effects model (column 1) does not fare much better; only the coefficient of the second quartile is significant.

Similar to Section 4.3 the inclusion of dummy variables has a negative impact on some of the coefficients of past returns for the fixed effect models. In both fixed effect models all the past return coefficients became insignificant. The results of the fixed effects models in Section 4.1 and 4.2 therefore do not seem to be robust when possible non-linearities of returns are taken into account. However, this is not the case for the random effects where the coefficients of past returns remain positive and significant. The random effects models thus appear to be more robust to the inclusion of non-linear effects. However, the sizes of the coefficients differ quite substantially from the baseline estimation (Table 3), but do not vary in any predictable manner.

Table 6: Impact of size of stock return

Variable	Description	Linear Fixed Effects	Linear Random Effects	Conditional Logit Fixed Effects	Ordered Probit Random Effects
Size of return	2nd Quartile	0.2989**	0.0561	0.6778*	0.0354
		0.1458	0.0948	0.347	0.0725
	3rd Quartile	0.0755	-0.1883	0.7664*	-0.1273
		0.1759	0.133	0.4225	0.1045
	4th Quartile	0.2897	-0.0366	1.2167**	-0.0155
		0.2166	0.1544	0.518	0.1193
AEX Returns	1 year lagged	-0.0799	0.2951*	-0.9633	0.1928
		0.241	0.1677	0.5993	0.1338
	2 years lagged	-0.1101	0.2317***	0.0876	0.2026***
		0.2123	0.0802	0.572	0.065
	3 years lagged	-0.1391	0.2875***	-0.7213	0.2587***
		0.2356	0.0811	0.5894	0.0639
	4 years lagged	-0.0624	0.2546***	0.0388	0.1866***
		0.1883	0.0652	0.4827	0.0524
	5 years lagged	-0.1822	0.2084**	0.1569	0.1853***
		0.2724	0.0817	0.7182	0.066
	6 years lagged	0.0644	0.2857***	-0.3469	0.2029***
		0.1548	0.0875	0.3992	0.0702
Inflation	1 year lagged	-0.0618*	-0.1018***	0.0004	-0.0748***
		0.0369	0.0313	0.0899	0.0245
Unemployment Rate	1 year lagged	-0.1589	0.0264**	-0.192	0.0332***
		0.1025	0.0127	0.2674	0.0106
Demographic Controls		Yes	Yes	Yes	Yes
Statistics	Rho	0.6980	0.4754	--	--
	(Pseudo) R2	0.0205	0.084	0.02	0.0275
	N	18219	18219	7681	18219

Note: Robust standard errors (clustered on households) are used in all four models. These are presented below the coefficients
***, **, * represent significance at the 1, 5 and 10 percent level

The coefficients of inflation and unemployment remain relatively robust to the inclusion of the size dummies. The coefficient of inflation remains negative and significant in three of the four models whilst the coefficient of unemployment rate persists in being positive and significant in the random effects models.

The overall results for a size effect are inconclusive. Although the logit fixed effects model provided some evidence of a size effect, the model as a whole performed poorly. Furthermore there was no evidence of a size effect in any of the other specifications.

6) Conclusion

This paper has examined the link between risk attitudes and previous stock market returns. Past returns were found to be positively and significantly related to an individual's willingness to take risks. Positive stock returns are therefore associated with an increase in willingness to take risks, whilst negative stock returns are associated with a decrease. This finding is consistent with concept of projection bias. According to projection bias individuals expect the current market trends to continue and adapt their attitude towards risk based on these beliefs. The relationship between risk attitudes and past stock returns was found to be relatively robust across models and different specifications, with the exception of the fixed effects models when adding non-linearities. Inflation was consistently found to have a strong and negative relationship with willingness to take risks. Therefore higher inflation is associated with lower willingness to take risks. No clear relationship between unemployment rate and willingness to take risks was established, since the results were neither robust across models nor specifications.

The relationship between willingness to take risks and past stock returns is significant regardless of whether or not an individual actually owns risky assets, although the effect is much more pronounced for risky asset owners. This is an important finding for stock owners as altering willingness to take risks due to changes in stock markets is likely to lead to behaviour which lowers the realised return for the stock holder in the long run. There is a possibility that stock owners may buy when prices are high (following high returns) and sell when prices are low (following low returns). An interesting research possibility that stems from these results is to investigate how changes in risk attitudes due to past stock returns influence actual behaviour. How do changes in risk attitudes affect the amount and type of risky assets held by an individual? Could it lead individuals to become stock holders? If it does impact on actual behaviour then does this partially explain the existence positive or negative feedback loops, leading to hypes and panics?

The finding that stock market returns also affect individuals who do not own any risky assets is also important. Proponents of the expected utility framework may argue that the results are driven by wealth - positive stock market returns increases the wealth of individuals and therefore has a positive relationship with the willingness to take risks. However, since this result also applies to individuals who do not own any risky assets this is ruled out as an explanation. Again it should be noted that since a link between theoretical risk tolerance and the risk attitudes obtained from the DHS has not yet been established no assertions on the legitimacy of utility theory can be made.

There was no robust evidence of asymmetry between positive and negative returns or that the size of the return impacts on risk attitude in a non-linear way. However, these specifications were constrained by the short time dimension that was available in this dataset. Only having 14 observations for stock returns, inflation and unemployment is a possible explanation for the inconclusive results when testing for asymmetry and size effects of stock returns. The lack of observations results in larger standard errors and makes it difficult to clearly identify any possible relationships. Repeating these specifications with a dataset with longer time series component may provide more insightful and conclusive results. This paper has also been somewhat constrained by the lack of time series variations for each individual. The lack of time series observations per individual also led to large standard errors in the fixed effects models. It also meant that cohort effects were assumed to be zero, despite evidence to the contrary by Malmendier and Nagel (2009). Another constraint is that the DHS dataset does not contain any measures of individual wealth. This could potentially bias the results since wealth is almost certainly correlated with the willingness to take risks and is also likely to be correlated with several of the variables included. In order to account for this several financial variables were included (income, financial situation and future income expectations), however the extent to which the results remain biased is unknown.

The findings of this paper are based on the assumption that the risk attitude variable used does in fact measure a form of risk tolerance and that this variable is linked to actual risky behaviour. The validity of this assumption is demonstrated by the finding that the risk attitude variable is correlated with actual risky behaviour. There is however scope to prove this in a more rigorous way. Another avenue for future research is to replicate this study using responses from lotteries (hypothetical or actual).

7) Appendix: Solving the incidental parameter problem

The incidental parameter problem can be overcome if there is exists a set of statistics, t_i, so that an individual's likelihood function, conditional on t_i, no longer depends on α_i. In this case t_i is said to be sufficient for α_i. Such a statistic does not appear to exist for the ordered probit (or logit) model. One of the few non-linear models for which a sufficient statistic does exist is the binomial logit model (Greene, 2001). The example is taken from Verbeek (2004) and Maddala (1987).

For the T=2 case the statistics is set so that $t_i = \bar{y}_i = 1/2$. The conditional distribution is degenerate if there is no variance in y_{it} (if $t_i = 0$ or $t_i = 1$). Such individuals do not contribute to estimating β. These individuals could have a very large negative or positive α_i (corresponding to $\bar{y}_i = 0$ and $\bar{y}_i = 1$ respectively) and are therefore not included in the estimation. This also highlights that the fixed effect model is only identified from the within dimension of the data. For T=2, this leaves two possible outcomes (1, 0) and (0, 1). The conditional probability of the latter is given by

$$P\{(0,1) \mid t_i = 1/2, \alpha_i, x_{it}, \beta\} = \frac{P\{(0,1) \mid \alpha_i, x_{it}, \beta\}}{P\{(0,1) \mid \alpha_i, x_{it}, \beta\} + P\{(1,0) \mid \alpha_i, x_{it}, \beta\}} \tag{2}$$

In order to simplify this equation, note that

$$P\{(0,1) \mid \alpha_i, x_{it}, \beta\} = P\{y_{i1} = 0 \mid \alpha_i, x_{it}, \beta\} P\{y_{i2} = 1 \mid \alpha_i, x_{it}, \beta\} \tag{3}$$

Assuming that the underlying latent model follows a standard logistic distribution, then

$$P\{y_{i1} = 0 \mid \alpha_i, x_{it}, \beta\} = \frac{1}{1 + \exp\{\alpha_i + x_{i1}'\beta\}}' \tag{4}$$

and

$$P\{y_{i2} = 1 \mid \alpha_i, x_{it}, \beta\} = \frac{\exp\{\alpha_i + x_{i2}'\beta\}}{1 + \exp\{\alpha_i + x_{i2}'\beta\}}' \tag{5}$$

Substituting (4), (5) and (3) into (2) and simplifying

$$P\{(0,1) \mid t_i = 1/2, \alpha_i, x_{it}, \beta\} = \frac{\exp\{\alpha_i + x_{i2}'\beta\}}{\exp\{\alpha_i + x_{i1}'\beta\} + \exp\{\alpha_i + x_{i2}'\beta\}} \tag{6}$$

This can be simplified once more (dividing by $\exp\{\alpha_i + x_{i1}'\beta\}$), to give the conditional probability

$$P\{(0,1) \mid t_i = 1/2, \alpha_i, x_{it}, \beta\} = \frac{\exp\{(x_{i2} - x_{i1})'\beta\}}{1 + \exp\{(x_{i2} - x_{i1})'\beta\}} \tag{7}$$

which is not dependent on α_i. Similarly it can be shown for the (1, 0) case that the conditional probability is

$$P\{(1,0) \mid t_i = 1/2, \alpha_i, x_{it}, \beta\} = \frac{1}{1 + \exp\{(x_{i2} - x_{i1})'\beta\}} \tag{8}$$

which is also not dependent on α_i. These results show that the distribution of (y_{i1}, y_{i2}), conditional on $t_i = 1/2$, is independent of the individual specific effect. Using conditional maximum likelihood for the logit model will thus result in a consistent estimate of β. This result extents to samples where T>2, however the derivations are somewhat more involved (Verbeek, 2004).

8) Reference

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