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Do Macroeconomic Downturns Impact Risk Preferences?: Recession Babies!

Author: Eve Whittaker
Student number: 585156ew
Thesis supervisor: Dr. Ruben de Bliek
Second reader: Amy Li
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ABSTRACT

In this thesis, I examine whether individuals' financial risk taking is influenced from the different macroeconomic conditions and shocks that they have experienced throughout their lifetimes. This has often been suggested with the generation that witnessed the great financial crisis. The Survey of Consumer Finances questionnaire data, from the survey waves of 2014 to 2019, is collected and analysed against the real stock market returns of the Dow Jones index. I have found that the individuals who experienced lower stock market returns throughout their lifetime tend to be more risk averse when making current financial decisions. This means that the macroeconomic conditions that each generation experience are pivotal in understanding the risk tolerances and decision making that they make when making any financial decisions.

Keywords: Risk preferences, Macroeconomic conditions, Behavioural finance, Investment, Real returns

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CHAPTER 1 Introduction

Standard economic models assume that an individual's preferences and their attitudes towards risk are stable overtime, and thus are not affected by exogenous variables (Stigler and Becker, 1977). Further to this, they find that individuals consider all historical knowledge when predicting outcomes of risky decisions. Nevertheless, there is growing evidence of the presence of behavioral biases when investing. Simon (1956) developed the theory of bounded rationality which suggests that people make suboptimal decisions due to a lack of information and memory errors. Understanding and acknowledging systematic changes in risk preferences allows for new policy possibilities and the creation of social environments (Schildberg-Hörisch, 2018). This paper concerns the investigation of behavioral biases on risk preferences of investors due to the macroeconomic experiences throughout their lifetime.

Previous literature, such as Kumar and Goyal (2016), have examined the impact of behavioral biases, specifically overconfidence, disposition effect and herding behaviors, on an individual's investment decisions. They have all concluded that risk preferences are time varying and impacted by exogenous variables. Guiso et al. (2014) expand on these findings by examining the effect of the 2008 financial crisis on the risk preferences of Italian investors. The authors conclude that investors were more risk averse after the crisis, even if they did not personally suffer any losses during the crisis. The decision to invest in the stock market is influenced by an individual's macroeconomic experiences, which shape their expectations of future personal and economic circumstances. Thus, their study underscores the significant impact of experiencing a financial crisis on changes in individuals' attitudes towards risk, regardless of the timing of the event. This was then examined further to see the relationship between an individual's general lifetime experiences of macroeconomic events and their level of risk taking (Malmendier and Nagel, 2011). They developed the "Depression Babies" hypothesis, which concludes that individuals who experienced cyclical economic downturns during their formative years, such as the Great Depression, tend to be less willing to take financial risks and are less likely to participate in the stock or bond market.

In this paper, I will replicate the study by Malmendier and Nagel (2011) in the U.S.A. I will alter the time period to more specifically the effect on household risk preferences when investing since 2014. This period is relevant to study as there have been many structural shifts in the stock market over the past two decades, thus allowing us to test the robustness of their previous findings. Rapid technological developments have facilitated access to real-time stock market information, democratizing access for even the average American investor (Hong et al. 2004). The emergence of stock market charting software has enabled individuals to conduct back tests and forecast the outcome of investment decisions. Consequently, this access to more comprehensive information has the potential to mitigate the behavioral biases that can arise, resulting in more stable risk preferences and informed investment decisions. Furthermore, the stock market continues to expand as new participants enter the market and robotic trading gains momentum. Since the 2000s the US has experienced two significant recessions that have had far-reaching consequences. Primarily, the Dot-com recession, which resulted in a fall in investment and employment in the technology sector. Secondly, the Great Recession was the most severe economic downturn since the Great Depression and had significant impacts on individuals, businesses, and countries worldwide (Bohlen, Carlotti and Mihas, 2011). Therefore, this paper investigates the following research question: How do macroeconomic lifetime experiences impact risk preferences?

The methodology will replicate that of Malmendier and Nagel (2011), who used repeated cross-sectional survey data on the US household asset allocations. This will be collected from the Survey of Consumer Finances (SCF) from 2014 to 2019, (which is released every 3 years) providing observations on various household characteristics and asset holdings. From this data Malmendier and Nagel (2011) created four measures of risk-taking, of which I will use the main key measure. This is the willingness to take risks in financial decision making as stated in the survey question. In this measure, survey participants are asked to what extent they and their partner are willing to take financial risk. This is measured on a scale from zero to ten, where zero is not willing at all and ten is very willing to take financial risks. Dohmen et al. (2011) has validated that using a risk scale from a survey can be sensibly interpreted in terms of actual risk-taking. Similarly, to Malmendier and Nagel (2011), I will control for household characteristics such as total family income, wealth, race, marital status, and age groups (the household head must be older than 24 and younger than 75 years old). I will use the annual real returns of the US stock market (S&P 500) from the year of birth of each household head in order to analyze the relationship between macroeconomic experiences whilst growing up on risk preferences. Annual past returns clearly differ depending on the investment made, the interest rates and other unobservable variables, nevertheless, Malmendier and Nagel (2011) illustrates the likely significant positive correlation between stock market returns and individual experiences, therefore it serves as a good proxy for the personal macroeconomic lifetime experiences.

I hypothesize that individuals that grew up with low economic growth such as the Dot-com recession or the Great Recession periods, will be used to the lower real returns, consequently being more risk averse and these individuals will be less willing to make risky financial decisions. Given all previous literature and research conducted on this topic, I believe that this period will allow us to test the validity of the results previously found by Malmendier and Nagel (2011) and verify if the new structure of the stock market has had an impact on individual's risk preferences. These findings will allow policymakers to counter the patterns in countercyclical risk aversion (investors are less willing to take risk in financial decisions during a recession rather than during a boom), to try and prevent an amplification of macroeconomic downturn by encouraging investment in stocks (Schildberg-Hörisch, 2018). These findings along with the previous research should provide conclusive evidence that macroeconomic experiences do influence the risk preferences of individuals.

The remainder of this paper is structured as follows. Section 2 discusses the relevant literature and previous research done on these topics. Section 3 denotes the data that was used to complete this study. Section 4 illustrates the methodology that I followed in order to complete my analysis. Section 5 discusses and displays the results and robustness tests that I completed. Finally, section 6 concludes the study and provides a discussion on areas of further research that could develop this hypothesis further.

CHAPTER 2 Theoretical Framework

2.1 Risk Preferences

Decision making under uncertainty happens every day, whether it's from insignificant decisions that only have minor impacts, to important decisions that can have long lasting effects on an individual's life. The decisions taken and the choices individuals prefer are influenced by their risk preferences (Fehr-Duda and Epper, 2012). In economics, risk preferences are viewed as the preferences held regarding the choice between actions that hold an equal expected value but have different relative variances in the potential monetary outcome. Hertwig et al. (2018) gives an example of receiving a safe and low risk option of a guaranteed €500, or a risky option where there is a 50% chance of receiving €1000, and a 50% chance of receiving nothing. The expected values of these options are both €500 (0.5*1000 + 0.5*0 = 500), hence a risk-neutral individual would be indifferent between the two, nevertheless if an individual was to prefer an option relative to the other (risky option is a risk seeking individual, the safe option is a risk averse individual), this would represent their preferences towards risk. Conversely, in psychology, risk preferences are viewed as the inclination to participate in an action that, although may be rewarding, has the potential for harm or loss to oneself or others (Hertwig et al., 2018). These preferences are essential for understanding basic economic models, such as consumption, investment, asset pricing, incentives, and social insurance programs (Barseghyan, Molinari, O'Donoghue and Teitelbaum, 2018), but also in understanding individual's decisions, such as financial investments, employment choices, health choices and unlawful behaviour choices (Schildberg-Hörisch, 2018).

2.1.1 Impacting Factors

When trying to explain the differences in individual's behaviors under uncertainty, economists investigate attitudes towards risk with some of the highest priority. Age, gender, education, wealth, and a wide range of individual characteristics are all found to be correlated with the risk taking of individuals (Dohmen et al., 2011). Nevertheless, there is still little known about the determinants and impacts of different factors on the risk attitudes of investors, and how these preferences are created (Dohmen, Falk, Huffman, and Sunde, 2012). The deviations away from rational choices that individuals make when under risky and uncertain circumstances has been widely researched (E.g. Kahneman and Tversky, 1979; Thaler, 1980; Tversky and Kahneman, 1981), and the behavioral biases that have been discovered are now being used by researchers and policymakers for a broader understanding.

2.1.2 Background of Risk Preferences

Daniel Bernoulli (1738) revolutionised social choice theory and behavioural economics by introducing the concept that maximising the expected value of monetary payoffs alone is not a justifiable description of individuals behaviour, because it doesn't consider the risks that are associated with low payoffs or small probabilities. Kenneth J Arrow took this paradox further by demonstrating that decision making should be based on individual's preferences (Maskin, 2019). Since then, most empirical studies have measured risk preferences using the expected utility theory, and have relied heavily on lab experimental approaches, including Binswanger's (1980) and Eckel & Grossman's (2002) selection between different cash gambles, Holt and Laury's (2002) price list approach, and Gneezy and Potters' (1997) risky investment task approach. All these experimental methods typically involve individuals participating in a lottery and deciding between two different outcomes, where the highest expected payoff normally comes at the cost of a higher variance of payoff. This means higher payoff but at a higher risk.

2.1.3 Endogenous Preference Formation

When individuals form their preferences, they are affected by the internal responses to external factors. This is known as endogenous preference formation, and many researchers have examined the specific influence of market risk and market institutions (Palacios-Huerta and Santos 2004). Bowles (1998) explored the impact of determining social norms and their effects on social and individual behaviors. Nagel (2012) demonstrated one key norm shift that occurs from the impact of a recessionary period on the attitudes of society towards stock market participation. Society's endogenous preferences tend to become more cautious and less risk seeking since they are experiencing an uncertain economic period. This means that the participation rate typically falls during these periods as individuals prefer to save instead of investing. The tendency to exhibit herd behavior means that social norms play a pivotal role in determining the stock market participation rate and other key decisions. Hong and Kacperczyk (2009) illustrate the impact of social norms by using the example of 'sin' stocks. Their research proves that social norms play a significant role in the pricing and returns of publicly traded companies that are involved in 'taboo' industries, such as gambling, tobacco, and alcohol industries.

2.1.4 Direct Experiences

Further research has illustrated that when endogenous preferences are formed, individuals assign a greater importance to the information they have obtained via direct experiences rather than from descriptions or observations. The heuristic updating cognitive framework of reinforcement learning depicts that an individual bases their behavior on the payoffs of the same action that happened in the past, inclusive of if the circumstances and beliefs of predicted payoffs have changed (Erev and Roth, 1998). Erev and Roth (2014) further built on their framework and found that descriptions of major events or threats do not hold the same potent impact on behavior as the firsthand experience of encountering them. The prisoner's dilemma in game theory demonstrates this influence of direct experiences, where Simonsohn, Karlsson, Loewenstein, and Ariely (2008) find evidence that individuals show a greater responsiveness to the actions of players they have direct interactions with compared to those they merely observe. Camerer and Ho (1999) examined the "experience-weighted attraction" model and found that belief and reinforcement learning play a pivotal role. This is because individuals tend to be influenced by past choice payoffs when making subsequent decisions. The experimental tests of social learning, conducted by Schlag's (1999a and 1999b) have proposed that individuals will often try to replicate previous actions that had successful outcomes.

2.2 Macroeconomic Lifetime Experiences

Several pieces of literature have documented that macroeconomic experiences throughout an individual's lifetime are a fundamental factor in impacting various individual and societal behaviors. Being exposed to macroeconomic shocks during an individual's founding years can impact their educational opportunities, career trajectories (Oreopoulos, von Wachter and Heisz, 2012), happiness (Blanchflower, 2007), health and mortality rates (Cutler, Huang and Lleras-Muney, 2015) and overall life quality. Blanchard and Summers (1986) discuss the hysteresis phenomenon which proves that there are significant and long-lasting effects of macroeconomic experiences on an individual's behavior for the remainder of their lives.

2.2.1 Reinforcement Learning

The reinforcement learning framework has been proven to impact investors' behavior also in financial decision-making contexts. Choi et al. (2009) demonstrates that investors tend to over-extrapolate from their previous personal saving experiences with 401(k) saving accounts. This means that individuals who earned a high average return before, tended to increase their savings rate by a higher amount than other investors who experienced less returns on their accounts. In terms of initial public offerings (IPO) on the stock market, Kaustia and Knupfer (2008) find that investors, whose previous IPO investments performed well and gave significant returns, are positively correlated to the quantity of their future IPO investments. One key finding by Malmendier and Nagel (2011) is that young individuals are more sensitive to recent events compared to more distant events, and by a greater amount than older individuals. This finding is consistent with Greenwood and Nagel's (2007) discovery that during the late 1990s technology bubble, young mutual fund managers portrayed trend-chasing behavior in their technology stock investments compared to their older colleagues and took on a higher exposure to technology stocks. Similarly, Vissing-Jorgensen (2003) provides evidence that during the late 1990s stock market boom, young retail investors had the highest stock market return expectations.

2.2.2 Depression Babies Hypothesis

Consistent with the view that personal experiences are crucial in shaping behavior of individuals, Malmendier and Nagel (2011) created the "Depression babies" hypothesis, where individuals lifetime experiences of growing up through the Great Depression hold long-lasting effects on society and on individual's behaviors. Malmendier and Tate (2005) provide evidence that corporate managers who experienced the Great Depression, hence "Depression Babies", are more risk averse and thus prefer to finance internally. The literature written to confirm this hypothesis takes on different individuals who have experienced a crisis while growing up and examines their risk preferences. Farvaque, Malan and Stanek (2017) show the tendencies of central bankers, Cohn, Fehr and Marechal (2012) confirm the risk averseness of financial professionals, and Graham and Narashimhan (2004) prove that managers choose capital structures with less leverage to reduce the risks.

2.2.3 Background of macroeconomic lifetime experiences

The relationship between macroeconomic crises and risk preferences of individuals has been studied across different countries and contexts. For example, Necker and Ziegelmeyer (2016) use the Great Recession in the German population. They found that individuals that viewed the crisis as the cause of their losses, tended to reduce their risk taking and became more risk averse. This relationship in Germany was confirmed while combining the political aspect, of Germany's capitalist and communist past (Cordes and Dierkes, 2017). Ampudia and Ehrmann (2017) studied the effect for the Euro area as a whole and found that previous experiences of better returns and financial stability lead to households being more willing to take financial risk and participate more in the stock market. Furthermore, Weber, Weber and Nosic (2014) examined the impact of the Great Recession on UK households, by using 3-month expectations of risks and returns of the market and their portfolios to determine their willingness to take risk.

2.2.4 Long lasting impact

Friedman and Schwartz (1963) changed the perspective of macroeconomics by promoting the long-lasting pessimistic beliefs that are formed post experiencing the Great Depression or any financial crisis for that matter. Their evidence proves that lifetime macroeconomic conditions affect the risk attitudes of individuals at a micro and macroeconomic level. This means that their experiences could affect asset prices and the macroeconomy, while also affecting the individual investor's risk preferences, portfolio allocation and overall wealth. This confirms that when individuals learn from personal experiences of economic conditions, the Great Recession or other crises have various long-lasting impacts.

CHAPTER 3 Data

I will replicate the examination and analysis conducted by Malmendier and Nagel (2011) in order to verify that risk preferences of individuals are indeed impacted by macroeconomic experiences throughout their lifetime. Similarly to Malmendier and Nagel (2011), I will use data provided from the Survey of Consumer Finances for the US population. I will alter the timeframe in order to take on a more recent robustness check and see whether the results remain the same after the Great Recession and with a more developed, accessible and technologically advanced investment society. I will use a comparison analysis of the timeframe between 2001 and 2019 and by using the regression analysis proposed by Malmendier and Nagel (2011) I expect to gather evidence that substantiate the claim that experiencing an economic crisis invokes risk averse preferences and behaviors of individuals.

To test this relationship, I have combined US household risk taking preferences from the Survey of Consumer Finances, with the annual historical US Dow Jones real stock returns. The Survey of Consumer Finances (SCF) provides household level microdata, which has household characteristics, different asset class holding information and preferences of the households. The survey is released from the Board of Governors of the Federal Reserve System every 3 years, and for my analysis I have collected the data from the 2016 and 2019 survey waves, which means that the data is spanning from 2014 to 2019. Over 90% of the 2019 survey wave was conducted before February and therefore this data is before COVID-19 had significant impact on the financial wellbeing of the US population. Since the household data retrieved from the SCF dates to 2014, and I have included household heads up to the age of 74 in the sample, I need the stock returns stretching back to 1921. I used Yahoo Finance to obtain the annual real returns of the Dow Jones stock market index.

The dependent variable, the individual's ***elicited willingness to take financial risk***, was collected from the SCF for the US population for 6 years (2014-2019). The respondents of the survey waves in 2016 (31,270 observations with 6,254 household respondents) and 2019 (28,915 observations with 5,783 household respondents) were asked to rate their and their partner's (husband/wife) willingness to take financial risk, where 10 is very willing to take risks and zero is not at all willing to take risks. To make referencing easier, I refer to this measure as the "***elicited risk aversion***". It must be noted that this variable may differ from the individual's actual risk tolerance, since there may be differences between the allocation of risky assets and the thought of how much risk they are willing to take on. Nevertheless, as previously stated, Dohmen et al. (2011) has provided evidence that it is a sensible interpretation of the actual risk taken by individuals. Additionally, this variable can be interpreted in a cardinal sense as the individuals are able to rate quantitatively how they interpret their answer.

The explanatory variable of interest is the ***economic experiences*** that the household respondents had throughout their lifetime, and this was collected from Yahoo Finance dating back to 1921 until the year of the survey wave. My objective is to test the relationship between the risk preferences and long-run return experiences, however there are some obstacles with doing so. If I included a separate explanatory variable for each previous year of experienced return until the year of birth for each household head, it would mean that there are a huge number of variables and coefficients which makes estimating with economic meaning, imprecise. Additionally, the number of variables would differ depending on the age of the household head. Therefore, to construct a single explanatory variable, I have summarized experienced returns as the weighted average of their lifetime returns and for reference this explanatory variable is named the "***Experienced real stock return***". This weighted average will allow the possibility that stock experiences in the distant past have a different influence than more recent experiences, such as the experiences witnessed at a young age, e.g., from parental influence, having significant influence on later life decisions or on the other hand, memories from the past fade away with time and have less influence on later life decisions. To calculate this variable A per person i for sample year t, the following equation was used:

$$A_{it}(\lambda) = \sum_{k=1}^{age_{it}-1} w_{it}(k,\lambda) R_{t-k}$$

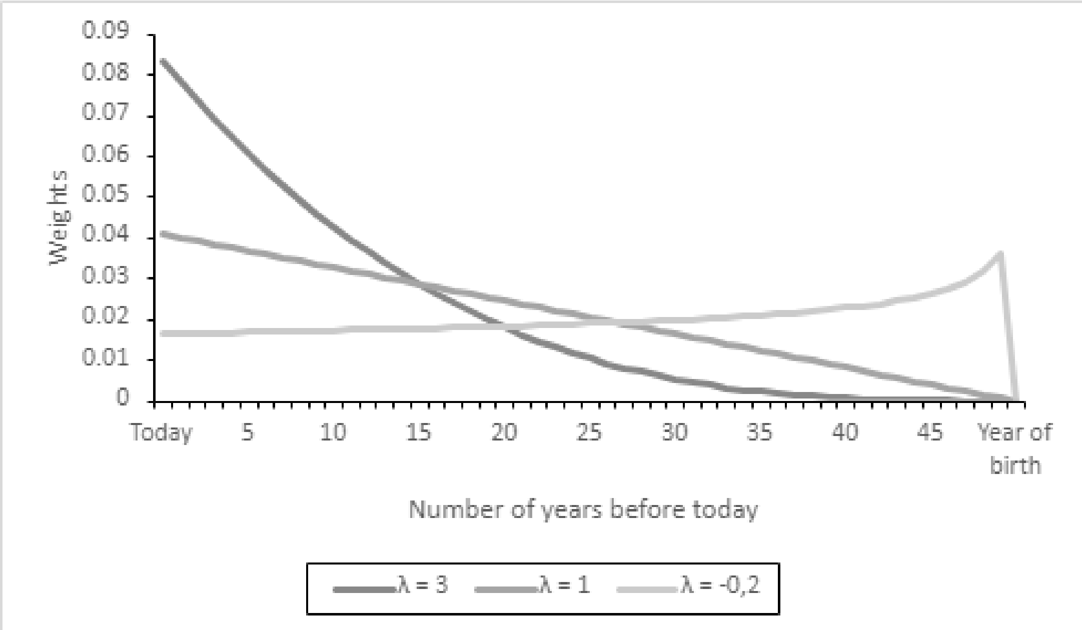
$$where\ w_{it}(k,\lambda) = \frac{(age_{it}-k)^{\lambda}}{\sum_{k=1}^{age_{it}-1}(age_{it}-k)^{\lambda}}$$

with "w_{it}"being the weights depending on the age of the household head at the time "$t(age_{it})$" , "k" is how many years ago the return occurred, "λ" the parameter that controls the weighting function, and the "R_{t-k}" is the realized returns in the year "$t-k$". This parameter controlling the weighting function is estimated from the data. If λ > 0, the weights are decreasing with the lag of k, meaning they are convex; if λ = 0 we have a constant weighting function, where $A_{it}(\lambda)$ is the average of all the past returns since birthyear of the household head, and finally with λ < 0, the weighting function is increasing with the lag of k, meaning it is concave.

Figure 1 shows an illustration of the shape of the weighting function for three different values of the parameter λ for a household head of the age 50. The figure denotes that the weighting function is flexible in the way that it can either be increasing, decreasing or flat. From further research, the results found from having a flexible weighting function are very closely matched to the results of a decreasing weighting function, which is what I shall use for the rest of my analysis, $\lambda = 1.5$.

Figure 1

Weighting function on the experienced real stock returns for different values of λ for a 50-year-old household head



Note. Graph showing for an average 50 year old household head, the different weighting function examples that can be used to show the sensitivity to the experienced real stock returns. This has used three examples of a lambda with value 3, 1 and –0,2 respectively. After this analysis, a lambda value of 1,5 is used as this is the baseline estimation that has been used by further research also (Malmendier and Nagel, 2011).

In terms of the control variables, I have retrieved a variety of income and household characteristic controls from the survey of consumer finances along with year and age effects. By creating a year dummy (***Yr***) to indicate which survey wave the respondent came from, it removes any aggregate effects or time trends. The ***Age*** (***AGECL***) control is a categorical dummy variable which indicates what age cohort the respondent is in, such that 1:<35years old, 2: 35 to 44 years old, 3: 45 to 54 years old, 4: 55 to 64 years old, 5: 65 to 74 years old and finally 6: >=75 years old. Since our household head must be less than 74 years old, we automatically remove any observations that have an age category of 6 and some of the observations in category 1 as they are less than 24 years old. The age effects permit the possibility to identify results from life-cycle effects, for example as age increases the risk aversion also may increase due to retirement plans.

In terms of household characteristics, I obtained a dummy variable for the ***marital status*** of the respondents (***Married***), this was transformed from scores (1,2) to (0,1) where 1 indicates married or living with a partner and 0 not. The number of children was also used, along with its square (***Kids*** and ***Kids^2***). This is a continuous variable with the maximum value of 7 children (49 for the squared variable). The categorical dummy of the race of the respondents is also used as a control, this variable is called ***Racecl4***. *Racecl4* has the scores such that 1: denotes a white non-Hispanic individual, 2: indicates a black or African American non-Hispanic individual, 3: depicts a Hispanic or Latino individual and finally 4: indicates an individual with multiple races or a different race. I created two separate dummy variables to illustrate the highest level of education reached by the household respondents. This is to test for financial sophistication and literacy rates having effect on the sensitivity of the individuals. The first dummy was whether the respondent completed high school (***HS***), and the next is whether the respondent completed some form of college or bachelor's degree education (***UNI***). Finally, I created a dummy variable to identify if the respondent is ***retired,*** again this allows us to distinguish if results are from the effect of a lack of labour income during the retirement.

In terms of income and wealth control variables, they attempt to remove the possibility wealth-dependent risk aversion. Previous studies and literature have found that there are likely to be significant wealth effects for stock market participants (Vissing-Jorgensen, 2003), nevertheless there is proof that these effects don't exist for the risky asset share of the stock market participants (Brunnermeier and Nagel 2008) or for elicited risk aversion (Sahm 2007). Total family income and its square (***Ln_Income*** and ***Ln_Income2***) are used as my income control and after observing the standard deviation of this variable, there is a lot of variation in the observations, therefore I logarithmically transformed these variables, and since there were 79 observations with a score of 0, I added one point to each observation to avoid undefined observations. Nevertheless, due to collinearity, this variable was removed when performing the regressions. ***Liquid assets*** and its square ***(Ln_LIQ*** and ***Ln_LIQ2)*** is the next control variable along with its square. This is defined as the sum of the checking account, saving account, MMA, call account and prepaid account, which fundamentally means it is the sum of all types of transactions accounts. Again, after observing the standard deviation, there is a large quantity of variation, therefore again I logarithmically transformed these variables. There are 174 observations with a value of 0, therefore I added one point to each observation again to avoid undefined observations. The last dummy variables are in order to identify if the respondent or their partner has a defined benefit pension on their current job, ***DBPLANCJ***, or any type of account-based plan on their current job ***DCPLANCJ***.

In the survey of consumer finance data, it suffers from missing values within the survey information. In order to correct for this, the Federal Reserve Board has used a multiple imputation technique, which imputes missing values from the other information in the survey to try and disguise any observations that could reveal the identity of the household respondents. This means that they have a dataset of five complete copies of data, known as "implicates", and only the values differ between the five implicates if they are imputed to account for the missing observations. Since I am only using a subset of variables in my analysis, the survey has provided J Code variables which are variables corresponding to each X-variable within the survey. They provide numerical values that define if there were any issues with each individual observation and the nature of the issue. This means that it is possible to test whether any observations were altered. A value of less than 90 indicates that the observation obtained was not altered, or that it can be inferred from the response of the participant with a high degree of accuracy. A value between 90 and 1096 depicts that the respondent gave a type of a range response, which can lead to large number of paths of answers, therefore altered observations. A value of more than 1096 indicates that the observation was completely missing. Within the *elicited risk aversion* variable in both survey waves, there were three different J Codes which indicate altered observations. Primarily, there were a total of 20 observations within the J Codes of 13 and of 5, which means that there was a bare minimum judgement involved and the value was not altered in any way, therefore it is unnecessary to remove these observations from my dataset. Additionally, there were a total of 20 observations with the score of 2050, which denotes an initially missing value, and hence I dropped those observations. Finally, after dropping the altered observations, I then removed the imputed observations so that my dataset is complete with the initial total 10,468 observations.

Table 1

Summary Statistics

Variable	**Observation**	**Mean**	**Std. Deviation**	**Min**	**Max**
Risk	10,468	4,844192	2,731598	0	10
Experienced Real Stock Return	10,468	8,642802	0,4752689	7,225779	9,286667
Age	10,468	3,161142	1,313751	1	5
Married	10,468	0,643901	0,4788678	0	1
Kids	10,468	0,8618779	1,167492	0	7
Kids2	10,468	2,105741	4.233127	0	49
RACECL4	10,468	1,634158	1,033764	1	4
RETIRED	10,468	0,1918044	0,3937388	0	1
Ln_INCOME	10,468	23,76623	2,330413	0	25.32823
Ln_LIQ	10,468	16.57027	7.863541	0	25,3175
Ln_LIQ2	10,468	33,13496	15,73768	0	50,635
DBPLANCJ	10,468	0,2290572	0,4202462	0	1
DCPLANCJ	10,468	0,4069157	0,4912824	0	1
HS	10,468	0,9058172	0,2920969	0	1
UNI	10,468	0,6972013	0,4594908	0	1
YR	10,468	0,4797975	0,4996156	0	1

Note. The sample period is 2014-2019. Stock returns are defined in real returns and are deflated with the Consumer Price Index (CPI) inflation rates. Income and wealth variables are also all deflated with the CPI into September 2019 dollar values.

Table 1 provides the summary statistics of the variables included in my regression for the full sample. We can see that the households that satisfy our requirements on average are willing to commit to 4.844 points of risk on the scale of 0-10, thus being more on the risk averse side.

CHAPTER 4 Method

To analyse the collected data and test the relationship between individual's sensitivity towards average lifetime returns, I will run a regression analysis. *Elicited risk aversion* is a categorical variable with eleven distinct categories $y_{it} \in \{0,1,2,3,4,5,6,7,8,9,10\}$. I will use an ordered probit model to model the cumulative probability of these cardinal outcomes:

$$P\big(y_{it} \leq j \big| \big(x_{it}, A_{it}(\lambda)\big) = \phi\big(\alpha_j - \beta A_{it}(\lambda) - \gamma' x_{it}\big) \quad j \in \{0,1,2,3,\dots,10\} \big|\big)$$

where ϕ (.) illustrates the cumulative standard normal distribution function, x_{it} illustrates the vector of control variables of the individual households (i) at time (t), including income controls (Ln_Income, Ln_Income2), demographic variables (Kids, Kids^2, Married, Retired, Racecl4, HS and UNI), wealth variables (Ln_LIQ, Ln_LIQ2, DBPLANCJ, DCPLANCJ), categorical age variable and a dummy for the year of the survey wave. $A_{it}(\lambda)$ is the weighted average stock market return throughout the lifetime of each respondent and depends on the weighting function, α_j illustrates the cut-off point that needs to be estimated where $(\alpha_1 = 0 < \alpha_2 < \alpha_3 < \alpha_4 = \infty)$. A standard ordered probit model has that $\phi(.)$ maps a linear function of the explanatory variables as a response to the probability P, but this is not the case with this ordered probit model and instead the $A_{it}(\lambda)$ creates a non-linear function of the weighting parameter λ.

In order to have a more defined and specific analysis of the effect that lifetime economic experiences have on individuals risk preferences, I decided to use a hierarchical approach with my ordered probit model. This is where the explanatory variables are entered into the model in a systematic and hierarchical manner that is based on theoretical considerations. In this instance, I have grouped together the control variables with their economic meaning, so that each block of control variables represents a specific level of influence on the risk preferences of the individuals. This means that initially I ran the simple ordered probit model with no control variables to see whether there exists an effect. Then, I added in the income specific control variables. These hold a high level of importance in understanding the risk preferences of individuals as they are fundamental socioeconomic factors that can significantly influence an individual's risk-taking behaviours. People with higher income levels may have more financial resources and are able to withstand potential losses and exhibit higher risk tolerances. Therefore, I wanted to extrapolate to see if these bared a high significance on the risk preferences of the individuals. Next, I removed the income specific control variables and included only the household characteristic control variables. This was to see whether these also played a significant role on the risk preferences of the individuals. Finally, I ran a complete model with all the control variables (both income specific and household characteristics), this was the fourth model that was run. I then ran a goodness of fit test using the information criterion to see which of the four models was the best fit for the data. Using the Bayesian Information Criteria (BIC), the smallest value illustrates the model that fits the data the best and we can see from the results that the complete model is the best representation for the dataset. Therefore, the full model is optimal:

$$y_{it} = \alpha + \beta A_{it}(\lambda) + \gamma' x_{it} + \varepsilon_{it}$$

I have ensured that the model has been estimated using maximum likelihood to effectively estimate the parameters β, λ, γ and to describe the relationship between the explanatory variables and the probabilities of observing the different ordered categories of the dependent risk variable. Nevertheless, it is not possible to directly interpret the coefficients, instead it is important to interpret and analyse the partial effects of the experienced real stock return $A_{it}(\lambda)$ on the different probabilities of obtaining one of the eleven risk-aversion categories. The parameter β depicts the partial effect of the average returns on the individual's sensitivity, and this is conditional on the weighting function defined in the equation above. It illustrates how much the *elicited risk aversion* of the individuals changes when the average experienced real stock returns changes, ceteris paribus. I ran my models both with normal standard errors and robust standard errors in order to see if the error term specification made a difference to the results and found that the most efficient way to avoid any misspecification errors was to use robust standard errors.

CHAPTER 5 Results & Discussion

Within this section, I will discuss the results from my main model using an ordered probit model. I will also display the different robustness tests that I conducted to check the validity of my results. I conducted 4 robustness tests and all the tables presenting the results are displayed throughout this section with the relevant conclusions that can be drawn.

Table 2 illustrates the results of the ordered probit model, which is estimated from the sample of 2014-2019. An ordered probit model is a form of statistical regression analysis when the dependent variable is a ranked categorical variable. The results provide insight into the relationship between the independent variables and the probabilities of obtaining results in each category of the dependent variable. The coefficients provided for each variable denote the probability of moving into the next higher category in the ordered response variable of risk preferences, thus leading to having more risk seeking behaviors. The significance is provided by the * at the side of each coefficient, and this illustrates whether each variable has a statistically significant relationship with the risk preferences of individuals at the 5% level. The robust standard errors, provided in parentheses, are adjusted to account for potential misspecification of the likelihood function.

Table 2

Results table

	Model 1	**Model 2**	**Model 3**	**Model 4**
Number of obs	10468	10468	10468	10468
Wald chi2	Chi2(1) 24,64	Chi2(4) 228,87	Chi2(12) 950,54	Chi2(15) 977,27
Prob > chi2	0,0000	0,0000	0,0000	0,0000
Pseudo R2	0,0005	0,0060	0,0234	0,0266
BIC values	47787,06	47554,55	46798,72	46673,31

RISK	**Coefficient (1)**	**Coefficient (2)**	**Coefficient (3)**	**Coefficient (4)**
ALamda	0,1026032*	0,4830952*	0,0809122	0,1077731*
	(0,0206715)	(0,0365203)	(0,0465258)	(0,0468548)
Ln_Income	-	-0,0222586*	-	-0,01886*
		(0,0045295)		(0,0045356)
Ln_LIQ	-	-1.035123*	-	0,1619683
		(0,4769706)		(0,5040568)
Ln_LIQ2	-	0,5321755*	-	-0,0608255
		(0,2382622)		(0,2513056)
AGECL	-	-	0,0452267*	0,0276255*
			(0,0099888)	(0,0101687)
MARRIED	-	-	0,3125054*	0,2727809*
			(0,023192)	(0,0234528)
KIDS	-	-	-0,0556556*	-,0608667*
			(0,0233484)	(0,0234002)
KIDS2	-	-	0,0166583*	0,0173942*
			(0,0065382)	(0,0065454)
RACE	-	-	-0,0180625	-0,0111281

			(0,0100779)	(0,0100861)
RETIRED	-	-	-0,3723046*	-0,3529576*
			(0,0321931)	(0,0322087)
DBPLANCJ	-	-	-0,1390553*	-0,1414129*
			(0,0229102)	(0,0229236)
DCPLANCJ	-	-	0,0880038*	0,0708453*
			(0,0213126)	(0,0214506)
HS	-	-	0,1115054*	0,0692539
			(0,0474303)	(0,0480636)
UNI	-	-	0,4264767*	0,390261*
			(0,0268796)	(0,0269948)
YR	-	-	-0,0291459	0,5322578*
			(0,0425985)	(0,081561)

Average partial effect of experienced real stock return on category probability	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**
Risk aversion = 0 (not willing)	-0,0187631* (0,00379)	-0,0869264* (0,0067354)	-0,0137493 (0,0079036)	-0,0180844* (0,0078573)
Risk aversion = 1 (high risk aversion**)**	-0,0045251* (0,0009313)	-0,0210028* (0,0018321)	-0,0034668 (0,0019992)	-0,0045875* (0,0020044)
Risk aversion = 2	-0,0061302* (0,0012544)	-0,0285011* (0,0023396)	-0,0046783 (0,0026952)	-0,0062066* (0,0027071)
Risk aversion = 3	-0,0066757* (0,0013614)	-0,0311318* (0,0024944)	-0,0050437 (0,0029057)	-0,00671* (0,0029258)
Risk aversion = 4	-0,0033697* (0,0006927)	-0,0157903* (0,0013444)	-0,0025207 (0,0014556)	-0,0033658* (0,0014729)
Risk aversion = 5	-0,0004431 (0,0002351)	-0,0022461* (0,0010202)	-0,0003107 (0,0002379)	-0,0004589 (0,0002878)
Risk aversion = 6	0,004436* (0,0009108)	0,0206198* (0,0017195)	0,0033138 (0,0019085)	0,0043812* (0,0019094)
Risk aversion = 7	0,0098334* (0,001999)	0,0457371* (0,0036188)	0,0072205 (0,0041564)	0,0095666* (0,0041659)
Risk aversion = 8	0,0105577* (0,0021413)	0,0490408* (0,003921)	0,0076997 (0,0044306)	0,0102034* (0,0044423)
Risk aversion = 9	0,0042848* (0,0008964)	0,0198551* (0,001873)	0,0031266 (0,0018069)	0,0041327* (0,0018132)
Risk aversion = 10 (low – risk seeking)	0,0107951* (0,0021908)	0,0503457* (0,0040306)	0,0084088 (0,0048424)	0,0111293* (0,0048485)

Note. Ordered probit model estimated with maximum likelihood. The sample period spans across 2014-2019. The U.S. Dow Jones index real returns have been used to calculate the experienced real stock returns. The liquid asset control variable has been logged. The household characteristics include the dummy variable to indicate the marital status, whether the individual has retired, the race, the level of education received, whether they have a defined benefit or defined contribution pension plan, and finally the number of children and its square. The standard errors are shown in the brackets, and these are robust to potential misspecification of the likelihood function and they have all been adjusted to account for the multiple imputation error.

We were left with the best fitting model having a Pseudo R^2 value of 0,0266. This means that my independent variables explain 2,66% of the variance in the dependent variable, namely the individual's *elicited risk aversion*. When evaluating each model presented, the models increase with the goodness of fit as more control variables are included. Models 3 and 4 have the best fits for the dataset compared to model 1 with the lowest scoring BIC value and the lowest scoring pseudo R^2 value. This Pseudo R^2 value is relatively low compared to Malmendier and Nagel's (2011) value (of between 7% and 10% for the different models) when analyzing the *elicited risk aversion* and in general it illustrates that this isn't a very good model fit.

The weighted average of the lifetime economic experiences (ALamda) is significant at a 5% level in all models apart from model 3, which is only significant at a 10% level. It has the strongest effect on the risk preferences in model 2 (with only the income specific control variables). In all models, this lifetime economic experiences variable has a positive effect on the probability of moving to a higher risk seeking category. In the lower part of Table 2, in column 4, estimated on the 2014-2019 sample, it shows that having a higher experienced real stock returns throughout the lifetime, slightly increases the probability that risk aversion is in the higher categories (from category 6 to 10), has little to no effect on the probability of being in category 5, and decreases the probability that the reported risk aversion is in the lowest categories (categories 1,2,3, and 4). Therefore, this implies that a higher economic lifetime experience influences the individual to exhibit more risk seeking behaviors, and thus the real stock market returns that are experienced in the individual's past have a positive and significant effect on risk tolerance. In conclusion, Hypothesis 1 which stated that the *experienced real stock returns* will have a positive effect on the *elicited risk aversion* of the US population, is not rejected based on these results. This is also consistent with the literature discussed before.

With ceteris paribus, for my main model 4, on average, having a higher income tends (Ln_Income) to decrease the willingness to take financial risk, whereas having a higher stock of liquid assets (Ln_LIQ, Ln_LIQ2) tends to increase the willingness to take financial risks. For model 2, holding other factors constant, both variables tend to decrease the willingness and it is possible to see that the stock of liquid asset variable illustrates non-linearities. This is visible from the statistical significance of the squared term. Education is another important control variable, where in both model 3 and 4 with ceteris paribus, on average having a higher level of education is associated with more risk seeking behaviors. This is particularly suggested from the university dummy variable (UNI) having a larger magnitude than the high school dummy (HS). Understandably, this can be interpreted as individuals with a further education have a deeper understanding of the financial sector and the risks associated with investing. A would be expected, being retired and having children both tend to decrease the probability of having a higher willingness to take financial risks while holding other factors constant.

These results are consistent with Schlag's (1999a and 1999b) proposal that individual's try to replicate successful previous decisions, thus illustrating how any previous successes or previous experiences of higher stock market returns, tend to increase the willingness of the individual to invest in slightly riskier stocks.

In order to examine the robustness of my results, I have performed the same model during the period of 2007-2013. The Survey of Consumer Finance has measured the dependent variable of interest, the individual's *elicited risk aversion*, on a different scale for any survey wave that was conducted before 2014. In this measure, the survey participants were asked whether they are willing to take (1) substantial financial risks expecting to earn substantial returns; (2) above average financial risks expecting to earn above average returns; (3) average financial risks expecting to earn average returns; or finally (4) not willing to take any financial risks. I have then coded these responses as 1 to 4. Using the same method as described above and a hierarchical approach for the ordered probit model, I am interested in whether similar results will be obtained.

Table 3

Robustness test of altering the time period results table

	Model 1	**Model 2**	**Model 3**	**Model 4**
Number of obs	10961	10961	10961	10961
Wald chi2	Chi2(1) 10,11	Chi2(3) 315,61	Chi2(12) 1486,92	Chi2(14) 1495,40
Prob > chi2	0, 0015	0,0000	0,0000	0,0000
Pseudo R2	0, 0004	0,0180	0,0714	0, 0756
BIC values	25910,89	25473,77	24176,8	24084,64

RISK	**Coefficient (1)**	**Coefficient (2)**	**Coefficient (3)**	**Coefficient (4)**
ALamda	-0,0679491 *	-0,0488664*	-0,03159	-0,0256483
	(0,02137)	(0,0216872)	(0,0411681)	(0,0413359)
Ln_Income	-	0,0289606 *	-	0,0258735*
		(0,004054)		(0,0042696)
Ln_LIQ	-	- 0,0389299*	-	-0,0176115*
		(0,0024384)		(0,0026485)
AGECL	-	-	0,0087523	0,0167894
			(0,0111515)	(0,0111953)
MARRIED	-	-	-0,2801422 *	-0,2603655 *
			(0,0256747)	(0,0257481)
KIDS	-	-	0,0429155*	0,0421704
			(0,0214449)	(0,0215999)
KIDS2	-	-	-0,0050651	-0,0052165
			(0,0050898)	(0,0051368)
RACE	-	-	0,0969323*	0,0898888*
			(0,012124)	(0,0121408)
RETIRED	-	-	0,311967*	0,2969651*
			(0,0351702)	(0,0352584)
DBPLANCJ	-	-	0,0802276 *	0,0873853*
			(0,0253133)	(0,025327)

DCPLANCJ	-	-	-0,2671237*	-0,2583182*
			(0,0230529)	(0,0232362)
HS	-	-	-0,3612585 *	-0,3146698*
			(0,0550131)	(0,0555966)
UNI	-	-	-0,584949 *	-0,5526989*
			(0,0271378)	(0,0272908)
YR	-	-	0,0034321	-0,0040144
			(0,0375911)	(0,0377019)

Average partial effect of experienced real stock return on category probability	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**
Risk aversion = 1 (low)	0,0064596*	0,0046299*	0,0029362	0,0023758
	(0,0020326)	(0,0020545)	(0,0038275)	(0,0038294)
Risk aversion = 2	0,0137523*	0,0096066*	0,0055645	0,0045008
	(0,0043319)	(0,0042672)	(0,007253)	(0,0072547)
Risk aversion = 3	0,0056807*	0,0038473*	0,0022567	0,0017904
	(0,0018095)	(0,0017209)	(0,0029404)	(0,0028849)
Risk aversion = 4 (high)	-0,0258927*	-0,0180838*	-0,0107573	-0,0086669
	(0,0081363)	(0,0080236)	(0,0140173)	(0,0139665)

Note. Ordered probit model estimated with maximum likelihood. The sample period spans across 2007-2013. The U.S. Dow Jones index real returns have been used to calculate the experienced real stock returns. The liquid asset control variable has been logged. The household characteristics include the dummy variable to indicate the marital status, whether the individual has retired, the race, the level of education received, whether they have a defined benefit or defined contribution pension plan, and finally the number of children and its square. The standard errors are shown in the brackets, and these are robust to potential misspecification of the likelihood function and they have all been adjusted to account for the multiple imputation error.

As visible in table 3, only the first two models have significant ALamda variables. This means that once the household characteristic control variables are included into the model, there is not enough evidence to conclude that the lifetime economic experiences have a significant impact on the risk preferences of the households, holding all other factors constant. Nevertheless, the first models (1 and 2) have a statistically significant relationship at the 5% level. These models solely show the relationship between the risk preferences and the lifetime economic experiences (model 1), along with income control variables (model 2). With ceteris paribus, in models 1 and 2 (column 1 and 2 of the lower part of the table), it is visible that on average, a higher experienced real stock return in the past increases the probability that the reported risk aversion is lower (categories 1,2, and 3), and tends to decrease the probability of reporting a higher risk aversion (category 4). This means that the individuals tend to be more risk seeking, and again this is consistent with the findings in my main model. This shows that having a larger experienced real stock return means that the individual is accustomed to the higher returns and is therefore willing to take more substantial risks when investing.

The next robustness test that I conducted to verify the validity of my results, was to change the weighting function that I used to calculate the weighted average stock returns of the individual's past. This involved changing the time span that the calculation was conducted on. Undeniably, this change to the weighting function will cause a change in the magnitude of the beta coefficient since it depends on the starting point.

Initially, I postponed the starting point of the weighting function to 10 years after the birth of the household head. This caused the coefficients to fall in value and in significance. This conveys that the observations in the early stage of these individuals' lives, are excluded from the weighted average returns, making the sample shorter and giving each value a higher weight, hence lowering the coefficients. The full model (4), shown in table 4, has the best goodness of fit for the model, nevertheless the experienced real stock returns independent variable is insignificant at the 5% level which again illustrates that once the household characteristic controls are included into the model, there is not enough evidence that lifetime stock market real return experiences impact the risk preferences of households.

Table 4

Robustness test 2 of altering the weighting function to 10 years post birth results table

	Model 1	Model 2	Model 3	Model 4
Number of obs	10469	10469	10469	10469
Wald chi2	Chi2(1) 28,32	Chi2(4) 166,84	Chi2(12) 949,07	Chi2(15) 975,44
Prob > chi2	0, 0000	0,0000	0,0000	0,0000
Pseudo R2	0, 0006	0,0041	0,0233	0, 0265
BIC values	47787,89	47647,22	46804,2	46679,8

RISK	Coefficient (1)	Coefficient (2)	Coefficient (3)	Coefficient (4)
ALamda	0,0869631* (0,0163405)	0,2300876 * (0,022117)	0,0420344 (0,0276212)	0,0528847 (0,0278523)
Ln_Income	-	-0,0221019 * (0,0045448)	-	-0,018827 * (0,0045421)
Ln_LIQ	-	-1,305999* (0,4762993)	-	0,1674821 (0,5042335)
Ln_LIQ2	-	0,6616844 * (0,2379916)	-	-0,0636631 (0,2513953)
AGECL	-	-	0,0448662 * (0,0104032)	0,0278201 * (0,0105834)
MARRIED	-	-	0,3122625 * (0,0231816)	0,2725077 * (0,0234458)
KIDS	-	-	-0,0545486 * (0,0232941)	-0,0588936 * (0,0233524)
KIDS2	-	-	0,0165294 * (0,0065401)	0,017141 * (0,0065502)
RACE	-	-	-0,0179203 (0,0100784)	-0,0109647 (0,0100869)
RETIRED	-	-	-0,3733361 * (0,0321863)	-0,354926 * (0,0322012)
DBPLANCJ	-	-	-0,1393177 * (0,0229125)	-0,141914 * (0,0229276)
DCPLANCJ	-	-	0,088687 * (0,0212849)	0,0719898 * (0,0214182)
HS	-	-	0,1114749 * (0,0474342)	0,0693006 (0,0480628)
UNI	-	-	0,4262641 * (0,0268786)	0,3900808 * (0,026995)

YR	-	-	0,0011417 (0,0304988)	0,5728035 * (0,0773325)
Average partial effect of experienced real stock return on category probability	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**
Risk aversion = 0 (not willing)	-0,0159003* (0,0029932)	-0,041665* (0,0040592)	-0,0071425 (0,0046922)	-0,0088746 (0,0046717)
Risk aversion = 1 (high)	-0,0038317* (0,0007368)	-0,0100438* (0,0010568)	-0,0018011 (0,0011855)	-0,0022514 (0,0011889)
Risk aversion = 2	-0,0051916* (0,0009931)	-0,0136186* (0,0013826)	-0,0024305 (0,0015996)	-0,0030459 (0,0016079)
Risk aversion = 3	-0,0056569* (0,0010789)	-0,0148617* (0,0014883)	-0,0026204 (0,0017245)	-0,0032928 (0,0017378)
Risk aversion = 4	-0,0028601* (0,0005514)	-0,0075345* (0,0007863)	-0,0013107 (0,0008644)	-0,0016529 (0,0008748)
Risk aversion = 5	-0,0003766 (0,0001983)	-0,0010319* (0,0004939)	-0,0001604 (0,0001333)	-0,0002235 (0,0001554)
Risk aversion = 6	0,0037599* (0,0007208)	0,0098697* (0,0010093)	0,0017219 (0,0011331)	0,0021505 (0,0011347)
Risk aversion = 7	0,0083352* (0,0015818)	0,0218855* (0,0021662)	0,0037513 (0,0024672)	0,0046947 (0,0024755)
Risk aversion = 8	0,0089474* (0,0016962)	0,0234707* (0,0023416)	0,004 (0,0026299)	0,0050068 (0,0026394)
Risk aversion = 9	0,0036302* (0,0007122)	0,0095063* (0,0010594)	0,0016242 (0,0010716)	0,0020278 (0,0010748)
Risk aversion = 10 (low – risk seeking)	0,0091446* (0,0017334)	0,0240235* (0,0023967)	0,0043683 (0,0028729)	0,0054614 (0,0028792)

Note. Ordered probit model estimated with maximum likelihood. The sample period spans across 2014-2019. The U.S. Dow Jones index real returns have been used to calculate the experienced real stock returns. The liquid asset control variable has been logged. The household characteristics include the dummy variable to indicate the marital status, whether the individual has retired, the race, the level of education received, whether they have a defined benefit or defined contribution pension plan, and finally the number of children and its square. The standard errors are shown in the brackets, and these are robust to potential misspecification of the likelihood function and they have all been adjusted to account for the multiple imputation error.

Next, I changed the starting point of the weighting function to 10 years before the birthyear of the household head. This means that the economic experiences that the parents of the individual experienced are important and included into the weighted average, therefore concluding that each observation holds a lower weight since the sample is longer. It would be expected that the beta coefficients would hold a higher value, nevertheless this is not the case, and the significance is also lower. The results in table 5 show that, with our weighting function including an extra 10 years pre the birthyear of the household head, there is no evidence to conclude that lifetime stock market returns have any impact on the risk preferences of individuals.

These results are consistent with the cognitive framework previously discussed in Section 2.1.4, how experiences that an individual directly encounters has more impact. Erev and Roth's (1998 and 2014) findings are coherent with the fact that the experience effect that these individuals will not have encountered, since it was 10 years before their birth, will have less potent influence on their risk preferences and subsequent decision making.

This means that, from both robustness tests of changing the time frame of the weighting function of the lifetime economic experiences, the results found in my main analysis are not consistent. Malmendier and Nagel's (2011) results are not coherent with this finding, as they found that changing the starting point of the weighting function had little effect on their results.

Table 5

Robustness test 3 of altering the weighting function to 10 years before birth results table

	Model 1	**Model 2**	**Model 3**	**Model 4**
Number of obs	10469	10469	10469	10469
Wald chi2	Chi2(1) 12,05	Chi2(4) 167,61	Chi2(12) 945,58	Chi2(15) 973,17
Prob > chi2	0, 0005	0,0000	0,0000	0,0000
Pseudo R2	0, 0002	0,0042	0,0233	0, 0264
BIC values	47804,16	47644,56	46806,35	46683,73

RISK	**Coefficient (1)**	**Coefficient (2)**	**Coefficient (3)**	**Coefficient (4)**
ALamda	0,0678683*	0,3257491*	-0,0204001	0,0008035
	(0,0195548)	(0,0310364)	(0,0356055)	(0,03586)
Ln_Income	-	-0,0233997*	-	-0,0189241*
		(0,0045241)		(0,0045409)
Ln_LIQ	-	-1,24061*	-	0,1712813
		(0,4794338)		(0,5044706)
Ln_LIQ2	-	0,6311963*	-	-0,065694
		(0,2395292)		(0,2515172)
AGECL	-	-	0,0543062 *	0,0381911*
			(0,0091695)	(0,0093431)
MARRIED	-	-	0,310963*	0,2715146*
			(0,0231853)	(0,0234496)
KIDS	-	-	-0,046189 *	-0,0513975*
			(0,0232962)	(0,0233472)
KIDS2	-	-	0,0152456 *	0,0159282*
			(0,0065303)	(0,0065374)
RACE	-	-	-0,0176634	-0,0107742
			(0,0100832)	(0,0100922)
RETIRED	-	-	-0,3816625*	-0,363506*
			(0,0320118)	(0,0320229)
DBPLANCJ	-	-	-0,1419563*	-0,1446642*
			(0,0228894)	(0,0229048)
DCPLANCJ	-	-	0,0920146 *	0,0752051*
			(0,0212585)	(0,0213833)

HS	-	-	0,1098701* (0,0474338)	0,0681166 (0,0480538)
UNI	-	-	0,4253266* (0,0268669)	0,3893056* (0,0269851)
YR	-	-	0,0528582 (0,0349795)	0,6125762* (0,0789247)

Average partial effect of experienced real stock return on category probability	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**
Risk aversion = 0 (not willing)	-0,0124182* (0,0035842)	-0,0589214* (0,0057288)	0,0034667 (0,0060515)	-0,0001349 (0,0060193)
Risk aversion = 1 (high)	-0,0029967* (0,0008723)	-0,0142618* (0,0014951)	0,0008746 (0,0015272)	-0,0000342 (0,0015278)
Risk aversion = 2	-0,0040586 (0,0011781)	-0,0193236* (0,0019378)	0,0011802 (0,0020603)	-0,0000463 (0,0020665)
Risk aversion = 3	-0,0044174 * (0,0012805)	-0,0210484* (0,0020779)	0,0012719 (0,0022197)	-0,00005 (0,0022328)
Risk aversion = 4	-0,0022308 * (0,0006488)	-0,010649* (0,0010924)	0,0006359 (0,0011095)	-0,0000251 (0,0011202)
Risk aversion = 5	-0,000291 (0,0001658)	-0,00143* (0,0006942)	0,0000776 (0,000141)	-3.37e-06 (0,0001505)
Risk aversion = 6	0,0029352* (0,000855)	0,0139687* (0,0014246)	-0,0008357 (0,0014588)	0,0000327 (0,0014585)
Risk aversion = 7	0,0065078* (0,0018852)	0,0309445* (0,003043)	-0,0018208 (0,0031776)	0,0000713 (0,0031839)
Risk aversion = 8	0,0069889 * (0,0020194)	0,0331932* (0,0032751)	-0,0019417 (0,0033898)	0,0000761 (0,0033956)
Risk aversion = 9	0,0028368* (0,000833)	0,0134527* (0,0014905)	-0,0007884 (0,0013765)	0,0000308 (0,0013753)
Risk aversion = 10 (low – risk seeking)	0,007144 * (0,0020624)	0,034075* (0,0033589)	-0,0021201 (0,0037013)	0,000083 (0,0037037)

Note. Ordered probit model estimated with maximum likelihood. The sample period spans across 2014-2019. The U.S. Dow Jones index real returns have been used to calculate the experienced real stock returns. The liquid asset control variable has been logged. The household characteristics include the dummy variable to indicate the marital status, whether the individual has retired, the race, the level of education received, whether they have a defined benefit or defined contribution pension plan, and finally the number of children and its square. The standard errors are shown in the brackets, and these are robust to potential misspecification of the likelihood function and they have all been adjusted to account for the multiple imputation error.

The final robustness test that I conducted was to investigate the strength of the experience effect when we alter the financial sophistication of the households. I used two proxies for financial sophistication: a dummy variable to illustrate whether the household owned more liquid assets than the cross-sectional median each year, and the next is a dummy variable to denote whether the household head had completed their university degree. I interacted these dummy variables with the independent experienced real stock return variable while continuing with the same weighting function used for my main model.

As is visible in Table 6, there is not a large difference between the strength of the experience effect that households with higher and lower financial sophistication encounter. Although the interaction effect term of both the higher liquid assets measure and the university degree measure both are statistically significant for their coefficients, they haven't made a large impact on the magnitude of the effects. Having liquid assets above the median of the cross-section within a given year has a bigger interaction effect than having a university degree. This illustrates that the households that have finished further education, or the households that own more than the average number of liquid assets for that year, do on average tend to marginally increase the willingness of the households to take on financial risk. Nevertheless, this experience effect is only slightly different than to the experience effect that the households with less financial sophistication experience, meaning that it shouldn't make a major impact overall to our results.

These results are all in accordance with the relevant literature discussed in the reinforcement learning part in Section 2.2.1.

Table 6

Robustness test 4 of altering the financial sophistication of the households results table

	Model 1	**Model 2**	**Model 3**
Number of obs	10468	10468	10468
Wald chi2	Chi2(1) 24,64	Chi2(2) 34,24	Chi2(2) 478,39
Prob > chi2	0, 0000	0,0000	0,0000
Pseudo R2	0, 0005	0,0007	0,0114
BIC values	47787,06	47786,05	47274,86

RISK	**Coefficient (1)**	**Coefficient (2)**	**Coefficient (3)**
ALamda	0,1026032* (0,0206715)	0,189695 * (0,034755)	0,0557301* (0,0209191)
ALamda x $I_{Liquid\ assets>median}$	-	0,2023358* (0,0380785)	-
ALamda x $I_{Univeristy\ degree}$	-		0,1139323* (0,0208171)

Average partial effect of experienced real stock return on category probability	**Model (1)**	**Model (2)**	**Model (3)**
Risk aversion = 0 (not willing)	-0,0187631* (0,00379)	-0,0358582* (0,0066718)	-0,0155626* (0,0036796)
Risk aversion = 1 (high)	-0,0045251* (0,0009313)	-0,0086352* (0,0016451)	-0,0041761* (0,000928)
Risk aversion = 2	-0,0061302* (0,0012544)	-0,0116972* (0,0022083)	-0,0058079* (0,0012467)
Risk aversion = 3	-0,0066757* (0,0013614)	-0,0127393* (0,0023995)	-0,0065809* (0,0013394)
Risk aversion = 4	-0,0033697* (0,0006927)	-0,0064308* (0,0012265)	-0,0035684* (0,0006758)

Risk aversion = 5	-0,0004431	-0,0008308	-0,0015149*
	(0,0002351)	(0,0004459)	(0,0002328)
Risk aversion = 6	0,004436*	0,008483*	0,0035485*
	(0,0009108)	(0,0016035)	(0,0008942)
Risk aversion = 7	0,0098334*	0,0187911*	0,0086945*
	(0,001999)	(0,0035219)	(0,0019351)
Risk aversion = 8	0,0105577*	0,0201578*	0,0098056*
	(0,0021413)	(0,0037829)	(0,0020664)
Risk aversion = 9	0,0042848*	0,0081742*	0,0041013*
	(0,0008964)	(0,0015881)	(0,0008682)
Risk aversion = 10 (low – risk seeking)	0,0107951*	0,0205854*	0,0110609*
	(0,0021908)	(0,0038566)	(0,0022054)

Note. Ordered probit model estimated with maximum likelihood. The sample period spans across 2014-2019. The U.S. Dow Jones index real returns have been used to calculate the experienced real stock returns. The standard errors are shown in the brackets, and these are robust to potential misspecification of the likelihood function, and they have all been adjusted to account for the multiple imputation error. Two proxies were used to illustrate financial sophistication: owning more liquid assets than the cross-sectional median in that year and to denote if they have completed university education. These dummy variables have been interacted with the experienced real stock return variable.

CHAPTER 6 Conclusion

This paper was conducting a replication study of Malmendier and Nagel's (2011) depression babies hypothesis experiment. I specifically investigated with a more recent timeframe from 2014-2019, to demonstrate whether individuals exhibit different risk averseness when investing in the stock market depending on the macroeconomic conditions they experienced throughout their lifetime. I collected the Dow Jones real stock market returns from Yahoo Finance back to the year of birth of the oldest household head and used the weighted average of this as a proxy for the lifetime economic experiences, exhibiting the impact of booms and busts. I used the Survey of Consumer Finances with the survey waves in 2016 and 2019, to provide the responses of the US population's risk preferences towards investing in the stock market. This examined whether Malmendier and Nagel's (2011) previous findings are still coherent given the structural changes that the stock market has experienced and the technological advances that the world has benefitted from, which both allow further access to the stock market and allow for deeper understanding, knowledge, and more potential investment opportunities.

My results were mostly significant and positive. This means that an individual that experienced a higher real stock market return throughout their lifetime, increases their risk willingness relatively compared to an individual that experienced lower real stock market returns. This was consistent with my hypothesis and the previous literature discussed. Specifically, it is visible that holding a risky asset over the course of an individual's life, will have a significant impact on the subsequent tolerance and willingness to take on financial risk. I used a weighting function as it is also evident that individuals put a higher weight on the recent experiences relatively to more distant experiences. Nevertheless, all the real stock returns experienced do hold some influence on the individual's current risk taking, just at different strengths. This illustrates that the magnitude of the economic effect of each experience is economically and financially important.

This topic is highly relevant for a wide range of stakeholders, from policymakers, regulators, CEOs wanting to invest, and different financial institutions. For regulators, such as the Bank of England, there exists an importance to understanding the risk preferences and expected behaviours of stakeholders. To be able to see trends in individuals' behaviours can allow the regulators to forecast any periods of potential instability and amend their risk models to acknowledge this. This alone has a huge impact on the wider economy within one country and the global economy too. For policymakers, typically they assume stable risk preferences when creating their new policies. It is important to remain up to date with the systematic changes that exogenous shocks can have on the current populations risk preferences and tolerances. This allows policymakers to forecast periods of potential risk averseness and adjust policies to adequately consider these behavioural responses. In terms of CEOs and financial institutions, they often use selfreported measures to assess their client's risk preferences, and this may not always be coherent with the wider economy's tendencies. If they can predict when there may be higher demand in the stock market and the key drivers behind these increases in demand, they can fully exploit these periods. Finally, for individuals, understanding why they exhibit certain tendencies is inherently important for creating the most effective investment strategies and creating well-balanced portfolios that will align to their risk preferences and financial goals. By understanding risk preferences, investors can avoid making emotionally based investment decisions, and instead focus on data-driven, rational decisions.

For areas of further research on this topic, additional risk measures should be taken into account. Using the Survey of Consumer Finance question on the *elicited risk aversion*, has the limitation of providing the risk measure on a scale of 0-10. This makes it difficult for people to fully distinguish which category they belong to, thus questioning the reliability of this measure. If researchers were to combine together multiple different measurement tools of risk preferences to create a single measure, such as survey responses and multiple experiments together, it may reduce the measurement error that is incurred and improve the reliability of our results.

It can also be assumed that these economic lifetime experiences impact the risk taking by influencing the beliefs that the individual holds about the future. For example, an individual that experienced a higher real return on their previous stock holdings will have a more optimistic belief about the future returns they can earn through stock market investment. Generally, this experience effect is a result from the individual trying to learn from their direct experiences rather than accumulating all the available historical knowledge and data to make an informed rational decision. This supports my hypothesis that individuals' decision making under uncertainty does not follow the expected utility theory and it is crucial to understand their risk preferences in order to make educated predictions.

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