Stock Market Participation in the European Union

by

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ABSTRACT

Understanding why most people shy away from stock market participation, both on individual and country level, is very important. Stock market participation explains consumption smoothing and this in turn can have a significant effect on household welfare. Literature has shown that welfare loss from withholding to invest in the stock market can be substantial. Furthermore, it has been estimated that limited stock market participation influences the distribution of wealth and wealth effects on consumption.

A well-known phenomenon known as the stock market participation puzzle stems from the significance that most people do not invest in stocks despite the remarkable risk premium and gains from diversification involved.

In this research, stock market participation both on household- and country-level are investigated for most countries in the European Union. This is done by using the Household Finance and Consumption Survey (HFCS). Influencing factors such as behavioural aspects and household characteristics are investigated. This adds to the growing literature on stock market participation especially in the field of behavioural and household finance. In this research a wide range of variables are considered in order to try and explain the stock market participation puzzle. This takes most prior literature, that only focus on one determining factor, a step further.

Key words:

Stock market participation; Household finance; HFCS; Probit model; Tobit model; Individual- and household-level influences; Country-level influences

OPSOMMING

Dit is baie belangrik om te verstaan hoekom sekere mense kies om nie in die aandele mark te belê nie, aangesien dit op 'n individuele-vlak en op landelike-vlak voorkom. Deelname aan die aandele mark verduidelik hoe verbruikers kies om hul geld te optimeer. Dit het dan 'n groot invloed op die welvaart van huishoudings. In die literatuur is dit al gewys dat die verlies aan welsyn enorm kan wees omdat individue nie deelneem aan die aandele mark nie. Verder is dit ook al gevind dat beperkte deelname aan die aandele mark 'n groot invloed het op die verspreiding van rykdom en rykdom effekte op verbruiking.

'n Baie bekende verskynsel genaamd die aandeelmarkverwarring spruit van die feit dat meeste mense nie in aandele belê nie, tenspyte van die feit dat die risikopremie en winste deur diversifikasie so groot is.

In hierdie navorsing word deelname aan die aandelemark ondersoek op individuele-vlak en op landelike-vlak. Ondersoek word gedoen vir meeste Europese Unie lande deur gebruik te maak van die "Household Finance and Consumption Survey (HFCS)". Gedragsaspekte en huishoudlike eienskappe is van die faktore wat in die ondersoek na gekyk word. Hierdie ondersoek dra by tot die groeiende literatuur rakende deelname aan die aandeelmark veral in die veld van gedragsfinansies en huishoudelike finansies. 'n Wye reeks veranderlikes word gebruik in hierdie tesis om die aandeelmarkverwarring te probeer verduidelik. Aangesien meeste vorige literatuur net op een bepalende faktor fokus vat hierdie navorsing vorige bevindinge 'n stap verder.

Sleutelwoorde

Aandeelmark deelname; Huishoudelike finansies; "HFCS"; Probit model; Tobit model; Individuele- en huishoudelike-vlak invloede; Landelike-vlak invloede

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LIST OF ABBREVIATIONS

CAPI Computer-Assisted Personal Interviews

CPI Corruption Perception Index

DB Defined-Benefit

ECB European Central Bank

EIGE European Institute for Gender Equality

EPP Equity Premium Puzzle

FKP Financially Knowledgeable Person

HFCN Household Finance and Consumption Network

HFCS Household Finance and Consumption Survey

HMR Household Main Residents

HRS Health and Retirement Survey

ISCED International Standard Classification of Education

ISCO International Standard Classification of Occupations

LPM Linear Probability Model

MI Multiple Imputation

MLE Maximum Likelihood Estimate

OLS Ordinary Least Squares

PSU Primary Sampling Unit

TI Transparency International

CHAPTER 1
INTRODUCTION

Understanding the reasoning behind why certain people invest in the stock market and others do not, is extremely important. Their choice can lead to economic implications that affects many aspects such as consumption behaviour, welfare, and the design of regulation, to name a few. In 1989 already, Mankiw and Zeldes find differences in the consumption behaviour and patterns of stock market participates and non-participates (Mankiw and Zeldes, 1989). Almost a decade later, Palacios-Huerta (2001), find that the international diversification puzzle, can be partly explained through the stock market participation puzzle. This well-known phenomenon also called the "stock-holding" puzzle, addresses the fact that individuals tend to underinvest in the stock market (Campbell, 2006). It is also well-known that this puzzle is particularly noticeable in Europe - more than in other countries.

Further, Basak and Cuoco (1998), Ait-Sahalia et al. (2001), and Cohen et al. (2008), all find that restricted stock market participation contributes to explaining the equity premium puzzle (EPP), which labels the bizarrely higher historical real returns from stocks as opposed to government bonds and the fact that most investors still do not invest in stocks. This clearly highlights the large amount of risk aversion amongst investors. The ironic fact is that stock market participation facilitates consumption smoothing which in turn may contribute significantly to the welfare of households. Cocco et al. (2005), estimate the welfare loss of non-participants to be almost 2% of their annual consumption when using calibrated life-cycle models. Further, Guvenen (2006), find limited stock market participation leads to wealth inequalities.

All of these puzzles and outlandish points mentioned so far, serves as a starting point for the importance of understanding stock market participation. It also inspires specifically examining stock market participation in the European Union.

Since the global financial crisis of 2008, risk aversion of most investors, banks and financial markets around the world have increased. Specifically, focussing on households in countries that were severely hit by the crisis, pronounced underinvestment in the stock market has been evident (Ampudia and Ehrmann, 2013). It is therefore suggested that risk aversion varies over time and depends on the experiences of economic agents.

Studies done in the field of behavioural finance have presented new variables affecting household financial decisions. These studies and the search for more explanatory variables currently enjoy the empirical forefront. Most prior research focus on a single explanatory factor or area. This is the first problem addressed in this research, since many different influential factors are collectively examined.

Further, in a number of papers, time-varying risk aversion related to financial markets have been investigated. However, not so much have been done regarding the exploration of time-varying risk aversion of consumers and households. In this research, the focus is specifically on risk aversion of households in the European Union. What drives households in European

countries to invest in the stock market, or rather, to not invest? This question is answered by examining behavioural finance effects together with household finance effects.

Lastly, country-specific effects are also used in examining stock market participation. The reason for incorporating country-specific effects is because different countries have different tax rules, different overarching religious beliefs, and different levels of financial stability, to name a few. These factors are believed to also contribute to individuals and households attitude towards stock market participation. Therefore, this research is roughly divided into two main segments of information and results. The one part focusses mainly on individual and household influences whereas the other part focusses on country-specific influences and aggregating individual level information to a country level.

The Household Finance and Consumption Survey (HFCS) dataset is used in order to examine stock market participation in the European Union. This survey provides detailed household-level data on various features of household balance sheets and associated economic and demographic variables. Because of its comprehensive nature and wide geographical focus, the HFCS fits well for this research. Furthermore, a few studies have been done using the first wave of the HFCS, but not so much regarding the second wave, since the results from the second wave was only released at the end of 2016. In this research both waves will be used and therefore the results add to the existing evidence of the HFCS literature.

This research is structured as follows. Chapter 2 provides a broad literature review of previous findings regarding stock market participation. The literature review is also divided into two main parts in order to separate the literature done on individual- and household-level, and country-level. Chapter 3 takes a deeper look into the HFCS dataset by highlighting its different features and explaining the different methodologies used to build the survey. Chapter 4 is quite a lengthy chapter in that it provides the methodology used in this research as well as the results found after investigating individual- and household-level influences. Chapter 5 continues in a similar format, however, country-level influences are the main focus. Finally, Chapter 6 takes everything together in concluding and encouraging further research.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

The literature that tries to explain the stock market non-participation puzzle is rapidly growing. Especially around behavioural and psychological factors that is believed to serve as barriers to stock market participation.

Several studies have been done regarding wealth, income and education and how these factors influence stock market participation. However, beyond these traditional factors, more recent studies have also focused on other factors such as sociability (Hong et al., 2004), trust (Guiso et al., 2007), health (Rosen and Wu, 2004), optimism (Puri and Robinson, 2007), political preferences (Kaustia and Torstila, 2011), cognitive abilities (Christelis et al., 2010; Grinblatt et al., 2011), religion (Changwony, 2015; Kaustia and Luotonen, 2016), and even physique where Addoum et al. (2016) find taller and less obese individuals to be more likely to participate in the stock market. Note that the above references are not complete and merely serve as evidence of the growing literature regarding stock market participation. In this research, the goal is to try and account for as many as possible of the previous literature's results in order to conclude which factors truly influence stock market participation.

In this chapter, the supporting literature regarding stock market participation, is discussed. Individual, household and country-specific factors are portrayed and serve as motivation for the methodology that is used in this research. The first part of the literature review consists of literature relating to individual and household level factors, whereas the second part looks at country-level factors. A brief third part is added in order to show how certain individual- and household-level factors behave at country-level.

2.2 Individual and Household Level Influences

The majority of the variables explained in this section are available in the HFCS and will be used in the methodology to follow, however, a few variables are mentioned for interest sake and to encourage further research. In this section the focus is also on examining certain individual- and household-level influences and characteristics that also play a very important role at country-level. It is clear that certain individual characteristics are to an extent due to the country the individual or household find themselves in.

2.2.1 Portfolios of the Rich

More than a century ago, with the work of Pareto, economists and financial analysts have come to understand that wealth is extremely unevenly distributed across individuals all around the world. This undeniable feature accounts for the complexity of survey design

regarding wealthy households. However, in order to understand any data regarding households, it is extremely important to understand the behaviour of the small percent of wealthy households. Wealthy households control the majority of aggregate wealth.

Birdsall (2000) find the principal conclusion of how the portfolios of the wealthy differ from the rest of the population to be that the wealthy hold a much larger proportion of their portfolios in risky investments and have a large concentration of net wealth in their own entrepreneurial undertakings. Stock market participation should potentially increase strongly with wealth since fixed costs of investing are less of a barrier for wealthier individuals. If fixed costs are seen as time and money spent, this statement is almost inevitable. Paiella (2001) and Vissing-Jørgensen (2014), find even small amounts of participation costs to sidetrack investors. Unfortunately, there is further also significant variation in participation even amongst the wealthy. Therefore, the belief that paying fixed costs explains non-participation is challenged.

The same arguments hold for income. It makes sense that higher income households and individuals would also have a higher probability of participating in the stock market. In this research income and wealth are seen as separate variables. The exact definition of each will become clear in the fourth chapter where the methodology is explained.

2.2.2 Gender

There is a large gender gap in the stock market with men on average owning more stocks and many studies have shown that men invest and actively trade more aggressively than women. But why is this the case? Cárdenas et al. (2012), explored the relationship between the gender gap and financial literacy. They conclude that the gender gap can partly be narrowed if basic financial literacy were to increase among woman. Further, in the Swedish survey they used, women reported being more risk averse than men. Lusardi (2008) also find men to be typically more financially literate relating to much less women working in financial environments. Further, Croson and Gneezy (2009) also find evidence that the gender gap is related to differences in risk preferences between men and women. Supporting the results from Cárdenas et al. above, most women do not enjoy taking on high risks as much as men do.

Brooks et al. (2018), investigate the importance of social norms and how it shapes the decisions that both men and women make regarding participation. They identify inequality by using the gender inequality index of the World Economic Forum and data from four different European household surveys. They find evidence that women's risk taking behaviour are related to the gender inequality index of their country. For example, Italian women refrain more from participation in the stock market than the average European woman and Italy has very high asymmetric gender role prescriptions.

2.2.3 Risk Aversion

The fact that so many households around the world do not participate in the stock market, is puzzling to understand. In fact, Viceira (1999), and Massa and Simonov (2006), found that by looking at a standard portfolio model that contains no trading costs and that has constant relative risk aversion, all investors will hold the same portfolio of risky assets. This portfolio is the market portfolio, i.e., it contains all the risky assets in the economy. The only way household portfolios will differ from each other under this model, is because of an investor's risk aversion and because of the correlation between non-financial income and the return of the portfolio. As was mentioned earlier, the fixed costs associated with stock market participation terrify investors and could even entirely prevent individuals from participating.

2.2.4 Education

A handful of papers strengthens the believe that education is strongly correlated with stock market participation. Specifically, Hong et al. (2004), found that investors who has a university degree are more likely to invest in stocks than other investors that have lower levels of education. The explanation for their findings are that education considerably decreases the fixed costs associated with stock market participation, since educated investors are able to understand different factors of participation better and/or because they obtain the ability to learn faster.

Except for the level of education investors portrays, it has also been found that the type of education plays an extremely important, if not more important role in explaining participation. Christiansen et al. (2008), specifically examined the type of education investors undertook and the type of information they gather concerning the stock market. They found, firstly, the costs linked to participation cannot only be seen as monetary. For example, the time it takes to understand and gather information on the stock market, should also be seen as a cost. Therefore, more effective information-gathering agents have higher probability of partaking in the stock market, since the cost associated therewith is lower. Second, Christiansen et al., also find that the probability of participation increases after an investor completed economics-related education. And so, they conclude that the type of education and investor portrays, plays an extremely important role in understanding stock market participation, and not just the level. Lastly, Cole and Shastry (2009) find a 7% to 8% increase in the probability of participation when one year of schooling is added to their model. Clearly, education with all of its different features mentioned above, have been proven to contribute strongly to stock market participation. However, the exact explanation for the strong relationship is still vague. Education is definitely to cognitive ability, however, it might also, for example, be related to social networks and job opportunities.

Unfortunately, education is difficult to account for since two individuals in two different countries might have the same level of education, but the quality thereof might differ significantly. Another country-level difference is the fact that in certain European countries, such

as Germany, education is free, whereas in other, such as the Netherlands, study fees for EU students at any degree level can be up to 2,000 EUR per year. These different facts can considerably affect the level of education of different individuals an so in turn affect stock market participation.

2.2.5 Religiosity

Amongst many, Renneboog and Spaenjers (2012), investigate the differences between religious and non-religious households in relation to their economic and financial behaviour and decisions. They specifically examined Dutch data, and found religious households consider themselves to be more trusting and generous and also to have a longer planning horizon. When looking at specific religions, they found Catholics to be more risk averse, while Protestants have a greater sense of financial responsibility. Interestingly, they also found religious households more likely to save than non-religious households.

Another extremely interesting aspect regarding religion, is Islamic finance. According to the Pew Forum, the total amount of Muslims in Europe was 44 million (6%) in 2010, which is about 19 million (3.8%) in the European Union. Cyprus has the biggest Muslim population out of all of the European Union countries used in the HFCS. The reason it is important to examine the Islamic religion, is because Islamic finance has different rules and regulations than other finance systems. Muslims work on a basis called the Shari'ah Basis of Stock Exchange. The majority of current Muslim jurists allow the trading of common stocks, however, preferred stocks, which earns part of its shares in profits realised at a known pre-fix rate, and loan stocks, which earns profit at a fixed rate of interest, is not allowed.

Furthermore, a Shari'ah compatible partnership defines a partnership that meet the condition of niyyah which means intention. This relates to the fact that such a partnership is not just a formal contract like under conventional law, in fact, it is seen a contract that includes personal conviction and belief as well as personal association with a family of partners. This aspect therefore guarantees the shareholder's determination and zeal to ensure a successful partnership. It is believed that a person dealing in such a contract would not listen to or suddenly act upon the rumours often spread by financial brokers. Among many of the Islamic Finance rules, the fact that profit should only come as a result of efforts contradicts the usual case of interest dominated investments. Furthermore, the Shari'ah boosts the use of profit-sharing and partnerships, but it prohibits interest, gambling and pure games of chance, selling something that is not owned or selling something that cannot be accurately defined in terms of size, type or amount (Wajhi et al., 2014).

Unfortunately, the problem that usually arises with regards to using religiosity as an influencing factor, is the issue of causality. Most information regarding religious views are self-reported, and it is difficult to disguise between individuals who really believe and individuals who just say they do. Obviously, people who do not feel strongly about their religion might have totally different values and beliefs than others who do feel strongly about the same religion. Kaustia (2016), tried to overcome this limitation by measuring religiosity by

how often individuals pray. On a scale of 0 to 5 they assigned a 0 to individuals who never pray and a 5 to individuals who pray more than once a day. However, in order to follow this methodology one requires a dataset with such information and this is seldom the case in household surveys.

According to the Human Truth Foundation (2015), religion in Europe has made a strong decline over the last 60 years. On average throughout the 27 EU countries, only half of its people believe in God and more than a quarter directly say that they have no religion. However, there is still much variation across countries. For example, in Malta, 94% (2010) of the population claim to be believers, whereas in Estonia it is only 18% (2010).

2.2.6 Social Interaction

Sociability is a common area of focus in the recent behavioural finance research. Sociability can take on several forms and so when investigating its influence on stock market participation, it is important to identify the different channels. Initial research mainly focus on social interaction with peer groups. For example, Hong et al. (2004), find decisions regarding participation to be highly correlated with choices made by co-workers. Further, Hong et al., uses two mechanisms to describe the relationship between social interaction and participation. They find information to be exchanged either by means of word-of-mouth or through observational learning, i.e, individuals prefer talking to their friends about finance rather than contacting financial professionals. They also find investors who have friends that participate in the stock market are more likely to also participate than those who do not have such friends or interact with such people. Another interesting result is the fact that households that interact with their neighbours or attends church occasionally are more likely to participate than non-social households (Hong et al., 2004).

It seems as though the influence of social interaction on stock market participation reflects a "keeping up with the Joneses" effect. Social individuals follow financial decisions made by their social group and try to maintain the same level of consumption. This emphasizes the fear of individuals standing out in a negative way. Many have studied evidence of this behaviour by making use of conformity models (Bernheim, 1994), habit formation models (Campbell and Cochrane, 1999), and individuals relative concern regarding their relative wealth in their neighbourhood (Brown et al., 2004).

Further channels of sociability relate to education, marital status, activity in organisations or clubs, to name a few. The ongoing research regarding sociability and stock market participation supports the fact that it is a challenging feature to understand and investigate. Nonetheless, different channels of sociability will be used in this research and the exact channels will become evident in chapter four where the methodology is explained.

2.3 Country Level Influences

Several explanations regarding differences in stock holding across countries have been looked at in the literature. Across countries, differences have even arose amongst people of the same wealth, i.e., showing the extreme importance of not only focussing on individual or household level influences, but also examining country level influences. The economic, political and cultural environment in which individuals find themselves also prove to be important (Georgarakos, 2009; Christelis et al., 2013). In this research four different country-level influences will be examined, namely, internet access, political preferences, corruption and capital gains tax. It is important to note that none of these influencing factors are available in the HFCS dataset and so the data from other resources is used.

2.3.1 The Internet

The rapid rate at which the internet has developed over the last century is one of the most significant technological advances of all time. The internet is an extremely powerful tool that has caused many good and many bad effects for humans. However, in the light of stock market participation it is believed that access to the internet can considerably lower information and transaction costs and so increase participation rates. Bogan (2008), study this phenomenon by using the Health and Retirement Survey (HRS) of the United States and found that households with access to the internet considerably increases their stock investing when compared to households that do not use the internet.

Here, it is very important to note that Bogan did her study in 2008, which is already ten years ago. The development of the internet has since then exponentially grown and almost all Euro area households have access to the internet. However, on a country level, it will still be interesting to examine how participation rates differ because of different levels of internet access.

2.3.2 Political Preferences

Political preferences is another influence that can take on many different forms. It can affect investment behaviour through risk aversion, trust, social capital, and economic incentives. Different types of people have different political believes and this could in turn be related to stock market participation choices. Kaustia and Torstila (2011), found that left-wing voters, i.e., people who support social equality and egalitarianism, and politicians are less likely to participate in the stock market. In fact, specifically in Finland, they found a moderate left-voter to be 17-20% less likely to invest in stocks, than a moderate right-voter. These results contribute to the believe that personal values also play an important role in major investment decisions, since even after accounting for wealth and income the relationship remain significant.

Unfortunately, in the HFCS, individual level information on political views are not available, however, when looking at country-specific effects, average political views of the Euro area countries are used as dummy variables. This gives a average effect of political views and its relation to stock market participation on country-level.

2.3.3 Corruption

One of the recent focuses of country research has been the economic trust that households have in the specific country they live. Guiso and Jappelli (2005), find that high social capital enhances the level of trust in a society. They further find that this in turn encourages financial development and increases the probability of households participating in the stock market. It is to be expected that households living in countries where the financial and economic climate is cloudy, will not participate as actively in risky assets as households living in sunnier conditions. Furthermore, countries experiencing negative political pressures also dampen the overall trust of individuals and so contributes to the non-participation figures.

In this research the Corruption Perception Index (CPI) will be used in order to represent trust in each country. Transparency International (TI) has published the CPI since 1995, annually ranking countries by their perceived levels of corruption, as determined by expert assessments and opinion surveys. CPI is given on a scale of 0 to 100, where 0 represents a highly corrupt country and 100 represents a very "clean" country. TI defines corruption as “the abuse of entrusted power for private gain”. Corruption can either be classified as grand, petty or political, depending on the amounts of money lost and the sector where the loss occurs. Grand corruption consists of acts committed at a high level of government that distort policies or the central functioning of the state, enabling leaders to benefit at the expense of the public good. Petty corruption refers to everyday abuse of entrusted power by low- and mid-level public officials in their interactions with ordinary citizens, who often are trying to access basic goods or services in places like hospitals, schools, police departments and other agencies. Political corruption is a manipulation of policies, institutions and rules of procedure in the allocation of resources and financing by political decision makers, who abuse their position to sustain their power, status and wealth.

2.3.4 Taxes

Probably the least researched aspect related to stock market participation, is tax. One of the main reasons it is so difficult to investigate is because different countries have different rules and regulations, and the information in one country cannot be used as a general measure for other countries. For example, in 2011, Hungary had the highest Standard VAT rate at 25% in comparison to Luxembourg who had 15%. 15% is the minimum allowed standard VAT rate in the European Union. Also in 2011, Hungary had the smallest Individual Income Tax Rate at 16% as opposed to Greece at 45%. This shows how different types of taxes are collected in different ways depending on the country one lives in. However, the crucial tax-type used in

this research would rather be wealth tax or tax on shares or dividends such a capital gains tax, since this would perhaps rather affect choices regarding stock market participation.

In Belgium, for example, there is no capital gains tax whereas in Austria the capital gains tax on selling shares range between 25% and 27.5%. France is probably the European Union country in which selling shares is most restricted, since it is taxed as income and income tax can be as high as 45%. The different taxes that households are exposed to in the HFCS are not available, however, in the country-level analysis, that follows in chapter five, dummy variables are used in order to see whether capital gains tax on shares affect stock market participation in different countries.

2.4 Conclusion

In this chapter most of the literature relating to stock market participation is described. The literature consists of individual-, household- and country-level influences and how all of them relate to participation in the European Union. It is very interesting how certain factors, such as education, contribute in two different ways depending on which level the investigation takes place. In the next chapter, an in depth description on the data used in this research is given.

CHAPTER 3
THE DATA

In December 2006, the Household Finance and Consumption Network (HFCN) was established and tasked by the Governing Council of the European Central Bank (ECB) to implement the Household Finance and Consumption Survey (HFCS). The HFCN also has the responsibility to act as a forum for research regarding survey data and to continue developing the HFCS. It is a network that involves a number of experts from the ECB in the fields of statistics, surveys and economics. The national central banks of the Eurosystem and a few national statistical organizations are also involved. The HFCN manages the HFCS, which is a survey that collects household-level data on the finances and consumption behaviour of households across countries in the European Union.

3.1 Introduction

Capturing real assets, financial assets, debt, expenditure, and useful characteristics of individuals of households, allows the Eurosystem Household Finance and Consumption Survey (HFCS) to be a comprehensive compilation of data. In-depth scientific analyses of household balance sheets, aligned with international standards, is possible.

The household-level data collected through the HFCS took place in two waves, with the third wave currently taking place. The research and information-gathering were done between 2010 and 2011, and between 2013 and 2015 for the first and second wave respectively. However, the data was only made available in April 2013 for the first survey and in December 2016 for the second survey. In the first wave, 62 000 households from 15 countries were surveyed, and in the second wave more than 84 000 households from 20 countries were surveyed. The countries that participated in the survey are displayed in the table below.

The HFCS follows an ex ante harmonised methodology in that it uses an output-oriented approach where survey variables are provided according to a communal set of definitions and standards. This feature makes the HFCS comparable across all Euro area countries. A set of core output variables have been developed and all participating countries are required to report these variables to the ECB. In addition to these variables, a set of non-core variables have also been proposed, however, countries can collect these variables voluntarily. Nonetheless, even though a common set of core variables are available, there are still significant cross-country differences in the participating countries and therefore, the questionnaires sent out in each country requires room for flexibility and certain adaptions.

Because of the large cross-country heterogeneity in the European Union regarding financial markets, banking regulations, pension systems and fiscal policies, household samples have been designed for each country. This is done in order to ensure that the results are comparative, but more importantly, country-representative.

Country	Survey	Country	Survey
1. Austria	1,2	11. Italy	1,2
2. Belgium	1,2	12. Latvia	2
3. Cyprus	1,2	13. Luxembourg	1,2
4. Estonia	2	14. Malta	1,2
5. Finland	1,2	15. Netherlands	1,2
6. France	1,2	16. Poland	2
7. Germany	1,2	17. Portugal	1,2
8. Greece	1,2	18. Slovakia	1,2
9. Hungary	2	19. Slovenia	1,2
10. Ireland	2	20. Spain	1,2

Table 1: Countries Surveyed in the HFCS

3.2 The HFCS Questionnaire

In the HFCS the main unit of collection are households, however, some data are also collected at individual level. Here, a household is defined as an individual living alone or a group of people living together in the same private dwelling. The individual or individuals share household expenses and take expenditure decisions together. Members of a household can be defined as:

- Individuals who are related to one another and live together.
- Individuals who share household expenses and live together, but are not related to one another.
- Individuals who usually live together, but might be temporarily absent because of travel, business or boarding school.
- Children who receive education away from home, but that are still dependent on the household financially.

All employees of the household, short-time visitors or subtenants are considered separately. The information required for the HFCS is mainly collecting using Computer-Assisted Personal Interviews (CAPI). This means, the interviews are face-to-face, and the interviewer uses a computer to record the answers from the respondents. Before the interviews can start a few important aspects needs to be considered. The main household respondent needs to be chosen, and they are called the financially knowledgeable person (FKP). Since financial

information is collected over a whole household, the FKP is responsible for providing this information.

The topics that are covered by the HFCS core questionnaires, are made up of nine categories. These sections are then further split between personal level and household level. Personal level cover information collected individually for all household members aged 16 and older. The topics that are covered in the survey are:

1. Demographics

   This section consists of basic information regarding all household members. It includes: age, gender, country of birth, and the duration of living in the specific country. Marital status and highest level of education achieved are also collected, but only for household members aged 16 and older.

2. Real assets and their financing

   This section covers a large amount of valuable information. Current values of real estate assets, vehicles, valuables and a remaining item for other real assets are collected. Further, it is also made known how much rent is paid, how many properties are privately owned, and what the purpose of each property owned is.

   Questions are also asked on the characteristics of each mortgage collateralised by the properties. Finally, information is also gathered with regards to loans collateralised by real estate. The purpose of the loan, the year when the loan was issued, the initial amount borrowed, the initial maturity, details on the interest rate, and the monthly payments made are collected.

3. Other liabilities and credit constraints

   Here, all information regarding non-mortgage debt instruments are collected. This includes instruments such as leasing contracts, credit lines or credit overdrafts, credit cards, private loans or other loans not collateralised by real estate. The final part of this section gathers information regarding loan application. These questions allow the survey to understand which households have been refused for credit or are experiencing credit constraints.

4. Private businesses and financial assets

   This section is divided into two parts, were the first part gathers information regarding self-employment private businesses and the second part looks at financial assets. Financial assets include sight accounts, saving accounts, mutual funds, bonds, publicly traded shares, additional assets in managed accounts, money payable to the household, and a remaining question on any other financial assets. Lastly, this section also includes a self-assessment question on the risk attitudes of the household members.

5. Employment

   The questions in this section are only asked to household members aged 16 and older.

Firstly, the labour status of each household member is collected. Those household members, having an occupation, are further asked questions regarding their status, the sector in which they work, the hours they work etc. Those that currently do not have a job, are also asked questions on previous employment if relevant. All household members currently employed, are also asked what their planned age of retiring is.

6. Pensions and life insurance policies

   In this HFCS, pension wealth is classified as voluntary pension schemes and life insurance contracts, occupational pension plans and public pension plans. This section is marked as indicative and open to specific national implementations. For example, in Finland and in the Netherlands, defined-benefit (DB) schemes for occupational pensions are substantial components of household wealth, even though it does not meet the definition of occupational pension schemes with an account balance. In this case, one would find it natural that a non-core variable regarding occupational plans without an account balance, has been proposed for these countries.

7. Income

   One of the biggest purposes of the HFCS is to establish information on household wealth. Therefore, the biggest target of this section is to gather information regarding the main components that make up the total gross household income. This section looks at personal level questions and household level questions. The reference period used in for this section is 12 months.

8. Intergenerational transfers and gifts

   This section contributes to understanding the wealth accumulation patterns of households. Information on inheritances and considerable gifts are collected. Further, questions regarding expected inheritance and/or expected substantial gifts are also asked.

9. Consumption and saving

   This is a very important section, since according to literature, information regarding consumption and saving can be used to infer total household consumption. This section includes information on: amount spent on food, in and out of home, amount spent on utilities, and overall spending on consumer goods and services. All information refers to spending in a typical month.

The core HFCS variables is covered by the questionnaire explained above. All of the variables that will be used in this research are core variables and they will be explained in more depth in the next chapter on Methodology and Results.

3.3 Sample Design

When choosing sample designs it is very important that it be accurately representative of the reality of its target population. Survey data are collected from a sample that represents a

larger population. Therefore, each observation in the dataset represents multiple observations in the total population of interest. One of the biggest concerns for wealth surveys, is gathering information from the wealthy and ensuring it is representative of the true population. If the sample design is not a good representation of the true population it will lead to large errors in estimation procedures, such as coverage errors, sample selection and estimation bias.

There are many ways of selecting a sample, but the most straightforward way is using simple random sampling-sampling units that are selected from the sampling frame with equal probability. Usually, a single-stage random sampling design is however impractical. The reason being that it is difficult to draw up a complete list for the entire population, since the sample might contain too few representatives of certain sub-populations, or because it is expensive or logistically difficult to visit all households in a randomly selected sample. These and other constraints lead to many surveys making use of what is called complex survey design.

The HFCS uses probability sampling. This means, each household in the true population is considered to have a non-zero probability of being selected to participate in the sample and the probability of this selection is known beforehand. Even though probability sampling is used in the HFCS, countries have also used a variety of other approaches relevant to the data they have available. Stratification is one of these popular techniques. It is also important to note that all countries used sample sizes that were country representative.

Further, since wealth is unequally distributed, all participating countries are encouraged to use methods to oversample the wealthy. It is well-known that the distribution of wealth is skewed, and that certain assets are only held by the wealthy, i.e., by a small part of households. For this reason, the sample will only be accurately representative of the population if a large proportion of wealthy households are used. However, collecting data from the wealthy is a strenuous task. This is because, firstly, wealthier households are more likely to be absent from their primary residence for longer periods at a time, and secondly, the wealthy might refuse to participate since they do not have time. If this non-response rate is left unattended, it will lead to measurement bias. For this reason, fifteen out of the twenty countries did make use of strategies to oversample the wealthy.

Further, stratification of the population prior to sample selection is used. This means, the population is divided into relatively homogeneous sub-populations, known as strata, and then a simple random sample is taken from each stratum. Strata can consist of geographical areas, but it can also consist of socio-demographic groups. After strata is selected, clusters are made. This means the strata is further divided. Clusters are also known as primary sampling units (PSUs). Finally, after multiple layers, individual households are chosen.

In the HFCS, region and population size of regional units were the most used stratification variables. In most cases regions were divided according to the degree of urbanisation. Some of the other stratification criteria that were also used includes personal average income, labour status and personal taxable wealth.

Another important feature from the HFCS is the use of replacements. Replacements are

reserve units that replace non-response units during the information-gathering process. In the HFCS replacements are done under extremely strict control, and so interviewers can only call for a replacement once certain criterion has been met and after special efforts have been made to renovate refusing units.

3.4 Unit Non-Response and Weighting

Unit non-response occurs when information cannot be obtained from a qualified unit. It increases the variability of estimates drawn from a sample. Further, since non-response is non-randomly distributed, it may introduce biased estimates. Because of the sensitivity of the wealthier households, it has been seen that unit non-response is generally higher in wealth surveys than in income surveys (Pérez-Duarte et al., 2010). For this reason, it is important that the basic survey weights are adjusted to account for non-response. In the HFCS a lot of attention is given to minimise non-response rates in order to minimise the non-response bias. This is done by emphasising the use of best practices. The following indicators are used to examine the quality of the HFCS:

$$Response\ Rate = \frac{Achieved\ Interviews}{Eligible\ Sample\ Units}$$

$$Refusal\ Rate = \frac{Sample\ Units\ Refusing\ to\ Participate}{Eligible\ Sample\ Units}$$

$$Cooperation\ Rate = \frac{Achieved\ Interviews}{Contacted\ Sample\ Units}$$

$$Contact\ Rate = \frac{Sample\ Units\ Contacted}{Eligible\ Sample\ Units}$$

The use of weights in survey data can help to overcome, to a certain extent, bias caused by unit non-response as well as other irregularities present in the sample. In the HFCS, all participating countries uses common high-level weighting procedures in order to ensure that the data is comparable. Computation and adjustment of weights in the HFCS takes into account the following four factors:

1. Probability of selecting a unit
2. Coverage issues
3. Unit non-response
4. Calibration of external data

The formula for the design weights are defined as the inverse of the selection probability of the unit in consideration. The unit can be either responding or non-responding. The weighting procedure used in the HFCS proceeds in the following consecutive manner:

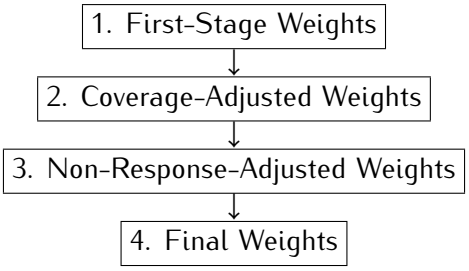

Figure 1: Weighting Procedure used in the HFCS

Moving from first-stage weights to coverage-adjusted weights means adjustments are made for both non-eligible units in the initial sample and for the probabilities of multiple selection. Adjusting the coverage-adjusted weights even further, leads to the non-response-adjusted weights. This adjustment is made by estimating the response probabilities as functions of the responding and non-responding households' characteristics. Then the coverage-adjusted weight of each unit in the sample is divided by the response probability. In the HFCS these adjustments are specifically made at group level, however it can also be made at individual level. This second adjustment that gives non-response-adjusted weights is very important in order to minimise bias that is introduced by inconsistencies between the characteristics of the respondents and the non-respondents.

Finally, to obtain the final weights, auxiliary information is required. This information aligns the estimates of variables in use with the corresponding population estimates. This adjustment reduces bias that arises because of inconsistencies between the sample and the population that was not properly captured by the coverage-adjusted weights. Effective calibration would require the calibrated variables to be almost perfectly comparable in both the survey and the population. Further, the calibrated variables need to be correlated with the study variables, but not too closely correlated with each other. The following table shows the different calibration variables used by the 20 different countries in the HFCS:

Country	Age	Gender	Household Size	Region	Education	Home Ownership	Municipality Size	Labour Status	Other
Austria			√	√		√			
Belgium	√	√	√	√					
Cyprus	√	√	√	√					
Estonia	√	√	√	√	√	√			Urbanisation
Finland	√	√	√	√					Income, listed share holders
France	√	√		√	√			√	Urbanisation, wealth
Germany	√	√	√	√	√	√	√	√	Nationality
Greece			√	√		√			
Hungary	√	√		√				√	Locality
Ireland	√	√	√	√		√			Deprivation
Italy	√	√		√			√	√	Income
Latvia	√	√		√					Income
Luxembourg	√	√	√					√	Nationality
Malta	√	√	√	√				√	
Netherlands	√	√			√	√			
Poland	√	√	√						Urbanisation
Portugal	√	√	√	√					Home loans
Slovakia	√	√	√	√				√	
Slovenia	√	√	√	√					
Spain	√	√	√				√		

Table 2: Calibraton Variables per Country (HFCS, 2013)

From the above table one sees that age, gender, household size and region are the most common used calibration variables by all countries in the HFCS.

In the following table, the outcomes of the above weighting procedures are presented. The total sum of the final estimation weights corresponds to the total size of the population, i.e., in this data set, it represents the total number of households. The mean weights represent the average number of households shown by one net sample. Finally, the coefficient of variation represents the relative standard deviation of the final estimation weights, i.e., the variability of the final weights in the net sample.

Country	Sum	Mean	Coefficient of variation (%)
Austria	3 862 526	1 289	41
Belgium	4 796 647	2 143	106
Cyprus	303 242	235	156
Estonia	571 857	258	49
Finland	2 662 745	238	81
France	29 017 678	2 441	85
Germany	39 672 000	8 896	118
Greece	4 266 745	1 421	55
Hungary	4 127 671	665	64
Ireland	1 690 073	312	52
Italy	24 694 122	3 028	89
Latvia	828 907	690	87
Luxembourg	210 965	132	70
Malta	159 427	160	63
Netherlands	7 590 228	5 911	56
Poland	13 492 882	3 905	60
Portugal	4 017 981	647	114
Slovakia	1 855 392	869	104
Slovenia	820 541	321	66
Spain	17 429 812	2 855	148

Table 3: Outcomes of Weighting Procedures per Country (HFCS, 2013)

Therefore, by making use of a weighting procedure, not a very large number of households are required in order to represent the whole population. This is a very useful and effective tool used in surveys.

3.5 Item Non-Response and Multiple Imputation

Since certain observation in the HFCS has no valid response, they need to be imputed. According to Rubin (1996), the main purpose of imputation is to preserve the characteristics of the distribution of the variables as well as the relationship between different variables. A few simple methods for dealing with item non-response can also be used. The simplest method being to fill in missing values with the mean value of observed data. However, this leads to a large decrease in variance and so would not reproduce the distributions obtained from the data at hand. Other methods include stochastic regression imputation and drawing imputed values from certain distributions. Unfortunately, even though most of these methods preserve the distribution of the imputed values, the uncertainty as a result of the process is unclear.

The solution, therefore, is using multiple imputation (MI). This leads the imputed values, based on different random draws, to be used as missing values. This means, M copies of the complete dataset are obtained. When comparing MI to single imputation, it shares the advantage of allowing complete-data methods of analysis and using all the available information. The extra advantage of MI is that the uncertainty resulting from the imputation can be taken into account. This entails the resulting variance to not be underestimated.

The MI models in the HFCS are constructed in much the same way as similar surveys by the Federal Reserve Board and Banco de Espana. Five implicates are available for each missing value, i.e., in the HFCS $M=5$. On top of this, a broad-conditioning approach is also used, which means that a large number of covariates are included in the models for all variables to be imputed. In the HFCS, MI is based on the assumption of "missing at random", therefore, the complete data set's distribution depends on the observed data conditional on the determinants of item non-response and other covariates.

3.6 Variance Estimation

This section allows researchers to distinguish between statistically significant results and results that are merely caused due to the random nature of the sample in use. This is done using variance estimation. When dealing with survey data, variance estimation is extremely important. If estimates have underestimated variance it will lead to incorrect conclusions and results. On the other hand, if the variance is overestimated, the usefulness of the data decreases substantially. Several component make up variance. One is the sampling error due to random selection of units and the other is item non-response, which was described previously. Ultimately, total variance estimation and multiple imputation will be connected when examining the HFCS in this research.

In order to effectively use the HFCS, the variance of many indicator variables needs to be computed. In this research bootstrapping is used. The motivation behind using a replication-based method, such as bootstrapping, is because sampling error is related to the sample design and therefore its estimation relies on the precision of the sample design's information. Even if all of the information is available, like in the case of the HFCS, it is extremely difficult to calculate the variance estimates. For this reason, replication based methods is used since it provides a robust and flexible way to estimate variance.

The rescaling bootstrap of Rao and Wu (1988), that was later further specified by Rao, Wu and Yue (1992), is used. Like all variants of bootstrap methods, the rescaled bootstrap is computationally very intensive. However, it has been implemented in computer software, such as SAS and Stata, which makes it a little bit easier to use. Mathematically the Rao-Wu bootstrap can be defined as follows. Let the number of strata be indexed by $h = 1, 2, \ldots, H$, where there is $i = 1, 2, \ldots, N_h$ units in each of them and out of which n_h are sampled without replacement. Therefore, the sampling fraction is defined as:

$$f_h = \frac{n_h}{N_h}, \tag{1}$$

Further, each unit, defined as (h,i), has a variable of interest y_{hi} and a weight, defined as

$$w_{hi} = \frac{N_h}{n_h}, \tag{2}$$

assigned to it. This results in a total variable of:

$$Y = \sum_{h=1}^{H} \sum_{i=1}^{N_h} y_{hi}, \tag{3}$$

which can then be estimated without bias by making use of the weights as follows:

$$\widehat{Y} = \sum_{h=1}^{H} \sum_{i=1}^{n_h} w_{hi} y_{hi}, \tag{4}$$

Finally, the parameter of interest θ is then defined as a function of this total amount as $\widehat{\theta} = f(\widehat{Y})$. Now, this method is taken a step further, since rescaling needs to be taken into account. Therefore, the following procedure is carried out $B = 1000$ times.

- From each stratum, a sample of size $m_h = n_h - 1$ is taken with replacement.
- The units (h, i) are re-sampled $r^*_{h_i}$ times and the weights are taken as:

$$w^*_{h_i} = (1 - \lambda_h + \lambda_h \frac{n_h}{m_h} r^*_{h_i}) w_{h_i} \tag{5}$$

with $\lambda_h = \sqrt{\frac{m_h(1-f_h)}{n_h - 1}}$

- The bootstrap total is then computed as:

$$\widehat{Y_b^*} = \sum_{h=1}^{H} \sum_{i=1}^{n_h} w_{h_i}^* y_{h_i} \; and \; \widehat{\theta_{*_b}} = f(\widehat{Y_b^*}) \tag{6}$$

- Finally, the bootstrap variance is calculated as follows, where $\bar{\hat{\theta}}$ is the mean of the total bootstrap over all the iterations:

$$V_{*(\theta)} = \frac{1}{B-1} \sum_{b=1}^{B} (\widehat{\theta_{*_b}} - \bar{\hat{\theta}}_*)^2 \tag{7}$$

As was mentioned earlier, it is required that the replicate weights for the variance estimation be combined with the multiple imputation that was described in a previous section. A weight of w_i is assigned to each observation. However, using multiple imputation, there are M implicates indexed by m and further from the bootstrapping there are B replicate weights w_{i_b} that is indexed by b. In this research $M = 5$ and $B = 1000$.

Now, to calculate the estimator of interest θ_m, the estimation weight w_i of each implicate m is used. The variance of the estimator is then estimated from the bootstrap weights as follows:

- For the $B = 1000$ replicates with their w_{i_b} replicate weights, $\theta_{m_b}^*$ can be calculated with a mean of $\bar{\theta}_m^* = \frac{1}{B} \sum_{b=1}^{B} \theta_{m_b}^*$
- The partial variance, which is also the standard bootstrap variance used in the complete case analysis, for implicate m is then defined as:

$$U_m = \frac{1}{B-1} \sum_{b=1}^{B} (\theta_{m_b}^* - \bar{\theta}_m^*)^2 \tag{8}$$

- The total variance can then be calculated using the MI formula as follows:

$$T = W + \left(1 + \frac{1}{M}\right) Q \tag{9}$$

Here,

$$W = \frac{1}{M} \sum_{m=1}^{M} U_m = Within \; variance \tag{10}$$

and

$$Q = \frac{1}{M-1} \sum_{m=1}^{M} (\theta_m - \bar{\theta})^2 = Between \; imputation \; variance \tag{11}$$

Using multiple imputation theory, the quantity $(\theta - \bar{\theta}) T^{-\frac{1}{2}}$ is approximately distributed as a t-distribution that has $v_m = (M-1)(1 + \frac{W}{1+\frac{1}{M}})Q^2$ degrees of freedom.

3.7 Conclusion

This chapter introduced and explained the dataset, namely the HFCS, that is used in this research. It is clear that the HFCS data are characterised by many special features that must be taken into account when using the data. Not only is the data multiple imputed, but it also contains survey weights and replicate weights. All of the features mentioned in this chapter will be taken into account when analysing the data. Analysis includes, but is not limited to, performing regressions, estimating variables, and calculating summary statistics. In the next chapter, the methodology used to perform the analysis will be looked at as well as the results that were found.

CHAPTER 4
METHODOLOGY AND RESULTS: INDIVIDUAL- AND HOUSEHOLD LEVEL

4.1 Introduction

Household survey variables are seldom continuous and fully observed. They can, for example, be discrete (age), censored (consumption expenditure), or durational (expected time to retirement). The same argument holds for country-level variables. For this reason, multivariate analysis of a dependent variable requires non-linear estimation procedures. In this chapter, the methodology used in this research will be discussed and the results obtained from applying the different methods will be fully examined. This chapter is divided into two main parts, namely, mathematical background, and individual and household-level influences.

Firstly, the mathematical background required to understand the different models being used, will be looked at. Thereafter, each predictor variable will be examined and explained individually. Aside from the literature that has already promoted certain predictor variables, different reasons for choosing specific variables within the HFCS will become clear. Next, probit models will be used in order to predict which of the initially chosen predictor variables are indeed significant in predicting stock market participation in the European Union amongst households. Tobit models will also be used on order to help answer the questions around how much investment takes place once participation is a given. All calculations in this research were done in STATA, which is a data analysis and statistical software tool.

4.2 Mathematical Background

4.2.1 Binary Dependent Variable

The first step of the analysis in this research, was to answer the question regarding if households hold stocks or not. For this, the dependent variable is obviously binary, since the answer can only take on two values. If y_i is the answer of interest, then $y_i = 1$ indicates that a certain household do hold stocks and $y_i = 0$ indicates the opposite, i.e., a household does not hold any stocks. In general, a binary response model takes the following form:

$$E[y_i|\mathbf{X}_i] = P(y_i = 1|\mathbf{X}_i) = F(\mathbf{X}_i'\boldsymbol{\beta}) \tag{12}$$

where $E[\ |\ ]$ indicates conditional expected value and $P(\ |\ )$ probability. Different functional forms for $F(\ )$ will result in different specific models. A very simple example is the linear case, where $F(\mathbf{X}_i'\boldsymbol{\beta}) = \mathbf{X}_i'\boldsymbol{\beta}$ and then results in the linear probability model (LPM). Unfortunately, this simple model has a few drawbacks. Often it is believed that the LPM can consistently be estimated using the ordinary least squares (OLS), however, this has been proved to only be true if $\mathbf{X}_i'\boldsymbol{\beta}$ has a zero probability of lying outside the range (0,1) (Horrace and Oaxaca, 2006).

Unfortunately, the predicted probability given by the equation above, is not constrained to only fall in the range (0,1) and so it makes it difficult to interpret if such a situation does arise.

Another problem with the OLS is that the errors are non-normal and heteroscedastic. This means the estimator may not be efficient and conventional standard errors are in most cases invalid. This can partially be fixed using weighted least squares (Wagstaff et al., 2007), however, a common response to these problems is to rather choose a functional form for $F(\ )$ that forces estimated probabilities to lie within the (0,1) range. In order words, fitting a functional form that is non-linear. The most popular choices are the cumulative standard normal distribution and the cumulative standard logistic distribution. They lead to the probit and logit models, respectively.

To explain these models, it helps to think of the binary response as being driven by some unobservable, underlying characteristic. If y_i^* represent the propensity to participate in the stock market, then when, for example, $y_i^* > 0$, i.e., breaches some threshold, it means the individual or household in question participates in the stock market. If one then specifies the latent variable to be a linear function of observable and unobservable factors, such that, $y_i^* = \mathbf{X}_i^{'}\boldsymbol{\beta} + \epsilon_i$, and choosing the distribution of the error term, ϵ_i , to be either standard normal or logistic, gives the probit or logit models, respectively. In this case estimation is no longer carried out using OLS, but rather using maximum likelihood estimation (MLE).

In most cases, it is not that important whether one chooses to use a probit or a logit model, since they are usually very similar. Both methods will yield similar inferences. The logit model is more popular in health sciences like epidemiology partly because coefficients can be interpreted in terms of odds ratios. Probit models can be generalized to account for non-constant error variances in more advanced econometric settings, also known as heteroskedastic probit models, and hence are used more generally by economists and political scientists. If these more advanced applications are not of relevance, then it does not really matter which method one uses. However, in this research a probit model will be used.

In the probit model, the parameters $\boldsymbol{\beta}$, as shown above, provide information on the relative, partial effects on the latent index y_i^*. Therefore, if one requires the estimated partial effect of a continuous regressor, say X_k, on a conditional probability, it can be derived as follows:

$$\frac{\delta P(\mathbf{X}_i^{'}\widehat{\boldsymbol{\beta}})}{\delta X_{k_i}} = \frac{\delta F(\mathbf{X}_i^{'}\widehat{\boldsymbol{\beta}})}{\delta X_{k_i}} = f(\mathbf{X}_i^{'}\widehat{\boldsymbol{\beta}})\widehat{\boldsymbol{\beta}}_k \tag{13}$$

where, $f(\ )$ represents the standard normal density function. Given dummy regressors, X_k, the estimated partial effects can be calculated as follows:

$$F(\widehat{\beta}_1 X_{i_1} + ... + \widehat{\beta}_{k-1} X_{i_{k-1}} + \widehat{\beta}_k) - F(\widehat{\beta}_1 X_{i_1} + ... + \widehat{\beta}_{K-1} X_{i_{k-1}}) \tag{14}$$

From equations, (13) and (14), one clearly observes the partial effects to be observation specific and not contents.

4.2.2 Number of Independent Variables

When dealing with any type of regression model, it is very important to choose the right number of independent variables. One cannot just throw in every single variable available in the dataset that is being used. However, using too few variables could do just as much harm. The most important consideration when deciding on which variables to use, is to look at its theoretical relevance (Dranove, 2004). One of the most practical reasons to keep unimportant variables out of one's final regression model is due to the fact that added arbitrary variables takes up valuable degrees of freedom. This in turn reduces precision of estimates of the valid predictor variables by increasing standard errors. This imprecision is enlarged when few observations are available in the data. Luckily, the HFCS contains a lot of observations, however, variables should still be chosen with caution. According to Dranove, the following is valuable rules of thumb:

- If a good predictive model is being used, i.e., one where most predictors are significant, one should not use more than one predictor for every 5 observations.
- If a weaker model is being used, i.e., one where few predictors are significant, not more than one predictor should be used for every 10 observations.
- However, using categorical variables, should be dealt with a bit different, as each included category can be seen as half of a "normal" predictor.

There is another few problems to consider. Firstly, unimportant variables may be statistically significant due to random chance and reproducing the chosen model and methods on other data might not work. Another problem that should not be overlooked, is the fact that a certain variable might be highly correlated with the dependent variable. The correlation could allow the predictor variable to appear wrongly insignificant.

It is obviously also possible that one or more predictor variables are correlated, and this should also be taken into account when choosing variables. If for example, one uses a model with 1000 observations in which two of the predictor variables have a correlation of, say, 0.9 with each other. Very roughly, this will mean the two predictors will move together 90% of the time and so move independently of each other for 10%, or 100 observations. This simple example verifies that having more observations, i.e., a larger sample, will help to tolerate higher correlations among predictors.

There are a few warning signs to look out for when testing multicollinearity. Some are mentioned below.

- When predictor variables are entered into the regression model one at a time they appear significant, however, when entered into the model together, they are insignificant.
- An F-test that shows added predicted power from two correlated variables, but the both have insignificant coefficients.
- When predictor variables have the same sign when used interdependently, but opposite signs when used together.

With regards to using too few variables, it is important to remember adding significant predictor variables improves not only the predictive power of the model, but also improves the precision of the estimates. Another thing that might occur when using too few predictor variables is omitted variable bias. This occurs when relevant variables are omitted incorrectly by a statistical model. The bias leads the model to assign the effects of the omitted variables to the estimation effects of the variables that are included.

4.2.3 Limited Dependent Variable

After finding all the significant variables that influence stock market participation and realising how little number of households in the HFCS actually partake in the stock market, another important question arises: from the households that do hold stocks, how much do they hold? This is a important question, since there is a big economical and risk aversion difference between two households holding stocks, but the one invests, say, 60% of their portfolio in stocks, whereas the other one only invests, say, 5%.

A limited dependent variable is one that is continuous over the biggest part of its distribution, however, it has a mass of observations at one or more specific values. A number of statistical approaches can be used for modelling a limited dependent variable, such as two-part models, sample selection models and hurdle models, however, in this research the Tobit model will be used.

The Tobit model assumes a single decision and the model can be described using a latent, desired level of investing:

$$y_i^* = \mathbf{X}_i^{'}\boldsymbol{\beta} + \epsilon_i, \;\; \epsilon_i \sim IN(0, \sigma^2) \tag{15}$$

The observed investment is assumed to be related to the latent value using the following equation:

$$y_i = \begin{cases} y_i^*, & \text{if } y_i^* > 0 \\ 0, & \text{otherwise} \end{cases} \tag{16}$$

The Tobit model is also estimated using MLE and the predicted amount of investment is based on the following equation:

$$E[y_i|\mathbf{X}_i] = P(y_i > 0|\mathbf{X}_i)E[y_i|y_i > 0, \mathbf{X}_i] \tag{17}$$

where the second part can be formulated as:

$$E[y_i|y_i > 0, \mathbf{X}_i] = \mathbf{X}_i^{'}\boldsymbol{\beta} + \boldsymbol{\sigma}\lambda_i, \;\; \lambda_i = \frac{\phi(\frac{\mathbf{X}_i^{'}\boldsymbol{\beta}}{\boldsymbol{\sigma}})}{\Phi(\frac{\mathbf{X}_i^{'}\boldsymbol{\beta}}{\boldsymbol{\sigma}})} \tag{18}$$

where, $\phi(\,)$ and $\Phi(\,)$ are the standard normal probability density and cumulative density functions and λ_i is defined as the inverse Mill's ratio. The inverse Mill's ratio arises in regression analysis to take account of a possible selection bias. If a dependent variable is censored it causes a concentration of observations at zero values. Tobin (1958), first came to

identify this problem by showing that if this is not taken into consideration in the estimation procedure, an ordinary least squares estimation will produce biased parameter estimates.

In the next section, probit models are run over all the different individual- and household-level variables available in the HFCS in order to better understand which of these variables highly influence stock market participation.

4.3 Individual- and Household-Level Influences: Probit Models

A lot of research has been done regarding the first wave of the HFCS, however, the first wave's field work was carried out between 2010 and 2011, i.e., the global financial crisis and its after effects are captured within this survey. Adding the second wave of the HFCS, which was carried out between 2013 and 2015, means that the effect of the global financial crisis might not be the same as was experienced in the first wave. Nonetheless, the first and second wave will be used for this research, and it will be very interesting to see how the results differ from previous literature and investigations that only used the first wave.

The household level variables that will be used in order to help answer the question on stock market participation are amongst other things: risk attitude, net wealth, income, education, age, marital status, gender, occupation and retirement. For this purpose, probit models are used, however, only looking at the coefficient of the probit model's result is not enough. In linear regression, if the coefficient on a certain independent variable x is, say, β, then a 1-unit increase in x increases the dependent variable Y by β. In probit regression it does not work the same way. The increase in the dependent variable is not constant. Mathematically the difference can be explained as follows:

For the linear regression the model takes the following form:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n \tag{19}$$

so that,

$$\frac{\delta Y}{\delta x_i} = \beta_i \tag{20}$$

The probit model, however, takes the following form:

$$Y = \Phi(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n) \tag{21}$$

so that,

$$\frac{\delta Y}{\delta x_i} = \beta_i \phi(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n) \tag{22}$$

Here, other than with the linear model, the expression does not just depend on β_i, but on the value of all the other x_i's in the equation as well. Therefore, in order to calculate the marginal effect of x_i on Y, one has to choose values for every x_i in one's model. Typically the means of these values are used and that is also what will be used in this research. In all

the result tables to follow, the coefficients from the probit model will be displayed alongside the marginal effect from using the equation as above. From this, one realises the coefficient helps to answer the direction of the effect on stock market participation from the different independent variables, whereas the marginal effect value shows the actual change in stock market participation from one unit change in the different independent variables.

Together with the coefficient and the marginal effect, a test statistic, say, z is displayed in brackets. It represents the ratio of the coefficient to its standard error. The z value follows a standard normal distribution which is used to test against a two-sided alternative hypothesis that the coefficient is not equal to zero. In order to understand the z statistic, one examines the p-value. This is the probability that the z test statistic would be observed under the null hypothesis and that a particular predictor's regression coefficient is zero. For a given alpha level, $p>|z|$ determines the statistically significant level of a parameter. In this research significance levels of 10%, 5% and 1% will be looked at. They are represented by either *, ** or *** depending on the significance level and this can be seen alongside the brackets containing the z statistic.

4.3.1 Risk Attitude

Understanding an individual's attitude towards risk is one of the most important aspects regarding stock market participation. Individuals who are not willing to take financial risks will most probably not invest in the stock market. In the HFCS all individuals are asked to describe the amount of financial risk they are willing to take by choosing between the four statements listed below:

1. Not willing to take any financial risk
2. Take average financial risks expecting to earn above average returns
3. Take above average financial risks expecting to earn above average returns
4. Take substantial financial risks expecting to earn substantial returns

In the table below, the amount of participants within each investment attitude category are displayed. The percentages in brackets represent the percentage of each category that do participate in the stock market. These results are no surprise since individuals willing to take financial risk are probably also those willing to invest in stocks.

	Participate	
Investment Attitude	**No**	**Yes**
1	135 880	10 589 (7%)
2	42 033	11 594 (22%)
3	12 033	2 631 (18%)
4	1 988	671 (25%)

Table 4: Investment Attitudes and Participation

From the results one sees the largest number of households fall in the first category of the investment attitudes. This category also contains the smallest amount of participating households. The smallest amount of the households fall in the fourth category and, not surprisingly, consists of the largest number of participants. These results show the importance of understanding investment attitudes when investigating stock market participation.

In the next table, the results from running a probit model over investment attitude is shown. The first variable, namely, Investment Attitude, is built using all categories at the same time, whereas the others are dummy variables focussing on one category at a time. For example, Investment Attitude 1 takes on the value 1 when a household falls in category 1, and the value 0 otherwise. The same holds for Investment Attitude 2, Investment Attitude 3 and Investment Attitude 4. The Investment Attitude variable is run without including the dummy variables, namely, Investment Attitude 1 to Investment Attitude 4. Thereafter, the first two dummy variables are ran, showing the negative effect towards stock market participation. Finally, the last two dummy variables, namely Investment Attitude 3 and Investment Attitude 4, are ran.

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
Investment Attitude	0.41	0.07
	(20.34)***	(28.92)***
Investment Attitude 1 (dummy)	-0.68	-0.18
	(-13.23)***	(-19.48)***
Investment Attitude 2 (dummy)	-0.43	-0.02
	(-10.45)***	(-10.71)***
Investment Attitude 3 (dummy)	0.14	-0.05
	(12.23)***	(-16.47)***
Investment Attitude 4 (dummy)	0.41	0.01
	(1.34)	(1.62)

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 5: Participation by Investment Attitude - Probit model

As expected, investment attitude as a whole contributes positively towards participation. However, investigating each attitude by themselves, the results are a bit different. Investment Attitude 1 contributes negatively and significantly to participation. This is not surprising, since individuals who are not willing to take financial risk will not partake in a risky investment such as the stock market. Looking at Investment Attitude 4, as expected a positive relation is seen towards participation. Interestingly, the marginal effects, except for Investment Attitude 1, is very close to zero showing that overall investment attitude might not influence stock market participation in the HFCS as greatly as one would have expected.

4.3.2 Net Wealth

Almost all papers and studies regarding wealth of households or individuals, have found large heterogeneity across countries and within countries. Although the result of wealthier households having the ability to own more assets (risky and non-risky) is not surprising, it does highlight the fact that there is a direct relationship between diversity of asset holdings and the level of wealth (Arrondel et al., 2014).

In this research net wealth will be measured as the difference between the total assets of the household, excluding public and occupational pension plans, and the total outstanding balance of the household's liabilities. The main components of household assets are household main residence (HMR), other real estate, risky financial assets (bonds, mutual funds and shares), safer financial assets (deposits, life insurance and voluntary private pension

plans), and business wealth which is interpreted as self-employment participation. Since this influence will be used for investigating stock market participation, shares are removed from the net wealth variable. The households' liabilities include outstanding mortgage debt on all properties owned by the household and outstanding other, non-mortgage debt such as outstanding balances on credit lines and/or overdrafts, on credit cards, and on all other loans.

Since the data used in this research is multiple imputed, it consists of more than 300 000 observations. For this reason, the net wealth variable was divided into 6 categories, making the divisions at the 25th percentile, the median, the 75th percentile, the 90th percentile and the 95th percentile. These categories therefore divide the poorest from the wealthiest. The reason the 90th and 95th percentiles are added is because of the skewed distribution of wealth. The following table shows the stock market participation of households in the different wealth categories.

	Participate	
Net Wealth	**No**	**Yes**
1	68 308	2 037 (3%)
2	73 700	5 061 (6%)
3	83 249	11 800 (12%)
4	49 584	15 665 (24%)
5	17 118	9 237 (35%)
6	20 028	19 339 (49%)

Table 6: Net Wealth and Participation

As expected, participation increases significantly together with wealth, with the largest participation percentage in the highest wealth category. The rapidly increasing percentages in the last net wealth categories further confirm the skewed distribution of wealth. This also confirms the literature.

Running a probit regression, firstly taking the log of total net wealth and then using the different wealth categories as dummy variables, the results below are found. As expected, wealth as a whole has a positive impact on participation. Running the dummy variables, however, the total opposite impact from being poor as opposed to being wealthy on participation, is confirmed. Moving from the third net wealth category to the fourth, the impact signs change. Further, as expected, the first net wealth category has the largest negative impact on participation, whereas the last category has the largest positive impact.

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
log(Net Wealth)	0.28	0.08
	(13.01)***	(27.21)***
Net Wealth 1 (dummy)	-0.93	-0.32
	(14.06)***	(-39.38)***
Net Wealth 2 (dummy)	-0.28	-0.24
	(12.05)***	(-41.96)***
Net Wealth 3 (dummy)	-0.04	-0.16
	(12.03)***	(-13.77)***
Net Wealth 4 (dummy)	0.42	0.16
	(13.03)***	(11.79)***
Net Wealth 5 (dummy)	0.65	0.23
	(15.05)***	(19.27)***
Net Wealth 6 (dummy)	0.91	0.31
	(16.04)***	(16.75)***

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 7: Participation by Net Wealth Category - Probit model

4.3.3 Total Gross Income

The income variable used in this research is defined as the total household gross income. This includes the following:

- The sum of all household members' employment or self-employment income.
- All income from public, occupational and private pension plans.
- All unemployment benefits and gross income from regular social transfers.
- All income from private transfers.
- All income from real estate assets.
- All income from financial investments excluding income from shares.
- All income from private businesses or partnerships.

- All income from other sources.

Just as with the net wealth variable, income is also divided into 6 categories, where the highest category represents those households who enjoy the largest amount of income. In the table below the number of individuals participating in the stock market per income category are shown.

	Participate	
Income	**No**	**Yes**
1	88 140	4 111 (4%)
2	73 256	7 178 (9%)
3	72 107	13 517 (16%)
4	45 658	15 062 (25%)
5	16 536	8 402 (34%)
6	16 290	14 869 (48%)

Table 8: Income and Participation

The results for the income categories are almost identical to the wealth categories above, with the highest percentage of participating individuals in the biggest income bracket. Running a probit regression on these categories the results below are found. As opposed to net wealth, the income variables change sign when moving from the second to the third category. However, the impact of the third category is almost zero. As expected, the first category has the largest negative impact and the last category the largest positive impact.

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
log(Income)	0.55	0.14
	(13.02)**	(14.65)***
Income 1 (dummy)	-0.76	-0.28
	(15.05)**	(-14.46)***
Income 2 (dummy)	-0.38	-0.20
	(16.04)**	(-13.56)***
Income 3 (dummy)	0.01	-0.13
	(14.04)**	(-16.12)***
Income 4 (dummy)	0.38	0.14
	(16.04)**	(17.11)***
Income 5 (dummy)	0.60	0.21
	(15.06)*	(19.92)***
Income 6 (dummy)	0.93	0.29
	(16.05)**	(15.99)***

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 9: Participation by Income Category - Probit model

4.3.4 Age

Sir Warren Buffet made his first investment when he was 11 years old and said that: "I was wasting my life until then." (Buffett, 2003). Even though investing has no age bar, it is not expected that many children follow Sir Warren Buffet's example. Age will also be used as an independent variable for explaining stock market participations. In the HFCS age is divided into 18 categories. The largest portion of the individuals that were surveyed are between 29 and 78 years of age, with approximately between 4000 and 7000 individuals per age group. At age 85 and above almost 10 000 individuals were surveyed. The table below shows investing individuals per age group as percentage of the age group they find themselves in at the time of the surveys.

	Participate	
Age Group	**No**	**Yes**
(0-6)	6	0 (0%)
(7-13)	6	0 (0%)
(14-15)	0	0 (0%)
(16-19)	3 475	870 (20%)
(20-24)	9 832	759 (7%)
(25-29)	15 054	1 165 (7%)
(30-34)	19 078	2 590 (12%)
(35-39)	22 742	3 852 (15%)
(40-44)	28 571	5 308 (16%)
(45-49)	30 412	6 400 (17%)
(50-54)	30 200	6 718 (18%)
(55-59)	29 194	7 430 (20%)
(60-64)	30 863	8 792 (22%)
(65-69)	24 172	6 436 (21%)
(70-74)	23 204	5 042 (18%)
(75-79)	19 139	3 380 (15%)
(80-84)	13 254	2 365 (15%)
85+	8 144	1 402 (15%)

Table 10: Age and Participation

From the above results and from the graph below, one sees that age together with participation follows an almost upside-down U-shape, as expected.

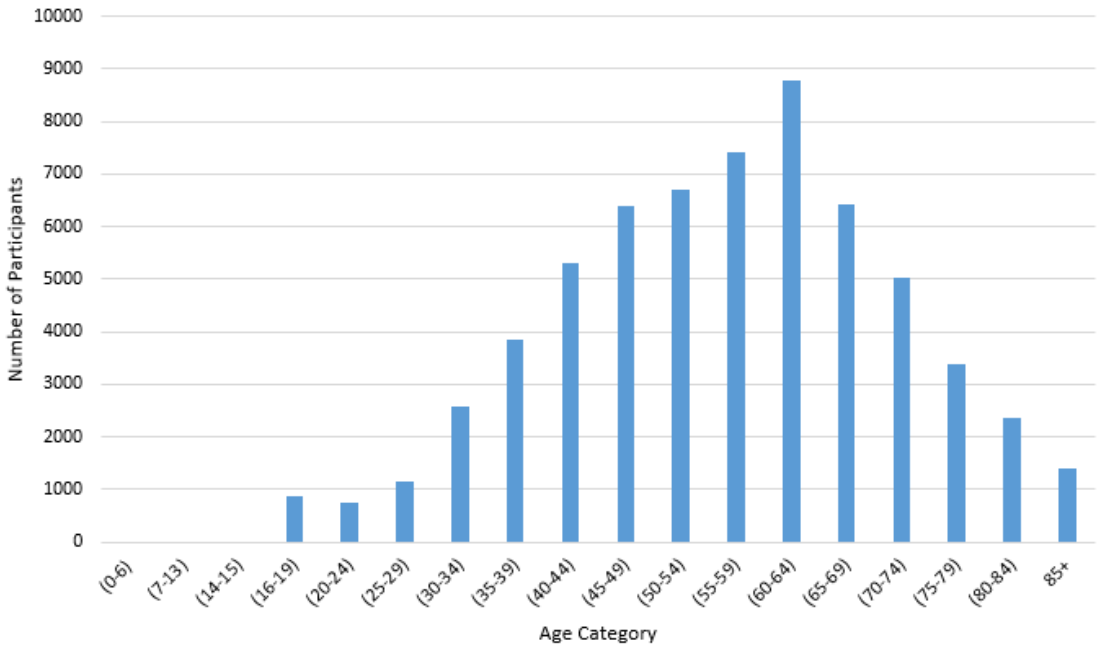

Figure 2: Stock Market Participation vs Age

In this research, the age variable is divided into four groups in order to distinguish between the different stock market participation percentages. Group 1 is from age 15 to 34, group 2 from age 35 to 54, group 3 from age 55 to 74, and group 4 is all ages above 75. From the above results one expects group 2 and group 3 to contribute the most towards positive stock market participation. In fact when only using the four different age variables in a probit model the following results are found, clearly showing the significance of group 2 and 3. Interestingly, investigating age as a single variable shows almost zero impact on participation.

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
Age	0.009	0.006
	(20.34)***	(32.77)***
Age 1 (dummy)	-0.25	-0.92
	(-3.45)*	(-7.04)***
Age 2 (dummy)	0.07	0.99
	(5.34)**	(7.87)***
Age 3 (dummy)	0.15	1.03
	(6.78)**	(10.78)***
Age 4 (dummy)	-0.18	-0.97
	(-5.68)**	(-7.88)***

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 11: Participation by Age Category - Probit model

4.3.5 Education

Does having a higher education qualification relate to stock market participation in any way? Perhaps being relatively smarter means one would know when to take risks and when not to. Or one would know in which stocks to invest and in which rather not. Nonetheless, the highest level of education obtained by household members above the age of 16 are available in the HFCS dataset, and so this will also be used as an independent variable. The International Standard Classification of Education (ISCED) is used for classifying levels of educations obtained. The levels are as follows:

1. Primary education or below primary education.
2. Lower secondary education.
3. Upper secondary education.
4. Post-secondary education.
5. First stage tertiary education.
6. Second stage tertiary education.

The following table shows the results of having different levels of education and how individuals choose to participate in the stock market:

	Participate	
Education Level	**No**	**Yes**
1	74 896	4 081 (5%)
2	53 883	7 599 (12%)
3/4	116 614	19 988 (15%)
5/6	65 483	31 348 (32%)

Table 12: Level of Education and Participation

From these results, it is expected that higher level of education will have a positive influence on stock market participation, since the largest portion of educated individuals that participate all have some form of tertiary education. After running a probit regression model using the level of education it is clearly found that it indeed positively influences stock market participation. The output from this regression is displayed below. Once again, Education as a whole was used as a variable in the first run. Thereafter, Education Level 1 and Educations Level 2 (dummy variables) were used in the second run, with Education Level 3 and Education Level 4, following in the last run.

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
Education	0.24	0.06
	(4.01)**	(18.03)***
Education Level 1 (dummy)	-0.32	-0.08
	(-0.83)	(-7.01)***
Education Level 2 (dummy)	-0.16	-0.03
	(-0.42)	(-2.57)**
Education Level 3 and 4 (dummy)	0.16	0.05
	(0.40)	(4.73)***
Education Level 5 and 6 (dummy)	0.61	0.19
	(1.56)	(16.90)***

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 13: Participation by Level of Education - Probit model

4.3.6 Marital Status

Marital status is one of the variables used to investigate social interaction of individuals. Marital status is divided into 5 groups, namely, single or never married, married, consensual union on a legal basis, widowed, or divorced. The table below shows how these different groups partake in the stock market.

	Participate	
Martial Status	**No**	**Yes**
Single/Never Married	64 810	9 831 (13%)
Married	172 696	44 042 (20%)
Consensual Union	3 206	604 (16%)
Widowed	38 938	4 479 (10%)
Divorced	32 039	4 143 (11%)

Table 14: Marital Status and Participation

More than half (57.83%) of the households reference persons are married. It is clear that out of all categories, the largest percentage of individuals participating in the stock market are married. 20% of married individuals participate, which represents 70% of all participating individuals. Clearly, the marital status of the reference person in a household influences the households' stock market participation, particularly being married or not. Again, running a probit model using the marital status as independent variable, the following output was obtained.

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
Single/Never Married (dummy)	-0.07	0.02
	(5.04)**	(0.73)
Married (dummy)	0.23	0.09
	(5.03)**	(3.98)***
Consensual Union (dummy)	0.07	0.04
	(1.09)*	(1.99)**
Widowed (dummy)	-0.30	-0.02
	(6.05)**	(-0.90)
Divorced (dummy)	-0.18	-0.01
	(1.06)*	(-0.22)

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 15: Participation by Martial Status - Probit model

From the results one sees being married contributes positively towards participation. The other variables show small significance and seem to not be as important. When looking at the marginal effects, being married shows the largest contribution.

4.3.7 Gender

A lot of research has been done regarding gender and stock market participation and the table below confirms the literature for the HFCS that men participate more in the stock market than woman.

	Participate	
Gender	**No**	**Yes**
Male	163 481	40 663 (20%)
Female	148 506	22 476 (13%)

Table 16: Gender and Participation

Using a binary variable for gender with male equal to 1 and female equal to 0, the following probit regression output was found. Being a male, clearly has a positive influence on

participating in the stock market.

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
Male (dummy)	0.32	0.07
	(10.94)***	(55.59)***

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 17: Participation by Gender - Probit model

4.3.8 Occupation

A lot of information regarding household members' occupation is available through the HFCS. In this research three topics will be used in order to examine the effect thereof on stock market participation. These topics are the main occupation of the reference person, the type of company the reference person works for, and the type of contract he or she has, i.e., permanent or temporary.

In the HFCS the main occupation of respondents is recorded using occupational codes provided under the International Standard Classification of Occupations (ISCO). The ISCO is a useful tool to organise and identify different occupations in order to classify jobs in a standard and comparative manner. The ISCO starts by dividing jobs into ten different major groups coded from 0 to 9. These groups are: armed forces occupations, managers, professionals, technicians and associate professionals, clerical support workers, service and sales workers, skilled agricultural, forestry and fishery workers, craft and related trades workers, plant and machine operators and assemblers, and finally, elementary occupations. These major groups are then further divided into sub-major, minor and in some cases even unit groups. Each division adds another number to the one-digit number given initially. In the HFCS, however, two-digit ISCO codes are used, i.e., the major groups are only divided into sub-major groups.

When investigating stock market participation, occupation-type is believed to play a very important role. One would assume individuals working in the financial and/or business world or individuals living in a household with such a person, to have a better understanding of the stock market and therefore have a bigger chance of participating than, say, fishery workers. The table below shows the different ISCO codes with their descriptions that are present in the HFCS.

ISCO	Description	ISCO	Description
11	Chief executives, senior officials and legislators	52	Sales workers
12	Administrative and commercial managers	61	Market-oriented skilled agricultural workers
13	Production and specialised services managers	62	Market-oriented skilled forestry, fishery and hunting workers
21	Science and engineering professionals	71	Building and related trades workers
22	Health professionals	72	Metal, machinery and related trades workers
23	Teaching professionals	73	Handicraft and printing workers
24	Business and administrative professionals	74	Electrical and electronic trades workers
31	Science and engineering associate professionals	81	Stationary plant and machine operators
32	Health associate professionals	82	Assemblers
33	Business and administrative associate professionals	83	Drivers and mobile plant operators
34	Legal, social and related associate professionals	91	Cleaners and helpers
41	General and keyboard clerks	92	Agriculture, forestry and fishery labourers
42	Customer services clerks	93	Labourers in mining, construction, manufacturing and transport
51	Personal services workers		

Table 18: ISCO code with description

In the graph below the number of participants per ISCO group are displayed. A decreasing trend in participants are seen over the groups. This trend is also related to the amount of income individuals make in each group.

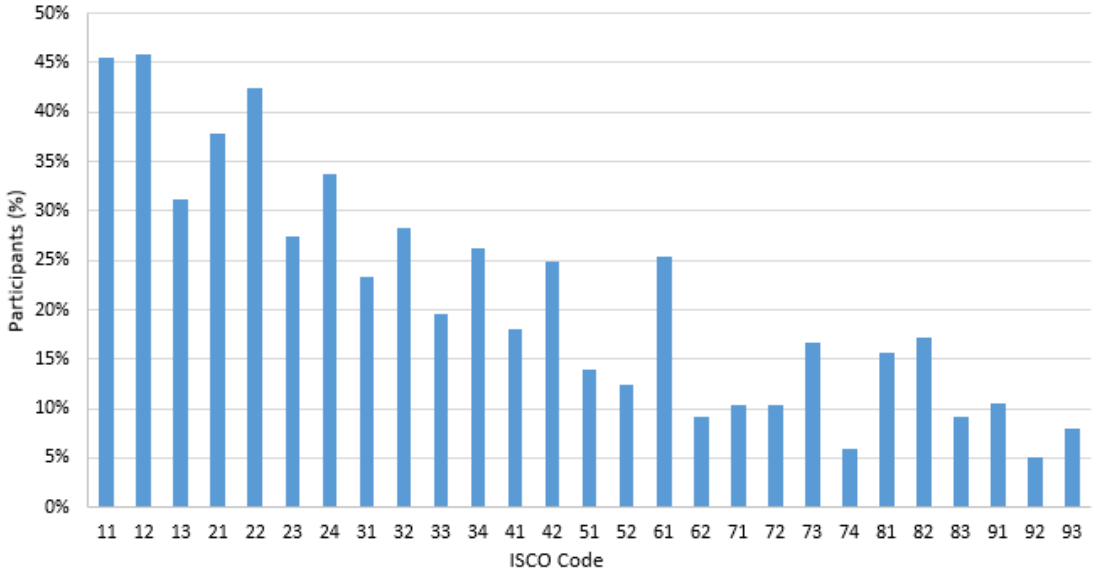

Figure 3: Participation per ISCO code

Again, a probit model is run over all ISCO groups in order to investigate the influence these different groups have on stock market participation. One sees that the largest positive

influence comes from the first group, ISCO code 11, which relates to chief executives, senior officials and legislators. This is also the highest income group. The largest negative influence comes from ISCO code 62, which represents market-oriented skilled forestry, fishery and hunting workers. This is not surprising!

Another interesting result is the fact that many non-business or non-financial occupations also contribute positively towards stock market participation. For example, health professionals (ISCO code 22) show a significant positive coefficient and marginal effect. However, in this case, other factor might also contribute to this impact, such as sociability and income. Nonetheless, these results highlight the importance of not only focusing on business- or financial-type occupations as one would expect to have an influence.

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
ISCO 11	1.316	0.321
	(3.55)***	(16.61)***
ISCO 12	0.721	0.324
	(3.69)***	(24.36)***
ISCO 13	0.935	0.177
	(3.49)***	(13.76)***
ISCO 21	0.947	0.244
	(4.31)***	(17.75)***
ISCO 22	0.791	0.289
	(3.34)***	(18.56)***
ISCO 23	0.567	0.140
	(2.72)***	(10.40)***
ISCO 24	0.619	0.202
	(3.05)***	(15.25)***
ISCO 31	0.209	0.098
	(0.86)	(7.03)***
ISCO 32	0.256	0.147
	(1.26)	(11.09)***
ISCO 33	0.288	0.061
	(1.40)	(4.46)***

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
ISCO 34	0.374	0.127
	(2.10)**	(10.23)***
ISCO 41	0.231	0.046
	(1.27)	(3.74)***
ISCO 42	0.372	0.112
	(2.04)**	(8.60)***
ISCO 51	0.050	0.005
	(0.23)	(0.44)
ISCO 52	-0.193	-0.011
	(-0.75)	(-0.82)
ISCO 61	0.134	0.118
	(0.63)	(9.41)***
ISCO 62	-1.544	-0.044
	(-5.26)***	(-1.18)
ISCO 71	-0.286	-0.031
	(-1.04)	(-2.43)**
ISCO 72	0.153	-0.032
	(0.70)	(-2.59)**
ISCO 73	0.069	0.032
	(0.29)	(2.13)**
ISCO 74	-0.062	-0.075
	(-0.15)	(-5.65)***
ISCO 81	0.500	0.022
	(1.27)	(1.28)
ISCO 82	0.194	0.037
	(1.05)	(2.93)***
ISCO 83	-0.273	-0.043
	(-1.08)	(-3.44)***

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
ISCO 91	0.006	-0.029
	(0.03)	(-2.40)***
ISCO 92	-0.949	-0.085
	(-3.09)***	(-3.69)***
ISCO 93	-0.468	-0.056
	(-1.90)*	(-4.25)***

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 19: Participation by ISCO - Probit model

The second topic, namely, the type of company an individual works at, is also believed to play a very significant role. People who surround themselves with other stock holders or other informed individuals are believed to have a bigger probability of participating in the stock market, than those that never interact with such individuals. In the HFCS, the type of company an individual works for is identified through the NACE which is the acronym for "Nomenclature statistique des activités économiques dans la Communauté européenne", but also known as the statistical classification of economic activities in the European Community. NACE classifies different companies/organisations/firms of the same type together by assigning different letters to it. The table below displays the different NACE codes with their descriptions. Figure 4 that follows, shows the amount of participants per NACE group. Clearly, financial and insurance activities (NACE K) has the largest number of participants.

NACE	Description	NACE	Description
A	Agriculture, forestry and fishing	K	Financial and insurance activities
B	Mining and quarrying	L	Real estate activities
C	Manufacturing	M	Professional, scientific and technical activities
D	Electricity, gas, steam and air conditioning supply	N	Administrative and support service activities
E	Water supply, sewerage, waste management and remediation	O	Public administration and defence, compulsory social security
F	Construction	P	Education
G	Wholesale and retail trade, repair of motor vehicles	Q	Human health and social work activities
H	Transportation and storage	R	Arts, entertainment and recreation
I	Accommodation and food service activities	S-U	Other services
J	Information and communication		

Table 20: ISCO code with description

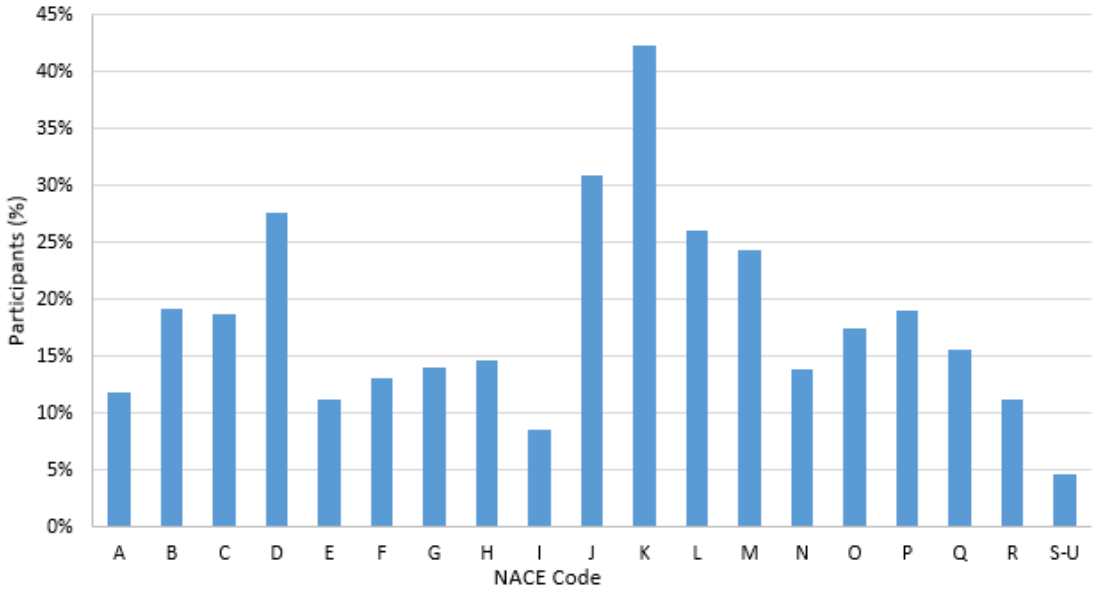

Figure 4: Participation per NACE code

Running a probit model over all the NACE groups the following results were found. Only financial and insurance activities, NACE code K, showed significant results. It also showed the largest marginal effect, with all the others being close to zero.

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
NACE A	0.180	0.052
	(0.24)	(2.13)**
NACE B	0.766	0.126
	(1.01)	(4.33)***
NACE C	0.843	0.122
	(1.18)	(5.12)***
NACE D	1.010	0.211
	(1.39)	(7.88)***
NACE E	0.436	0.045
	(0.58)	(1.79)*
NACE F	0.471	0.066
	(0.66)	(2.75)***
NACE G	0.554	0.074
	(0.77)	(3.12)***
NACE H	0.699	0.080
	(0.97)	(3.34)
NACE I	0.399	0.020
	(0.56)	(0.83)
NACE J	1.249	0.243
	(1.75)	(9.86)***
NACE K	1.522	0.958
	(2.14)*	(14.63)***
NACE L	0.815	0.195
	(1.11)	(7.06)***
NACE M	0.808	0.178
	(1.06)	(7.26)***
NACE N	0.303	0.073
	(0.42)	(3.00)***

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
NACE O	0.644	0.109
	(0.74)	(4.56)***
NACE P	0.900	0.125
	(1.26)	(5.22)***
NACE Q	0.529	0.091
	(0.74)	(3.81)***
NACE R	0.257	0.046
	(0.33)	(1.85)*
NACE S-U	0.291	0.022
	(0.37)	(0.91)

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 21: Participation by NACE category - Probit model

The last topic that will be examined under occupation information is the type of contract an individual holds. One might argue individuals with a permanent contract might have a larger probability of participating in the stock market since they are more certain of their income and able to plan ahead. Individuals with temporary contracts might rather choose to keep their money safe, since they do not know when they might lose their job and so their income. In the table below, once again the variable is divided under those that do participate and those that do not. Almost 26 times more individuals with permanent contracts participate than those that have temporary contracts. This information will also be used in a probit regression model.

	Participate	
Type of contract	**No**	**Yes**
Permanent	86 510	16 088 (16%)
Temporary	11 792	619 (5%)

Table 22: Type of Occupation Contract and Participation

After running the probit regression model the following results are found, showing that the type of contract definitely influences stock market participation, however the influence is very small.

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
Permanent Contract (dummy)	0.22	0.01
	(8.05)***	(11.60)***

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 23: Participation by Type of Contract - Probit model

4.3.9 Retirement

It has been found that most individuals nearing retirement start to invest less in the stock market, and after retirement they tend to exit the stock market entirely (Fagereng, Gottlieb and Guiso, 2015). For this reason retirement is also investigated in this research. In the HFCS, the labour status of individuals are available as displayed in the table below. The table also shows how the different labour groups participate in the stock market. The table confirms the literature as retirement has a negative influence. Interestingly, but not surprisingly, all other labour statuses, except for working, contributes negatively toward participation. However, none of these are really significant and very close to zero.

	Participate	
Labour status	**No**	**Yes**
Working for pay	149 219	34 148 (19%)
On sick/maternity leave	1 488	96 (6%)
Unemployed	19 285	1 645 (8%)
Student or unpaid intern	7 576	1 244 (14%)
Retiree or early retiree	103 762	22 022 (18%)
Permanently disabled	5 524	841 (13%)
Compulsory military or equivalent social service	198	72 (27%)
Fulfilling domestic tasks	21 741	2 574 (11%)
Other not working for pay	2 890	481 (14%)

Table 24: Labour Status and Participation

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
Working for pay (dummy)	0.24	0.187
	(7.03)**	(6.37)***
On sick/maternity leave (dummy)	-0.33	-0.024
	(-0.27)	(-0.74)
Unemployed (dummy)	-0.47	-0.057
	(-2.07)*	(-1.94)*
Student or unpaid intern (dummy)	-0.62	-0.142
	(-0.12)	(-4.77)***
Retiree or early retiree (dummy)	-0.03	-0.178
	(-5.03)**	(-6.01)***
Permanently disabled (dummy)	-0.44	-0.132
	(-0.17)	(-4.41)***
Compulsory military or equivalent	0.39	0.254
social service (dummy)	(0.28)	(7.11)***
Fulfilling domestic tasks (dummy)	-0.32	-0.099
	(-2.06)*	(-3.34)***
Other not working for pay (dummy)	-0.27	-0.143
	(-0.12)	(-4.76)***

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 25: Participation by Labour Status - Probit model

4.3.10 Countries

The last variable that will be looked at in this section, is country. Here the purpose is to investigate how the country the individuals live in influence their participation. In the next chapter analysis will be done for each country individually, however, this variable provides the first evidence regarding the importance of considering the country individuals live in and not just using all individuals at once.

The table below shows the results from running a probit model with countries as the inde-

pendent variables. Here countries are used as categorical variables. The largest positive contribution comes from Cyprus, whereas the largest negative contribution comes from Slovakia. Overall, it is clear the country one lives in definitely plays a very important role in this investigation as the results are very distributed. These results will become even more clear in the following chapter.

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
Austria	0.812	0.012
	(7.00)***	(15.56)***
Belgium	0.568	0.135
	(8.94)***	(15.38)***
Cyprus	1.218	0.328
	(18.33)***	(15.03)***
Estonia	0.356	0.170
	(5.78)***	(18.85)***
Finland	0.848	0.223
	(15.87)***	(16.27)***
France	0.564	0.158
	(10.40)***	(17.38)***
Germany	0.367	0.126
	(5.41)	(18.88)***
Greece	-0.311	-0.030
	(-3.07)***	(-13.48)
Italy	-0.072	-0.001
	(-1.20)	(-0.52)
Luxembourg	0.332	0.077
	(4.22)***	(15.83)***
Malta	0.507	0.079
	(6.62)	(15.37)
Netherlands	0.358	0.078
	(4.51)***	(18.19)***

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
Portugal	0.008	-0.006
	(0.12)	(-2.67)***
Slovakia	-0.812	-0.046
	(-7.00)***	(-21.81)***
Slovenia	0.333	0.096
	(3.56)***	(11.86)***

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 26: Participation per Country - Probit Model

4.3.12 Final Probit Models

After investigating all of the different independent variables, a full analysis is done on all of the variables together. This model explains which of the initial variables significantly influence stock market participation, on an individual level, when taking all variables into account at the same time. After doing a thorough analysis, the following results are found showing which variables has the largest influence on stock market participation in the Euro Area.

The first model in Table 27 takes into account the first initial variables that were proven to be significant. These results agree with the literature, since all of them have previously been used in studies regarding stock market participation.

In the second model, the occupation-type variables are added. As in the individual results regarding the NACE codes, NACE K (financial and insurance activities), is the only working-environment that were found to be significant when participating in the stock market. For the ISCO codes, all the significant codes is used in the analysis that were found in the individual results, however, only the five found in the table below proved to be significant when taking all other significant variables into account. Interestingly, when moving from the first model to the second model, i.e., adding occupation-type variables, all the coefficients (and marginal effects) decreases, except for Age and Wealth (Highest 5%). This means when adding occupation-type variables as influencing factors, an individuals age and the upper 5% of the wealth distribution plays an even more important role than without occupation-type influences.

In the third model, countries are added as categorical variables. This is shown in Table 28. The reason this model is displayed by itself is because when countries were added certain ISCO variables originally used did not prove to be significant any more. Furthermore,

not all countries showed significant results. This final model shows the overall effect of individuals living in different countries in the Euro Area and how this affects participation when considering the other influencing factors.

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect	Coefficient	Marginal Effect
Male (dummy)	0.207	0.027	0.195	0.024
	(6.25)***	(13.85)***	(5.93)***	(11.29)***
Age	0.021	0.007	0.027	0.008
	(4.07)***	(18.21)***	(5.19)***	(12.10)***
Education Level	0.181	0.039	0.168	0.038
	(15.52)***	(14.37)***	(14.45)***	(19.19)***
Wealth (Lowest 25%) (dummy)	-0.689	-0.135	-0.672	-0.132
	(-10.67)***	(-14.44)***	(-10.22)***	(-13.16)***
Wealth (Highest 5%) (dummy)	0.474	0.130	0.502	0.132
	(10.42)***	(18.64)***	(10.81)***	(11.55)***
Income (Lowest 25%) (dummy)	-0.407	-0.102	-0.393	-0.100
	(-7.85)***	(-19.53)***	(-7.58)***	(-18.68)***
Income (Highest 5%) (dummy)	0.449	0.088	0.399	0.082
	(7.85)***	(19.98)	(6.66)***	(16.68)***
NACE K (dummy)			0.715	0.111
Financial & insurance activities			(7.29)***	(12.21)***
ISCO 11 (dummy)			0.678	0.073
Chief executives, senior officials & legislators			(1.80)*	(8.82)***
ISCO 13 (dummy)			0.308	0.054
Production & specialised services managers			(2.39)**	(15.34)***
ISCO 21 (dummy)			0.428	0.057
Science & engineering professionals			(3.40)***	(13.57)***
ISCO 62 (dummy)			-2.133	-0.180
Market-oriented skilled agricultural workers			(-4.94)***	(-3.66)***
ISCO 92 (dummy)			-0.770	-0.123
Agriculture, forestry & fishery labourers			(-3.00)***	(-2.86)***
cons	-2.123		-2.184	
	(-26.00)***		(-26.58)***	

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 27: Final Probit Model of Household- and Individual-Level Influences

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
Male (dummy)	0.204	0.030
	(5.82)***	(18.23)***
Age	0.030	0.008
	(5.10)***	(13.22)***
Education Level	0.180	0.033
	(15.00)***	(12.44)***
Wealth (Lowest 25%) (dummy)	-0.695	-0.129
	(-9.69)***	(-15.55)***
Wealth (Highest 5%) (dummy)	0.484	0.122
	(10.44)***	(17.67)***
Income (Lowest 25%) (dummy)	-0.360	-0.067
	(-6.41)***	(-19.87)***
Income (Highest 5%) (dummy)	0.474	0.077
	(7.59)***	(16.08)***
NACE K (dummy)	0.762	0.129
Financial & insurance activities	(7.47)***	(10.13)***
ISCO 21 (dummy)	0.432	0.026
Science & engineering professionals	(3.34)***	(6.85)***
ISCO 62 (dummy)	-2.573	-0.238
Market-oriented skilled agricultural workers	(-7.01)***	(-5.25)***
ISCO 92 (dummy)	-0.768	-0.081
Agriculture, forestry & fishery labourers	(-2.92)***	(-2.03)**
Austria	-0.199	-0.034
	(-2.98)***	(-10.80)***
Belgium	0.247	0.051
	(4.22)***	(18.91)***
Cyprus	0.930	0.160
	(15.01)***	(10.88)***
Estonia	0.218	0.076
	(4.25)***	(19.90)***
Finland	0.734	0.147
	(17.01)	(12.27)***
France	0.488	0.092
	(11.40)***	(11.09)***
Greece	-0.364	-0.077
	(-3.55)***	(-18.21)***
Luxembourg	-0.361	-0.081
	(-4.12)***	(-17.43)***
Netherlands	0.169	0.018
	(2.07)**	(4.91)***
Slovakia	-0.816	-0.127
	(-6.52)***	(-18.80)***
Slovenia	0.286	0.089
	(3.13)***	(13.57)***
cons	-2.427	
	(-24.23)***	

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 28: Final Probit Model of Household- and Individual-Level Influences (cont.)

4.4 Individual- and Household-Level Influences: Tobit Models

The second important question that is to be addressed in this research regards the amount of money individuals actually put towards participation in the stock market. In the previous section the different positive and negative contributing factors are seen, however, how much do these variables contribute, is still to be answered. If one knows, for example, wealth has a positive influence on participation, the next step is to understand how large is that influence in euro terms. For this purpose, Tobit models are used. Here, the dependent variable is no longer a yes or a no, but an amount - the amount of money (in euro) that individuals invest in the stock market.

In order to answer this question, four categories are used. Namely, investments under €1 000, investments between €1 000 and €10 000, investments between €10 000 and €500 000 and finally, investments larger than €500 000. The reason for this division is clear in the following table. Most individuals invest less than €1 000, with very few investing more than €500 000.

Amount of investment	Number of investors
Less than €1 000	336 480
Between €1 000 and €10 000	17 442
Between €10 000 and €500 000	20 064
More than €500 000	129

Table 29: Number of investors per investment group

Tobit models were run over all of these groups in order to better understand how different amounts of investments are affected by the different influencing factors. For example, if one invests, say, between €1 000 and €10 000, then for every one unit change in the log of one's net wealth, there will be a €7 836 change in one's investment. The results from running the Tobit models are extremely interesting, as one finds differences in how investments are affected for the same variable, but over different investment groups. For example, if one looks at Education Level 2 and Education Level 3 and 4. Having a Level 2 Education, i.e., lower secondary education, or Level 3 and 4, i.e., upper secondary or post-secondary education, will positively influence one's investment if one invests between €0 and €500 000. Only when investing more than €500 000, i.e., the last investment group, will one's investment be negatively influenced if only a secondary-type education is held.

The different age variables are also another example of influencing factors that differ across investment groups. If an individual falls in the Age 4 category, i.e., above the age of 75, then investing less than €1 000 or more than €500 000 will have a positive outcome, whereas anything in between will have a negative outcome.

Further, holding a permanent contract and investing between €0 and €10 000 will have a positive impact on one's investment, whereas investing more than €10 000 will not. Also, when looking at retirement, only investing less than €1 000 has a negative influence. As for the rest of the variables, all of them show either positive increases over all the investment groups, or negative increases. Interestingly, the first few ISCO codes are not consistent over all investment groups. ISCO 11 (chief executives, senior officials and legislators), ISCO 13 (production and specialised services managers) and ISCO 21 (science and engineering professionals) all show positive increases in the first 3 investment groups, however, when investing more than €500 000 these three groups show a negative influence. ISCO 62 (market-oriented skilled forestry, fishery and hunting workers) and ISCO 92 (agriculture, forestry and fishery labourers) show exactly the same values across all groups, since these variables are in the same industry.

Dependent Variable:	Less than €1000	Between €1000 and €10 000	Between €10 000 and €500 000	More than €500 000
Investment in Stocks				
log(Net Wealth)	23	7 836	62 368	1 539 497
	(24.30)***	(13.02)***	(11.35)***	(3.01)***
Wealth Level 1	-143	-35 242	-259 526	-1.01e+07
	(-22.97)***	(-12.30)***	(-9.39)***	(-2.87)***
Wealth Level 2	-108	-18 196	-130 458	-4 438 926
	(-13.26)***	(-10.16)***	(-8.08)***	(-1.45)
Wealth Level 3	-97	-15 875	-109 236	-3 615 381
	(-13.78)***	(-10.67)***	(-11.42)***	(-1.63)
Wealth Level 4	82	16 030	98 755	2 559 917
	(11.14)***	(11.32)***	(9.54)***	(1.47)
Wealth Level 5	138	23 413	146 174	2 683 798
	(10.74)***	(11.49)***	(11.99)***	(1.60)
Wealth Level 6	196	29 399	199 768	5 496 850
	(14.43)***	(14.31)***	(13.22)***	(2.44)**
log(Income)	64	14 694	88 473	2 095 811
	(19.58)***	(13.60)***	(11.29)***	(2.92)***
Income Level 1	-137	-28 756	-158 348	-2 627 860
	(-19.77)	(-13.00)***	(-12.03)***	(-2.29)**

Dependent Variable: Investment in Stocks	Less than €1000	Between €1000 and €10 000	Between €10 000 and €500 000	More than €500 000
Income Level 2	-118	-20 874	-131 124	-3 028 515
	(-15.77)	(-11.22)***	(-10.83)***	(-2.90)***
Income Level 3	-93	-14 017	-86 921	-2 045 715
	(-11.73)	(-10.09)***	(-8.34)***	(-2.76)***
Income Level 4	73	14 399	78 257	1 146 535
	(9.48)***	(10.21)***	(8.81)***	(2.12)**
Income Level 5	133	21 119	115 078	1 299 859
	(7.65)***	(9.72)***	(9.30)***	(1.92)*
Income Level 6	227	30 451	185 571	3 770 845
	(12.85)***	(14.19)***	(12.68)***	(3.04)***
Attitude	60	11 943	68 073	711 080
	(11.95)***	(10.34)***	(11.51)***	(1.62)
Attitude 1	-30	-8 575	-63 049	-1 398 687
	(-5.87)***	(-6.79)***	(-7.40)***	(-1.49)
Attitude 2	74	11 744	66 725	719 373
	(7.51)***	(7.68)***	(8.11)***	(1.34)
Attitude 3	32	7 564	48 758	661 473
	(2.62)***	(3.78)***	(3.94)***	(0.95)
Attitude 4	83	14 691	100 385	2 574 668
	(2.82)***	(4.00)***	(3.96)***	(1.04)
Education Level	32	6 782	40 047	509 089
	(17.17)***	(13.68)***	(13.77)***	(1.56)
Education Level 1	-6	-2 774	-68 513	-2 324 311
	(-0.31)	(-0.31)	(-1.36)	(-1.44)
Education Level 2	6	3 055	93 043	-339 564
	(0.31)	(0.35)	(1.83)*	(-0.25)
Education Level 3 and 4	36	11 527	137 664	-345 839

Dependent Variable: Investment in Stocks	Less than €1000	Between €1000 and €10 000	Between €10 000 and €500 000	More than €500 000
	(1.85)*	(1.31)	(2.72)***	(-0.53)
Education Level 5 and 6	117	24 335	220 124	1 255 202
	(5.62)***	(2.72)***	(4.30)***	(1.53)
Age	2	593	7 133	216 230
	(2.81)***	(4.21)***	(7.19)***	(2.02)**
Age 1	38	-11 009	-112 312	-1 765 360
	(8.19)***	(-5.50)***	(-8.10)***	(-1.03)
Age 2	73	1 052	-12 930	-752 880
	(18.25)***	(1.03)	(-1.73)*	(-1.14)
Age 3	84	6 392	55 375	278 409
	(19.18)***	(5.72)***	(7.18)***	(0.59)
Age 4	46	-4 570	-5 053	1 324 649
	(11.99)***	(-3.61)***	(-0.59)	(2.16)**
Male	43	10 348	62 861	1 339 534
	(10.42)***	(9.31)***	(8.88)***	(2.08)**
Married	31	7 009	52 430	1 452 746
	(6.64)***	(5.60)***	(6.30)***	(2.46)**
Permanent Contract	23	3 549	-7 786	-528 144
	(4.73)***	(3.51)***	(-1.09)	(-0.65)
Retirement	-3	1 038	29 490	661 683
	(-0.62)	(1.05)	(4.09)***	(1.35)
NACE K	210	23 621	103 825	1 186 393
	(6.25)***	(7.48)***	(5.18)***	(0.38)
ISCO 11	355	19 457	45 785	-9 591 703
	(2.24)**	(2.53)**	(1.31)	(-2.98)***
ISCO 13	50	8 122	50 640	-216 158
	(2.60)***	(2.77)***	(2.71)***	(-0.24)

Dependent Variable: Investment in Stocks	Less than €1000	Between €1000 and €10 000	Between €10 000 and €500 000	More than €500 000
ISCO 21	208	24 679	130 882	-1 236 101
	(4.79)***	(5.70)***	(5.32)***	(-0.45)
ISCO 62	-61	-38 905	-703 580	-9 591 703
	(-13.68)***	(-0.82)	(-17.62)***	(-2.98)***
ISCO 92	-52	-22 186	-703 580	-9 591 703
	(-2.94)***	(-0.40)	(-17.62)***	(-2.98)***
Austria	-32	-7 890	-25 905	-500 034
	(-12.23)***	(-10.89)***	(-7.87)***	(-0.98)
Belgium	67	13 331	78 342	926 588
	(7.58)***	(6.33)***	(5.40)***	(0.38)
Cyprus	151	20 090	91 850	-391 676
	(10.09)***	(7.97)***	(5.46)***	(-0.10)
Estonia	48	10 475	61 411	-474 722
	(6.18)***	(5.05)***	(4.35)***	(-0.21)
Finland	169	23 566	110 398	1 179 705
	(26.02)***	(11.23)***	(8.38)***	(0.49)
France	11	2 669	20 426	-113 707
	(2.03)**	(1.45)	(1.59)	(-0.05)
Germany	49	10 920	60 349	-191 566
	(5.73)***	(4.91)***	(4.47)***	(-0.08)
Greece	-15	-6 828	-45 793	-9 739 246
	(-2.16)**	(-2.12)**	(-2.03)**	(-2.88)***
Italy	-10	-3 648	-18 448	-2 585 177
	(-1.92)*	(-1.81)*	(-1.32)	(-0.52)
Luxembourg	38	8 843	71 136	1 655 159
	(3.44)***	(3.20)***	(3.48)***	(0.57)
Malta	87	16 832	72 834	-9 739 246

Dependent Variable: Investment in Stocks	Less than €1000	Between €1000 and €10 000	Between €10 000 and €500 000	More than €500 000
	(6.43)***	(6.82)***	(4.28)***	(-2.88)***
Netherlands	46	9 443	29 511	527 479
	(4.05)***	(3.79)***	(1.72)*	(0.14)
Portugal	4	-1 149	-25 008	-1 556 845
	(0.75)	(-0.52)	(-1.33)	(-0.30)
Slovakia	-36	-35 590	-186 990	-9 739 246
	(-7.57)***	(-3.91)***	(-1.87)*	(-2.88)***
Slovenia	18	-2 418	-144 709	-9 739 246
	(1.72)*	(-0.82)	(-4.96)***	(-2.88)***

Table 30: Tobit Models: Investment in Stocks

4.5 Conclusion

In this chapter, a thorough investigation is done regarding stock market participation in the Euro area on a household-level. The chapter starts with an explanation on the mathematical background of the models used where after a long list of variables are examined individually and in groups in order to conclude which household-level variables influences stock market participation significantly. It is found that the financial and insurance activity independent variable contributes largely towards stock market participation. Furthermore, working as a market-oriented skilled agricultural worker has a large negative influence on participation. Other positive influences come from the highest 5% of the wealth distribution, being a male, age and level of education. Negative influences come from the lowest 25% of the wealth and income distribution. Living in Cyprus or Finland also contributes positively. Whereas, living in Slovakia has the largest negative influence of the countries.

Tobit models were also ran in order to understand how much these individuals invest in the stock market and how the different influencing variables affect their investments in euro terms. Here the results vary considerably across different countries. In the next chapter a thorough analysis is done on a country-level. Probit models are also used, as in this chapter, however, each country has different contributing variables which makes the analysis very interesting.

CHAPTER 5
METHODOLOGY AND RESULTS: COUNTRY-LEVEL

5.1 Introduction

In this section the exact same analysis will be done as in the individual- and household-level case, however, here the independent variables are aggregated in order to use it at country-level. For each country in the HFCS a probit model will be run. The other feature that is added in these probit models as opposed to the previous model, is the other country-level influences of which some is briefly mentioned in the literature review. These added influences is not available in the HFCS and so other data platforms were used for collecting the data. Before performing the probit regression at country-level, all the different variables will first be examined - this time at country-level. The additional country-level variables will also be explained.

5.2 Country-level Influences

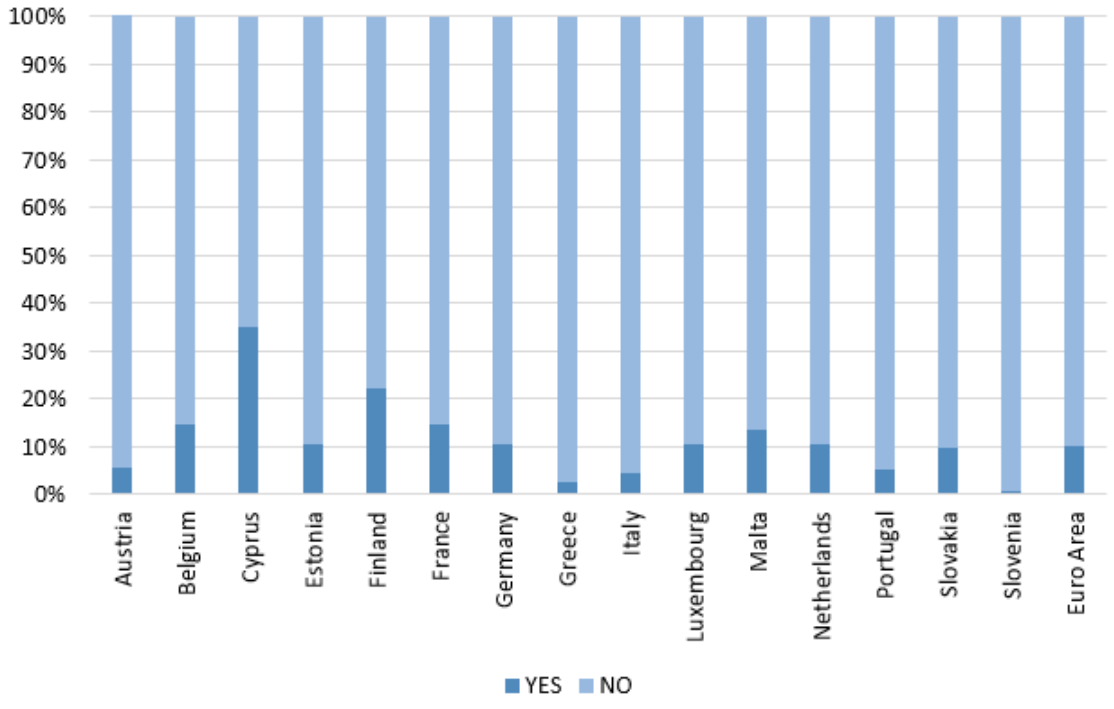

Figure 5: Stock Market Participation per Country (%)

Since the purpose is still to investigate stock market participation, here at country level, the figure above and the table below, show how participation is divided across the different countries in the HFCS. Cyprus has the largest portion of participation individuals at 38% and Slovakia has the least at only 1%. These numbers emphasise the importance of investigating countries individually, since clearly factors explaining the participation of Cypriots are going to be considerably different from those of Slovakians. In fact, in countries such as Slovakia, Austria, Portugal, Greece and Italy it would be much more interesting to look at reasons against individuals participating, than reasons for.

	Participate		
Country	**No**	**Yes**	**Total**
Austria	13 497	783 (5%)	14 280
Belgium	11 305	2 657 (19%)	13 962
Cyprus	4 583	2 839 (38%)	7 422
Estonia	28 835	8 347 (22%)	37 182
Finland	47 628	18 306 (28%)	65 934
France	70 885	19 151 (21%)	90 036
Germany	17 514	3 876 (18%)	21 390
Greece	17 385	441 (2%)	17 826
Italy	45 144	2 562 (5%)	47 706
Luxembourg	4 948	752 (13%)	5 700
Malta	4 380	678 (13%)	5 058
Netherlands	6 769	1 037 (13%)	7 806
Portugal	25 139	1 285 (5%)	26 424
Slovakia	12 228	114 (1%)	12 342
Slovenia	1 747	311 (15%)	2 058

Table 31: Stock Market Participation per Country

The results clearly show that stock market participation vary considerably across different countries. These results already prepare the way for certain conclusions, such that different countries will have different influential variables explaining stock market participation or rather non-participation.

5.2.1 Initial Independent Variables

All of the independent variables that are used in the individual- and household-level analysis is also used in this section. Therefore, it is important to first understand how the different variables vary from one country to the next. For every country, and with every independent variable, probit models will be run. This enables one to compare different influential factors across countries.

5.2.1.1 Risk Attitude

From the above results, one would expect the percentage of households identifying with the first investment attitude to be the most, since most countries show very little participation in the stock market. This is confirmed in the graph below. Unfortunately, investment attitude questions were not asked in Finland or France and so the reason thy are not displayed in Figure 6.

Comparing Figure 5 and Figure 6, it is clear that the countries with less households participating in the stock market are also those showing the most risk aversion. This is an obvious result, however, what is not so obvious, is why this result exists. Why are so little number of households not participating in the stock market and why are they so extremely risk averse?

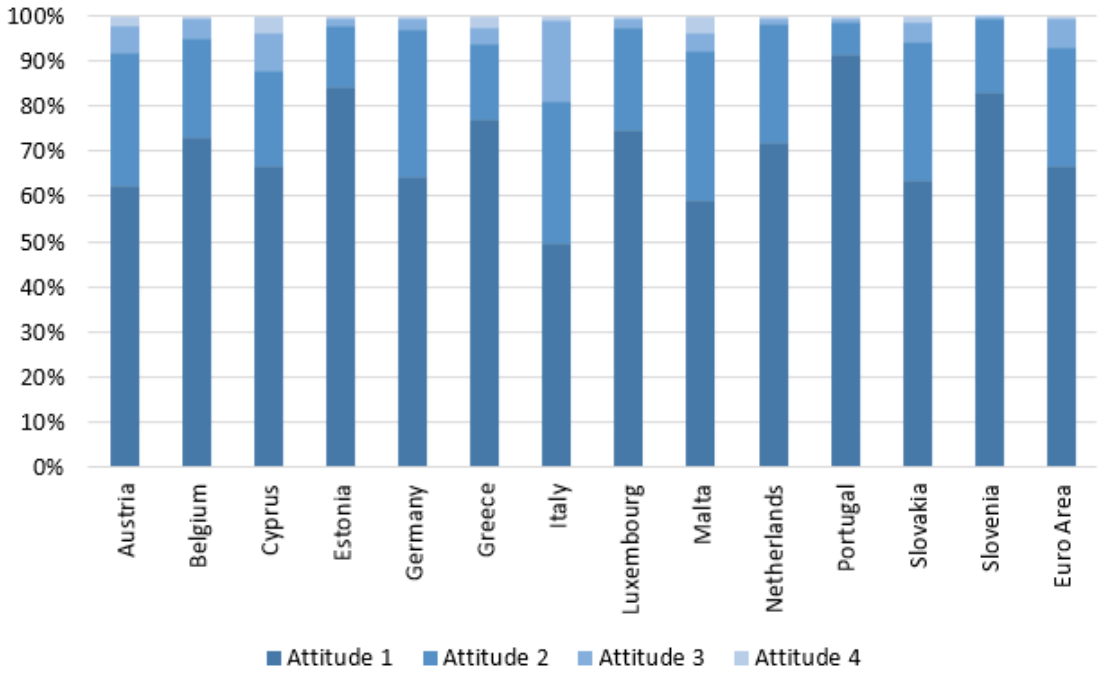

Figure 6: Investment Attitude per Country

Table 32 shows the results from running probit models per country, over the investment

attitude variables. Looking at Attitude as a whole, one sees it has a positive influence across all countries, however, Luxembourg shows the largest coefficient whereas Cyprus shows the smallest coefficient. Cyprus is also the country with the most participating individuals, which makes this result very interesting. Nonetheless, on average, across all countries having a more risk tolerant attitude, i.e., Attitude 3 or Attitude 4, contributes positively towards participation. The opposite is true for Attitude 1 and Attitude 2, i.e., being more risk averse. Note that there is no result for Slovenia under Attitude 3 since none of the Slovenians had such an investment attitude.

Dependent Variable: Participate (dummy)	Attitude	Attitude 1 (dummy)	Attitude 2 (dummy)	Attitude 3 (dummy)	Attitude 4 (dummy)
Austria	0.491	-1.047	-0.187	-0.226	0.418
	(8.65)***	(-3.15)***	(-0.56)	(-0.63)	(1.08)
Belgium	0.735	-1.071	0.896	1.058	0.425
	(10.83)***	(-12.29)***	(9.97)***	(6.22)***	(1.08)
Cyprus	0.182	-0.359	0.297	0.262	0.248
	(3.01)***	(-3.46)***	(2.53)***	(1.43)	(1.04)
Estonia	0.556	-0.867	0.884	0.560	-0.478
	(7.82)***	(-9.62)***	(9.12)**	(2.59)**	(-1.81)*
Germany	0.633	-0.838	0.716	0.563	0.430
	(8.81)***	(-9.62)***	(8.61)***	(2.91)***	(0.89)
Greece	0.349	-0.619	0.409	0.559	0.721
	(5.51)***	(-4.26)***	(2.16)**	(2.28)**	(1.70)*
Italy	0.290	-0.517	0.266	0.257	0.875
	(6.13)***	(-6.18)***	(3.99)***	(2.80)***	(3.26)***
Luxembourg	0.976	-1.205	0.900	1.743	1.499
	(8.01)***	(-8.50)***	(6.55)***	(4.17)***	(2.18)**
Malta	0.260	-0.453	0.355	0.576	0.179
	(3.43)***	(-3.79)***	(2.91)***	(1.89)*	(0.39)
Netherlands	0.799	-0.913	0.913	0.804	0.972
	(7.29)***	(-7.31)***	(7.29)***	(2.21)**	(0.88)
Portugal	0.740	-1.101	0.959	1.764	1.032
	(8.77)***	(-9.75)***	(8.42)***	(5.72)***	(2.63)***
Slovakia	0.576	-0.789	-0.032	1.220	0.816
	(4.71)***	(-2.13)**	(-0.13)	(4.58)***	(1.40)
Slovenia	0.754	-0.881	0.843	-	1.501
	(4.74)***	(-4.88)***	(4.55)***	-	(3.57)***

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 32: Participation by Investment Attitude per Country - Probit model

5.2.1.2 Net Wealth

In the literature, but also in Chapter 4, it is found that wealth is unevenly divided across individuals. Figure 7 confirms this phenomenon at country-level. Figure 7 also further highlights the importance of investigating countries individually when considering wealth. In countries such as France and Estonia, different influences will be evident as opposed to countries such as Malta and Slovenia.

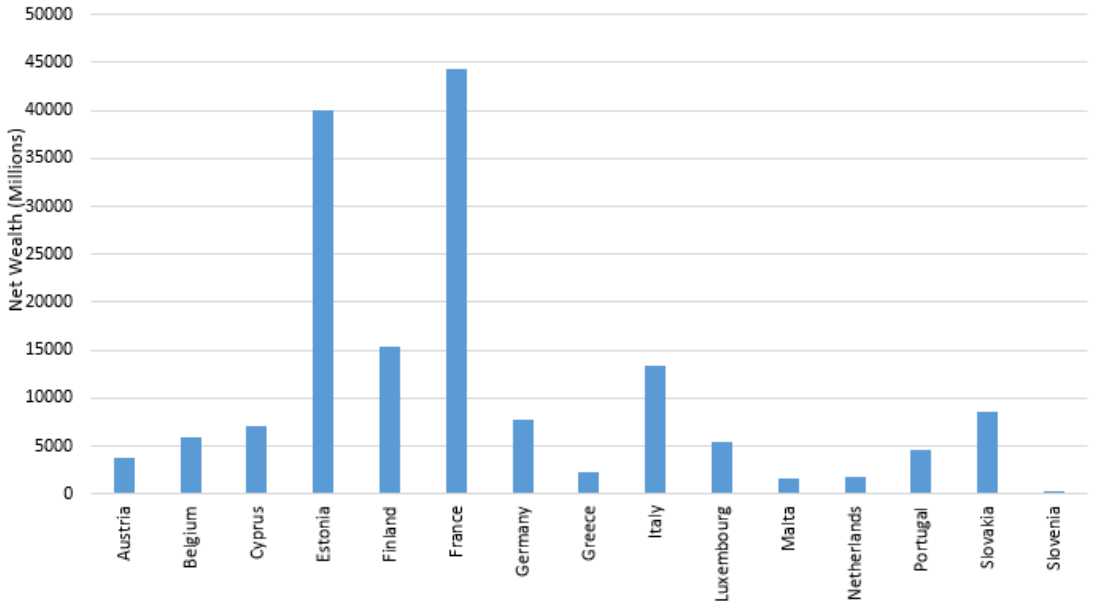

Figure 7: Net Wealth per Country

Table 33 shows the results from running probit models per country, across all the different wealth variables used in this research. Again, as with investment attitude, one observes overall wealth to have a positive influence on stock market participation in all countries. From the probit results it is also clear that the influence of wealth on stock market participation is larger for the countries with more wealth than those with less. Interestingly, all countries show negative coefficients for Net Wealth 1, Net Wealth 2 and Net Wealth 3. These variables represent the lower 25%, 50% and 75% of the total wealth distribution respectively. This further confirms how extremely unevenly wealth is distributed.

Furthermore, the Net Wealth 4, Net Wealth 5 and Net Wealth 6 variables all contribute positively across all countries. These variables represent the upper 25%, 10% and 5% of the total wealth distribution respectively.

Lastly, when looking across all wealth variables it is interesting how almost all of the variables prove to be significant. This result is very important as it shows the overall importance of including wealth into one's analysis when investigating stock market participation across Euro Area countries.

Dependent Variable: Participate (dummy)	log(Net Wealth)	Net Wealth 1	Net Wealth 2	Net Wealth 3	Net Wealth 4	Net Wealth 5	Net Wealth 6
Austria	0.221	-1.438	-0.698	-0.425	0.646	0.941	0.583
	(6.55)***	(-3.69)***	(-5.11)***	(-3.54)***	(5.75)***	(6.31)***	(2.23)**
Belgium	0.408	-1.710	-1.028	-0.604	0.875	1.026	1.229
	(7.22)***	(-7.41)***	(-7.67)***	(-6.27)***	(8.58)***	(6.85)***	(9.04)***
Cyprus	0.205	-1.054	-0.900	-0.480	0.594	1.094	1.133
	(5.12)***	(-7.01)***	(-6.17)***	(-3.30)***	(4.04)***	(4.24)***	(4.79)***
Estonia	0.451	-1.388	-1.035	-0.595	0.726	1.062	1.282
	(8.51)***	(-11.27)***	(-9.63)***	(-6.57)***	(7.79)***	(6.54)***	(9.45)***
Finland	0.292	-1.428	-1.062	-0.703	0.804	1.120	1.558
	(14.49)***	(-22.93)***	(-21.83)***	(-16.44)***	(18.67)***	(18.04)***	(27.23)***
France	0.311	-1.537	-0.826	-0.530	0.667	0.957	1.246
	(17.07)***	(-17.10)***	(-13.90)***	(-10.01)***	(12.87)***	(12.43)***	(20.66)***
Germany	0.242	-1.615	-0.750	-0.448	0.624	0.911	1.024
	(9.18)***	(-8.20)***	(-6.44)***	(-4.35)***	(6.16)***	(6.77)***	(8.56)***
Greece	0.493	-1.212	-0.795	-0.649	0.619	0.865	1.197
	(5.23)***	(-5.44)***	(-3.41)***	(-3.30)***	(3.45)***	(3.73)***	(6.40)***
Italy	0.400	-1.395	-0.851	-0.621	0.665	0.894	1.251
	(9.59)***	(-11.45)***	(-7.32)***	(-6.81)***	(7.46)***	(9.01)***	(12.13)***
Luxembourg	0.191	-0.883	-0.480	-0.692	0.393	0.818	1.142
	(3.55)***	(-3.88)***	(-2.84)***	(-3.82)***	(2.31)**	(3.76)***	(4.66)***
Malta	0.416	-1.200	-0.844	-0.355	0.596	0.963	0.809
	(6.09)***	(-5.62)***	(-4.66)***	(-2.09)**	(3.37)***	(3.82)***	(3.13)***
Netherlands	0.305	-0.863	-0.547	-0.447	0.404	0.710	0.949
	(5.18)***	(-3.44)***	(-3.03)***	(-3.14)***	(2.87)***	(2.82)**	(5.08)***
Portugal	0.406	-1.124	-1.031	-0.418	0.478	0.700	1.336
	(8.55)***	(-6.19)***	(-6.33)***	(-3.09)***	(3.36)***	(4.11)***	(10.06)***
Slovakia	0.329	-0.681	-0.660	-0.322	-0.136	0.839	0.793
	(2.41)**	(-2.41)**	(-1.20)	(-0.86)	(-0.25)	(2.05)**	(1.79)*
Slovenia	0.216	-0.931	-0.743	-0.281	0.550	0.662	0.679
	(3.08)***	(-4.23)***	(-3.17)***	(-1.21)	(2.67)***	(2.07)**	(2.49)**

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 33: Participation by Net Wealth per Country - Probit model

5.2.1.3 Income

Income is another factor that is unevenly distributed across individuals and, as confirmed by Figure 8, also across countries. Figure 7 and Figure 8 almost look identical, except for Finland and Estonia almost switching places. Nonetheless, the large division between countries with regards to income is just as clear as with wealth.

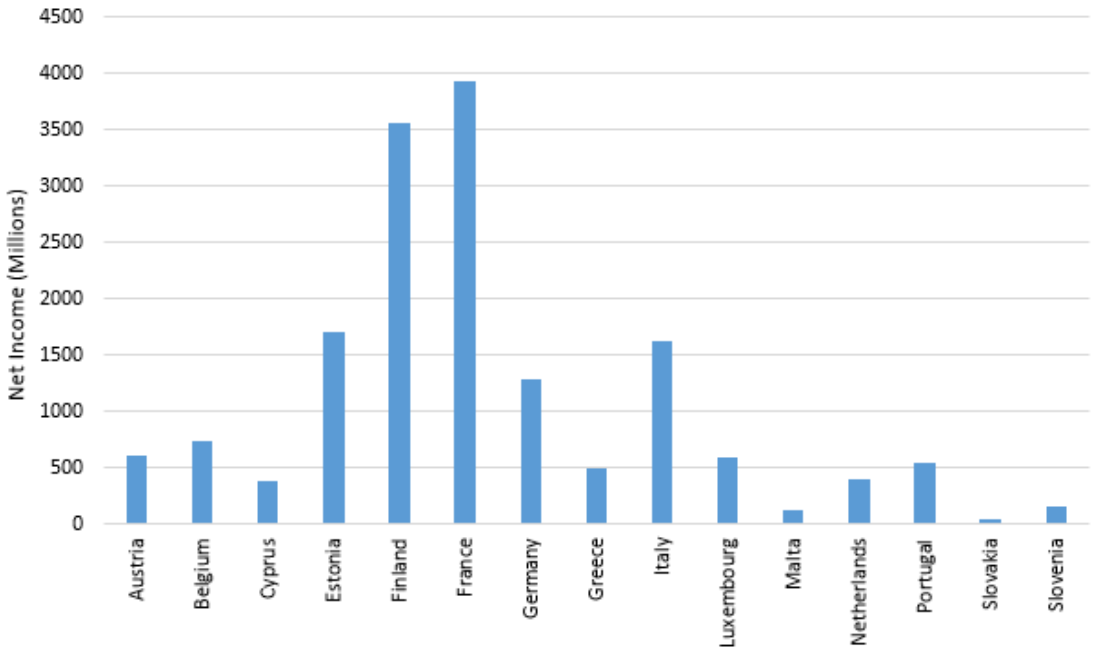

Figure 8: Net Income per Country

In Table 34, the results from running probit models across all income variables for all countries are displayed. Once again, overall income has a positive influence on stock market participation. However, when comparing the influence of the log of net wealth and the log of income one sees the range of the income coefficients is much greater than that of wealth. Wealth ranges between 0.191 and 0.493, whereas income ranges between 0.075 and 0.813.

Equivalent to wealth, it is again the lower 25%, 50% and 75% (Income 1, Income 2 and Income 3) of the total income distribution that shows negative influences on participation across all countries. Whereas the upper 25%, 10% and 5% (Income 4, Income 5 and Income 6) show positive influences. Note that Slovakia shows no results in Income 6, i.e., the upper 5% of the total wealth distribution, as there were to few observations to give a valid result.

Once again, most of the variables prove to be significant highlighting the importance of also including income into one's investigation regarding stock market participation in the Euro Area.

Dependent Variable: Participate (dummy)	log(Income)	Income 1	Income 2	Income 3	Income 4	Income 5	Income 6
Austria	0.416	-0.847	-0.683	-0.363	0.568	0.555	0.749
	(4.96)***	(-4.51)***	(-4.73)***	(-3.07)***	(4.22)***	(2.65)**	(3.84)***
Belgium	0.354	-1.036	-0.601	-0.419	0.628	0.590	0.747
	(7.02)***	(-7.72)***	(-5.57)***	(-3.97)***	(6.14)***	(3.18)***	(5.32)***
Cyprus	0.468	-0.989	-0.799	-0.537	0.699	0.898	0.833
	(6.51)***	(-6.65)***	(-5.53)***	(-3.85)***	(4.97)***	(3.95)***	(3.81)***
Estonia	0.571	-1.014	-0.696	-0.677	0.491	0.933	1.297
	(9.78)***	(-9.69)***	(-7.61)***	(-6.26)***	(5.59)***	(5.41)***	(10.45)***
Finland	0.576	-1.022	-0.624	-0.531	0.457	0.799	1.302
	(20.37)***	(-18.62)***	(-13.92)***	(-13.68)***	(11.49)***	(13.51)***	(25.88)***
France	0.662	-1.196	-0.807	-0.533	0.632	0.805	1.227
	(14.90)***	(-17.92)***	(-14.20)***	(-10.66)***	(12.03)***	(10.90)***	(20.64)***
Germany	0.560	-1.203	-0.927	-0.457	0.595	0.988	1.088
	(8.30)***	(-7.88)***	(-6.16)***	(-4.66)***	(5.35)***	(7.22)***	(8.81)***
Greece	0.550	-1.055	-0.949	-0.381	0.673	0.299	0.965
	(4.69)***	(-4.15)***	(-3.75)***	(-2.12)***	(4.05)***	(1.05)	(4.13)***
Italy	0.701	-1.479	-0.909	-0.498	0.598	0.873	1.220
	(6.52)***	(-6.82)***	(-7.88)***	(-6.69)***	(6.21)***	(8.38)***	(10.98)***
Luxembourg	0.668	-1.137	-1.437	-0.548	0.781	1.035	1.200
	(5.92)***	(-4.25)***	(-3.82)***	(-3.31)***	(4.62)***	(4.54)***	(5.75)***
Malta	0.374	-0.662	-0.536	-0.478	0.530	0.450	0.719
	(4.19)***	(-3.97)***	(-3.13)***	(-2.67)***	(3.11)***	(1.77)*	(2.68)***
Netherlands	0.278	-0.429	-0.417	-0.066	0.194	0.255	0.533
	(2.70)***	(-2.39)**	(-2.07)*	(-0.40)	(1.08)	(1.03)	(2.44)**
Portugal	0.813	-1.435	-1.182	-0.737	0.717	1.068	1.620
	(10.38)***	(-8.03)***	(-7.89)***	(-6.09)***	(5.22)***	(5.89)***	(11.05)***
Slovakia	0.075	-0.125	-0.236	-0.241	0.347	-0.050	-
	(0.57)	(-0.32)	(-0.74)	(-0.66)	(1.15)	(-0.07)	-
Slovenia	0.219	-0.644	-0.423	-0.461	0.379	0.770	0.625
	(2.40)**	(-2.91)***	(-2.01)**	(-2.21)**	(1.92)*	(1.85)*	(1.83)*

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 34: Participation by Income per Country - Probit model

5.2.1.4 Age

The results from Figure 9 show how different countries have different amounts of individuals in the four age categories. Interestingly, Estonia has the largest percentage (19%) of individuals falling in the highest age group, namely older than 75 years. Furthermore, Estonia also has the largest percentage (73%) of individuals older than 55 years. This result might be inherently related to Estonia's large wealth number. On the other hand, Slovakia has no individuals older than 75 years and more than a third of its individuals being younger than 34 years of age. Slovakia was also one of the countries with the least wealth and income. Once again, this phenomenon might be inherently related to Slovakia's income and wealth.

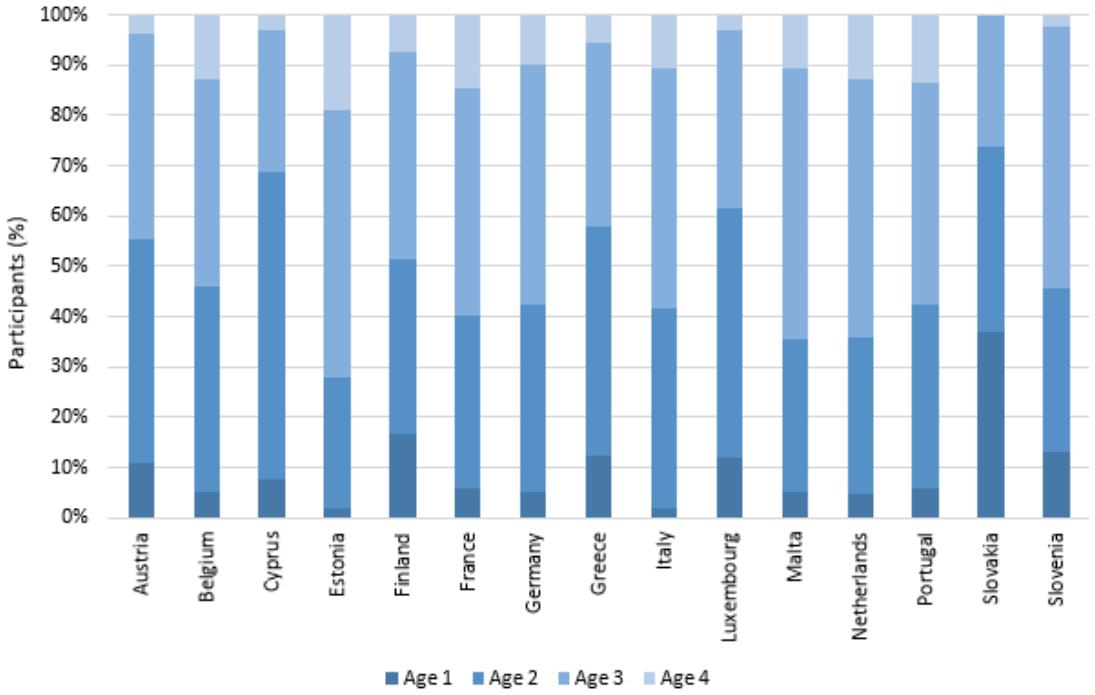

Figure 9: Participation by Age per Country

The results form running probit models across all countries and for all age variables are displayed in Table 35. When looking at the continuous variable, Age, it is interesting how age has a different influence in different countries. For most countries this variable shows an almost zero coefficient, with no country showing a significant positive influence. Italy shows the largest coefficient at -1.534.

Overall, it is clear that variables Age 1 and Age 4, i.e., individuals between 15 and 34 years of age and older than 75 years of age shows negative influences on stock market participation. Age 2 and Age 3, representing age 35 to age 74, mostly has a positive influence. This corresponds to what was found on an individual level in Chapter 4, therefore, confirming the importance of age as an influencing factor in the Euro Area.

Dependent Variable: Participate (dummy)	Age	Age 1	Age 2	Age 3	Age 4
Austria	0.003	-0.376	0.422	0.390	-0.482
	(0.29)	(-2.67)***	(3.20)***	(2.83)***	(-1.72)
Belgium	0.039	-0.527	0.131	0.113	0.074
	(3.65)***	(-3.39)***	(1.67)*	(1.47)	(0.66)
Cyprus	0.029	-0.788	0.325	0.329	-0.705
	(2.03)**	(-5.27)***	(3.38)***	(3.21)***	(-3.48)***
Estonia	0.019	-0.285	-0.061	0.287	-0.209
	(1.85)*	(-1.73)*	(-0.90)	(4.02)	(-2.33)**
Finland	0.034	-0.341	-0.004	0.290	-0.022
	(7.62)***	(-8.04)***	(-0.12)	(8.56)***	(-0.37)
France	0.011	-0.290	0.122	0.177	-0.234
	(2.16)**	(-4.99)***	(3.22)***	(4.59)***	(-4.51)***
Germany	0.008	-0.292	0.132	0.129	-0.206
	(0.72)	(-1.85)*	(1.76)*	(1.63)	-1.62()
Greece	0.017	-0.284	0.060	0.243	-0.430
	(1.20)	(-1.64)	(0.55)	(1.86)*	(-1.53)
Italy	-1.534	-0.520	0.110	0.129	-0.237
	(0.06)	(-2.87)***	(1.56)	(1.89)*	(-2.37)**
Luxembourg	-0.014	0.051	0.061	-0.036	-0.258
	(-0.62)	(0.31)	(0.50)	(-0.25)	(-0.69)
Malta	0.019	-0.185	-0.186	0.250	-0.013
	(0.93)	(-0.66)	(-1.53)	(2.09)**	(-0.06)
Netherlands	0.027	-0.125	-0.086	0.133	0.043
	(1.19)	(-0.49)	(-0.71)	(1.18)	(0.26)
Portugal	-0.022	-0.038	0.144	-0.028	-0.227
	(-1.85)	(-0.21)	(1.47)	(-0.30)	(-2.04)
Slovakia	-0.002	-0.113	0.044	0.086	-
	(-0.07)	(-0.53)	(0.20)	(0.32)	(-)
Slovenia	0.002	-0.225	-0.033	0.382	-0.964
	(0.10)	(-1.23)	(-0.20)	(2.43)***	(-3.96)***

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 35: Participation by Age per Country - Probit model

5.2.1.5 Education

Just as with all the previous variables, education is also dispersed across countries. A few

countries, namely, Austria, Finland, Germany and Slovakia has no individuals falling in the first education category. This category represents primary education or below primary education. Very interestingly, Slovakia shows the largest percentage for Education category 5 & 6 which represents tertiary education.

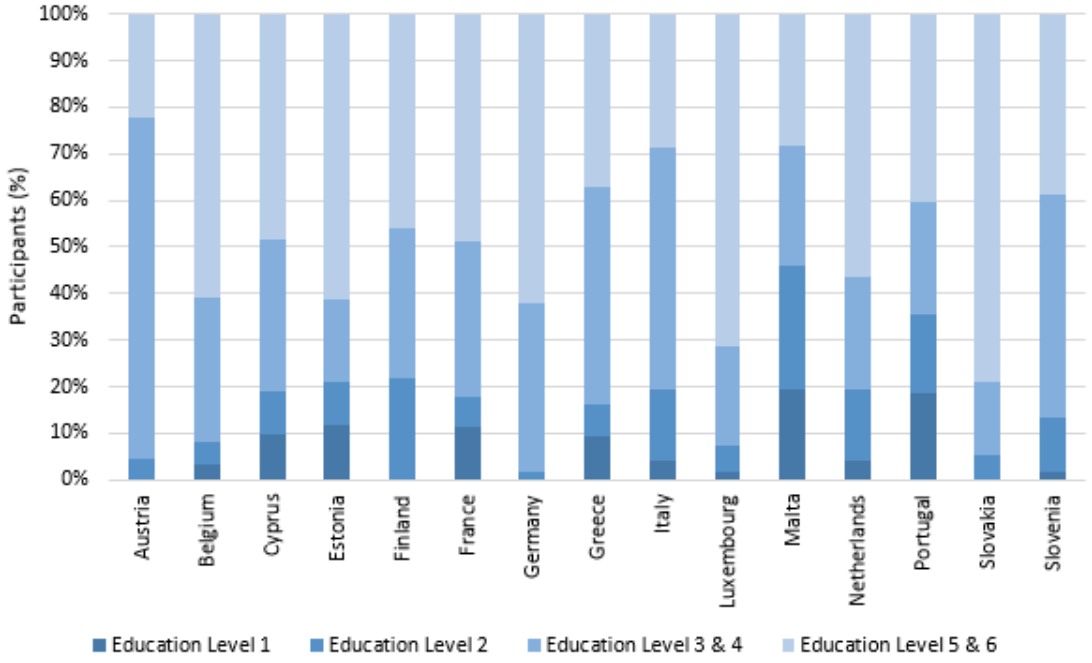

Figure 10: Participation by Level of Education per Country

Looking at table 36, which shows the results from the probit models, one sees education plays an overall positive role on stock market participation. The higher one's education, the larger the probability of participating in the stock market. Tertiary education shows significance in all countries. In some countries, such as Belgium, Finland, Germany, Luxembourg, Slovakia and Slovenia only holding a secondary education (Education category 3 & 4) is not enough as for all these countries the coefficients are negative.

The results from Table 36 confirms the importance of including education when investigating stock market participation across the Euro Area. Especially, education as a continuous variable and tertiary education as both of these variables show significant results across all countries.

Dependent Variable: Participate (dummy)	Education	Education 1	Education 2	Education 3 & 4	Education 5 & 6
Austria	0.218	-	-0.718	0.075	0.369
	(4.96)***	-	(-3.08)***	(0.77)	(3.25)***
Belgium	0.248	-0.564	-0.670	-0.192	0.607
	(7.65)***	(-3.23)***	(-3.85)***	(-2.35)**	(7.53)***
Cyprus	0.082	-0.353	-0.061	0.074	0.165
	(2.51)***	(-2.69)***	(-0.34)	(0.74)	(1.66)*
Estonia	0.232	-0.631	-0.352	0.110	0.690
	(10.06)***	(-7.64)***	(-3.40)***	(1.36)	(8.76)***
Finland	0.215	-	-0.235	-0.322	0.594
	(16.06)***	-	(-6.49)***	(-9.61)***	(17.96)***
France	0.204	-0.652	0.097	0.025	0.532
	(16.66)***	(-13.01)***	(1.28)	(0.63)	(13.92)***
Germany	0.298	-	-0.731	-0.308	0.613
	(8.31)***	-	(-2.98)***	(-3.95)***	(7,58)***
Greece	0.154	-0.429	0.153	-0.451	0.367
	(3.25)***	(-2.34)**	(-1.82)*	(1.30)	(2.39)**
Italy	0.278	-0.904	-0.397	0.392	0.547
	(11.15)***	(-5.32)***	(-4.62)***	(5.79)***	(6.37)***
Luxembourg	0.369	-0.907	-0.450	-0.377	1.021
	(6.02)***	(-3.89)***	(-1.51)	(-2.73)***	(7.76)***
Malta	0.195	-0.194	-0.513	0.325	0.550
	(4.27)***	(-1.31)	(-3.96)***	(2.11)**	(3.63)***
Netherlands	0.090	0.203	-0.390	0.055	0.218
	(2.06)***	(0.63)	(-3.03)***	(0.42)	(1.83)*
Portugal	0.318	-0.949	0.156	0.325	0.963
	(11.30)***	(-9.72)***	(1.11)	(2.78)***	(8.21)***
Slovakia	0.431	-	0.239	-1.095	1.022
	(2.37)**	-	(0.31)	(-3.45)***	(3.37)***
Slovenia	0.265	-0.595	-0.518	-0.148	0.593
	(3.97)***	(-2.27)**	(-2.92)***	(-0.97)	(3.47)***

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 36: Participation by Education Level per Country - Probit model

5.2.1.6 Marital Status

Martial Status is one of the variables used in this research to represent social interaction of individuals. Table 37 shows the martial status per country. In all countries, except for Austria, more than halve of the individuals are married. In all countries the largest percentage of individuals are married. In chapter 4 when martial status was investigated at individual-level, it was already found that being married contributes positively and significantly towards stock market participation. Being widowed also showed significant results (negatively), however, this did not prove to be significant at country-level. For this reason only results from being

married will be shown at country-level.

Country	Single/ Never Married	Married	Consensual Union	Widowed	Divorced
Austria	3 451	6 879 (48%)	360	1 548	2 037
Belgium	2 394	7 476 (54%)	750	1 668	1 674
Cyprus	534	5 790 (78%)	54	474	528
Estonia	4 873	23 415 (63%)	834	5 519	2 539
Finland	20 334	34 440 (52%)	0	3 624	7 536
France	19 578	48 792 (54%)	1 176	11 220	9 180
Germany	3 677	13 760 (64%)	12	1 880	2 055
Greece	3 804	10 704 (60%)	240	1 860	1 218
Italy	5 958	29 736 (62%)	0	8 364	3 648
Luxembourg	1 284	3 382 (59%)	0	354	679
Malta	642	3 474 (69%)	0	558	384
Netherlands	1 878	4 830 (63%)	72	336	498
Portugal	2 982	16 446 (62%)	0	4 542	2 454
Slovakia	2 952	6 432 (52%)	72	1 242	1 644
Slovenia	300	1 182 (57%)	240	228	108

Table 37: Marital Status per Country

From the probit results in Table 38 below, one sees marriage to be a significant positive contributor towards stock market participation across most countries. However, comparing a country such as Belgium that shows a coefficient of 0.516 with a country such as Slovakia that shows an almost zero coefficient at 0.009, it is clear that marriage has different levels of impact in different countries.

These results are very interesting and yet again confirms the importance of including social interaction between individuals, such as marital status, when investigating stock market participation.

Dependent Variable: Participate (dummy)	Married
Austria	0.250
	(2.72)***
Belgium	0.516
	(6.29)***
Cyprus	0.368
	(3.39)***
Estonia	0.254
	(3.30)***
Finland	0.394
	(12.45)***
France	0.376
	(10.19)***
Germany	0.205
	(2.24)**
Greece	0.344
	(2.22)**
Italy	0.287
	(3.69)***
Luxembourg	0.110
	(0.85)
Malta	0.223
	(1.68)*
Netherlands	0.303
	(2.43)**
Portugal	0.443
	(4.53)***
Slovakia	0.009
	(0.04)

Dependent Variable: Participate (dummy)	Married
Slovenia	0.193
	(1.25)

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 38: Participation by Martial Status per Country - Probit model

5.2.1.7 Gender

In the HFCS, 204 144 males were surveyed compared to 170 982 females. However, as shown in Chapter 4, a larger percentage of males participate in the stock market than females. This is also confirmed in literature and further confirmed in Table 39 below. In all countries, except for Slovakia, more men than woman are participating in the stock market. In fact, in some countries such as Luxembourg, Netherlands and Portugal more than 75% of total participants in these countries are males.

According to the European Institute for Gender Equality (EIGE), Portugal is one of the countries in the European Union with the lowest gender equality score (Barbieri et al., 2017). This could inherently explain the large amount (83%) of participants being males in Portugal. However, this is not true for Luxembourg and Netherlands, as both of these countries are above average in gender equality across the European Union.

	Participate	
Country	**Female**	**Male**
Austria	272	511 (65%)
Belgium	723	1 934 (73%)
Cyprus	793	2 046 (72%)
Estonia	2 580	5 767 (69%)
Finland	8 964	9 342 (51%)
France	6 042	13 103 (68%)
Germany	1 112	2 764 (71%)
Greece	195	246 (56%)
Italy	666	1 896 (74%)
Luxembourg	180	572 (76%)
Malta	216	462 (68%)
Netherlands	252	777 (76%)
Portugal	222	1 063 (83%)
Slovakia	54	60 (39%)
Slovenia	191	120 (53%)

Table 39: Gender and Participation per Country

From the results of running the probit models across all countries for the male dummy variable, it can be confirmed that being a male positively influences stock market participation. Except for Slovakia and Slovenia, all other countries showed significant coefficients.

Dependent Variable: Participate (dummy)	Male
Austria	0.485
	(5.30)***
Belgium	0.456
	(5.52)***
Cyprus	0.368
	(3.81)***

Dependent Variable: Participate (dummy)	Male
Estonia	0.321
	(4.64)***
Finland	0.077
	(2.37)**
France	0.272
	(7.07)***
Germany	0.387
	(4.73)***
Greece	0.320
	(2.56)**
Italy	0.457
	(6.77)***
Luxembourg	0.363
	(2.59)***
Malta	0.334
	(2.61)***
Netherlands	0.340
	(2.54)**
Portugal	0.252
	(2.01)**
Slovakia	0.069
	(0.31)
Slovenia	0.070
	(0.44)

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 40: Participation by Gender per Country - Probit Model

5.2.1.8 Occupation

This section investigates the occupation-type variables at a country-level. The first set of variables looked at is the ISCO code variables. Here, only the five most significant variables, found at an individual level, is used. The reason for this decision is because in the final individual models, it is already accounted for country-effects and these were the five ISCO codes that proved to be significant. Table 41 shows the results from investigating these variables across the different countries. The first thing that stands out is that ISCO 62 and ISCO 92 were only observed in one country each and both of the coefficients are large and significant. The other three variables all show positive coefficients across all countries, except for Austria, where ISCO 11 shows a negative influence. Nonetheless, these results confirm what was found on an individual-level and emphasises the importance of considering these occupation-types when investigating stock market participation across the Euro Area.

Dependent Variable: Participate (dummy)	ISCO 11 (Chief executives, senior officials & legislators)	ISCO 13 (Production & specialised services managers)	ISCO 21 (Science & engineering professionals)	ISCO 62 (Market-oriented skilled forestry, fishery & hunting workers)	ISCO 92 (Agriculture, forestry & fishery labourers)
Austria	-0.270	0.513	0.623	-	-
	(-0.34)	(1.70)*	(1.46)	-	-
Belgium	1.143	0.610	0.974	-	-0.664
	(2.39)**	(2.50)**	(4.12)***	-	(-2.09)**
Cyprus	0.542	0.724	0.496	-1.917	-
	(2.64)***	(2.41)**	(1.58)	(-4.53)***	-
Estonia	-	-	-	-	-
	-	-	-	-	-
Finland	0.826	0.156	0.562	-	-
	(2.03)**	(1.69)*	(6.46)***	-	-
France	1.460	0.674	0.897	-	-
	(2.01)**	(6.79)***	(4.07)***	-	-
Germany	1.497	0.361	0.905	-	-
	(1.69)*	(1.19)	(4.66)***	-	-
Greece	-	-	-	-	-
	-	-	-	-	-
Italy	-	-	-	-	-
	-	-	-	-	-
Luxembourg	-	-	-	-	-
	-	-	-	-	-
Malta	-	-	-	-	-
	-	-	-	-	-
Netherlands	1.304	0.153	0.074	-	-
	(0.70)	(0.46)	(0.07)	-	-
Portugal	1.661	0.466	0.341	-	-
	(4.34)***	(2.24)**	(0.92)	-	-
Slovakia	-	-	-	-	-
	-	-	-	-	-
Slovenia	-	-	-	-	-
	-	-	-	-	-

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 41: Participation by ISCO Code per Country - Probit Model

Table 42 displays the second occupation-type variable, investigating NACE codes across countries. Here, once again, as with the ISCO variables, only the significant one is used. The results prove this variable to indeed be significant, since for all countries, except the Netherlands and Slovakia, significant coefficients are found.

Dependent Variable: Participate (dummy)	NACE K (Financial and Insurance Activities)
Austria	0.517
	(1.88)**
Belgium	0.784
	(3.82)***
Cyprus	0.819
	(3.20)***
Estonia	0.889
	(3.84)***
Finland	0.643
	(4.50)***
France	0.847
	(5.81)***
Germany	0.906
	(4.37)***
Greece	0.698
	(1.84)*
Italy	1.351
	(6.73)***
Luxembourg	0.949
	(5.62)***
Malta	1.269
	(4.15)***
Netherlands	0.421
	(1.13)
Portugal	1.849
	(6.76)***

Dependent Variable: Participate (dummy)	NACE K (Financial and Insurance Activities)
Slovakia	0.397
	(0.64)
Slovenia	2.125
	(6.78)***

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 42: Participation by NACE Code per Country - Probit Model

The last occupation-type variable investigated across countries, is the type of contract individuals hold. Whether permanent or temporary. Across all countries, it does not seem as if this variable greatly affects participation, since most coefficients are close to zero or not significant. Note that for Finland, these results were not found in the HFCS.

Dependent Variable: Participate (dummy)	Permanent Contract
Austria	-0.043
	(-0.48)
Belgium	0.243
	(3.14)***
Cyprus	0.228
	(2.40)**
Estonia	0.343
	(4.67)***
Finland	-
	-
France	0.217
	(5.80)***
Germany	0.283
	(3.95)***
Greece	0.373

Dependent Variable: Participate (dummy)	Permanent Contract
	(2.32)**
Italy	0.128
	(2.23)**
Luxembourg	0.177
	(1.48)
Malta	0.132
	(1.00)
Netherlands	0.097
	(0.79)
Portugal	0.307
	(3.29)***
Slovakia	0.536
	(1.51)
Slovenia	0.189
	(1.18)

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 43: Participation by Type of Contract per Country - Probit Model

5.2.1.9 Retirement

Finally, the last variable used from results found in the HFCS, is investigated, namely retirement. At an individual level, retirement did not really show interesting results. Even though the coefficient were significant, it was almost zero. Nonetheless, for the purpose of this research and in order to confirm the literature, this variable will be investigated across countries.

Table 44 shows the amount and percentage of participants in the specific countries that are retired. Clearly, across countries the results are extremely varied. In Cyprus just more than a third of retirees participate, whereas in Slovakia, almost 0% do.

Country	Retired Participants
Austria	270 (5%)
Belgium	1 067 (20%)
Cyprus	436 (34%)
Estonia	3 364 (29%)
Finland	4 722 (31%)
France	8 250 (23%)
Germany	1 399 (20%)
Greece	132 (3%)
Italy	984 (5%)
Luxembourg	186 (13%)
Malta	258 (16%)
Netherlands	311 (13%)
Portugal	493 (5%)
Slovakia	6 (0.3%)
Slovenia	144 (17%)

Table 44: Stock Market Participation by Retirement per Country

After running probit models across all countries, the results in Table 45 is found. Agreeing with the individual-level results, retirement does not seem to be very significant across countries. Some countries show significant coefficients, however, once again they are very close to zero. Therefore, it can be concluded that retirement is not necessarily such an important variable to consider when investigating stock market participation across the Euro Area.

Dependent Variable: Participate (dummy)	Retirement
Austria	-0.053
	(-0.57)
Belgium	0.162
	(2.10)**
Cyprus	-0.146

Dependent Variable: Participate (dummy)	Retirement
	(-1.26)
Estonia	0.208
	(2.81)***
Finland	0.178
	(5.13)***
France	-0.003
	(-0.07)
Germany	-0.100
	(-1.20)
Greece	-0.061
	(-0.46)
Italy	-0.187
	(-3.18)***
Luxembourg	-.050
	(-0.33)
Malta	0.120
	(0.98)
Netherlands	0.113
	(0.91)
Portugal	-0.229
	(-2.86)***
Slovakia	-0.342
	(-0.51)
Slovenia	-0.025
	(-0.17)

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 45: Participation by Retirement per Country - Probit Model

5.2.2 Extra Country-Level Independent Variables

In this section, the extra country-level variables are investigated. The results from these variables are not available from the HFCS. Two data platforms, namely, MarketLine Advantage and The Human Truth Foundation, are used to retrieve the data. In this section the focus is internet access, corruption, political preferences, capital gains tax and religion. All the data used in this section are from 2014. This year is chosen since it was the in the middle of the second survey done under the HFCS and since most of the data used in this research represents the second wave.

5.2.2.1 Internet Access

It has been shown that having internet access considerably lowers costs associated with stock market participation, but also that it enables individuals to be more aware of what is going on in the market. Whether it be through social platforms, news, advertisements or any other forms of media.

Table 46 below displays internet access as percentage of the population per country for 2013, together with how these percentages are assigned to different values that is used in the regression model. Percentages above 85% are given a 5, between 75% and 85% are given a 4, between 65% and 75% a 3, between 55% and 65% a 2, and finally, below 55% are given a 1. Even though internet access is much more global now as it use to be 10 years ago, one still sees from the table that certain countries do have a higher percentage of their population with internet access than others. For example, in the Netherlands and in Luxembourg, 91% of the population has internet access. In Greece, only 46% of the population has.

Country	Internet Access (% per population)	Assigned Variable
Austria	74%	3
Belgium	78%	4
Cyprus	53%	1
Estonia	74%	3
Finland	87%	5
France	77%	4
Germany	82%	4
Greece	46%	1
Italy	54%	1
Luxembourg	91%	5
Malta	63%	2
Netherlands	91%	5
Portugal	53%	1
Slovakia	79%	4
Slovenia	70%	3

Table 46: Internet Access per Country (MarketLine Advantage)

Table 47 shows the results from running a probit models across the internet variables. The first variable, Internet Access, represents the assigned values as in Table 45 that represent the percentages. Therefore, this is a continuous variable. The other 5 variables represent dummy variables for each level of internet access. As a continuous variable, internet access shows a positive significant coefficient, however, it is not very large. Looking at the dummy variables, one sees the first three variables, i.e., were between 0% and 75% of the population has internet access, has a negative influence on stock market participation. Even though the coefficients and marginal effects are not very large for any of the variables, except perhaps Internet Access 1, it is clear that more internet access leads to larger probabilities of participating.

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
Internet Access	0.155	0.046
	(15.75)***	(17.09)***
Internet Access 1 (dummy)	-0.483	-0.153
	(-15.05)***	(-16.78)***
Internet Access 2 (dummy)	0.169	-0.037
	(2.83)***	(-6.66)***
Internet Access 3 (dummy)	-0.041	-0.009
	(-1.17)	(-5.38)***
Internet Access 4 (dummy)	0.256	0.030
	(9.20)***	(13.61)***
Internet Access 5 (dummy)	0.182	0.097
	(4.50)***	(19.99)***

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 47: Participation by Internet Access per Country - Probit Model

5.2.2.2 Corruption Perception Index (CPI)

As mentioned in the literature review, a lot of research has recently been focussed on understanding the trust that individuals have in their government and economic environment. Guiso and Jappelli (2005), have found high trust from individuals in this regard lead to higher probability of participation in the stock market. Since this information is not available in the HFCS, another measure that is globally available will be used as a representative of trust, namely, Corruption Perception Index (CPI). The CPI is a combination of different international surveys and assessments of corruption that is collected by a variety of reputable institutions. The index draws on 13 surveys from independent institutions specialising in governance and business climate analysis covering expert assessments and views of businesspeople. The Transparency International (TI) publish a CPI value for each country annually. This value ranges between 0 and 100, where 0 represents a country with a lot of corruption, and 100 represents a country with no corruption.

Figure 11 gives a nice visual representation of how the CPI varies across Europe. The countries used in this research are visible on the figure and one sees the East and South countries are more towards the red side (more corruption), whereas the North and West countries are more towards the yellow side (less corruption).

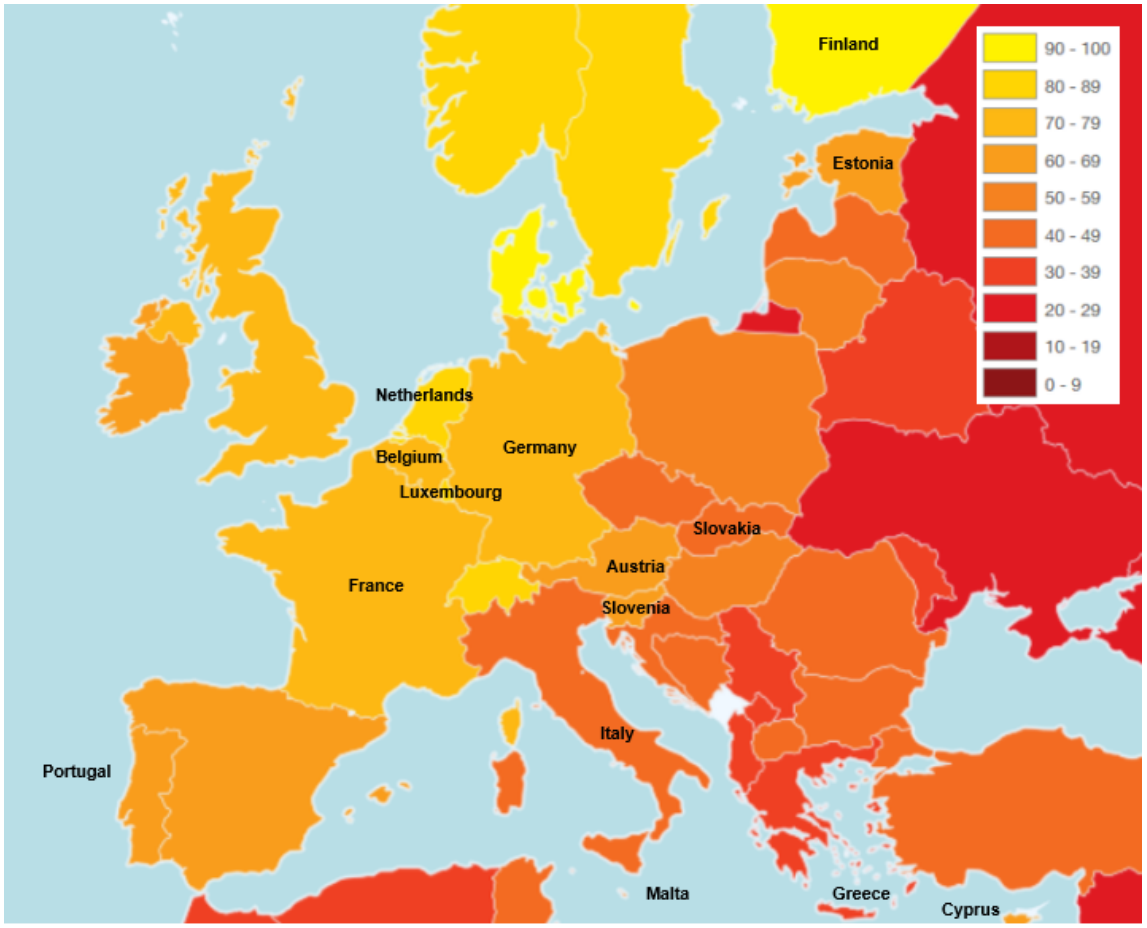

Figure 11: Corruption Perception Index per Country

The values that agree with the figure are displayed in Table 48. With these values, for the purpose of running a regression model, other variables are assigned to the CPI values in order to group them into different categories. Clearly Finland has the least corruption, whereas Greece, Italy and Malta all have the most corruption.

Country	CPI	Assigned Variable
Austria	69	3
Belgium	76	4
Cyprus	63	3
Estonia	69	3
Finland	90	6
France	70	4
Germany	79	4
Greece	43	1
Italy	43	1
Luxembourg	82	5
Malta	43	1
Netherlands	83	5
Portugal	63	3
Slovakia	50	2
Slovenia	60	3

Table 48: Corruption Perception Index per Country (MarketLine Advantage)

In Table 49 the results from running a probit model are displayed. The first CPI variable represents the actual CPI values as in Table 48. This shows a larger CPI value has a positive significant influence on stock market participation. This makes sense, since a larger CPI value represents less corruption.

The other 6 CPI dummy variables, represent the different categories as shown in Table 48 ("Assigned Variables"). These results makes the overall results a bit more clear, since one sees up until Category 3 a country's CPI value has a negative influence on the individuals stock market participation. From Category 4 onwards, the impact changes to positive.

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
CPI	0.172	0.047
	(17.27)***	(121.88)***
CPI Category 1 (dummy)	-0.514	-0.185
	(-13.98)***	(-16.52)***
CPI Category 2 (dummy)	-1.158	-0.347
	(-10.93)***	(-12.23)***
CPI Category 3 (dummy)	-0.066	-0.017
	(-2.08)**	(-11.82)***
CPI Category 4 (dummy)	0.285	0.053
	(10.23)***	(12.08)***
CPI Category 5 (dummy)	0.020	-0.040
	(0.33)	(-11.52)***
CPI Category 6 (dummy)	0.523	0.116
	(23.69)***	(19.62)***

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 49: Participation by CPI per Country - Probit Model

5.2.2.3 Political Preference

In the literature it has been found that left-wing voters are less likely to participate in the stock market than right-wing voters (Kaustia and Torstila, 2011). In order to investigate this phenomenon for the countries used in the HFSC, the countries are divided into either left-wing or right-wing, based on the majority of votes in the countries. This is visually shown in Figure 12.

A dummy variable is set up using these results, where a 1 is given if the country is right-wing and a 0 if the country is left-wing. Results from running a probit model with this variable is shown in Table 50 and one sees a right-wing country has a positive significant influence on stock market participation.

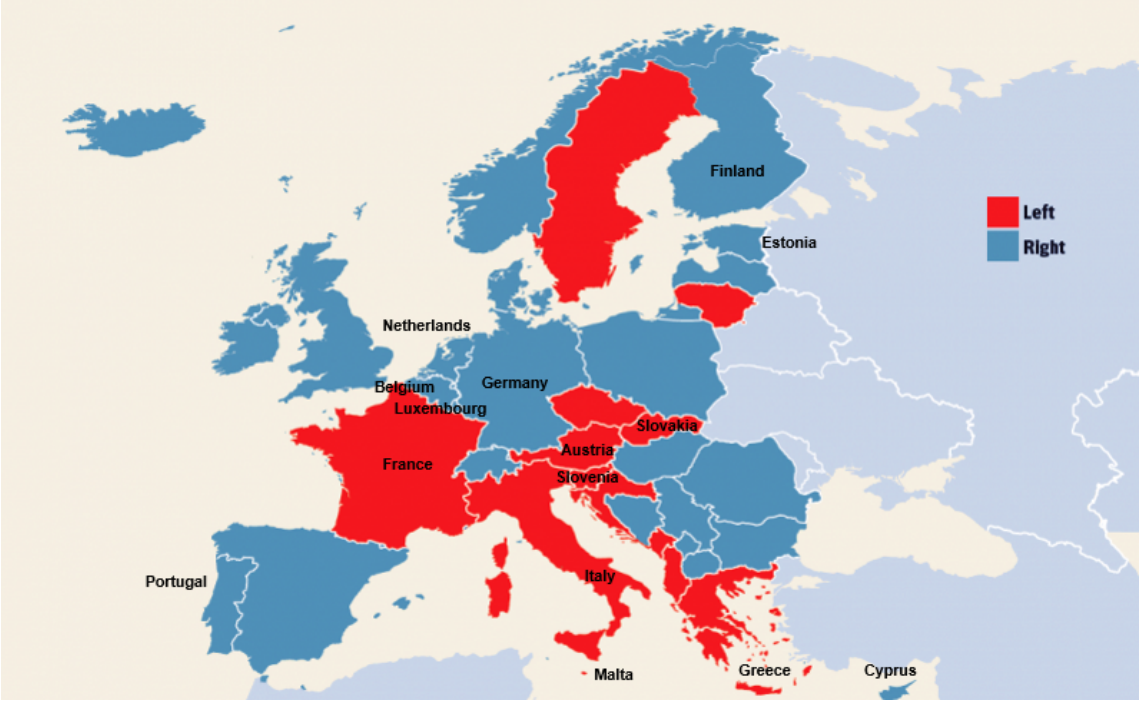

Figure 12: Political Preferences per Country

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
Right-wing (dummy)	0.116	0.083
	(3.80)***	(68.64)***

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 50: Participation by Political Preference per Country - Probit Model

5.2.2.4 Capital Gains Tax

As mentioned in the literature review, tax is probably the least research topic when investigating stock market participation. This section serves as a starting point for investigating tax, however, a lot of further research can still be done.

Capital gains tax is exactly what it says - tax on capital gains. Capital gains is the profit realized on the sale of a non-inventory asset that was greater than the amount realized on the sale. The most common capital gains are realized from the sale of stocks, bonds, precious metals and property. Since this research investigates stock market participation, capital gains tax is the preferred tax to investigate.

For the purpose of running a probit model, the countries used in this research were divided

into two groups, namely, countries with capital gains tax and countries without it. The countries that fall in the first category is assigned a 1. Table 51 shows the results from the probit model. Capital gains tax has a negative impact on stock market participation, as expected, however the impact is not very large and also not significant.

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
Capital Gains Tax (dummy)	-0.046	-0.038
	(-1.31)	(-22.28)***

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 51: Participation by Capital Gains Tax per Country - Probit Model

5.2.2.5 Religion

The last variable that is investigated in this research, is religion. Unfortunately, causality is a issue when investigating religion. Certain individuals claim to belong to a certain religion, but at the same time do not believe in a God. This is evident in Table 52 below. This evidence warns against using religion-type, especially Christianity, as an influence towards understanding stock market participation, since saying one belongs to a certain religion and actually believing in that religion, is not the same thing.

The countries used in this research where found to be largely Christian and/or Catholic and so no division will be made between specific religions. Looking specifically at the Muslim religion, it is clear that the countries used in the HFCS do not show considerable Muslim communities and so using this religion as an influencing factor is not feasible. In this research religion is used on a scale of 1 to 4, where 1 represents countries with very few true believers and 4 represents countries with many true believers. In this context, true believers refer to column two in Table 52 with the heading "I believe there is a God". The assigned categories from 1 to 4 are shown in the last column of Table 52.

Country	"I believe there is a God"	Christians	Assigned Variable
Austria	44%	80%	2
Belgium	37%	64%	2
Cyprus	88%	73%	4
Estonia	18%	39%	1
Finland	33%	81%	2
France	27%	63%	1
Germany	44%	68%	2
Greece	79%	88%	4
Italy	74%	83%	4
Luxembourg	46%	70%	2
Malta	94%	97%	4
Netherlands	28%	50%	1
Portugal	70%	93%	3
Slovakia	63%	85%	3
Slovenia	32%	78%	2

Table 52: Religion per Country (The Human Truth Foundation)

After running a probit model using religion as the influencing factor the results in the table below is found. One sees religion as a whole has a negative influence on stock market participation. However, when taking a deeper look at different levels of belief one finds countries where there are less true believers, show positive coefficients (Religion 1 and Religion 2). On the other hand, countries where there are more true believers, show negative coefficients (Religion 3 and Religion 4). Since most of the religious people in the countries used in this research claim to be Christians and/or Catholics, these results agree with what Renneboog and Spaenjers (2012) found in their study. As mentioned earlier, they found Catholics to be more risk averse. Adding to that, this research shows non-believers are definitely more risk tolerant than true believers.

Dependent Variable: Participate (dummy)	Coefficient	Marginal Effect
Religion	-0.181	-0.055
	(-16.93)***	(-96.62)***
Religion 1 (dummy)	0.230	0.065
	(7.87)***	(52.50)***
Religion 2 (dummy)	0.094	0.069
	(2.75)***	(54.60)***
Religion 3 (dummy)	-0.503	-0.218
	(-11.06)***	(-76.21)***
Religion 4 (dummy)	-0.477	-0.125
	(-13.60)***	(-73.69)***

*, **, and *** represent significance on the 10%, 5% and 1% levels, respectively.

Table 53: Participation by Religion per Country - Probit Model

5.3 Conclusion

This chapter explores different variables and how they influence stock market participation per country. The first set of variables agree with the variables used in Chapter 4, where the individual-level investigation is done. These variables are available in the HFCS. The second set of variable are extra variables from external resources that is added to the initial dataset in order to expand the results of this research. It is interesting how different variables behave differently across countries and this chapter therefore emphasises the importance of examining countries individually when investigating stock market participation in the Euro Area.

CHAPTER 6
CONCLUSION

The choice of individuals to participate in the stock market, whether it be positive or negative, has important economic implications. These implications include effects on consumption behaviour, welfare and things such as the design of regulation. Many research has been done on this ever-evolving topic and this research serves as an addition to this.

It can definitely be concluded that stock market participation is a scarce activity within the Euro Area, since less than 10% of the population participate. Because of this, recent research has been focussing more and more on "other" influencing factors and characteristics of individuals and countries in the hope that more concrete conclusions can be reached. A great deal of interesting results and conclusions has already been found and made, as was mentioned throughout this research. However, a final answer is still far from complete. Nonetheless, broadening one's beliefs with regards to the stock market and to the whole of the global climate, is definitely a step in the right direction. One cannot only focus on what use to work in the past and what use to make sense.

Throughout this research different influencing variables are used in order to try and explain and understand why individuals do (or do not) invest in the stock market across the Euro Area. Some of the interesting variables that were found to be significant include an individuals age, an individuals gender, the type of work they do and the type of company they work for. Other interesting factors include whether an individuals is married or not and which level of education is held. Furthermore, it is found that the country one lives in also plays a very important role, whether it be through the trust in the government, the type of government or simply the name of the country. These results serve as evidence that a lot of things can add and do add to individuals and their choices. It also serves as a building block for further research. The possibilities of more variables that can be included in further research is endless. Since this research deals with people and people are the most complex being on earth, almost anything can be investigated.

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