TALLINN UNIVERSITY OF TECHNOLOGY
DOCTORAL THESIS
49/2019

Investor Decisions and the Path to the Stock Market

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TALTECH PRESS

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This dissertation was accepted for the defence of the degree of Doctor of Philosophy in Finance on 17/10/2019

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Defence of the thesis: 19/11/2019, Tallinn

Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement submitted for the doctoral degree at Tallinn University of Technology, has not been submitted for any other doctoral or equivalent academic degree.

Tarvo Vaarmets

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signature

ISSN 2585-6898 (publication)
ISBN 978-9949-83-478-5 (publication)
ISSN 2585-6901 (PDF)
ISBN 978-9949-83-479-2 (PDF)

TALLINNA TEHNIKAÜLIKOOL
DOKTORITÖÖ
49/2019

Investori otsused ja teekond aktsiaturuni

TARVO VAARMETS

KIRJASTUS

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List of Publications

Paper I: Vaarmets, T., 2018. Gender, academic abilities and postsecondary educational choices. *Journal of Applied Research in Higher Education*, vol. 10, no. 3, pp. 380–398. DOI: https://doi.org/10.1108/JARHE-12-2017-0155. (ETIS 1.1).

Paper II: Vaarmets, T.; Liivamägi, K.; Talpsepp, T. 2019. From academic abilities to occupation: What drives stock market participation? *Emerging Markets Review*, vol. 39, June 2019, pp. 83–100. DOI: https://doi.org/10.1016/j.ememar.2019.04.004. (ETIS 1.1)

Paper III: Vaarmets, T.; Liivamägi, K.; Talpsepp, T. 2018. How Does Learning and Education Help to Overcome the Disposition Effect? *Review of Finance*, vol. 23, issue 4, pp. 801–830. DOI: https://doi.org/10.1093/rof/rfy006. (ETIS 1.1)

Author’s Contribution to the Publications:

Paper I – The author of the thesis is the sole author of the article.

Paper II – The author of the thesis had a leading role in preparing the dataset, running the estimations, systemising the literature and writing the draft article. The author of the thesis co-wrote the final version of the article.

Paper III – The author of the thesis had a leading role in preparing the dataset, running the estimations, systemising the literature and writing the draft article. The author of the thesis co-wrote the final version of the article.

Introduction

Human behaviour and decision making have taken centre stage in economic research for centuries. Until the middle of last century, it was believed that humans and organisations led by humans always make rational economic decisions. However, Simon (1955) started to doubt this widely held belief, concluding that the concept of the highly informed, rational "economic man" that was used in traditional economic models "is in need of fairly drastic revision." In his book Simon (1957) planted the seeds of his theory of bounded rationality, which is based on the idea that individuals' rationality is limited in their decision making.

These ideas started to spread and the works of Kahneman and Tversky (1979, 1992), who highlighted the importance of psychology in economic science, are considered to be the first manifestations of behavioural finance.

As a natural development, a growing number of studies in behavioural finance are now also challenging the widespread assumption made by modern financial economics that individuals behave with extreme rationality. Early recognition of possible cracks in that assumption appeared in research about the stock market crash in the USA in 1987, which indicated that investors may actually not have behaved rationally, leading Shiller (1989) to conclude: "Increasingly, there is statistical evidence that suggests the stock market may have a life of its own to some extent, unrelated to economic fundamentals". There were some studies before Shiller (1989) and have been many since that have tried to understand why our financial behaviour does not serve our best economic interests, and why our deviations from rationality are often in reality systematic[1]. Behavioural finance as a still relatively new scientific discipline tries to answer these questions by offering a better understanding of the complicated financial decision-making process.

Traditional finance relies on fundamental models and theories that try to explain how capital markets function and how investors should behave. These models include for example the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964) and Lintner (1965), the portfolio theory of Markowitz (1952, 1956), the option pricing model of Black and Scholes (1973), and also the efficient market hypothesis formulated by Fama (1970). Models in traditional finance assume that investors' decisions are based on the most beneficial combination of risk and return from among all the possibilities for investment, resulting in the optimal portfolio for the investor's individual risk aversion level given efficient markets. However, there is a lot of evidence in the literature on behavioural finance that in reality investors tend to behave differently to what traditional finance models predict.

Behavioural finance is defined as the study of how psychology affects finance (Shefrin, 2002). Since the beginning of the 1990s behavioural finance has gained popularity among researchers and also among market participants. However, the debate between supporters of traditional finance and supporters of behavioural finance is still ongoing. Do emotions and psychological biases affect our financial decisions?

Traditional finance assumes that investors are always rational, but Shefrin (2002) challenges that view and argues that investors driven by different biases are not always rational and that they also tend to make irrational financial decisions. This is in line with Pompian (2006), who argues that traditional finance is not based on principles that describe how investors actually behave, but rather on principles for how investors should behave. Studies in behavioural finance help to acknowledge the factors that influence investment decisions, as doing so could help to prevent bubbles forming in financial markets or at least soften their negative impact.

[1] As concluded by Barber and Odean (2001).

Incorporating the biases into asset pricing models can help to improve the pricing of securities and real estate and possibly reduce the uncertainty involved and the unnecessary volatility of asset prices.

Inspired by the debate between traditional and behavioural finance reflected in the earlier academic literature, including the finding that investors do not always behave rationally, the current thesis focuses on the micro level of behavioural finance (see e.g. Pompian, 2006), which examines the biases of investors (Shefrin, 2002). As an additional comparison it also studies investor's choices outside the stock market, in an environment where it is easier to control emotions as the pressure to make decisions is not so intense. From the perspective of making decisions, the stock market can be seen as an extreme environment, where the constant information flow tends to be very noisy and the emotional pressure from the market may be high. This makes it hard for investors to control their emotions and refrain from making harmful decisions. The contribution of the thesis is its new empirical evidence on how different socioeconomic characteristics influence the choices of investors about their field of study and their stock market participation, and the behavioural bias known as the disposition effect.

The thesis is based on three published papers (Vaarmets, 2018; Vaarmets, Liivamägi, and Talpsepp, 2019; Vaarmets, Liivamägi, and Talpsepp, 2018) of which the author of the thesis is the sole author or the first author. All three papers concentrate on individuals who had bought at least one share from the local stock market by the end of 2012. The stock market dataset is used in combination with educational data from the Estonian Ministry of Education and Science, income tax data from the Estonian Tax and Customs Board, information from the Estonian Census of 2011, and data taken from the Estonian Population Register. While the combined dataset covers over 200,000 individuals, the final sample sizes used in the papers are dependent on the research focus and the availability of the detailed data.

The two papers by Vaarmets et al. (2018, 2019) have been published in finance journals, while Vaarmets (2018) has been published in an education journal. All three research papers study the choices of investors and how these choices are affected by different socioeconomic characteristics, looking at how academic abilities affect the choice of field of study, what affects the decision of individuals to participate in the stock market, and how learning and education are related to the disposition effect.

The first paper in the thesis, "*Gender, academic abilities and postsecondary educational choices"*, focuses on the choices of field of study that investors usually make before they enter the stock market mostly by the age of 18. The paper makes a contribution to the existing literature by using a dataset that makes it possible to relate quantitative measures of very different academic abilities to all the major academic disciplines chosen in universities. This unique approach has not previously been taken in the literature because of data limitations. Instead of concentrating on one specific area, such as science, technology, engineering and mathematics (STEM), the paper takes a broader view and also extends the earlier findings about gender inequalities in higher education. Like the other two papers presented in the thesis, the findings from paper I focus around the decisions made by investors. The paper provides evidence that individual investors tend to choose their field of study to suit their academic abilities.

The article "*Gender, academic abilities and postsecondary educational choices"*, was published in the *Journal of Applied Research in Higher Education*, vol. 10, no. 3.

The second paper presented in the thesis studies how academic abilities together with education and occupation influence stock market participation. The article is entitled "*From academic abilities to occupation: What drives stock market participation?"* and combines five datasets with a sample of over 200,000 individuals, which makes it possible to observe the effect in the finest detail available so far. Earlier studies like Grinblatt, Keloharju, and Linnainmaa (2011) have some data limitations in their comparisons between genders of cognitive abilities, including mental abilities and IQ. The second paper fills this gap by answering the question of whether the market participation decisions of men and women are similarly affected by their characteristics. Furthermore, the paper extends the existing literature on stock market participation by offering new insights into economic activity and categories of occupation like manager, professional or service worker from the perspective of stock market participation. The study concludes that women are clearly less affected than men by their mental abilities in deciding about stock market participation. It is also found that economic activity, occupation and religion influence decisions about stock market participation, while stock market investors tend to be more ambitious, more open to risk and more intelligent than non-participants. While most of the literature has focused on how cognitive abilities affect stock market participation, the paper included in this thesis sheds some additional light on the findings about non-cognitive abilities (see for example Conlin et al., 2015; Kaustia and Torstila, 2011; Guiso, Sapienza, and Zingales, 2008).

The article "*From academic abilities to occupation: What drives stock market participation?"* was published in *Emerging Markets Review*, vol. 39, June 2019.

Finally, the third article "*How Does Learning and Education Help to Overcome the Disposition Effect?"* was published in Review of Finance, vol. 23, issue 4. The study combines complete detailed transaction data from 2004 to 2012 from the Nasdaq OMX Tallinn with data from the Estonian Ministry of Education and Science. The paper offers new empirical insights into how education, intelligence and mental abilities impact the disposition effect. This effect is the tendency of investors to hold on to losing positions and to give up winning positions too early, as first documented by Shefrin and Statman (1985). The disposition effect has been identified as a costly bias by Goulart, da Costa, Andrade, and Santos (2015), highlighting the importance of better understanding the phenomenon. The article "*How Does Learning and Education Help to Overcome the Disposition Effect?"* concludes that higher intelligence and stronger learning abilities as measured by education level and the type of education lessen the disposition effect. In addition, the paper provides evidence that more highly educated and intelligent investors learn faster by trading and that mathematical abilities are beneficial for overcoming the disposition effect. Lastly, the results presented in the paper indicate that learning ability is one of the most important components of intelligence in how it affects the disposition effect.

The remainder of thesis is organised as follows: Section 1 gives a broader overview of the articles included and section 2 offers final comments and conclusions combining all the articles.

1. Summaries of the Studies

Financial markets sometimes behave in ways that are difficult to explain with underlying economic fundamentals. There are bubbles, which are periods of extraordinarily fast increases in assets prices to levels that are hard to justify economically, and periods when the opposite happens and asset prices fall quickly to levels that can be considered very cheap as measured by different indicators, and these situations raise questions about the rationality of investors. Even though behavioural finance is gaining more and more supporters, as reflected for example in the increasing amount of academic research into it, traditional finance and the efficient market hypothesis have still not been disproved. Eugene Fama first presented his efficient market hypothesis in Fama (1970), and he still defended it 28 years later in his study (Fama, 1998) as a response to the doubts and questions raised by behavioural finance. The discussion between traditional finance and behavioural finance continues. The current thesis includes three papers that focus on the behaviour of individual investors and the following sections give a brief overview of these papers.

1.1 Gender, academic abilities and postsecondary educational choices

According to Hackett and Van der Werfhorst and Kraaykamp (2001), the choice of which field to study or work in clearly impacts peoples' lifestyles. Kalmijn and van der Lippe (1997) argue that the choice of academic discipline determines future earnings. These findings indicate that it is highly important to understand better what affects the choice of academic discipline. Several authors, including Klevan, Weinberg, and Middleton (2016), and Harackiewicz, Barron, Tauer, and Elliot (2002), have shown that academic performance in high school tends to impact the choice of what to study as an undergraduate. In general, men tend to be more attracted by subjects that are related to mathematics than women are, as concluded by Correll (2001) and Wang and Degol (2017) and as also reflected in the Estonian data used in the paper.

Motivated by these previous studies, the paper included in the current thesis concentrates on the final high school exam results and provides new information about how these results affect the gender gap in post-secondary educational choices. The unique dataset used in the study allows quantitative measures of very different academic abilities[2] to be related to all major academic disciplines. Data limitations have meant that this kind of approach has not been possible before. This allows the paper to take a broader view instead of focusing on a specific area like science, technology, engineering and mathematics (STEM).

The sample of total exam results used in the paper covers 221,774 individuals. However, detailed educational data are available only for those who had bought at least one share from the local stock market by the end of 2012. This means that study information is available for 3714 of the individuals who had attained a higher education qualification by the end of 2012. Even though the paper is based on a sample that only includes investors and may therefore have some limitations, the sample follows the same trends that are also found in previous studies, such as mathematics-related subjects attracting proportionally more men than women, or women dominating in higher education.

Like in the classification of the Estonian Ministry of Education and Science, fields of study are grouped into exact and natural sciences, humanities, social sciences and other sciences in the

[2] Following the previous literature, exam results are used as a proxy for academic abilities in the paper. Koenig, Frey, and Detterman (2008) show that academic abilities measured by American College Test (ACT) scores are also closely correlated with mental abilities (IQ). This is in line with Song et al. (2010), who use the grade point average (GPA) as a measure of academic ability.

paper. Logit and probit models together with post-estimated marginal analysis are employed for statistical analysis, as suggested by Correll (2001), Eccles, Vida, and Barber (2004), and Klevan et al. (2016). In addition, simple two-sample t-tests with equal variances are used to detect the significance of differences in exam results.

The broad conclusion from the results presented in the paper is that individual investors tend to choose their field of study to suit their academic abilities. More precisely, the data used in the paper indicate that higher scores achieved in the exact and natural sciences tend to lead to the choice of studies in the same area. Concomitantly, higher results in humanities exams tend to lead away from the exact and natural sciences. According to the t-test results, female students outperform male high school students in humanities, while the gender gap in other fields is not so clear. Using this comparative advantage, female high school graduates also choose to study humanities in higher education proportionally more often than men do, according to the data used in the study. As academic abilities in the natural and exact sciences are quite similar for men and women, men are in a better position to succeed in these disciplines than they are in the women-dominated humanities. This may also partly explain why men are more attracted to choose natural and exact sciences than women are. Another conclusion from the analysis in the paper is that women's superiority and preferences in humanities may be one reason why female high school graduates prefer social sciences for their undergraduate studies slightly more than men do as the choice of social sciences is also rather affected by the results in the humanities exams. Finally, the data used in the paper show that men with lower test scores tend to be keener to choose subjects that can be classed as professional higher education, which also covers more practical professions such as the police and the military, or work in construction.

1.2 From academic abilities to occupation: What drives stock market participation?

What affects stock market participation and why do so few people find their way into the stock market? Hong, Kubik, and Stein (2004) and Grinblatt et al. (2011) find that only about half of the households in the US participate in the stock market, while direct participation rates are even lower. Haliassos and Michaelides (2003) argue that the main reason why so few households invest in stocks is poor financial literacy. This view is supported by Van Rooij, Lusardi, and Alessie (2011), who conclude that people who are more financially literate tend to invest more in shares. From the emerging market perspective, participation rates are even lower than they are in developed markets[3] and this makes the paper included in the thesis even more relevant as it uses data from an emerging market.

The contribution of the paper to the literature is its new empirical insights into how stock market participation is influenced by academic and mental abilities, education, and career choices and characteristics. The unique dataset that it uses allows a focus on gender differences in order to answer the question of whether the decisions of men and women about stock market participation are affected by their gender characteristics. This is a step forward as the previous literature offers limited information about how cognitive and mental abilities affect stock market participation for the two genders. This also lets the paper provide analysis and

[3] The Household Finance and Consumption Network (HFCN) reports that the direct stock market participation rate in Estonia is 3.6%, while 3.2% of households have mutual fund assets. Those figures are comparable with Poland and Slovakia and slightly higher than in Latvia or Greece but lower than in all larger and more developed European countries. Germany, Belgium, France, Spain and Ireland have participation rates of around 10%, while Finland and Cyprus have participation rates of over 20%. The euro area average is 8.8%.

conclusions on how different types of cognitive ability measured with standardised exam results from all the main disciplines affect stock market participation. Considering that the general education level or measures of intelligence may not always capture the impact from different aspects of intelligence, this is an important contribution. Meta-analysis by Kim (2005) points to the limitations of general measures of intelligence. Finally, the dataset used also allows the paper to extend the existing literature by studying how economic activity and categories of occupation like manager, professional, or service worker affect the decisions of individuals about stock market participation.

The conclusions of Borghans, Duckworth, Heckman, and Ter Weel (2008) and Heckman, Stixrud, and Urzua (2006) indicate that personality factors are as important as cognitive abilities for achieving socio-economic success. Personality traits like extravagance, sentimentality, exploratory excitability, and dependence are also related to stock market participation, as found by Conlin et al. (2015). Kaustia and Torstila (2011) find a relationship between political views and investing in stocks, while Guiso et al. (2008) argue that people with a more trusting nature also tend to participate more in the stock market.

While the importance of financial knowledge has been highlighted by several authors, including Lusardi and Mitchell (2008), and Hilgert, Hogarth, and Beverly (2003), traditional education still matters. Guiso, Haliassos, and Jappelli (2003) provide evidence that stock market participation depends on the level of education and wealth. This is also consistent with the findings of Campbell (2006). Christiansen, Joensen, and Rangvid (2008) take a further step and argue that financial decisions are affected not only by the level of education, but also by the type of education. Grinblatt et al. (2011) find that the probability of men with a higher IQ participating in the stock market is higher than that of men with lower IQ participating.

There are only a few studies in the previous literature that relate occupational characteristics and economic activity to stock market participation. Grinblatt et al. (2011) classify individuals as entrepreneurs, farmers, finance professionals or unemployed and find that unemployed individuals are less likely to buy stocks than employed individuals are. They also conclude that entrepreneurs are not as eager to participate in the stock market as others are. This is in line with Heaton and Lucas (2000) but contradicts the findings of Barnea, Cronqvist, and Siegel (2010) and Conlin et al. (2015).

While the total sample used in the paper covers 221,572 individuals, detailed educational data on investors who have taken standardised exams since 1997 is available for 6811 investors, which represents 24.4% of all investors. Considering that the IQ data of Grinblatt et al. (2011) represent approximately 6.1% of all Finnish individual investors[4], this proportion is quite large. The paper uses the cohort data of national standardised exams to minimise the possible selection biases that could result if the sample is restricted with other characteristics of the investors. Thus the sample contains all investors under the age of 35. This is expected to soften the limitations of the salary-based wealth proxy as it basically only discards inheritance. The wealth accumulation process in Estonia could only start after independence was regained in the 1990s, which highlights that young individuals could have had only very limited access to inherited wealth during the sample period.

Following Bogan (2008), Christiansen et al. (2008), Grinblatt et al. (2011) and other prominent authors, the paper uses probit regression models as the main tool for data analysis. The binary dependent variable in the models indicates whether the individual participated in the stock market during the period under observation or not. Independent variables include

[4] The proportion of 6.1% is calculated as follows: Grinblatt et al. (2011) study include 44 651 investors with IQ information, while the same source (Finnish Central Securities Depository (FCSD) Registry) finds there were a total of 732 843 individual investors in Finland at the same time as reported by Karhunen and Keloharju (2001).

different characteristics of the individuals and also control variables like gender, age, income and higher education. Post estimated marginal analysis is used for easier interpretation of the regression results. Finally, two-sample t-tests with equal variances are used to compare average high school final exam results between stock market participants and individuals who did not hold any shares in the period observed. The size of the effect is calculated using Cohen's d and Hedges' g.

Using the data and the analysis, the paper provides empirical evidence that stock market participation depends on mental abilities in very different areas. The effect of mathematics and physics exam results on stock market participation is stronger than the effects from other subjects. The study concludes that a brighter mind, a higher level of education and better quantitative and language skills tend to increase the probability of stock market participation.

The paper offers evidence that the relationship between mental abilities and stock market participation is much stronger for men than for women. However, as the comparable academic results achieved by men and women are very similar, these differences cannot be explained by the differences in these results. Therefore, the reason for the gender gap that is described may be hidden in the differences in non-cognitive abilities or other currently unidentifiable factors that may affect participation.

The paper also argues that entrepreneurial activities and managerial positions tend to lead to the stock market. The psychological literature suggests that the common traits associated with occupation or socioeconomic status are a readiness to take risks, or openness to new experiences, ambition, and intelligence. This may also explain why entrepreneurs and managers tend to be more likely to buy shares than others. In addition to the economic activity and occupation, the paper also provides empirical evidence that socio-economic status, religious affiliation, nationality and citizenship impact stock market participation.

1.3 How Does Learning and Education Help to Overcome the Disposition Effect?

One bias that relates to investors' irrational behaviour is the disposition effect, which has been scrutinised intensively since the 1990s. The disposition effect is defined as the overall tendency of investors to hold on to their losing positions too long and to sell their winning positions too early. As the disposition effect has been found to be a costly bias, by Goulart et al. (2015) for example, it is important for investors to learn to reduce the related negative effect. This means that the ability of investors to learn from their own mistakes can also help them overcome the disposition effect. The disposition effect was first reported by Shefrin and Statman (1985), and this was followed by the influential works by Odean (1998), Grinblatt and Keloharju (2001) and others, who strongly document the existence of the disposition effect.

However, Dhar and Zhu (2006) show that while the disposition effect is clearly present at the aggregate level, there are differences at the individual level. They conclude that almost 20% of individual investors are not affected by the disposition effect and can even demonstrate a reverse disposition effect. Investors who are not influenced by the bias tend to have higher incomes, financial sector jobs, and higher trading frequency. The first two of these are proxies of investors' sophistication. Feng and Seasholes (2005) also argue that investor sophistication and trading experience together can eliminate the reluctance to realise losses.

The learning process that occurs in the financial markets can also reduce the disposition effect. Fenton-O'Creevy et al. (2012), and Nicolosi, Peng, and Zhu (2009) discuss how learning in the financial markets may occur in different forms. Feng and Seasholes (2005) focus mostly on learning from experience by showing that trading experience reduces the disposition effect.

Equally, Seru, Shumway, and Stoffman (2010) highlight the importance of learning about one's ability to trade. They conclude that investors who trade regularly are less affected by the disposition effect but also have a lower speed of learning.

The lack of data means the relationship between the disposition effect and mental or academic abilities has not received much attention in the previous literature. The various proxies that are used to measure sophistication in the literature relate rather weakly to mental and academic abilities. Even so, Goo, Chen, Chang, and Yeh (2010) show that the disposition effect is connected to education as highly educated investors experience a lower disposition effect.

The paper presented in the current thesis contributes to the literature by providing empirical insights into how education, intelligence and certain mental abilities affect the disposition effect. Combining the effect of education and intelligence with learning by doing allows the research to study how different abilities are related to the disposition effect with a level of detail that has not been possible until now. In addition, the paper offers insights into whether the speed and importance of learning by doing depends on education and intelligence.

The paper uses survival analysis as the main method for measuring the disposition effect, as also suggested by several prominent authors like Feng and Seasholes (2005), Seru et al. (2010) and others. Logit regression models were also employed for the robustness check, and they confirm the findings in all cases. The study uses a Cox proportional hazard model to measure the probability of an investor selling a stock they hold. The hazard rate is calculated to interpret the results. The hazard rate is the probability of a stock being sold at time t conditional on the stock being held at time t-1.

The paper concludes that educational characteristics and intelligence play an important role in influencing investor behaviour. The results presented in the paper indicate that the disposition effect is stronger for investors with lower intelligence. Furthermore, the sample used shows the effect to be stronger at the two ends of the education scale, meaning that investors with master's or doctoral degrees are less affected by the disposition effect and investors with vocational training or only high school education are more affected by it. Moreover, highly educated investors with master's or doctoral degrees are able to learn faster by doing, while investors with lower intelligence tend not to improve their trading even when they gain more experience.

The study also shows a relation between better number skills and lower levels of the disposition effect, highlighting that mathematical abilities offer some beneficial effects.

Interestingly, there is evidence in the paper that investors with financial education are clearly affected by the disposition effect even though they are expected to have better knowledge. This suggests that the importance of knowledge as a policy measure for helping to avoid behavioural biases cannot be overemphasised. The results of certain high school final exams show that even a strong ability at memorising information does not help, and these conclusions indicate that any one-off campaigns to increase investor knowledge and awareness will probably have a low impact, but are still not completely useless. Knowledge about the domain of finance seems to help investors learn a little faster when they enter the market. However, educating investors must be viewed as a long-term process and even then, some investors will still not be able to learn despite the efforts made.

2. Final Comments and Conclusion

The current thesis makes its main contribution to the behavioural finance literature through its aim to take the discussion about the rationality of investors in the financial markets a step further. Traditional finance and related models and theories as in Sharpe (1964), Lintner (1965), Markowitz (1952, 1956), Black and Scholes (1973), and Fama (1970) assume that investors' decisions are based on the most beneficial combination of risk and return, meaning that investors always behave rationally. However, behavioural finance challenges these assumptions by arguing that investors are influenced by their psychology and emotions in their decision making and therefore tend to make irrational financial decisions (see Shefrin, 2002 or Pompian, 2006 as examples).

All three papers included in the thesis study the behaviour of investors, looking at how academic abilities influence their choice of what subject to study, what affects their decision to participate in the stock market, and how learning and education are related to the disposition effect.

Answers to these research questions are found using unique Estonian data with a comprehensive dataset from the Nasdaq OMX Tallinn stock exchange as the core dataset. The stock market data consist of all the transactions made with a total of 23 listed Estonian companies in the nine years from 01 January 2004 to 31 December 2012, together with all the shareholdings from the same period. Four other datasets are used alongside this and they are combined in order to answer to the research questions highlighted in papers I, II and III.

The dataset from the Estonian Ministry of Education and Science includes all the high school marks, the results of high school final exams, and information about each individual's level of education, which gives their university degrees and type of education. Information on income taxes is added from the dataset provided by Estonian Tax and Customs Board together with information from the Estonian Census of 2011. The census data cover many characteristics such as socioeconomic status, information about health and religion, economic activity, detailed educational levels, and occupation. The last element of the combined dataset is from the Estonian Population Register and contains data such as legal marital status, nationality and citizenship.

The first paper studies the choices investors tend to make at a young age, mostly before entering the stock market and usually at the age of 18. The broad conclusion of the paper is that investors tend to choose their field of study to suit their academic abilities, which is quite justified behaviour. The paper further concludes that, on average, women are more attracted by humanities than men are, and men are more attracted by exact and natural sciences than women are. As stock market activities relate more to exact and natural sciences than to humanities, the finding is also consistent with the sample used in paper II, which shows that 73.2% of the investors are male.

Paper II provides empirical evidence that stock market participation depends on mental abilities in very different areas, as the results of mathematics and physics exams affect stock market participation more than those of results in other subjects. The effect of mental abilities on stock market participation is much stronger for men than for women in the results presented in the paper. The paper also argues that a higher level of education and better quantitative and language skills help to increase the probability of stock market participation. Finally, the paper finds relationships between economic activity, occupation, socioeconomic status, religious affiliation, nationality, citizenship and stock market participation. Involvement in entrepreneurial activities or managerial positions tend to increase participation rates in the findings of the study.

Paper III focuses on the disposition effect, which is the well-known bias investors tend to have for holding onto losing positions and selling winning positions. The paper concludes that the disposition effect is stronger for investors with lower intelligence. The data used show that investors who have master's or doctoral degrees are less influenced by the disposition effect, while investors who have chosen vocational training instead or have only high school education are more influenced by the effect. Highly educated investors tend to be able to learn faster by doing and by actually making trades, while increasing experience does not improve trading for investors with lower intelligence. The paper also finds some beneficial effects from mathematical abilities, as better number skills can be associated with a weaker disposition effect.

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Acknowledgements

I would like to thank:

- Senior Researcher Tõnn Talpsepp, the thesis supervisor, for basically everything. For ten years he has been the driving force behind my academic achievements. His advice and support, his guidance, relaxed attitude and friendship has kept me focused and motivated. His IT skills and his deep knowledge in finance and in the general academic world has helped to push the papers included in current thesis to a level I can be really proud of. Thank you Tõnn;
- My family, my mother Tiina Vaarmets for teaching me the importance of education and her beyond earthly care, my sisters Jaana Laur and Age Aavasalu for always being beside me and for always believing in me;
- Co-author Kristjan Liivamägi for his contribution to the papers, and his sense of humour and friendship, which has made my long PhD journey a lot more fun. Thank you, Kristjan;
- Professor Marc Oliver Rieger from the University of Trier for his valuable suggestions about the papers and parts of the thesis;
- Dean Enn Listra for inviting me to apply for the doctoral programme;
- Associate Professor Karin Jõeveer for her suggestions, optimism and support and other professors, staff and doctoral students at Tallinn University of Technology for their ideas and suggestions, and the contributions to improving the papers;
- Kalle Viks and Nasdaq OMX Tallinn Stock Exchange, Marko Mölder and Estonian Ministry of Education and Science, Lauri Veski and Innove, Aime Lauk and Statistics Estonia for the foundation of this thesis – the data. Thank you, your support made this research and thesis possible;
- Robin Hazlehurst for his proofreading of the research papers and the final thesis manuscript;
- The European Union Social Fund, the DoRa programme, Doctoral School in Economics and Innovation and Tallinn University of Technology for financial support for presenting my papers at various conferences;
- My friend Triin Sigus for inspiring me and showing that strong will and spirit can really take you higher; my friend Kadi Saar for reminding me that there is also life outside of the world of academia;
- My friends Erki Kivistik, Gert Kaju and Rainer Jürgenson for the emotional lifting and great humour that loaded my academic batteries;
- Composer Sven Lõhmus, mr. Happyman and Belgian electronic music group Lasgo for the musical opium for my mood and mind I truly needed during the writing process of the papers.

Abstract

Investor Decisions and the Path to the Stock Market

The current thesis contributes to the literature on both behavioural finance and education. It includes three papers, Paper I, Paper II and Paper III that focus on investor behaviour and providing insights into how different socioeconomic characteristics influence the choices of investors about their field of study and their stock market participation, and the disposition effect.

Traditionally, human financial behaviour has been described as rational, meaning that traditional finance assumes that individuals always make economically optimal and beneficial decisions. This assumption is the basis of various models and theories in traditional finance such as the efficient market hypothesis formulated by Fama (1970). However, since the early 1990s behavioural finance has attracted increasing attention, arguing that individuals do not always behave rationally when making their financial decisions (Shefrin, 2002; Pompian, 2006).

The current thesis contributes to the behavioural finance literature by offering new empirical evidence on how the decisions of investors are affected by different socioeconomic characteristics and biases with the conclusion that investors do not always behave in their own best economic interests. Additionally, the thesis contributes to the educational literature by showing that individuals tend to make justified decisions outside the stock market when they choose what field to study. The thesis uses a unique dataset with the full set of transactions from the Tallinn stock exchange in combination with four other datasets from the Estonian Ministry of Education and Science, the Estonian Tax and Customs Board, the Estonian Population Register, and the Estonian Census of 2011. This approach helps to provide new information that had earlier been missing from the literature due to data limitations.

The first publication, titled *"Gender, academic abilities and postsecondary educational choices"*, studies the relationship between choices about study subjects and academic abilities. The paper concludes that investors tend to choose their study courses to suit their academic abilities, which seems quite justified behaviour.

The second publication *"From academic abilities to occupation: What drives stock market participation?"* analyses how different socioeconomic characteristics influence stock market participation and concludes that higher mental abilities, a higher level of education and better quantitative and language skills tend to increase the probability of stock market participation. The study also argues that economic activity, occupation, socio-economic status, religious affiliation, nationality, and citizenship affect stock market participation.

The third publication *"How Does Learning and Education Help to Overcome the Disposition Effect?"* studies how educational characteristics and learning impact the disposition effect and concludes that the disposition effect is stronger for investors with lower intelligence, and that gaining more experience does not improve their trading. In contrast, the paper argues that highly educated investors tend to learn faster by doing and are less prone to the disposition effect.

All three publications included in the thesis study the behaviour of investors and provide new empirical evidence on how different socioeconomic characteristics impact the decisions made by investors, highlighting the importance of intelligence and education.

Kokkuvõte

Investori otsused ja teekond aktsiaturuni

Antud doktoritöö *"Investori otsused ja teekond aktsiaturuni"* kuulub käitumusliku rahanduse valdkonda ning keskendub üksikinvestori käitumise uurimisele, lähtudes seega mikrotasandi perspektiivist. Töö keskendub investorite erialavaliku, aktsiaturul osalemise ja dispositsiooni efekti tagamaade ja seotud valikute põhjuste analüüsimisele, baseerudes kolmele teadusartiklile: Vaarmets (2018), Vaarmets, Liivamägi ja Talpsepp (2019) ja Vaarmets, Liivamägi ja Talpsepp (2018). Doktoritöö annab ülevaate uurimuse lähtepunktiks ning inspiratsiooniks olnud teoreetilisest taustast, töös kasutatud andmetest, metodoloogiatest ning tulemustest ja tehtud järeldustest.

Traditsiooniline rahandus baseerub erinevatele fundamentaalmudelitele ja teooriatele, mis püüavad kirjeldada finantsturgude toimimist ja seda, kuidas investorid peaksid käituma. Siinkohal võib näiteks tuua Sharpe (1964) ja Lintner (1965) poolt välja töötatud finantsvarade hindamise ehk CAPM (Capital Asset Pricing Model) mudeli, Markowitzi (1952, 1956) portfelliteooria, optsioonide hindamismudeli (Black and Scholes, 1973), aga ka Fama (1970) efektiivse turu hüpoteesi. Traditsiooniline rahandus eeldab, et investorite otsused põhinevad kõikide investeerimisvõimaluste parimal riski ja tulu kombinatsioonil, mille tulemusena saavutatakse investori isiklikule riskitasemele vastav optimaalne portfell ning seeläbi ka efektiivsed finantsturud. Käitumusliku rahanduse uurimistööd pakuvad aga tõestuse, mille järgi investorid kipuvad käituma siiski teisiti kui traditsioonilise rahanduse mudelid ja teooriad eeldavad.

Käitumusliku rahanduse lihtsa definitsiooni kohaselt on tegemist valdkonnaga, mis uurib kuidas psühholoogia mõjutab rahandust (Shefrin 2002). Teadusharu juured ulatuvad Kahnemann ja Tversky (1979, 1992) töödesse, kes tõid psühholoogia kontseptsiooni, eelkõige otsuste tegemise ebamäärases keskkonnas, majandusteadusesse. Alates 1990. aastate algusest on huvi käitumusliku rahanduse vastu kasvanud nii akadeemikute kui praktikute hulgas. Diskussioon traditsioonilise ja käitumusliku rahanduse vahel aga jätkub – kas emotsioonid ja psühholoogia ikkagi mõjutavad meie rahandusotsuseid?

Käesolev doktoritöö annab omapoolse panuse antud diskussiooni, pakkudes uusi empiirilisi tõendeid selle kohta, kuidas erinevad sotsioökonoomilised karakteristikud mõjutavad investorite erialavalikuid, aktsiaturul osalemist ja dispositsiooni efekti nimelist käitumuslikku kalduvust. Kuna töös sisalduv investorite erialavalikut puudutav uurimus on avaldatud haridusajakirjas, panustab antud doktoritöö ka haridusteadusesse. Doktoritöö kasutab unikaalset, üheksa-aastase perioodi kõiki tehinguid sisaldavat Tallinna Börsi andmestikku, millele on liidetud veel neli erinevat muud andmestikku Eesti Haridus- ja Teadusministeeriumist, Maksu- ja Tolliametist, Eesti Rahvastiku Registrist ja 2011. aasta rahvaloendusest. Sellise viie erineva andmestiku kombineerimise tulemuseks on laiapõhjaline hariduslike ja muude sotsioökonoomiliste karakteristikute kogum, mis võimaldab uurida investorite käitumist sellise detailsusastmega ja sellistest aspektidest, mis varasemas käitumusliku rahanduse kirjanduses ei ole olnud andmepiirangute tõttu võimalik.

Doktoritöö esimene publikatsioon *"Sugu, akadeemilised võimed ja keskhariduse järgsed valikud"* keskendub investorite erialavalikutele, mis on üldjuhul tehtud enne kui investorid börsile sisenevad ehk tavaliselt 18. aastaselt. Kuigi artikkel on avaldatud haridusajakirjas, annab uurimus teatud võimaluse saada teavet investorite käitumise kohta ka börsivälises, eeldatavalt vähemate emotsioonide ja väiksema tahtmatu psühholoogilise mõjuga keskkonnas. McKenzie ja Schweitzer (2001) leiavad, et ülikooli sisseastumistulemused on seotud ka ülikoolis saavutatud eduga ning sarnaselt järeldavad ka Harackiewicz et al. (2002), et keskkoolis näidatud tulemuste abil saab prognoosida akadeemilist edu kõrgkoolis. Neist töödest motiveerituna, kasutab artikkel I andmestikku, mis võimaldab seostada erinevate akadeemiliste võimekuste kvantitatiivsed mõõdikud kõikide peamiste kõrgkoolides õpetatavate teadusvaldkondadega. Tegemist on unikaalse lähenemisega, mis on senisest teaduskirjandusest piiratud andmete tõttu puudunud. Selle asemel, et keskenduda kindlale teadusvaldkonnale nagu näiteks reaalteadusele (vaata näiteks Correll, 2001; Meyer et al., 2015) pakub artikkel laiemat vaadet ja täiendab seniseid, kõrghariduses esinevate ebavõrdsuste kohta leitud tulemusi.

Artikkel I esitatud tulemuste kohaselt lähtuvalt investorid erialavaliku tegemisel keskmiselt oma akadeemilistest võimetest. Kõrgemad tulemused reaal- ja loodusteadustes viivad tavaliselt ka sama valdkonna erialavalikuni, samal ajal kui kõrgemad tulemused humanitaarteadustes vähendavad reaalteadustega seotud erialavaliku tõenäosust. Vastavalt t-testide tulemustele saavutavad naised humanitaarvaldkonnas meestest kõrgemaid akadeemilisi tulemusi, samas kui muudel aladel sellist selget sugude vahelist erinevust ei esine. Kasutades viidatud humanitaarvaldkonna eelist kalduvad naised, meestega võrreldes, proportsionaalselt rohkem ka humanitaarteadusi oma erialaks valima. Kuna reaalteadustes naistel sarnast akadeemiliste võimete eelist ei ole, on ka meeste eeldused edule siin kõrgemad kui naiste domineeritud humanitaarteadustes. See võib olla üks põhjus, miks mehed reaalteadusi naistest enam eelistavad. Kokkuvõttes pakub artikkel empiirilise tõestuse, et investorite erialavalik baseerub üldjuhul akadeemilistele võimetele, viidates sellega ka valiku põhjendatusele või isegi ratsionaalsele käitumisele.

Doktoritöö teine publikatsioon *"Akadeemilistest võimetest elukutseni: mis määrab aktsiaturul osalemise?"* täiendab olemasolevat käitumusliku rahanduse kirjandust uue teabega, kuidas akadeemilised võimed koos hariduse, elukutse ja muude sotsioökonoomiliste näitajatega aktsiaturul osalemist või mitte osalemist mõjutavad. Artikkel kombineerib viite erinevat andmestikku ja, haarates enam kui 200 000 inimest, võimaldab viidatud mõjusid uurida detailsemalt kui see on seni võimalik olnud. Varasemad uurimused nagu Grinblatt et al. (2011) kasutavad kognitiivsete ja mentaalsete võimete analüüsimiseks sugude vahelise võrdluse vaatenurgast vaid piiratud andmeid. Artikkel II täidab selle tühimiku, vastates muuhulgas ka küsimusele: „Kas meeste ja naiste börsil osalemise otsused on sotsioökonoomilistest karakteristikutest sarnaselt mõjutatud?" Veelgi enam, artikkel täiendab seniseid börsil osalemise uurimusi ka näiteks infoga majandusliku tegevusala ja elukutsete kohta.

Artikkel II järeldab, et võrreldes meestega on naiste puhul seos vaimsete võimete ja börsil osalemise vahel selgelt nõrgem. Kasutatud andmetele tuginedes mõjutavad börsil osalemist veel ka majanduslik tegevusala, elukutse ja religioon, ja investorid kalduvad olema ambitsioonikamad, riskialtimad ja intelligentsemad kui inimesed, kes börsil ei osale. Seega, kui varasemad teaduslikud uurimused keskenduvad peamiselt kognitiivsete võimete ja börsil osalemise seostele, siis käesolevas doktoritöös sisalduv artikkel pakub lisateavet ka mittekognitiivsete võimete kohta (vaata võrdluseks näiteks Conlin et al., 2015; Kaustia ja Torstila, 2011; Guiso, Sapienza, ja Zingales, 2008).

Doktoritöös sisalduv kolmas artikkel *"Kuidas aitab õppimine ja haridus dispositsiooni efektist üle olla?"* pakub uusi empiirilisi arusaamu, kuidas haridus, intelligentsus ja teatud mentaalsed võimed dispositsiooni efekti mõjutavad. Dispositsiooni efekti all mõistetakse investorite kalduvust hoida liiga kaua kinni kahjumis positsioonidest ja müüa liiga vara kasumis positsioone (esmase, sellekohase uurimuse teostasid Shefrin ja Statman, 1985). Goulart et al. (2015) järeldavad, et dispositsiooni efekt on investorite jaoks kahjulik ning tähtsustavad seetõttu antud fenomeni paremat mõistmist. Artikkel III kasutab Nasdaq OMX Tallinna börsi detailset tehinguinfot vahemikust 2004 kuni 2012, mis on ühendatud Eesti Haridus- ja Teadusministeeriumist saadud andmetega. Selline lähenemine pakub unikaalse võimaluse töötada täieliku andmestikuga, millel puuduvad alamvalimite valikutest potentsiaalselt tulenevad soovimatud hälbed.

Artikkel III järeldab, et haridustaseme ja -valdkonna kaudu mõõdetav kõrgem intelligentsustase ja tugevam õppimisvõime vähendab dispositsiooni efekti. Lisaks esitab artikkel ka tõestuse, et kõrgemalt haritud ja intelligentsemad investorid on võimelised ka oma kogemustest ehk tehingutest kiiremini õppima. Artiklis kasutatud andmete põhjal osutuvad dispositsiooni efektist võitu saamisel eriti kasulikuks kõrgemad matemaatilised võimed. Viimaks viitavad artiklis esitletud tulemused, et dispositsiooni efekti mõjurina on õppimisvõime üks olulisemaid intelligentsuse komponente.

Kõik kolm doktoritöös sisalduvat teadusartiklit keskenduvad investorite käitumise uurimisele, pakkudes vastuseid küsimustele kuidas erinevad sotsioökonoomilised karakteristikud nimetatud käitumist mõjutavad. Artikkel I pakub uusi empiirilisi teadmisi erialavaliku ja akadeemiliste võimete seoste ning sugude vaheliste erinevuste kohta. Artiklid II ja III keskenduvad börsil osalemist (artikkel II) ja dispositsiooni efekti mõjutavatele (artikkel III) karakteristikutele.

Appendix 1. Paper I

GENDER, ACADEMIC ABILITIES AND POSTSECONDARY EDUCATIONAL CHOICES

Publication:

Vaarmets, T., 2018. Gender, academic abilities and postsecondary educational choices. *Journal of Applied Research in Higher Education*, vol. 10, no. 3, pp. 380−398. DOI: https://doi.org/10.1108/JARHE-12-2017-0155. (ETIS 1.1).

Draft as conference proceedings:

Vaarmets, T. 2015. *Mental Abilities, Specialty Choice and Gender Differences among Investors.* World Finance & Banking Symposium, 17–18 December 2015, Hanoi, Vietnam.

Received 2 December 2017
Revised 20 January 2018
10 March 2018
21 April 2018
Accepted 21 April 2018

Gender, academic abilities and postsecondary educational choices

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Abstract

Purpose – Gender inequalities in higher education have attracted interest in the academic literature. The paper aims to discuss this issue.

Design/methodology/approach – The author uses standardized high school final exam results and probit regression analysis to contribute to this highly important discussion.

Findings – Based on secondary, non-survey data, female students tend to outperform males in subjects requiring creativity. Consistent with this comparative advantage, female students also tend to be more affected by their abilities in choosing and preferring the related field of humanities as a higher education. In line with female students' choices, the results presented in the paper confirm that men are more inclined toward exact and natural sciences, even though they do not prove to have stronger abilities in related subjects. In addition, men are also more influenced by their abilities in obtaining a professional higher education. The choice of social sciences is quite similarly affected by the academic abilities of men and women. The paper also provides evidence that, on average, individuals choose their field of study according to their academic abilities.

Originality/value – For evidence, a data set that makes it possible to relate quantitative measures of very different academic abilities to all major academic disciplines is used in the paper. This unique approach has so far been lacking in the literature due to data limitations. In other words, instead of concentrating on a specific area, such as science, technology, engineering, and mathematics (STEM), the author takes a broader view.

Keywords Higher education, Field of study, Gender gap, Academic abilities, High school

Paper type Research paper

Introduction

The gender puzzle in the field of study choices has attracted considerable interest among scholars. The topic is highly important as well as intriguing due to the conflicts within it. The main controversial question is why are women reluctant to choose natural sciences if their related abilities are at least as good as those of men?

The choice of academic discipline, which in this paper is referring to the undergraduate field of study, itself is one of the most important decisions people need to make in their lives as choosing it often establishes the field and scope of issues in which people operate until old age. Hackett (1995) and van der Werfhorst and Kraaykamp (2001) conclude that the choice of field of study or field of work significantly affects different aspects of peoples' lifestyles related to the labor market, consumption pattern and socio-political orientation. Kalmijn and van der Lippe (1997) show that the choice of academic discipline determines future earnings. This clearly illustrates the need to understand the process of choosing academic disciplines and factors that influence it. A large part of answering the related complicated questions is connected to gender differences.

Klevan *et al.* (2016) state that nearly 60 percent of bachelor degrees in the USA are awarded to women. Buchmann and DiPrete (2006) extend that in developed countries women tend to attain higher education more often than men, as also reflected in Estonian data (see footnote in Data section). However, at the same time, women also seem to be more reluctant to choose mathematics-related fields of study than men. The conclusion is evident from the Estonian data used in this paper, as well as from previous studies, including Correll (2001) and Wang and Degol (2017), who additionally show that one explanation for such a gender gap is related to cognitive abilities.

Journal of Applied Research in Higher Education
Vol. 10 No. 3, 2018
pp. 380-398

2050-7003
DOI 10.1108/JARHE-12-2017-0155

There are also several other previous research papers that explain reasons underpinning choices concerning higher education and academic discipline. For example, Legewie and DiPrete (2014) argue that the high school environment plays an important role in choosing a field of study—stronger mathematics and science curricula tends to encourage and gender segregation in extracurricular activities tends to discourage female students to choose mathematics-related fields of study. Furthermore, Klevan *et al.* (2016) show that grade point average and social capital are drivers that influence high school students' future plans related to college enrollment. Taking these ideas partly as a lead, I focus on measurable outcomes for this period and how they influence the gender gap in postsecondary educational choices.

As an additional motivation and theoretical basis for my research, I use several other studies that relate higher education to academic results. According to McKenzie and Schweitzer (2001), university entry scores tend to be the most significant predictor of university performance. This is also in line with Harackiewicz *et al.* (2002), who show that high school results are predictors of academic success in college.

Existing research shows that academic performance in high school affects the choice a student makes regarding the undergraduate field of study. I build on these studies by estimating whether this relationship varies by student gender. I also propose that the choices of one gender may influence the choices of another—however, this hypothesis needs further research for confirmation.

For evidence, a data set that makes it possible to relate quantitative measures of very different academic abilities[1] to all major academic disciplines is used in the paper. This unique approach has so far been lacking in the literature due to data limitations. In other words, instead of concentrating on a specific area, such as science, technology, engineering and mathematics (STEM), I take a broader view.

In addition, many previous related studies have been based on questionnaires, which according to Betsworth (1999), may include response biases. Therefore, I use administrative data that render the results presented in the paper less affected by human biases. Different robustness tests reaffirm the findings. My results offer an additional explanation for the gender gap puzzle in the field of study choice, which should help educational policies benefit from the more targeted use of abilities.

Explanations for gender differences

A sizable body of previous studies from different decades reports the existence of gender gap in STEM fields, confirming the consistency of this phenomenon over time. For example, Meece *et al.* (1982) note that men tend to choose more mathematically oriented college courses, while in the sample employed by Jacobs (1995) only 31.2 percent of physical science degrees and 13.8 percent of engineering degrees at the bachelor level were obtained by women. Correll (2001) shows that engineering and physical sciences are extremely male dominated in different educational and career levels. Recent studies such as Meyer *et al.* (2015), who focus on university degrees, confirm these findings. Based on the extensive research from the fields of psychology, sociology, economics and education over the past 30 years, Wang and Degol (2017) add that while women continue to be underrepresented in STEM fields, the gender gap has narrowed in recent decades.

The most common explanation in the previous literature for the gender gap in STEM fields seems to be that mathematics-related fields are stereotyped as a male domain and therefore men tend to choose them and women tend to avoid them (e.g. Correll, 2001; Hyde, Fennema, Ryan, Frost and Hopp, 1990; Meece *et al.*, 1982). In addition, women seem to think that they are not good enough for mathematics-related tasks, as Betsworth (1999) concludes. Deaux and Farris (1977) argue that men's self-attribution bias is stronger and becomes especially clear in masculine tasks. This view is supported, for example, by Beyer (1990), Beyer and Bowden (1997) and Deaux and Emswiller (1974). Based on the results of meta-analyses, Hyde, Fennema, Ryan, Frost and Hopp (1990) conclude that gender differences in self-confidence and attitudes specific to mathematics are more dominant among high school and college students than among younger students. According to Wang and Degol (2017), other main explanations in existing literature for women's underrepresentation in STEM fields include cognitive ability, cognitive strengths, occupational interests and lifestyle values.

Motivated by these previous findings, I look further from the STEM fields and focus additionally on other main scientific disciplines with an aim to shed more light on the reasons for this extensively reported STEM gender gap. Existing literature suggests that cognitive abilities also play a role in the field of study choices, another dose of motivation for this paper comes from a research focusing on the academic performance.

Employing meta-analysis and covering all educational levels from elementary school to university, Voyer and Voyer (2014) show that female students earn higher teacher-assigned grades than male students, while the female advantage is the largest for language courses and the smallest for mathematics courses. These results are consistent with another meta-analysis by Steinmayr and Spinath (2008), who also note that personality and motivation explain gender differences in pre-university achievement. However, having high school students as participants in their study, Debacker and Nelson (2000) conclude that boys outperform girls in science. This view is supported by Armstrong (1981), who reveals that at the end of high school, males tend to perform better in mathematics, even though there is no such difference in earlier years of schooling.

However, the results of a meta-analysis conducted by Hyde, Fennema, and Lamon (1990) show that gender differences in mathematical achievement in different educational levels are small and have decreased over time. Similar conclusions are made by Hyde and Mertz (2009), who show that the gender gap in high school mathematical performance is close to zero based on their sample, even though men still tend to achieve more high-level scores than females. Cornwell *et al.* (2013) highlight that using grades or test scores may lead to different results as grades are also influenced by students' non-cognitive skills. This is also supported by Jacob (2002), who focuses on high school and college education. As I use non-survey data, the data are not impacted by non-cognitive aspects.

While previous studies consensually suggest that male dominance in mathematics-related disciplines have been present for at least several decades, the existing evidence related to the mathematical performance is not so homogenous. More precisely, results of the gender gap in mathematical performance have been mixed through time, as can be concluded from the studies highlighted above.

In this paper, I bind these two aspects—academic performance and field of study choices together and study how they relate to each other. Moreover, it seems that the direct focus on mathematics in the previous literature may underestimate the importance of the effect arising from other disciplines, such as humanities. Assuming that there are limited slots in each field of study, this means that the choice of one scientific discipline by a group of people may influence the choice of another group (to be confirmed by future research). As the secondary data set used in this study includes results from very different high school exams and also information about fields of study from all main scientific disciplines, I am able to extend the knowledge offered by previous literature. My findings suggest that female students tend to be more affected by their test scores in choosing and preferring humanities, which may give men an additional push toward the natural sciences.

More precisely, based on the participants in this study, women's choice of the humanities seems to be the expected outcome on average, as women tend to outperform men in subjects that require creativity. At the same time, academic results in the exact and natural sciences are similar for male and female students. By analyzing the data used in this study, I conclude that higher academic abilities are not the reason why men tend to choose more exact and natural sciences as their field of study, while the tendency to choose humanities seems to be justified for women.

Data

To study how gender-specific educational choices are dependent upon academic results, I use a data set obtained from the Estonian Ministry of Education and Science. The Ministry processed, controlled and approved the data. Subjects' anonymity and direct confirmation by the Ministry guarantees that the data set used complies with accepted ethical principles of human subjects' research. The data include high school grades, as well as the results of high school final exams and information concerning individuals' educational level (high school, vocational education, bachelor, master and doctorate) and education type (mathematics, statistics, economics, medicine, law, information technology, public administration, chemistry, physics, psychology, etc.). The study concentrates mainly on high school final exam results. I obtained the results for the period from 1997 (implementation of the national final exam system) to 2012. During this period, high school final exams were mandatory for graduation and identical for all high school graduates. Besides graduating high school, another reason for graduates to be highly motivated to take these exams seriously is that high school final exams also serve as entry exams for Estonian universities. Each student has to take five exams, three of which (mother tongue, English and mathematics) are compulsory as they are required to apply for the majority of fields of study. Other exams may be required in specific cases. Exams taken in different years are regarded as equal to university entry exams in the same year, namely the level of difficulty of the exams should be the same throughout the years. The maximum result for an exam is 100 points and the minimum is 0 points; in most cases, the minimum for applying to college or university is 20 points.

Students take exams at the end of high school (spring)—mostly at the age of 18—and they usually apply to university a few months later. There are three major universities and many smaller colleges in Estonia, meaning that in most cases students can choose their field of study of interest from several schools. Most commonly, an admission decision is based on the ranking derived from the exam results.

As high school final exam results are essential for applying to university, students wishing to obtain a higher education prepare very hard for them. This makes the exam results used in this study also a good proxy for students' academic abilities. Using test scores as a proxy for academic abilities has also found support from previous authors, including Coyle *et al.* (2014) and Harackiewicz *et al.* (2002), who note that students' abilities are "typically measured in terms of SAT or ACT test scores" (p. 562). SAT and ACT test scores are widely used for college admissions in the USA (in Estonia high school final exam results are used for the same purpose). In addition, the properties described allow comparison of the final exam results for males and females and enable the study of how these academic results influence different educational choices.

The sample for educational data includes 6,843 individuals. For these individuals, I have a full set of educational data, including high school final exam results, educational level and educational type. From the total of 6,843 individuals, I have a field of study information for 3,714 individuals who had attained a higher education qualification by the end of 2012. This means that 54.3 percent of individuals in the sample on average have a higher education qualification. However, 39.2 percent ($n = 590$) of women and 47.6 percent ($n = 2{,}538$) of men in the sample had not obtained an academic degree by the end of 2012.

Due to the availability of the field of study data, in absolute terms, there are more men represented in the sample than women. This means that I have a field of study data for those individuals, who have bought at least one share from the local stock market by the end of 2012. According to Talpsepp (2010), 68 percent of the individuals in Estonian stock market are men.

Still, the sample used in the research tends to follow a similar pattern found in previous studies, which conclude that mathematics-related specialties attract proportionally more men than women (see "Explanations for gender differences"). In addition, women's domination in higher education in Estonia[2] is also reflected in the sample used in this study as it shows that proportionally more women than men had obtained higher education qualification by the end of 2012. This is also consistent with Klevan *et al.* (2016). Finally, *t*-test results confirm the conclusions about the male and female students' exam result differences. Based on the sample used in the study as well as the total exam results sample ($n = 221{,}774$), female students tend to show higher exam results in humanities, while this is not evident in natural sciences (see "Who has superior academic abilities—men or women?").

Considering only individuals with a university degree, almost two-thirds ($n = 601$, 65.7 percent) of women and over half ($n = 1714$, 61.2 percent) of the men had earned a degree in social sciences by the end of 2012. Compared to men, females clearly show greater interest in humanities as 12.7 percent ($n = 116$) of women with higher education and only 4.5 percent ($n = 127$) of men chose this field. Finally, consistent with the studies by Meece *et al.* (1982), Jacobs (1995) and Correll (2001), a notably larger proportion ($n = 576$, 20.6 percent) of men than women ($n = 110$, 12.0 percent) with at least a bachelor's degree in the sample chose exact and natural sciences as their field of study.

Methodology

This section addresses the methods used to study the relationship between high school final exam results and the first important choice men and women make regarding their career paths. I also briefly describe which methods I use to analyze the differences in average exam results according to the educational type, as well as differences between male and female individuals' exam results.

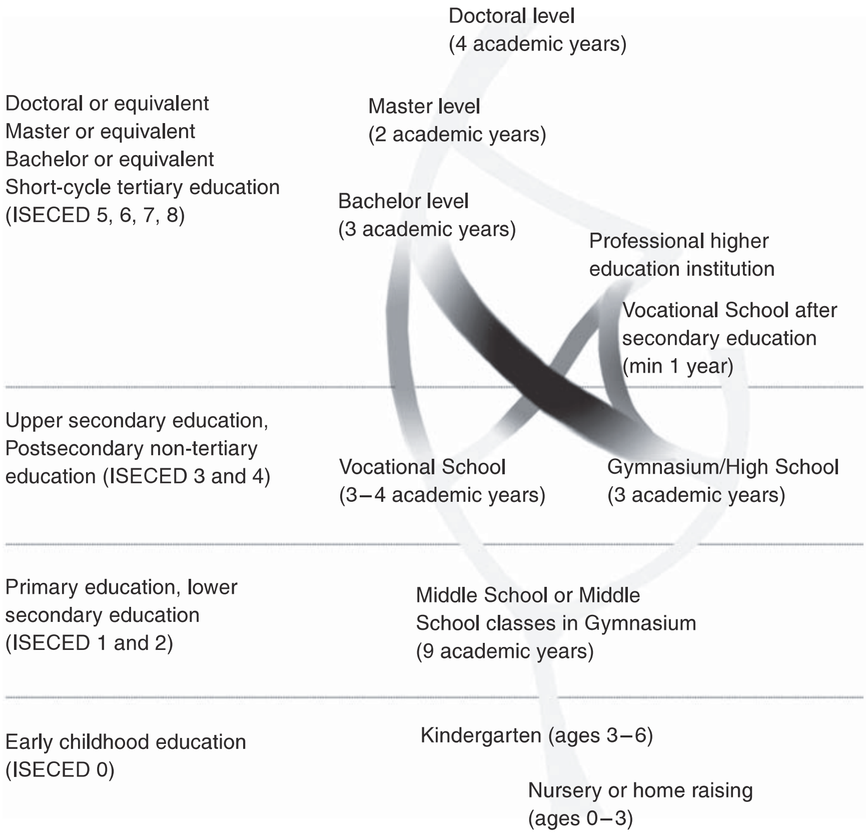
Estimating the relationship between exam results and field of study choices

To research the relationship between the field of study choices and high school final exam results, I define the dependent, endogenous variable y_i^* as Studycategory, which takes the value of 1 if an individual obtained a qualification in an academic discipline included in the related category group by the end of 2012 and a value of 0 otherwise.

Following the classification by the Estonian Ministry of Education and Science, I group fields of study into exact and natural sciences, humanities, social sciences and other sciences[3]. Exact and natural sciences include many engineering fields of study, as well as physics, biology chemistry, statistics, and mathematics. The humanities group is dominated by philology-related fields of study but also covers psychology, journalism, literature, theology and art. Social sciences include mostly economics-related fields of study, but also represent political science, law, semiotics, demographics. Other sciences include mainly fields of study, which are considered to be related to professional higher education, meaning that these fields of study are more practical (e.g. the police service, sea transport, recreation). This also means that in the models only fields of study related to higher education are included. Figure 1 illustrates the educational system in Estonia.

On the right side of the models, I use different approaches. I employ models in which the independent variables include ungrouped exam results and as a robustness check, I also divide the independent variables (exam results) into quartiles. The lowest 25 percent of the exam results are in the first quartile and the highest (or fourth quartile) includes the top 25 percent of all results. The variable Examresultquartile is equal to 1 if a person's results fall into the respective quartile and 0 otherwise. In addition, the control variables of gender and age are also used in the models.

As the dependent variable is a binary variable, logit or probit models are appropriate for addressing the questions concerning the field of study. Logit and probit models have also



Notes: Figure 1 illustrates the educational system in Estonia; the period focused on in this paper is highlighted by darker decision lines. The wider, dominating line between "Gymnasium/High School" and "Bachelor level" represents the decisions made by 3,244 students or 87 percent of individuals with a higher education qualification included in the study

Figure 1.
Estonian educational system

had support in previous literature—for example, Correll (2001) uses a probit model and Eccles *et al.* (2004) and Klevan *et al.* (2016) employ a logit model. I employ both probit and logit regression models (together with control variables). As the conclusions are the same for both of these models, only the results for the probit regression models are reported. I construct separate models for every academic discipline category.

The models used to determine if individuals choose their fields of study according to their academic results can be written as follows:

$$\mathrm{Probit}\left(\mathrm{Studycategory}_{ij}\right) = \beta_0 + \beta_1 \mathrm{Examresult}_{ij} + \sum_{k=2}^{K} \beta_k \mathrm{controls}_{\,ik} + \epsilon_i, \tag{1}$$

$$\mathrm{Probit}\left(\mathrm{Studycategory}_{ij}\right) = \beta_0 + \beta_1 \mathrm{Examresultquartile}_{ijl} + \sum_{k=2}^{K} \beta_k \mathrm{controls}_{\,ik} + \epsilon_i, \tag{2}$$

where $\text{Studycategory}_{ij}$ is the dependent variable, which equals 1 if person i has an educational qualification corresponding to the academic discipline category j. Examresult_{ij} represents person i's actual exam result for exam j, and $\text{Examresultquartile}_{ijl}$ is a dummy variable for quartiles and equals 1 if person i's exam j result was included in quartile l. $\sum_{k=2}^{K} \beta_k \text{controls}_{ik}$ represents the control variables gender and age.

In addition to probit models, I use post-estimated marginal analysis and calculate average marginal effects as well as marginal effects for males and females separately. This makes interpretation of the results of the probit regression models with quartile variables straightforward. Even though for the ungrouped exam result variables the marginal effects measure the instantaneous rate of change (rate of change at a particular point) rather than discrete change (rate of change over a range), they broadly show how a one-point change in exam results changes the Y variable.

Estimating differences in exam results

Next, I compare the average male and female students' high school final exam results to each other. To detect the significance of differences in exam results, I use simple two-sample t-tests with equal variances. I also measure the effect sizes of these differences by employing Cohen's d and Hedges' g. Cohen's d and Hedges' g are similar metrics, which make it possible to compute the standardized difference between two means. Cohen's d is simply determined as the difference in means divided by pooled sample standard deviation. According to Hedges (1981), Cohen's d includes sample bias and therefore he proposed an unbiased metric, which I also employ here.

In the case of Cohen's d and Hedges' g, an absolute value of around 0.2 is considered a small effect size, a result around 0.5 reflects a medium effect size and a value above 0.8 indicates a considerable difference–the effect size is considered large (Cohen, 1988). Nonetheless, for Cohen's d and Hedges' g, there is no universal scale that would give an exact estimate of the effect size.

Results

Do individuals choose their field of study according to their academic results?

In this section, I show how academic results in high school are related to the later choice of undergraduate field of study. The broad conclusion on the basis of the t-test results presented in Table I is as expected—on average, individuals achieve higher exam results in subjects related to their chosen academic discipline. The explanation why individuals with higher education in other sciences tend to perform poorly on all exams lies in the Estonian educational system and in the sample itself—the sample for other sciences consists of those individuals who mainly chose professional (applied) higher education rather than traditional academic education. Professional higher education in Estonia means essentially that students are preparing for a specific profession, such as policeman, coxswain, or travel agent, and traditionally these kinds of professions do not require the same academic results as professions related to academic education from traditional universities.

For the next step, I use probit regression models (models 1 and 2) to study the relationship between academic results and field of study choices. While controlling also for student characteristics, the results of these probit regression models and marginal analysis, reported in Table II, are consistent with the t-test results in Table I. This indicates that there is a statistical relationship between academic results and the type of higher education qualification obtained.

For example, regardless of gender, every extra point earned on the mathematics high school final exam increases the probability of the choice of exact and natural sciences as a field of study on average by approximately 0.19 percent and decreases the probability of the choice of humanities on average by approximately 0.06 percent based on the study sample.

Table I. Results of t-tests: comparison of the average exam results according to the fields of study

	Exact and natural sciences			Humanities			Social sciences			Other sciences		
	Diff. in means (%)	t	Effect size	Diff. in means (%)	t	Effect size	Diff. in means (%)	t	Effect size	Diff. in means (%)	t	Effect size
Mathematics	10.5	5.91***	0.27	−15.5	−4.47***	−0.41	1.5	1.01	0.04	−12.9	−6.07***	−0.34
Physics	10.2	3.68***	0.33	−14.7	−1.58	−0.48	−3.3	−1.28	−0.11	−11.0	−2.78***	−0.37
Chemistry	9.8	4.16***	0.30	−13.2	−2.68***	−0.41	1.7	0.80	0.05	−16.1	−5.23***	−0.51
Biology	10.7	5.10***	0.41	−8.0	−2.22**	−0.31	−4.5	−2.59***	−0.18	−2.0	−0.82	−0.08
Geography	10.1	5.29***	0.64	0.7	0.20	0.04	−5.7	−3.94***	−0.38	−0.8	−0.39	−0.05
Mother tongue	−3.7	−3.09***	−0.13	8.0	4.19***	0.28	6.1	6.01***	0.21	−11.6	−8.35***	−0.42
English	−4.5	−4.76***	−0.22	3.4	2.21**	0.16	6.5	8.08***	0.30	−9.0	−7.95***	−0.44
German	−0.3	−0.10	−0.01	5.1	1.26	0.23	1.9	0.82	0.08	−5.7	−1.93*	−0.26
History	−0.6	−0.30	−0.02	4.3	1.83*	0.16	5.1	3.58***	0.19	−14.1	−6.87***	−0.55
Social studies	−0.7	−0.26	−0.04	8.2	2.63***	0.48	1.7	0.91	0.10	−7.5	−3.10***	−0.45

Notes: The table reports the t-test results comparing differences between the averages of exam results according to the groups of fields of study. For example, the 10.5 percent difference in means in the "Mathematics" row and "Exact and natural sciences" column indicates that students choosing their field of study from exact and natural sciences tend to achieve 10.5 percent higher scores on average in their mathematics high school final exam than students with different choices. To measure the size of the difference, Cohen's d and Hedges' g have been used and reported ("Effect size"). *,**,***Significance at 10, 5 and 1 percent, respectively

Table II.
Results of probit models: field of study choices based on high school exam results

		Maths	Physics	Chemistry	Biology	Geography	Mother tongue	English	German	History	Social studies
Exact and natural sciences	Coefficient	0.007	0.009	0.009	0.014	0.031	−0.003	−0.008	−0.004	−0.000	−0.001
	z-value	5.640	3.170	4.060	4.610	4.520	−2.610	−5.060	−0.770	−0.200	−0.210
	Significance	***	***	***	***	***	***	***			
	Average ME	0.19%	0.33%	0.28%	0.41%	0.76%	−0.09%	−0.22%	−0.09%	−0.01%	−0.03%
	Pseudo R^2	0.018	0.023	0.031	0.047	0.095	0.015	0.020	0.026	0.012	0.020
Humanities	Coefficient	−0.007	−0.007	−0.009	−0.009	0.006	0.006	0.006	0.009	0.006	0.021
	z-value	−3.680	−1.090	−2.570	−2.230	0.690	3.570	2.390	1.530	2.220	2.610
	Significance	***		***	**		***	**		**	***
	Average ME	−0.06%	−0.03%	−0.08%	−0.10%	0.06%	0.08%	0.07%	0.14%	0.09%	0.32%
	Pseudo R^2	0.056	0.037	0.055	0.071	0.028	0.049	0.046	0.043	0.025	0.037
Social sciences	Coefficient	0.002	−0.001	0.003	−0.005	−0.017	0.007	0.013	0.004	0.006	0.005
	z-value	1.730	−0.290	1.310	−1.820	−3.140	5.880	8.620	1.050	3.250	0.840
	Significance	*			*	***	***	***		***	
	Average ME	0.07%	−0.03%	0.10%	−0.19%	−0.62%	0.25%	0.47%	0.16%	0.22%	0.17%
	Pseudo R^2	0.006	0.011	0.012	0.014	0.046	0.010	0.022	0.004	0.009	0.011
Other sciences	Coefficient	−0.010	−0.015	−0.015	−0.004	−0.005	−0.012	−0.016	−0.008	−0.016	−0.021
	z-value	−7.240	−3.840	−5.800	−1.310	−0.810	−8.030	−8.690	−1.830	−6.510	−3.120
	Significance	***	***	***			***	***	*	***	***
	Average ME	−0.20%	−0.27%	−0.29%	−0.10%	−0.12%	−0.24%	−0.31%	−0.21%	−0.28%	−0.45%
	Pseudo R^2	0.040	0.054	0.058	0.008	0.014	0.030	0.044	0.014	0.045	0.036
n		2,837	551	1,012	867	458	3,580	3,190	394	1,616	390

Notes: The table reports the probit regression results for the field of study choices made by individuals based on their high school final exam results (model 1). Each regression includes one high school final exam. The maximum result for an exam is 100 points and the minimum is 0 points. The sign of the coefficient indicates in which direction the exam result variable influences the field of study group variable, but coefficients themselves cannot be directly interpreted (therefore marginal effects are used). Average ME represents corresponding post-estimated marginal effects. For example, the average ME of 0.19 percent in the "Exact and natural sciences" row and "Maths" column indicates the instantaneous rate of change, meaning that every extra point earned on the mathematics high school final exam increases the probability of the choice of exact and natural sciences as a field of study on average by approximately 0.19 percent. n represents the number of observations. *,**,***Significance at 10, 5 and 1 percent, respectively

Is there a gender gap in choosing a field of study?
Next, for the gender differences, I focus on the post-estimated marginal effects of the probit regression models for males and females from the previous section (models 1 and 2). These results are presented in Table III.

Based on marginal effects, men tend to be more affected by their exam results than women when choosing natural sciences as an undergraduate field of study. For example, the instantaneous rate of change for men in the case of the geography exam is 0.87 percent and for women only 0.39 percent, indicating that every extra point earned on the geography high school final exam increases the probability of the choice of exact and natural sciences as a field of study more for men than for women (approximately by the size of marginal effects). It is rather difficult to explain why the geography exam results tend to influence the choice of exact and natural sciences clearly more than other subjects, but the reason may be that the Estonian study program in geography is closely associated with information technology (for example wide usage of different geographic information systems (GIS)). Therefore, higher results in the geography exam may indicate better knowledge and skills in information technology, which directly relates to engineering and other fields of study included in exact and natural sciences.

Mathematical performance tends to be positively related to the choice of exact and natural sciences, negatively to the humanities and has statistically weaker (significant at 10 percent level) effect on the choice of social sciences as a field of study. Compared to women, men tend to be more affected by their mathematics results in choosing exact and natural sciences, but less affected in choosing humanities as their field of study. Interestingly, in case of social studies, men and women tend to be similarly affected by their mathematical performance as the difference of their marginal effects is statistically not significant. The reason may be hidden in the combination of male and female students' similar mathematics results (see "Who has superior academic abilities—men or women?") and the nature of the discipline. As social sciences include fields of study requiring mathematical abilities (like finance) and also fields of study requiring creativity (like marketing), there is no such clear gender domination in the discipline as seen in the exact and natural science or humanities (see "Data"). Therefore, similar mathematics results and representation in the discipline seems also to lead to similar mathematics exam results' marginal effects for social sciences for men and women.

Similarly, the female students' instantaneous rates of change, seen in Table III, indicate that women are more affected by their exam results in choosing humanities. Also, analyzing grouped exam results (see Tables AI and AII), the conclusion is that top-performing female students are more likely to choose humanities as their undergraduate field of study than male students in the same group.

The marginal effects for social sciences are more homogenous in this respect when we study the probit regression models, in which actual exam results were used as the independent variable. However, as seen in Tables II and III, the choice of social sciences as a field of study seems to be more affected by humanities exams. This indirectly supports the conclusion that social sciences are favored more by women than by men.

The gender gap in choosing other sciences as a field of study is similar to that for exact and natural sciences in favor of men, as reflected in the results of probit models with actual, non-grouped variables. The probit regressions with grouped exam result variables found in the appendices confirm all the results presented here.

Who has superior academic abilities—men or women?
There have been several studies that have concentrated on the differences between men's and women's abilities, including Hyde, Fennema, Ryan, Frost and Hopp (1990), Hyde, Fennema and Lamon (1990), Baker and Jones (1993), Hyde and Mertz (2009), and Correll (2001),

Table III.
Marginal effects of probit models: gender differences in the field of study choices

		Maths	Physics	Chemistry	Biology	Geography	Mother tongue	English	German	History	Social studies
Exact and natural sciences	Coefficient	0.007	0.009	0.009	0.014	0.031	−0.003	−0.008	−0.004	−0.000	−0.001
	Significance	***	***	***	***	***	***	***			
	Male ME	0.20%	0.33%	0.30%	0.44%	0.87%	−0.10%	−0.24%	−0.09%	−0.01%	−0.03%
	Female ME	0.16%	0.35%	0.22%	0.35%	0.39%	−0.07%	−0.17%	−0.09%	−0.01%	−0.02%
	Diff significance	***	*	***	**	**	**	***			
Humanities	Coefficient	−0.007	−0.007	−0.009	−0.009	0.006	0.006	0.006	0.009	0.006	0.021
	Significance	***		***	**		***	**		**	***
	Male ME	−0.05%	−0.03%	−0.06%	−0.07%	0.05%	0.06%	0.05%	0.12%	0.08%	0.30%
	Female ME	−0.11%	−0.08%	−0.14%	−0.18%	0.10%	0.13%	0.12%	0.19%	0.13%	0.38%
	Diff significance	**		**	**		***	**		**	
Social sciences	Coefficient	0.002	−0.001	0.003	−0.005	−0.017	0.007	0.013	0.004	0.006	0.005
	Significance	*			*	***	***	***		***	
	Male ME	0.07%	−0.03%	0.10%	−0.19%	−0.65%	0.26%	0.48%	0.16%	0.22%	0.17%
	Female ME	0.06%	−0.03%	0.09%	−0.18%	−0.54%	0.25%	0.45%	0.16%	0.22%	0.15%
	Diff significance					**	*	**			
Other sciences	Coefficient	−0.010	−0.015	−0.015	−0.004	−0.005	−0.012	−0.016	−0.008	−0.016	−0.021
	Significance	***	***	***			***	***	*	***	***
	Male ME	−0.22%	−0.29%	−0.31%	−0.10%	−0.13%	−0.25%	−0.33%	−0.22%	−0.30%	−0.48%
	Female ME	−0.13%	−0.09%	−0.22%	−0.09%	−0.09%	−0.20%	−0.25%	−0.17%	−0.24%	−0.37%
	Diff significance	***	**	**			***	***		*	

Notes: The table reports the results of probit regression (model 1) together with post-estimated marginal effects for the field of study choices made by individuals based on their high school final exam results. Marginal effects are reported separately for male (Male ME) and female (Female ME) students. For example, the Male ME of 0.20 percent in the "Exact and natural sciences" row and "Maths" column indicates an instantaneous rate of change, meaning that every extra point earned by male students on the mathematics high school final exam increases the probability of the choice of exact and natural sciences as a field of study on average by approximately 0.20 percent for male students. Each regression includes one high school final exam. The maximum result for an exam is 100 points and the minimum is 0 points. "Significance" represents the statistical significance of coefficients, while "Diff significance" represents the statistical significance for the difference in male and female marginal effects. *,**,***Significance at 10, 5 and 1 percent, respectively but so far this question has not been addressed with the complexity that I use. As I use a detailed educational data set, I am able to study the differences between males' and females' academic results in very different fields.

In Table IV, I offer the results of t-tests which show if these differences are also statistically significant. As the differences in mathematics, chemistry and social studies are almost non-existent, it should not be a surprise that these differences are statistically insignificant. The difference between the results male and female students achieved in physics is also not significant.

Because men's and women's results were from very different exams, no generalizations about whether men or women performed at a superior level can be made. We can see women's statistical superiority in subjects requiring creativity, as language exams include writing essays and can be considered more creativity-based subjects than subjects related to the exact and natural sciences[4]. Finally, as in several previous studies that concentrate on mathematics (see "Explanations for gender differences"), the results presented here support the understanding that based on the used exam results' data there is no difference between male and female mathematical abilities.

Discussion and conclusions

The secondary data set used in the study provides an improved picture of the educational choices individuals tend to make and it also yields indications of how these different choices may relate to each other. Motivated by previous literature showing a relationship between high school academic performance and the choice of undergraduate field of study (Wang and Degol, 2017; Klevan *et al.*, 2016), I argue that this relationship varies by student gender.

I first studied how the choice of academic discipline relates to academic results in general and I concluded that individuals tend to consider their academic results and choose their field of study according to these results. More precisely, higher academic results in the exact and natural sciences tend to lead to the choice of a field of study in the same area and concomitantly higher academic results in the humanities tend to lead away from the exact and natural sciences. These conclusions are also clearly present when grouped exam results are used.

	Group differences		95% confidence interval of the difference					Effect size	
Group	Mean	SE mean	Lower	Upper	t	df	Significance	Cohen's d	Hedges' g
Mathematics	0.238	0.961	−1.645	2.122	0.248	4,638		0.009	0.009
Physics	0.949	3.288	−5.505	7.403	0.289	864		0.041	0.041
Chemistry	0.012	1.345	−2.627	2.651	0.009	1,551		0.001	0.001
Biology	−3.069	1.052	−5.132	−1.006	−2.918	1,500	***	−0.166	−0.166
Geography	2.275	1.046	0.222	4.328	2.174	1,221	**	0.163	0.163
Mother tongue	−6.178	0.610	−7.374	−4.982	−10.126	6,436	***	−0.304	−0.304
English	−0.975	0.555	−2.062	0.113	−1.757	5,447	*	−0.058	−0.058
German	−4.826	1.752	−8.266	−1.387	−2.755	667	***	−0.255	−0.255
History	1.620	0.883	−0.111	3.352	1.835	2,598	*	0.085	0.085
Social studies	−0.139	1.043	−2.185	1.906	−0.134	1,084		−0.010	−0.010

Notes: The table reports differences between the means of exam results achieved by male students and female students. For example, 0.238 in the "Mathematics" row and the "Mean" column indicate that male students earn on average 0.238 points higher scores in the mathematics high school final exam (total possible 100 points) than female students based on the study sample. To measure the size of the difference, Cohen's d and Hedges' g are reported. *,**,***Significance at 10, 5 and 1 percent, respectively

Table IV. Results of t-tests: comparison of male and female students' mean exam results

As might be expected, the findings are the opposite for humanities as a field of study—on average, every extra point earned in mathematics, chemistry or biology lowers the probability of choosing a field of study from the humanities. Humanities seem to be the preferred choice for those individuals who achieve higher scores in mother tongue, English and history and also in social studies.

However, high school mathematics final exam results also play a role in seeking an education in the social sciences according to the study sample. Individuals in the highest quartile for mathematics results also graduate with a degree in the social sciences with a 5.6 percent higher probability on average than individuals with lower scores in mathematics exam. The results (marginal effects) are even stronger in the case of mother tongue, English and history exams. Also, individuals who are not so capable in these subjects tend not to choose a field of study in the social sciences. Interestingly, every extra point achieved on the geography exam also tends to lower the probability of choosing social sciences as a field of study.

Similar to the *t*-test results presented in Table I, the outcomes of the probit regression models also indicate that individuals with lower academic results tend to choose other sciences as their field of study. At the same time, the negative sign of the estimated coefficients and marginal effects for the fourth quartiles suggest that individuals who show the highest academic results in different study areas tend to choose other sciences less often than other individuals. The explanation for this kind of behavior is given in the Results section.

The next natural step was to study gender-specific academic results and how these results influence the choice of academic discipline. The *t*-test results presented in Table IV indicate that female high school graduates outperform male graduates in humanities, while in other fields there is not such a clear gender gap in exam results. Using this comparative advantage, female students also tend to choose humanities as their field of higher education proportionally more often than men. While women do not have a similar comparative advantage in the natural and exact sciences (as can be concluded from the Table IV), it seems that the chances for men to succeed in this discipline are higher compared to the women-dominated humanities. This may also be one reason why men are keener to choose the natural and exact sciences than women based on their academic results in the same field.

In addition to the reasons highlighted in the paper (see "Explanations for gender differences"), another explanation may be, according to the previous studies, that for men salary is a more important factor in career choice than for women. This means that men may also have a higher motivation to choose a mathematics-related career, while women's choices are driven rather by other factors, such as interest and family issues (Dick and Rallis, 1991; Heckert *et al.*, 2002). This is consistent with Frehill (1997), who argues that "quantitative professions" are financially more rewarding.

My findings do not disprove the previous conclusions—on the contrary, they extend them by offering a new, additional explanation. This means that the question may not be so much "Why do women not choose engineering and technical fields of study?" but rather "What do they choose instead and why?" As the results presented in this study indicate, the answer seems to be that women choose subjects in the humanities based on their abilities and comparative advantage and men tend to choose the natural sciences as they may feel relatively more competent in the discipline. In other words, women tend to prefer the humanities over natural and exact sciences and men seem to be satisfied with mathematics-related fields of study, especially as undertaking such studies relates to a higher income in the future.

At the same time, the reasons why fewer women than men choose the natural and exact sciences cannot be because of the differences in academic ability, as I did not find any evidence that men achieve higher results in mathematics, physics or chemistry exams.

However, the *t*-tests showed that male students tend to outperform female students in geography, whereas the situation is the opposite for biology.

Dealing with mathematics-related problems require more confidence as suggested by Sax *et al.* (2015), who show a pervasive gender gap in mathematics self-concept over the past four decades, but also note that the relationship between women's lower confidence in mathematics and their underrepresentation in related fields has become weaker over time. At the same time Niederle and Vesterlund (2007) and Balafoutas *et al.* (2012) highlight men's higher willingness to compete, while several other studies, such as Betsworth (1999), Sturm *et al.* (2014) and Paustian-Underdahl *et al.* (2014), conclude that women tend to underestimate their abilities.

This may also explain why women tend to be more affected by their abilities in choosing the humanities. Importantly, higher results in language and history exams increase the probability of choosing a field of study from the humanities more for women than for men. This indicates that female students show more confidence in the "soft" sciences as they may underestimate their abilities related to the exact and natural sciences. As highlighted, this confidence is also justified because, according to the results presented in this study, women tend to show higher academic results in subjects that require creativity compared to men.

Considering the other possible implications of the results, I suggest that the situation presented here may be rather natural and the gender gap in academic disciplines, in general, is at least partly based on different abilities and preferences. This means that women, on average, prefer to study subjects in the humanities as they have a comparative advantage in the field. Moreover, even though men's position in terms of choice seems to be weaker compared to that of women, the exact and natural sciences may still be the most beneficial choice for them. On the other hand, economic development is rather related to the exact and natural sciences (Atkinson and Mayo, 2010) and from this perspective, it may be necessary to create an environment (high school) that will make women feel more confident in the exact and natural sciences as their abilities in the area are similar to those of men.

The finding that women's superiority and preferences tend to be more related to creativity may partly explain why women tend to choose the social sciences more than men. As the choice of social sciences is rather influenced by academic results shown in the humanities, it is also consistent that there are proportionally slightly more women who choose social sciences than men. At the same time, as other sciences in this study include fields of study classified as professional higher education (or in other words, more practical professions such as police, military and construction-related professions), men with lower test scores tend to be more eager to choose this field.

For future research, it would be useful to study men's attitudes toward the humanities—how they relate their abilities to women's abilities in this area and what their reasons are for being interested or not in the humanities. In addition are men's choices of mathematics-related fields of study influenced by women's choices? What could also be studied further is what motivates women to study the exact and natural sciences and what measures would be the most effective in raising women's confidence in this discipline?

Acknowledgment

The author would like to thank Dr Patrick Blessinger and two anonymous referees for their useful suggestions and comments. The author is grateful to Marko Mölder and Estonian Ministry of Education and Science, Lauri Veski and Innove, Aime Lauk and Statistics Estonia for the data and their supportive attitude and efforts for processing my data requests. The author thanks Kristel Vaarmets for proofreading the paper. The author is also grateful to Tõnn Talpsepp, Kristjan Liivamägi, Karsten Staehr and participants of various seminars and conferences for helpful suggestions. This work was supported by the Tallinn University of Technology and the European Union through the European Regional Development Fund.

Notes

1. Following previous literature, I use exam results as a proxy for academic abilities. According to Koenig *et al.* (2008) academic abilities measured by American College Test (ACT) scores are also closely correlated with mental abilities (IQ). This is consistent with Song *et al.* (2010), who use grade point average (GPA) as a measure of academic abilities.
2. In general women in Estonia are more educated than men (proportionally more women have a higher education qualification than men). According to the OECD's publication "Education at a glance 2014," 45% of 25 to 64-year-old women and 28 percent of men of the same age attained tertiary education in Estonia.
3. A similar classification has been previously used by several other authors, for example Voyer and Voyer (2014), Larivière *et al.* (2006) and Ishiyama (2002).
4. Using university students as participants of their study, Cheung *et al.* (2003) argue that humanities and social sciences relate to higher and science and technology to lower creativity. In addition, natural sciences require more effort than humanities (for the average person) as highlighted by Hofer and Pintrich (1997).

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Appendix 1

Table AI. Results of probit models: field of study choices based on grouped exam results

	Quartiles	Mathematics Highest	Mathematics Lowest	Physics Highest	Physics Lowest	Chemistry Highest	Chemistry Lowest	Biology Highest	Biology Lowest	Geography Highest	Geography Lowest
Exact and natural sciences	Coefficient	0.258	−0.267	0.344	−0.316	0.146	−0.381	0.317	−0.510	0.534	−0.892
	Significance	***	***	***	**		***	***	***	***	***
	Average ME	7.4%	−7.7%	12.6%	−11.7%	4.7%	−12.1%	9.3%	−15.0%	11.5%	−22.4%
	Male ME	7.8%	−8.1%	12.6%	−11.6%	5.0%	−13.0%	10.0%	−16.1%	15.1%	−25.6%
	Female ME	6.1%	−6.3%	13.4%	−12.4%	3.7%	−9.5%	7.7%	−12.5%	6.7%	−11.4%
	Pseudo R^2	0.014	0.011	0.020	0.015	0.018	0.025	0.033	0.036	0.075	0.066
Humanities	Coefficient	−0.330	0.230	0.048	0.320	−0.174	0.166	−0.188	0.450	0.137	−0.325
	Significance	***	**						***		
	Average ME	−2.9%	2.1%	0.2%	1.5%	−1.6%	1.5%	−2.2%	5.1%	1.4%	−3.4%
	Male ME	−2.2%	1.6%	0.2%	1.3%	−1.2%	1.1%	−1.5%	3.5%	1.2%	−2.8%
	Female ME	−5.5%	3.9%	0.6%	3.7%	−2.7%	2.6%	−3.7%	8.8%	2.3%	−5.5%
	Pseudo R^2	0.053	0.047	0.026	0.036	0.040	0.039	0.063	0.076	0.028	0.031
Social sciences	Coefficient	0.147	0.001	−0.138	−0.077	0.155	0.009	0.020	0.134	−0.360	0.410
	Significance	***				*				***	**
	Average ME	5.6%	0.1%	−5.4%	−3.1%	6.0%	0.3%	0.8%	5.2%	−13.3%	15.2%
	Male ME	5.7%	0.1%	−5.4%	−3.1%	6.1%	0.4%	0.8%	5.3%	−13.8%	15.8%
	Female ME	5.2%	0.0%	−5.4%	−3.0%	5.6%	0.3%	0.8%	5.2%	−11.5%	13.1%
	Pseudo R^2	0.007	0.005	0.013	0.011	0.013	0.011	0.011	0.012	0.043	0.037
Other sciences	Coefficient	−0.623	0.216	−0.445	0.605	−0.562	0.422	−0.370	0.059	−0.084	0.126
	Significance	***	***	***	***	***	***	***			
	Average ME	−12.3%	4.4%	−8.5%	11.4%	−10.7%	8.1%	−8.8%	1.4%	−2.0%	3.0%
	Male ME	−13.4%	4.8%	−8.9%	12.0%	−11.6%	8.8%	−9.1%	1.5%	−2.2%	3.3%
	Female ME	−8.1%	2.9%	−2.8%	3.6%	−8.0%	6.1%	−7.9%	1.3%	−1.5%	2.3%
	Pseudo R^2	0.048	0.018	0.033	0.044	0.037	0.026	0.019	0.006	0.013	0.013
n		2,837		551		1,012		867		458	

Notes: Table reports probit regression results for the field of study choices made by individuals based on grouped high school final exam results belonging to the exact and natural sciences (model 2). Each regression includes one high school final exam results' quartile. The sign of the coefficient indicates in which direction exam results' quartile variable influences field of study group variable, but coefficients themselves cannot be directly interpreted (therefore marginal effects are used). Average ME, Male ME and Female ME represent corresponding post-estimated marginal effects. For example, the Male ME of 7.8 percent in the "Exact and natural sciences" row and "Mathematics" (Highest) column indicates rate of change, meaning that achieving top 25 percent result on the mathematics high school final exam increases the probability of the choice of exact and natural science as a field of study for male students by approximately 7.8 percent compared to students with lower scores. n represents the number of observations. *,**,***Significance at 10, 5 and 1 percent, respectively

Appendix 2

Table AII.
Results of probit models: field of study choices based on grouped exam results

	Quartiles	Mother tongue Highest	Mother tongue Lowest	English Highest	English Lowest	German Highest	German Lowest	History Highest	History Lowest	Social studies Highest	Social studies Lowest
Exact and natural sciences	Coefficient	−0.193	0.001	−0.170	0.231	−0.041	0.051	−0.178	−0.024	−0.227	−0.340
	Significance	***		***	***			**			
	Average ME	−5.0%	0.0%	−4.5%	6.1%	−1.0%	1.3%	−3.9%	−0.5%	−4.1%	−6.1%
	Male ME	−5.4%	0.0%	−4.9%	6.6%	−1.0%	1.3%	−4.3%	−0.6%	−4.5%	−6.8%
	Female ME	−3.8%	0.0%	−3.4%	4.6%	−1.0%	1.2%	−2.9%	−0.4%	−2.8%	−4.1%
	Pseudo R^2	0.017	0.013	0.015	0.016	0.024	0.024	0.016	0.012	0.025	0.026
Humanities	Coefficient	0.162	−0.195	0.207	−0.164	0.264	−0.028	0.330	0.011	0.439	−0.016
	Significance	**	**	***	*			***		**	
	Average ME	2.0%	−2.4%	2.4%	−1.9%	4.0%	−0.4%	5.1%	0.2%	6.6%	−0.3%
	Male ME	1.6%	−1.9%	1.8%	−1.5%	3.5%	−0.4%	4.3%	0.1%	6.2%	−0.2%
	Female ME	3.4%	−4.0%	4.2%	−3.3%	5.5%	−0.6%	7.4%	0.3%	8.0%	−0.3%
	Pseudo R^2	0.045	0.044	0.047	0.044	0.040	0.033	0.033	0.020	0.028	0.005
Social sciences	Coefficient	0.260	−0.189	0.317	−0.322	0.083	−0.138	0.216	−0.209	0.186	−0.073
	Significance	***	***	***	***			***	**		
	Average ME	9.8%	−7.1%	11.8%	−12.0%	3.3%	−5.4%	7.8%	−7.6%	6.7%	−2.6%
	Male ME	9.9%	−7.2%	11.9%	−12.1%	3.3%	−5.4%	7.9%	−7.6%	6.8%	−2.7%
	Female ME	9.5%	−6.9%	11.3%	−11.5%	3.2%	−5.4%	7.7%	−7.4%	6.2%	−2.4%
	Pseudo R^2	0.009	0.004	0.013	0.011	0.002	0.003	0.009	0.007	0.013	0.010
Other sciences	Coefficient	−0.357	0.393	−0.606	0.375	−0.293	0.194	−0.600	0.383	−0.485	0.341
	Significance	***	***	***	***	*		***	***	**	*
	Average ME	−7.3%	8.0%	−11.5%	7.2%	−7.3%	4.9%	−10.7%	7.0%	−10.7%	7.6%
	Male ME	−7.7%	8.4%	−12.2%	7.7%	−7.7%	5.1%	−11.3%	7.3%	−11.3%	8.0%
	Female ME	−6.1%	6.8%	−9.3%	5.8%	−6.1%	4.1%	−9.0%	5.9%	−8.7%	6.3%
	Pseudo R^2	0.018	0.018	0.041	0.023	0.013	0.008	0.037	0.018	0.027	0.014
n		3,580		3,190		394		1,616		390	

Notes: Table reports probit regression results for the field of study choices made by individuals based on grouped high school final exam results belonging to the humanities and social sciences (model 2). Each regression includes one high school final exam results' quartile. The sign of the coefficient indicates in which direction exam results' quartile variable influences field of study group variable, but coefficients themselves cannot be directly interpreted (therefore marginal effects are used). Average ME, Male ME and Female ME represent corresponding post-estimated marginal effects. For example, Male ME of −5.4 percent in the "Exact and natural science" row and "Mother tongue" (Highest) column indicate rate of change, meaning that achieving top 25 percent result on the mother tongue high school final exam decreases the probability of the choice of exact and natural science as a field of study for male students by approximately 5.4 percent compared to students with lower scores. n represents the number of observations. *,**,***Significance at 10, 5 and 1 percent, respectively

Appendix 2. Paper II

FROM ACADEMIC ABILITIES TO OCCUPATION: WHAT DRIVES STOCK MARKET PARTICIPATION?

Publication:

Vaarmets, T.; Liivamägi, K.; Talpsepp, T. 2019. From academic abilities to occupation: What drives stock market participation? *Emerging Markets Review*, vol. 39, June 2019, pp. 83–100. DOI: https://doi.org/10.1016/j.ememar.2019.04.004. (ETIS 1.1).

Draft as conference proceedings:

Vaarmets, T., Liivamägi, K., Talpsepp, T. 2018. *How do cognitive and non-cognitive abilities influence stock market participation?* World Finance Conference, July 25–27, 2018, Mauritius.

Vaarmets, T., Liivamägi, K., Talpsepp, T. 2015. *The brilliant mind of investors.* World Finance Conference, July 21–24, 2015, Buenos Aires, Argentina.

Vaarmets, T., Liivamägi, K., Talpsepp, T. 2015. *The brilliant mind of investors*. INFINITI Conference on international finance, Ljubljana, Slovenia, June 8–9, 2015.

Vaarmets, T., Liivamägi, K., Talpsepp, T. 2014. *The brilliant mind of investors. The* 6th International Conference "Economic Challenges in Enlarged Europe", Conference Proceedings, June 15–17, 2014, Tallinn: Tallinn University of Technology.

Emerging Markets Review 39 (2019) 83–100

Contents lists available at ScienceDirect

Emerging Markets Review

journal homepage: www.elsevier.com/locate/emr

From academic abilities to occupation: What drives stock market participation?☆

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ARTICLE INFO

Keywords:
Stock market participation
Education
Cognitive abilities
Non-cognitive abilities
Gender effects

JEL classification:
G02
G11
I22
J24

ABSTRACT

We study how academic abilities along with education and occupation influence stock market participation. Combining five data sets from Estonia for a sample of over 200,000 individuals allows the effect to be observed in the finest detail available. We find that women are clearly less persuaded by their mental abilities to participate in the stock market than men are. Economic activity, occupation and religion affect stock market participation, and stock market investors tend to be more ambitious, more prone to risk and more intelligent than non-participants.

1. Introduction

It is extremely tricky to find ways to encourage household investment so as to reduce the negative effects of lost income and a lower standard of living before and during retirement. We contribute to the process of finding possible factors that can affect stock market participation. The positive effect of financial literacy has been widely recognised, and M. C. Van Rooij et al. (2012) argue that financial literacy is essential for other good money-related decisions to be made. This makes understanding the wealth generation process and its associated risks important for financial success, and a lack of financial knowledge may be one reason why stock market participation rates are so low.[1] Furthermore, participation rates in emerging markets are even lower[2] compared to developed markets, although returns in emerging markets tend to be higher (Huij and Post, 2011).

☆ We are grateful to Kalle Viks and Nasdaq Tallinn Stock Exchange, Marko Mölder and Estonian Ministry of Education and Science, Lauri Veski and Innove, Aime Lauk and Statistics Estonia for the data and their supportive attitude and efforts for processing our data requests. This work was supported by the European Union through the European Regional Development Fund. Declarations of interest: none.

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[1] Please see Lusardi and Mitchell (2008) and Hilgert et al. (2003) on the effects of limited financial knowledge. Hong et al. (2004); Grinblatt et al. (2011) find that only about half of the households in the US participate in the stock market, and direct participation rates are even lower. Poor financial literacy relates to various costs, which is the main reason why so few households hold shares (Haliassos and Michaelides, 2003).

[2] The Household Finance and Consumption Network (HFCN) conducts the Eurosystem's Household Finance and Consumption Survey, which collects household-level data on households' finances. HFCN reports direct stock market participation rate to be 3.6%, and 3.2% of households have mutual fund assets in Estonia. Those figures are at a comparable level with e.g. Poland and Slovakia, slightly higher than e.g. in Latvia or Greece but lower in all larger and developed European countries. Belgium, Germany, France, Ireland and Spain have a participation rate near or slightly over 10%; and Finland and Cyprus have a participation rate over 20%. The Euro area average is 8.8%.

https://doi.org/10.1016/j.ememar.2019.04.004
Received 30 October 2018; Received in revised form 15 March 2019; Accepted 23 April 2019
Available online 24 April 2019
1566-0141/

Most of the current literature focuses on how cognitive abilities affect stock market participation.[3] However, there are studies that conclude that non-cognitive traits play a role in market participation as well. Conlin et al. (2015) argue that personality traits are significant predictors of stock market participation, while Kaustia and Torstila (2011) conclude that personal values matter, and Guiso et al. (2008) find that having a trusting nature encourages stock market participation. The importance of separating cognitive and non-cognitive abilities has been emphasised in various areas of economic research. Brunello and Schlotter (2011) argue that abilities weakly related to cognition may be as important as cognitive abilities for individual development and economic success. Studies about schooling and labour market outcomes conclude that success in life depends not only on IQ or grades, but also on personality. Personality traits not only predict success in life, they can also cause it (Heckman and Kautz, 2012).

Our contribution to the current household finance literature is provision of new insights into how market participation is affected by academic and mental abilities and career related details. We highlight gender differences in the effects of education and academic abilities by contributing to the strand of gender studies.[4] Earlier literature provides limited data on comparison of cognitive abilities including IQ and mental abilities between genders[5] and we are able to fill the gap by answering the question whether market participation decisions of men and women are similarly affected by their characteristics. Our dataset lets us expand the current literature on stock market participation with more detailed information about the effects of academic abilities, education and career related characteristics.[6]

Furthermore, we extend the current literature by providing information about economic activity and occupation categories like manager, professional or service worker for all the individuals[7] participating in the stock market. We study a wide range of other characteristics which are common to shareholders as we have information about the results of standardized exams, high school grades and university courses along with information about degrees awarded and income later in life.

We also contribute to the literature on emerging markets which currently contains evidence from limited countries and often lacks detailed and reliable data at the population level. We provide evidence from a small emerging country with detailed registry data to extend current literature on stock market participation and financial choices in emerging markets.[8] The study is especially relevant from the emerging markets perspective as participation rates in emerging markets are even lower than in developed markets.

Our advantage is that we are able to extend previous studies and study how different type of cognitive abilities measured with standardized exam results from all main disciplines influence stock market participation. This is an important step further as general education level or intelligence measures may not always capture the effect arising from the different aspects of intelligence. Meta-analysis by Kim (2005) points to the limitations of the general intelligence measures. As our data includes exams results from humanities, natural and social sciences, among other things, we are able to offer additional insights to the existing literature.

The dataset used combines transaction level data from the Nasdaq Tallinn stock exchange with educational data from the Estonian Ministry of Education and Science, income tax data from the Estonian Tax and Customs Board, information from the Estonian Census of 2011, and data taken from the Estonian Population Register covering more than 200,000 individuals.

We find that academic abilities, a higher academic achievement, a higher level of education and certain types of education have a positive effect.[9] Our dataset lets us report the effects of extremely detailed characteristics of education and academic abilities. We provide clear evidence that the effects of mental abilities vary significantly depending on gender as decisions by women to participate in the stock market are influenced less by cognitive abilities and could be explained by non-cognitive abilities. All in all, investors tend to be more intelligent than non-investors in every subject, including soft and hard sciences. Our results also show that career related factor, occupational sector and type as well as socioeconomic status indicators play a role. Even when income and intelligence are controlled for, people in positions such as entrepreneurs or managers, which require traits like ambition, leadership, problem solving skills and willingness to take risks, are more likely to buy shares.

The reminder of the paper is organised as follows. Section 2 describes the findings of the earlier literature. Section 3 outlines the data and methodology. Section 4 provides the results. We discuss the results and possible policy measures to increase stock market participation in Section 5 and Section 6 gives the conclusions.

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[3] For example Campbell (2006) finds that financial literacy and stock market participation increase with overall education, while Grinblatt et al. (2011) conclude that IQ or the potential to obtain a good education also matter.

[4] See, for example, Almenberg and Dreber (2015) or Halko et al. (2012) for previous evidence of gender differences in market participation.

[5] For example Grinblatt et al. (2011) are able to study the effects of IQ for a sample consisting only of men whereas our study extends the data to a larger sample of both men and women with even more detailed information about cognitive abilities.

[6] We use registry based data for academic abilities and education and survey data from a national census about career related characteristics. The census data are comparable to the Health and Retirement Survey that has been conducted in the US since 1990 and The Survey of Health, Ageing and Retirement in Europe (SHARE). Our sample is clearly younger than the samples used in the Health and Retirement surveys, and it is also larger as it covers about 200,000 people.

[7] We start with data covering all the transactions made in the Nasdaq Tallinn stock exchange. We are able to match individuals participating in the stock market with their peers in the whole Estonian population in terms of their of socio economic variables such as age and gender. However, there are cases in which we might be missing some variables for some individuals in the sample, as the register of education does not contain data on all individuals for example. We also lack detailed information about foreign investors, and they are not included in our study.

[8] Guiso et al. (2008) provide evidence on market participation in a few emerging markets which are extended mostly by studies using data about China or India.

[9] Similar positive effects of higher education have been found by Calvet et al. (2007) and Guiso et al. (2003); the effect of the type of education has been found by Christiansen et al. (2007).

2. Previous literature

Economic success can be related to both cognitive abilities and personality traits, or non-cognitive abilities. Burks et al. (2009) argue that higher cognitive skills "systematically affect preferences and choices in ways that favour economic success". Herrnstein and Murray (1994) conclude that cognitive abilities measured in a child's adolescent years affect that person's socio-economic success later in life. Hanushek and Woessmann (2008) demonstrate that cognitive skills are important drivers for individual earnings and also for overall economic growth.

Heckman (2008) adds socio-emotional skills, physical and mental health, perseverance, attention, motivation, and self-confidence, all of which are important for achieving greater socio-economic success. At the same time there is evidence that personality factors are actually equally as important for achieving socio-economic success as cognitive abilities are (Borghans et al., 2008; Heckman et al., 2006). Moreover, Heckman and Kautz (2012) summarise by saying that soft skills like personality traits, goals, motivation, and preferences not only predict success in life but also produce that success.

Borghans et al. (2008) emphasise that many aspects of personality are influenced by cognitive processes and so the term "non-cognitive" should be avoided as both cognitive and non-cognitive abilities are interlinked. For example Burks et al. (2009) argue that individuals with better cognitive skills are more patient and have a greater willingness to take calculated risks, and this can be an important factor influencing stock market participation. Similarly, Benjamin et al. (2013) and Dohmen et al. (2010) provide evidence that greater cognitive ability is associated with more patient and less risk averse behaviour.

Literature focusing on non-cognitive abilities most commonly uses psychometric tests of various traits and abilities derived from psychometric inventories. For example Conlin et al. (2015) use a sample of a Finnish birth cohort and find that personality traits such as exploratory excitability, extravagance, sentimentality, and dependence affect stock market participation a lot. Kaustia and Torstila (2011) concentrate on personal values and find a relationship between political views and stock market participation. They show that left-wing voters and politicians are less likely to buy shares than other people are. Guiso et al. (2008) argue that people who invest in shares are more trusting in their nature. People who have faith in others are significantly more likely to buy shares and they also tend to hold a larger share of their overall wealth in shares. These findings are also consistent with those of Georgarakos and Pasini (2011), who conclude that trust and sociability impact the decision to participate in the stock market. Mental health (Bogan and Fertig, 2012), religion (Renneboog and Spaenjers, 2012) and the influence of family members (Goldfayn, 2016; Zetterdahl et al., 2013) can also affect financial behaviour and market participation.

The effects of financial literacy on stock market participation have gained a lot of attention. Using a household survey, M. Van Rooij et al. (2011) conclude that people with greater financial literacy tend to invest more in shares. The problems of a low level of financial knowledge have also been emphasised by Lusardi and Mitchell (2008), and Hilgert et al. (2003). The general lack of knowledge about finance and financial markets is consistent with reported figures, which show that participation in stock markets is very modest. According to Bricker et al. (2017), less than 20% of families in the US hold shares directly, and similar conclusions are reached earlier by Haliassos and Bertaut (1995). The rate of direct participation in the stock market varies across countries in Europe but tends to be even lower than in the US on average (Guiso et al., 2003).

Stock market awareness can be improved in different ways. Hong et al. (2004) propose that social activity makes people participate more in stock markets, so individuals with a more sociable nature, who communicate with their neighbours and go to church, tend to invest more in shares. They argue that learning from friends and neighbours reduces fixed participation costs and means that awareness and knowledge of the markets can be transmitted between individuals outside educational facilities. Bernheim and Garrett (2003) argue that financial education at work significantly increases the probability of people saving in general. They also find that households who were exposed to financial courses at high school have higher savings rates than others. The same findings can be seen in the study of Bayer et al. (2009), who conclude that financial education at work increases participation in retirement plans.

Traditional education still matters. Educational level and wealth are other drivers that make people participate in the stock market. Guiso et al. (2003) find a strong correlation between stock market participation and the level of education and wealth.[10] These findings are also supported by Campbell (2006), who concludes that less educated and less wealthy households tend to avoid investing in shares. He also proposes that this kind of behaviour may be reasonable, because less educated and less wealthy people tend to make more investment mistakes. Benjamin et al. (2013) find that mathematical skill is associated with more asset accumulation and greater financial market participation. Therefore financial knowledge and participation in the stock market increase with the overall level of education and household resources (Guiso and Jappelli, 2005).

The type of education also seems to play a role in whether people want to buy shares. Christiansen et al. (2007) propose that financial decisions not only depend on education level, but are also affected by the type of education. They show that people who have a university degree in economics have a higher tendency to hold shares. Talpsepp (2011) hypothesises that investors who invest in foreign markets are more sophisticated than local investors in those particular markets.

Grinblatt et al. (2011) conclude that men with higher IQ tend to participate in the stock market more than do men with lower IQ, which was typically tested by the Finnish armed forces at the age of 19 or 20. They also find that the IQ effect on participation is monotonic and notably larger than the effect of income. These findings are consistent with an earlier study by Christelis et al. (2010), who also find that the cognitive abilities of numeracy, verbal fluency and memory that are related to IQ play a role in stock market participation. Barnea et al. (2010) show that many factors that influence our financial behaviour are affected by our genetic background, which means that our financial behaviour is determined to a great extent even before we are born. However, consistent with

[10] The same conclusion can be made from the figures presented in the study by Bricker et al. (2017).

studies of stock market awareness,[11] they also show that family environment has a significant effect on the investment behaviour of young individuals, but this effect disappears as an individual gains experience for themselves.

Previously only limited number of characteristics about occupational background or field of activity has been studied. Grinblatt et al. (2011) classify individuals as entrepreneurs, farmers, finance professionals or unemployed. They conclude that the participation rate of unemployed individuals is lower than employed individuals and that finance professionals tend to participate in the stock market with higher probability than individuals with other professions. They also find that entrepreneurs tend to participate in the stock market with lower probability compared to others. The latter is consistent with Heaton and Lucas (2000) but contradicts to the findings of Barnea et al. (2010). Conlin et al. (2015) conclude also that entrepreneurs and managers are more likely to participate in the stock market. Using Health and Retirement Survey (HRS) data Bertaut (1998), Hong et al. (2004) and Bogan (2008) show that the stock market participation increases, if the head of the household is employed in a managerial or professional occupation.

Almenberg and Dreber (2015) argue that the gender gap in stock market participation is largely explained by the basic financial literacy but also by differences in risk taking behaviour. Halko et al. (2012) find that women are reluctant to participate in the stock market mainly because of their higher risk aversion. In addition, they argue that wealth and financial knowledge tend to be the reasons for the gender gap in stock market participation.

3. Data and methodology

We combine five different data sets in order to study the effects on stock market participation. The data cover 221,774 unique individuals. The availability of educational data mean that the individuals in our sample are rather young, as the average age is 29.2 for investors and 26.8 for non-investors. However, investors who trade in the Nasdaq Tallinn generally tend to be quite young, as shown by Talpsepp (2010), who also points out that the Estonian stock market is dominated by male investors. The same can be observed in our sample.[12]

Our base dataset comes from the Estonian Ministry of Education and Science and it includes all high school grades, the results of high school final exams and information about each individual's education level, which gives their university degrees and type of education. High school final exams are identical for all high school leavers and are designed to have the same level of difficulty across the years as they are used for admission to universities. These properties and other details of academic background let us draw conclusions about investors' academic abilities, which are closely correlated with their mental abilities (Deary and Johnson, 2010).

Stock market participation is derived from the data provided by Nasdaq Tallinn, which is the only stock exchange in Estonia. The stock market data consist of all the transactions made with the total of 23 listed Estonian companies in a period of nine years from 01 January 2004 to 31 December 2012 together with all the shareholdings from the same period. The small size of the Estonian stock market means there may be some liquidity constraints on active trading in it.[13] The stock market data cover a total of 33,843 investors, 27,859 of whom are individual investors who have had at least one stock in their account during our sample period. We use a sample of 6811 investors (24.4% of all investors) of whom we have detailed educational data available, which means that those investors have taken standardized exams since 1997.

We form a total sample of all individuals in Estonia on comparative basis who have taken standardized exams since 1997. Thus our total sample size is 221,572 individuals of whom about 3.1% are investors. We add income taxes information to the sample for 197,439 individuals (information about the rest of the sample is not available) from the Estonian Tax and Customs Board; and information for all individuals from the Estonian Census of 2011. The census data cover many characteristics such as socio-economic status, information about health and religion, economic activity, detailed educational levels and occupation. The last element of the dataset used is from the Estonian Population Register and contains data such as legal marital status, nationality and citizenship. As we use data combined from various sources, the used sample size in regressions can be smaller than the total sample size of about 220 thousand individuals because of data availability issues. For example, individuals are not obliged to answer all questions in census as they may feel that some questions are too private. In essence we have cohort data of all individuals in Estonia who have taken obligatory standardized exams after high school since those tests were established.

Stock market participation in Estonia is low compared to developed markets. Our data of stockholdings comes from Nasdaq Tallinn which amount[14] to around 80% of all direct stockholdings held by Estonian households. As investors with larger portfolios usually hold both domestic and foreign stocks, it means that a possible unmeasured participation rate (investors who have only foreign stocks) is very small[15] compared to our whole sample of about 200 thousand individuals. Mutual fund assets do not significantly increase indirect participation rate because the amount of mutual fund assets[16] is less than direct stock holdings and those two participation rates are not additive but overlap. Participation rates in voluntary pension and life insurance plans in Estonia is also

[11] For example Hong et al. (2004).

[12] In our sample 73.2% of the investors are male investors, which is comparable with the figure of 67.9% presented by Talpsepp (2010).

[13] Blitz and Huij (2012) highlight similar liquidity constraints along with higher trading costs in other emerging markets as well.

[14] Summary statistics is provided by the Bank of Estonia.

[15] Investing into foreign stocks means at least 2–3 times higher commissions for stock trades than for investing into the local stock exchange for most individuals and does not make economic sense for an investor with an average portfolio in our sample. It is plausible that a small number of large investors make up the majority of the 20% of total direct stockholdings invested abroad and it is reasonable to assume that many of those larger individual investors also hold domestic stocks because of home bias and thus are classified as participants of the stock market in our data set.

[16] Mutual fund assets held by households amount to 90% of direct stockholdings on average, fluctuating between 33% to 211% during the period from 2004 to 2012 in Estonia. The data is provided by the Bank of Estonia.

lower than in European countries with higher direct stock market participation rates and special cases are negligible.[17]

Our investor sample reveals that a typical shareholder in Nasdaq Tallinn is similar to a typical investor in developed markets like those in the USA or Denmark. Of all the investors in our sample, 73.2% are male, which is similar to the 78.7% in the sample used by Barber and Odean (2001). Almost 40% of the investors in our sample have a degree in economics or business, which is again similar to the sample used by Christiansen et al. (2007). Trading characteristics, portfolio size and holdings are very similar as previously reported by Talpsepp (2010) and in the similar magnitude to the figures reported about individual investors in the US, Finland and Denmark (with an exception of the average portfolio size, which is smaller because of the lower level of wealth and income in Estonia).

We use probit regression models as our main tool for the data analysis.[18] The dependent binary variable makes the probit model a suitable choice for addressing the question of participation and it has been widely used in the earlier literature on participation (Bogan, 2008; Christiansen et al., 2007; Grinblatt et al., 2011; Guiso et al., 2008; Hong et al., 2004).

The dependent variable indicates whether a person has been active in the stock market during our sample period. Independent variables include characteristics of the individuals and control variables like gender, age, income and higher education. The characteristics include dummy variables for economic activity, socio-economic status, health, legal marital status, religion, occupation, and nationality, as well as several variables for measuring intelligence such as high school exam results, educational level and the number of languages spoken. We use average income over a 7-year period as a control variable. Given the young age of our sample, average income can be also regarded as a proxy for wealth because mainly only the effect of inheritance does not get measured. The wealth accumulation process in Estonia could start only after gaining independence in 1990s which means that individuals in our sample cannot usually rely on inherited wealth.

Correlation between exam results ranges from 0.42 to 0.76. The highest correlation is between maths and physics exam and the lowest between biology and mother tongue exam. Correlation between exams associated with real sciences and humanities is approximately 0.5 and the same applies for correlations between three most important and widely taken exams of mother tongue, maths and English. For example only 11% of individuals were able to be among top 25% of exam takers in both math and any of the language exams. Thus, exam results in various subjects show abilities in different areas that can be associated with diverse mental abilities as well. The correlation between the average exam result and each of the individual exams is in the range from 0.75 to 0.85 in most cases.

We estimate the models by using variables for the characteristics individually and including control variables. This prevents any misleading conclusions being reached because of multicollinearity in the general model. For easier interpretation of the results of the probit regression models described, we use post estimated marginal analysis and calculate the average marginal effects and the marginal effects for males and females separately.

To compare average high school final exam results of stock market participants to the exam results achieved by individuals who did not hold any shares, we employ two simple sample *t*-tests with equal variances. In addition to testing the significances of the differences, we also compute the size of the effect by using Cohen's *d* and Hedges' *g*.

4. Results

4.1. Academic abilities and education

There have been several studies which concentrate on education and find that more educated people tend to participate more in the stock market. For example Kumar (2009) finds that more time spent in education means a higher probability of buying shares and making better investment decisions. Studies by Calvet et al. (2007) and Guiso et al. (2003) show that education matters. Christiansen et al. (2007) developed this question further and showed that not only does the level of education matter, but the type of education also plays a role in the participation in the stock market. However, previous studies were unable to find any evidence that investors are also mentally more capable than non-investors until Grinblatt et al. (2011) showed a positive relationship between IQ and stock market participation. We add a number of new aspects to the previous findings and offer a more detailed view of how stock market participation is affected by a range of characteristics that all reflect intelligence.

Our dataset provides detailed information on national exam results for over 220,000 individuals. When the results of such exams are compared, significant differences emerge between investors and non-investors in every case we studied. Investors get better results than non-investors in every subject, meaning that they are better at maths, and at history or languages (see Table 1).

Differences between the high school final exam results achieved by stock market participants and non-participants are statistically significantly different in every case studied. The scores investors achieved in the mathematics exam are on average 6.25 percentage points higher (see Table 1), those in physics are 7.89 percentage points higher and so on. All the differences between the exam results of investors and non-investors are remarkable and the size of the effect is notable in most cases.[19] In most cases the size of the effect,

[17] Special cases can include e.g. options of company stocks or individuals working in asset management firms who are not allowed to make direct investments. However, the tax system (extremely high tax on company stock options for employees during the sample period) or economic characteristics (very few people work in positions that could theoretically be affected by such special cases) make such cases negligible for our sample.

[18] A logit regression model was also used as a robustness check, but as the conclusions are the same for both types of model, only the results from the probit regressions are presented in the paper.

[19] As measured by Cohen's d and Hedges' g.

Table 1
Differences between investors and non-investors exam results.

Group	Group differences: Mean	Std. error mean	95% confidence interval of the difference: Lower	Upper	t	Df	Significance	Effect size: Cohen's d Hedges' g
Mathematics	6.253	0.381	5.507	6.999	16.420	92,608	***	0.251
Physics	7.803	0.885	6.069	9.537	8.822	11,979	***	0.323
Chemistry	3.777	0.587	2.626	4.928	6.433	38,351	***	0.169
Biology	5.485	0.513	4.480	6.491	10.695	59,121	***	0.280
Mother tongue	4.120	0.256	3.619	4.621	16.110	198,390	***	0.201
English	4.966	0.242	4.491	5.440	20.525	139,365	***	0.285
History	6.428	0.423	5.599	7.256	15.212	56,673	***	0.307

The table reports differences between the means of the exam results achieved by investors and non-investors, and the differences in standard errors reported together with the 95% confidence interval of these differences. In addition the t-values and degrees of freedom are shown and also the significance levels. In all cases the differences in exam results were statistically significant at the 0% level, which is represented by three stars ***. To measure the size of the difference Cohen's d and Hedges' g were used and are reported. The value of 0.2 can be considered as a small effect, the value of 0.5 a medium effect and a value over 0.8 can be considered a large effect.

with values between 0.2 and 0.4, means there is a small difference in the mental abilities of stock market participants and non-participants in those areas.

A similar conclusion that investors are more intelligent than non-investors can be drawn from the results (see Table 2) showing high school final exam results divided into adjusted deciles for every exam. A much lower proportion of investors than of non-investors can be seen in the lower groups. Similarly, higher proportions of investors are found in the higher deciles.

We estimated probit regression models for all deciles, using the exam variables independently by including only control variables in the regressions. We also re-estimated the model with all the exams and control variables, and the results for the lowest and highest adjusted decile and quartile are presented. In every case the coefficients for the lowest groups are negative and the coefficients for the highest groups are positive. This means that a change from 0 to 1 in the lowest groups decreases the predicted probability of stock market participation and a change from 0 to 1 in the highest groups increases the predicted probability of stock market participation. Individuals with high intelligence tend to be more likely to participate in the stock market and individuals who fail to demonstrate high intelligence tend to be less likely to participate.

In order to reach more precise conclusions, we perform marginal analysis of the coefficients. As interpreting the results of marginal analysis is straightforward for categorical variables that take the value of zero or one, we concentrate on the results presented in Table 3, the model with adjusted deciles. We conclude that the mathematics and physics exam results have a stronger impact on stock market participation than, say, language exams. The explanation may be that it is easier for people who have better mathematical abilities to understand the stock market, as the market is largely based on various mathematical operations and calculations, meaning the associated participation costs are lower.[20] Support for this view is the observation that the stock market participation rate is highest for those who have taken a mathematics and physics exam, as 4.8% of the people who took a mathematics exam and 6.7% of those who took a physics exam were engaged in the stock market in the period studied.[21] We also compare the marginal effects of the lowest adjusted decile with the second to tenth adjusted deciles. We find that in almost every case the probability of buying stocks increases monotonically when moving from the second adjusted decile to the tenth, or highest, adjusted decile.

As investors have stronger results in all of the exams, general findings on the impact of standardized final exams show a positive effect of higher scores on market participation (see Table 4). Marginal effects show that the overall effect of gender (marginal effect of 3.6%) and higher education (marginal effect of 2.4%) on market participation is higher than for example the impact of getting 12.5 points more (equalling to approx. 1 standard deviation) on the mathematics exam (marginal effect of about 0.88%). However, the differences between exam deciles can make the effect of certain academic abilities to be larger (as seen from Table 3).

We also run probit regressions which include various exam results in the same regression along with dummy variables related to socioeconomic status, occupation and economic activity (see Table 5 for results). The scores of exams are correlated and individuals can choose 3–5 exams. Thus, we cannot include a larger number of exam results in one regression (we have to drop observations for which an exam score is missing) and present results only for regressions where the three most popular exams are included. Although correlations between exam scores are far from perfect, we conclude that the mother tongue exam captures most of the effect of the history exam; the mathematics exam captures the effect of the physics exam. Moreover, we argue that most of the effect of all exam results is captured by mother tongue, English and mathematics exams. We also use a setup where we include an average exam score[22]

[20] Vissing-Jørgensen (2003) argues that fixed costs are the reason why US households tend to not participate in the stock market. Similar arguments are also made by Hong et al. (2004).

[21] Our data includes 92,610 individuals who took the mathematics exam and 4483 of them participated in the stock market during the period studied. As for the physics exam, comparable figures are 11,981 and 801, respectively. Participation rates in other exams are presented in Table 2.

[22] We experiment with different calculation methods for the average score either by including only certain exams or leaving out exams for which we want to study the additional effect. Our results are not affected by how we calculate the average exam score.

Table 2
Group proportions of exam results.

	Adjusted deciles													
	1	2	3	4	5	6	7	8	9	10	Total	Avg. score	Std. Dev	Propor-tion
Mathematics exam result														
Number of investors	327	314	321	425	393	496	432	462	565	748	4483	55.94	25.47	4.84%
Number of non-Investors	8856	8099	8743	9445	8382	9475	8685	8738	8892	8812	88,127	49.69	24.84	95.16%
Physics exam result														
Investor proportion	30	59	68	76	74	75	85	93	97	144	801	64.55	23.15	6.69%
Non-Investor proportion	1078	1185	1052	1194	1081	1071	1145	1175	1120	1079	11,180	56.74	24.26	93.31%
Chemistry exam result														
Investor proportion	88	149	138	141	149	161	117	183	152	239	1517	62.21	22.33	3.96%
Non-Investor proportion	3427	3763	3677	3953	3497	3784	3277	4134	3357	3967	36,836	58.43	22.42	96.04%
Biology exam result														
Investor proportion	68	113	128	138	139	144	161	181	202	225	1499	62.77	18.86	2.54%
Non-Investor proportion	5586	5557	6100	5671	5860	5846	5516	6078	5532	5878	57,624	57.29	19.62	97.46%
Mother tongue exam result														
Investor proportion	344	558	509	278	976	773	365	1101	758	991	6653	61.63	20.33	3.35%
Non-Investor proportion	15,555	21,802	16,370	11,057	31,637	18,675	13,093	25,455	16,550	21,545	191,739	57.51	20.51	96.65%
English exam result														
Investor proportion	326	380	405	401	454	503	645	678	631	983	5406	71.31	16.82	3.88%
Non-Investor proportion	12,703	13,433	14,441	11,794	13,002	13,643	13,957	13,373	12,642	14,973	133,961	66.35	17.46	96.12%
History exam result														
Investor proportion	111	172	210	220	248	262	287	301	386	376	2573	60.69	19.27	4.54%
Non-Investor proportion	5264	5535	5380	5462	5307	5488	5323	5089	5903	5351	54,102	54.26	21.02	95.46%

The table reports number of investors and non-investors divided into adjusted deciles by exam results. Deciles were adjusted where the cut-off point was in the middle of some specific exam result and the boundary was lifted so that every result remained in only one group. Average score, standard deviation are presented for each exam grouped by investors and non-investors. The investor proportion and the non-investor proportion are presented for each exam.

Table 3
Dynamics of high school final exam results and stock market participation.

	Adjusted deciles									
Independent variables estimated values	2	3	4	5	6	7	8	9	Highest	N	Pseudo R^2
Mathematics											
Coefficients	0.126***	0.156***	0.290***	0.344***	0.411***	0.412***	0.455***	0.535***	0.676***	92,610	0.085
z-values	3.400	4.240	8.250	9.550	11.840	11.550	12.870	15.570	20.300		
Average marginal effect	0.73%	0.93%	1.95%	2.43%	3.08%	3.09%	3.55%	4.48%	6.38%		
Marginal effects for males	1.14%	1.45%	3.00%	3.72%	4.69%	4.70%	5.37%	6.72%	9.44%		
Marginal effects for females	0.34%	0.43%	0.94%	1.18%	1.53%	1.53%	1.78%	2.30%	3.40%		
Physics											
Coefficients	0.359***	0.503***	0.549***	0.623***	0.646***	0.700***	0.770***	0.834***	1.010***	11,981	0.076
z-values	3.480	4.900	5.420	6.100	6.280	6.900	7.620	8.240	10.340		
Average marginal effect	2.17%	3.48%	3.97%	4.83%	5.10%	5.81%	6.81%	7.79%	10.92%		
Marginal effects for males	2.63%	4.20%	4.79%	5.81%	6.13%	6.97%	8.14%	9.29%	12.94%		
Marginal effects for females	0.73%	1.22%	1.42%	1.77%	1.89%	2.19%	2.64%	3.09%	4.62%		
Chemistry											
Coefficients	0.297***	0.302***	0.315***	0.414***	0.437***	0.376***	0.489***	0.501***	0.628***	38,353	0.083
z-values	4.850	4.850	5.080	6.670	7.130	5.790	8.110	7.970	10.580		
Average marginal effect	1.58%	1.61%	1.70%	2.46%	2.66%	2.16%	3.13%	3.24%	4.57%		
Marginal effects for males	2.71%	2.76%	2.92%	4.17%	4.49%	3.66%	5.25%	5.43%	7.53%		
Marginal effects for females	0.82%	0.83%	0.88%	1.31%	1.42%	1.13%	1.69%	1.76%	2.56%		
Biology											
Coefficients	0.264***	0.307***	0.408***	0.421***	0.457***	0.559***	0.578***	0.702***	0.739***	59,123	0.084
z-values	4.180	4.970	6.620	6.870	7.430	9.200	9.680	11.810	12.580		
Average marginal effect	0.78%	0.95%	1.41%	1.48%	1.67%	2.28%	2.42%	3.36%	3.67%		
Marginal effects for males	1.60%	1.94%	2.84%	2.97%	3.34%	4.50%	4.75%	6.47%	7.03%		
Marginal effects for females	0.39%	0.49%	0.74%	0.78%	0.89%	1.25%	1.32%	1.90%	2.10%		
Mother tongue											
Coefficients	0.109***	0.193***	0.237***	0.272***	0.374***	0.379***	0.468***	0.505***	0.555***	198,392	0.085
z-values	3.630	6.250	6.660	9.860	12.860	11.320	16.910	17.120	19.640		
Average marginal effect	0.46%	0.89%	1.14%	1.36%	2.07%	2.11%	2.83%	3.16%	3.65%		
Marginal effects for males	0.83%	1.59%	2.03%	2.41%	3.62%	3.69%	4.90%	5.46%	6.26%		
Marginal effects for females	0.20%	0.40%	0.52%	0.62%	0.98%	1.00%	1.37%	1.55%	1.82%		
English											
Coefficients	0.155***	0.186***	0.287***	0.319***	0.349***	0.461***	0.509***	0.513***	0.661***	139,367	0.096
z-values	4.550	5.510	8.370	9.540	10.610	14.530	16.050	15.970	21.800		
Average marginal effect	0.73%	0.90%	1.54%	1.75%	1.98%	2.91%	3.35%	3.39%	5.01%		
Marginal effects for males	1.25%	1.53%	2.59%	2.95%	3.31%	4.81%	5.52%	5.58%	8.10%		
Marginal effects for females	0.35%	0.43%	0.76%	0.87%	0.99%	1.50%	1.75%	1.77%	2.72%		
History											
Coefficients	0.190***	0.297***	0.320***	0.408***	0.432***	0.513***	0.559***	0.634***	0.699***	56,675	0.077
z-values	3.580	5.730	6.230	8.030	8.550	10.240	11.150	13.030	14.190		
Average marginal effect	0.96%	1.67%	1.85%	2.56%	2.77%	3.56%	4.05%	4.92%	5.76%		
Marginal effects for males	1.68%	2.89%	3.18%	4.37%	4.71%	5.99%	6.77%	8.14%	9.45%		
Marginal effects for females	0.47%	0.84%	0.93%	1.32%	1.44%	1.89%	2.18%	2.70%	3.22%		

The table reports coefficients and significance levels, z-values, pseudo R^2 and number of observations from probit regressions together with post estimated average marginal effects. Marginal effects show the difference between the reported adjusted decile and the lowest adjusted decile, which serve as a benchmark group and therefore are not included in the table. Probit regression models are constructed so that the dependent variable or investor dummy took the value 0 if the person has not held shares in our sample period and the value 1 if the person has had shares in the period observed. The independent variable representing specific exam result groups took the value from 1 to 10 according to the exam results. The weakest exam results fall into the first deciles and were coded as 1, the highest exam results were included in the tenth decile and took the value 10. Control variables for gender and age were also included in all the models, but in order to keep the table as simple as possible the estimated values for these control variables are not reported, except the marginal effects for males and females. Three stars indicate the 1% significance level, two stars 5%, and one star the 10% significance level. Results reported in the table are based on national high school final exams taken from 1997 to 2012 and on Estonian stock market data from 2004 to 2012.

which could be regarded as the closest proxy to a broad measure of intelligence and study whether the effects of individual subject scores remain significant. The results (see Table 5) show that quantitative knowledge and language skills as measured by the mathematics exam score and the English exam score, remain significant in all setups. The coefficient of the mother tongue exam becomes statistically not significant when the average exam score is included in the regression.

Table 4
National high school final exam results and stock market participation.

Independent variables	Coefficients	z-values	Pseudo R^2	N	Marginal effects All	Male	Female	Diff
Panel A. Probit regressions with actual exam result variables								
Mathematics exam result	0.005***	14.98	0.0853	92,610	0.05%***	0.07***	0.03***	***
Physics exam result	0.006***	6.69	0.0744	11,981	0.08%***	0.09***	0.03***	***
Chemistry exam result	0.003***	5.31	0.0815	38,353	0.03%***	0.04***	0.02***	***
Biology exam result	0.006***	8.81	0.0841	59,123	0.04%***	0.06***	0.02***	***
Mother tongue exam result	0.005***	15.45	0.0842	198,392	0.04%***	0.06***	0.02***	***
English exam result	0.008***	18.00	0.0956	139,367	0.06%***	0.1***	0.04***	***
History exam result	0.006***	9.97	0.0773	56,675	0.05%***	0.08***	0.03***	***
Gender	0.58184***	46.37	0.1186	221,774	3.62%			
Age	0.06062***	41.79	0.1186	221,774	0.38%	0.59%***	0.21%***	***
Income	0.09950***	21.93	0.1186	221,774	0.91%	1.44%***	0.54%***	***
Higher Education	0.26262***	10.81	0.1186	221,774	2.41%	3.81%***	1.42%***	***
Panel B. Probit regressions with exam result lowest and highest group variables								
Mathematics exam result groups								
Lowest adjusted decile	−0.186***	−6.28	0.0727	92,610	−1.61%***	−2.37%***	−0.86%***	***
Highest adjusted decile	0.241***	10.21	0.0741	92,610	2.66%***	3.83%***	1.54%***	***
Physics exam result groups								
Lowest adjusted decile	−0.383***	−4.1	0.0607	11,981	−3.76%***	−4.55%***	−1.3%***	***
Highest adjusted decile	0.264***	4.49	0.0586	11,981	3.72%***	4.44%***	1.5%***	***
Chemistry exam result groups								
Lowest adjusted decile	−0.222***	−4.06	0.0776	38,353	−1.57%***	−2.53%***	−0.9%***	***
Highest adjusted decile	0.2***	5	0.0754	38,353	1.83%***	2.86%***	1.13%***	***
Biology exam result groups								
Lowest adjusted decile	−0.336***	−5.96	0.0724	59,123	−1.49%***	−2.72%***	−0.89%***	***
Highest adjusted decile	0.152***	4.01	0.0693	59,123	0.96%***	1.69%***	0.61%***	***
Mother Tongue exam result groups								
Lowest adjusted decile	−0.228***	−8.24	0.0748	198,392	−1.53%***	−2.46%***	−0.85%***	***
Highest adjusted decile	0.133***	6.96	0.0744	198,392	1.13%***	1.77%***	0.66%***	***
English exam result groups								
Lowest adjusted decile	−0.24***	−8.48	0.0832	139,367	−1.64%***	−2.63%***	−0.9%***	***
Highest adjusted decile	0.257***	12.87	0.0845	139,367	2.39%***	3.71%***	1.4%***	***
History exam result groups								
Lowest adjusted decile	−0.259***	−5.64	0.0656	56,675	−2.02%***	−3.16%***	−1.19%***	***
Highest adjusted quartile	0.153***	4.76	0.0690	56,675	1.55%***	2.36%***	0.97%***	***

The table reports the coefficients together with the significance level, pseudo R^2 and the number of observations from probit regressions in which the dependent variable takes the value 1 if the individual has held shares or traded in the stock market during our sample period. In addition, post estimated average marginal effects and marginal effects for males and females separately are shown. Column "Diff." shows statistical significance of the difference of marginal effects between male and female. All the coefficients in panel A and panel B are significant at the 1% level (denoted as ***). Probit regressions for actual exam results and exam result groups were conducted independently. This means that in the model only one exam result or exam result group variable was tested together with the control variables. In Panel A the outcome of the probit model for actual exam results is presented, and in panel B the exam results are divided into two categories of adjusted deciles and adjusted quartiles. Deciles and quartiles were adjusted where the cut-off point of the decile or quartile was in the middle of some specific result and the boundary was lifted so that every result remained in only one group. Only the lowest and highest adjusted deciles and quartiles are reported. The results for the control variables for gender, age, income and higher education shown in panel A are from the general model, where all the actual exam results were included (in which case all the coefficients for exam results were also very similar to those reported in the table). The income variable reflects the annual average social tax paid to the government in the period 2004–2010 and is multiplied by 1000, making the marginal effect more meaningful (marginal effects show how the probability increases when annual average social tax paid increases by 1000 EUR per year). To keep the table as simple as possible the results for control variables in panel B are not shown. The data in the table are based on national high school final exams taken from 1997 to 2012 and on Estonian stock market data from 2004 to 2012.

The reason why the academic performance of investors is better on such a broad scale, as investors get better results than non-investors across the board, may be that people with better knowledge and better skills are also more ambitious and confident. They continue their studies, get better jobs and salaries, and try to find ways to secure themselves financially. This view is also supported by previous studies[23] that show the relationship between education and stock market participation.

[23] For example Calvet et al. (2007) and Guiso et al. (2003), but also Lusardi (2003).

Table 5
Combined effects on stock market participation.

Variable	Coef.	Coef.	Coef.	Coef.	Marginal effect
Mathematics exam result	0.261***	0.267***	0.306***		
Mother tongue exam result	0.086	0.091*	0.119**		
English exam result	0.528***	0.534***	0.322***		
Average exam score	0.019				
Mathematics exam, quartile 2				0.057*	0.55%
Mathematics exam, quartile 3				0.100***	1.01%
Mathematics exam, quartile 4				0.187***	2.01%
Mother tongue, quartile 2				0.047	0.47%
Mother tongue, quartile 3				0.107***	1.11%
Mother tongue, quartile 4				0.104***	1.07%
English exam, quartile 2				0.037	0.37%
English exam, quartile 3				0.083***	0.85%
English exam, quartile 4				0.129***	1.37%
Minority nationality			−0.405***	−0.405***	−3.45%
Other nationality			−0.386***	−0.387***	−3.20%
Employee			−0.129**	−0.128**	−1.42%
Entrepreneur-employer			0.146*	0.147*	1.73%
Self-employed			0.191**	0.194***	2.36%
Managers			0.302***	0.302***	3.82%
Professionals			0.186***	0.189***	2.16%
Technicians and associate professionals			0.155***	0.156***	1.80%
Clerical support workers			0.152**	0.152**	1.79%
Craft and related trades workers			−0.166**	−0.166**	−1.61%
Wholesale and retail trade			−0.122*	−0.125*	−1.34%
Information and communication			−0.118*	−0.117*	−1.26%
Financial and insurance activities			0.382***	0.381***	4.09%
Real Estate activities			0.288***	0.281***	3.02%
Public Administration and Defence			−0.108	−0.113*	−1.21%
Education			−0.312***	−0.312***	−3.36%
Human health and social work activities			−0.267***	−0.272***	−2.92%
Arts, entertainment and recreation			−0.146*	−0.148*	−1.59%
Gender	0.642***	0.642***	0.646***	0.649***	6.73%
Age	0.024***	0.024***	0.029***	0.027***	0.29%
Income	0.071***	0.071***	0.061***	0.062***	0.63%
Higher Education	0.257***	0.258***	0.227***	0.229***	2.46%
Master's or higher degree	0.073***	0.073***	0.104***	0.109***	1.17%
N	54,815	54,815	54,815	54,815	
Pseudo R^2	0.108	0.108	0.130	0.130	

The table reports the coefficients and significance levels from probit regressions. Post estimated average marginal effects are shown for the last regression. Probit regression models are constructed so that the dependent variable or investor dummy takes the value 0 if the person has not held shares in our sample period and the value 1 if the person has had shares in the period observed. The independent variable (other than exam scores or control variables) takes the value 1 if the individual belongs to the specific group. The base group represents the lowest quartiles of exam scores, majority national, non-religious, non-married, other economic status, elementary occupation and other service sector. Control variables for gender, age, income and higher education were also included. Three stars indicate the 1% significance level, two stars 5%, and one star the 10% significance level. The income variable reflects annual average social tax paid to the government in the period 2004–2010 and is multiplied by 1000, exam scores are multiplied by 100). Variables with coefficients not statistically significant are omitted from the table (but are included in the model).

We can also proxy intelligence by the number of foreign languages spoken. When we study how stock market participation relates to that variable, we again find evidence supporting the idea that higher intelligence increases the probability of participation in the stock market. Individuals who are able to speak zero or only one foreign language tend to be less likely to buy shares than individuals, who can speak more languages. However, there seems to be a limit where the probability of participating in the stock market does not increase any more. Individuals who are able to speak four foreign languages are already polyglots and adding one or more languages on top does not bring an additional increase in the probability of them buying shares.

Cattell-Horn-Carrol (CHC) theory on the structure of human cognitive abilities (Flanagan et al., 2000) lists eight broad abilities as components of intelligence (Alfonso et al., 2005). Fluid intelligence, quantitative knowledge, reading and writing, crystallized intelligence, and long-term retrieval are the components of intelligence which are at least partially measured by the scores of standardized academic exams.[24] Thus, the effects of the results of the mathematics and physics exams in our study show that the level of quantitative knowledge has a positive effect on participation rates and quantitative knowledge is probably one of the most important components of intelligence which affects market participation. According to the classification by the CHC theory (Alfonso et al.,

[24] See e.g. meta-analysis by Kuncel et al. (2004), Sackett et al. (2008) or Frey and Detterman (2004) for correlation between academic results and scores of IQ tests.

Table 6
Occupation and socioeconomic status by academic results.

	1st quartile		2nd quartile		3rd quartile		4th quartile	
	Coef.	Marginal effect	Coef.	Marginal effect	Coef.	Marginal effect	Coef.	Marginal effect
Occupation								
Manager	0.334***	1.76%	0.265***	1.86%	0.252***	2.09%	0.299***	3.40%
Professional	0.012	0.06%	0.001	0.01%	0.075**	0.62%	−0.036	−0.41%
Service and sales worker	−0.263***	−1.39%	−0.224***	−1.58%	−0.353***	−2.94%	−0.352***	−4.03%
Elementary occupation	−0.147*	−0.78%	−0.272***	−1.92%	−0.343***	−2.86%	−0.223*	−2.56%
Status								
Employee	−0.161***	−0.77%	−0.164***	−1.01%	−0.099***	−0.70%	−0.075***	−0.71%
Entrepreneur	0.480***	2.29%	0.440***	2.70%	0.593***	4.17%	0.656***	6.21%
Field of economic activity								
Information and communication	0.265***	1.41%	0.010	0.07%	0.215***	1.80%	0.025	0.29%
Financial and insurance	0.305***	1.63%	0.214***	1.50%	0.336***	2.81%	0.451***	5.14%
Real Estate activities	0.432***	2.31%	0.291**	2.04%	0.391***	3.28%	0.241**	2.77%
Education	−0.481***	−2.57%	−0.206***	−1.45%	−0.315***	−2.64%	−0.274***	−3.14%
Human health and social work	−0.320***	−1.71%	−0.525***	−3.68%	−0.454***	−3.80%	−0.374***	4.29%

The table reports the coefficients and significance levels from the probit regressions together with post estimated average marginal effects. The sample is divided into four quartiles based on the academic results in state administered high school final exams. Regressions are run for subsamples based on the quartiles. Lower quartiles indicate weaker results and higher quartiles represent a sample with stronger academic results. Probit regression models are constructed so that the dependent variable or investor dummy takes the value 0 if the person has not held shares in our sample period and the value 1 if the person has had shares in the period observed. The independent variable representing the specific occupation or socioeconomic status takes the value 1 if the individual was involved in this occupation or is in that socioeconomic group. Control variables for gender, age, income and higher education were also included in the regressions but the results are omitted from the table. Three stars indicate the 1% significance level, two stars 5%, and one star the 10% significance level.

2005), language skills belong to the category of crystallized intelligence which is another important component which has a positive effect on market participation. Nevertheless, examination results can also depend on other components of intelligence, such as short and long term retrieval or fluid intelligence.

We also test how mental abilities interact with occupation, socioeconomic status and economic activity. We divide the sample into four subsamples, using the average exam results as a proxy for intelligence. The results show (see Table 6) that for the subsample of more intelligent investors the effects from entrepreneurial status or managerial positions, become stronger for more intelligent subgroups. Even though we do not see any meaningful difference for the majority of the population, who are classified as employees, we observe a slight decrease in the probability for people in the service industry, where the probability of participation in the stock market decreases as intelligence increases. Entrepreneurial status or managerial positions could be associated with higher confidence and better adaptation to new situations Baron (1998) which can imply that certain combinations of cognitive and non-cognitive abilities can have an amplified effect on stock market participation.

Our result show (see Table 6) that familiarity with the stock market increases participation for all subsamples. The greatest effect comes from being involved in activities related to finance or insurance. The effect is largest for the most intelligent group of people. This implies that exposure to situations similar to the functioning of financial markets can increase participation rates, but it helps intelligent individuals more than less intelligent individuals. On the other hand, the size of the negative effect on market participation, which is related to higher risk aversion (what we proxy by variables indicating principal involvement in the field of education or social work), increases for smarter individuals.

Education is already well studied in the literature, but we are able to go even deeper. We use the International Standard Classification of Education to distinguish different education levels (the results confirm the results of more general classification presented in Table 7) and to offer results for more general levels. Our results show (see Table 7) that individuals with high school education are less likely to participate in the stock market. Higher education increases the probability of someone participating in the stock market, but vocational higher education does not increase the probability of participation in the stock market so much. Gaining a Master's or doctoral degree has only a limited additional effect on stock market participation when compared to the related marginal effects for individuals with a bachelor's degree.

We run a number of robustness checks. We consider alternative definitions of stock market participation to filter out some economically insignificant investors. For example, we define stock market participation only when an investor has made at least 3 trades during the period. Such a criterion eliminates 28% of previously identified investors who have made less than 3 trades. Still, our results remain the same (see Table 9). We use even a stricter criteria and classify individuals as investors only when their average portfolio is above a certain threshold. We present results of a robustness check where we require the average portfolio to be at least 900 euros in order to be classified as an investor. This portfolio size corresponds to being at least 2 times larger than the average trade size for our sample and only 47% of previously classified investors remain in the sample. We also introduce several other control variables measuring the economic conditions during the first market entry or during the investment period but none of the various specifications or alternative definitions of market participation changes our main findings.

Table 7
The effect of education and socioeconomic status on stock market participation.

			Marginal effects			
Independent variable	Coefficient	z-value	All	Male	Female	Diff.
Below High School	−0.292***	−7.41	−1.92%***	−2.23%***	−0.91%***	***
High School	−0.348***	−25.02	−2.27%***	−3.60%***	−1.35%***	***
Bachelor	0.284***	18.76	1.86%***	3.09%***	1.28%***	***
Master	0.317***	16.98	2.08%***	3.68%***	1.57%***	***
Doctor	0.019	0.26	0.13%	0.18%	0.08%	
Unemployed	−0.053**	−1.99	−0.34%**	−0.53%**	−0.2%**	**
Employee	−0.152***	−10.25	−1.07%***	−1.65%***	−0.63%***	***
Entrepreneur-employer	0.378***	10.24	3.40%***	5.08%***	2.14%***	***
Self-employed	0.409***	10.99	3.76%***	5.62%***	2.38%***	***
Conscript	−0.027	−0.42	−0.18%	−0.28%	−0.1%	
Student	0.121***	5.31	0.88%***	1.35%***	0.52%***	***
Person receiving pension	−0.066	−0.57	−0.42%	−0.65%	−0.24%	
Homemaker	0.058	1.16	0.40%	0.63%	0.24%	
On parental leave	0.023	0.68	0.15%	0.24%	0.09%	
Religious affiliation	−0.174***	−10.58	−1.1%***	−1.69%***	−0.64%***	***
Majority nationality	0.510***	27.82	2.63%***	4.23%***	1.41%***	***
Minority nationality	−0.506***	−26.19	−2.57%***	−4.13%***	−1.38%***	***
Other nationality	−0.366***	−7.23	−1.83%***	−2.9%***	−1%***	***

The table reports the coefficients, z-values and significance levels from the probit regressions together with post estimated average marginal effects. The probit regression models are constructed so that the dependent variable or investor dummy takes the value 0 if the person has not held shares in our sample period and the value 1 if the person has had shares in the period observed. The independent variable representing the specific socio-economic status takes the value 1 if the individual represents this status. Control variables for gender, age, income and higher education (except for regressions related to education level) were also included. The results for the control variables are omitted. Column "Diff." shows statistical significance of the difference of marginal effects between male and female. Three stars indicate the 1% significance level, two stars 5%, and one star the 10% significance level.

4.2. Economic activity and occupation

Christiansen et al. (2007) find the probability of people with education in economics participating in the stock market to be higher than the probability for individuals with other types of education. Our results show the same tendency of the positive effect of familiarity (see Table 8). Involvement in financial and insurance activities increases the probability of a person holding shares, and such jobs also need education in economics and finance. Involvement in real estate activities also has a positive effect on market participation because real estate activities involve buying and selling properties, which is similar to the activity in a stock market. This means people in those businesses are probably at least familiar with the concept of a financial market and are also less afraid to enter the stock market as investors. Involvement in information and communication technology increases the probability of market participation but the effect disappears when we include exam results in the same regression. A modern stock market is very reliant on information technology and so is finding information about the stock market, which can make it easier for people in IT to enter the market. All in all, familiarity with the operations of the stock market and with the basics of investing have a clear positive effect on market participation.

Economic activities that have a clear negative effect on stock market participation mostly include activities related to people-to-people communication, education, social work and customer service industries which include professions that generally do not require higher risk taking and can come with traits of being empathetic, humane or personal, which are all in contrast to the nature of the stock market.

The relationship between occupations and stock market participation has been poorly studied in the literature, with only very general classifications considered by Grinblatt et al. (2011) or Barnea et al. (2010) and Conlin et al. (2015). As we have comprehensive information about occupations, we are able to conclude that those occupations which require leadership skills or higher intelligence tend to increase the probability of a person participating in the stock market (see Table 8). These are also occupations that indicate an ambitious nature, as individuals with low expectations for a career and related achievements probably do not train themselves for such high-level jobs. We find that being a manager increased the probability that someone will participate in the stock market by an average of 2.1% over other occupations. Occupations which require high professional skills, denoted as professionals or associate professionals, or technical skills, denoted as technicians, do not necessarily need direct leadership skills, but still require a high level of specific knowledge and educational training. These qualities take a lot of effort and ambition to obtain, and it seems that such characteristics also lead along the way to the stock market.

Occupations which do not demand as much effort and high intelligence tend to lower the probability of participation in the stock market. These occupations include service and sales jobs, where employees are 1.32% less likely to own shares than are individuals in other occupations. All of the findings related to occupations still apply when income is controlled for.

Table 8
The effect of economic activity and occupation on stock market participation.

Economic activity	Coefficient	z-value	Marginal effects All	Male	Female	Diff.
Agriculture, forestry and fishing	−0.025	−0.41	−0.19%	−0.29%	−0.1%	
Mining and quarrying	−0.213*	−1.67	−1.38%**	−2.13%**	−0.74%**	*
Manufacturing	−0.151***	−7.13	−1.07%***	−1.64%***	−0.57%***	***
Electricity, gas, steam and air conditioning supply	0.040	0.60	0.32%	0.49%	0.18%	
Water supply; sewerage, waste management	0.100	0.98	0.83%	1.25%	0.47%	
Construction	−0.014	−0.53	−0.10%	−0.16%	−0.06%	
Wholesale and retail trade	−0.065***	−3.05	−0.48%***	−0.73%***	−0.27%***	***
Transportation and storage	−0.117***	−3.68	−0.83%***	−1.27%***	−0.45%***	***
Accommodation and food service activities	−0.075*	−1.88	−0.55%**	−0.83%**	−0.3%**	**
Information and communication	0.084***	3.58	0.68%***	1.03%***	0.39%***	***
Financial and insurance activities	0.513***	17.52	5.64%***	8.36%***	3.35%***	***
Real Estate activities	0.320***	5.38	3.14%***	4.65%***	1.86%***	***
Professional, scientific and technical activities	0.200***	8.18	1.76%***	2.64%***	1.01%***	***
Administrative and support service activities	0.051	1.43	0.41%	0.61%	0.23%	
Public Administration and Defence	−0.046**	−2.08	−0.35%**	−0.53%**	−0.19%**	**
Education	−0.175***	−5.48	−1.19%***	−1.82%***	−0.65%***	***
Human health and social work activities	−0.236***	−5.52	−1.53%***	−2.33%***	−0.83%***	***
Arts, entertainment and recreation	0.052	1.26	0.41%	0.63%	0.23%	
Other service activities	0.021	0.39	0.17%	0.25%	0.09%	
Armed forces occupations	−0.127***	−2.77	−0.89%***	−1.37%***	−0.48%***	***
Managers	0.239***	11.97	2.12%***	3.17%***	1.23%***	***
Professionals	0.102***	6.25	0.81%***	1.23%***	0.45%***	***
Technicians and associate professionals	0.073***	4.34	0.58%***	0.88%***	0.32%***	***
Clerical support workers	0.027	0.99	0.21%	0.33%	0.12%	
Service and sales workers	−0.196***	−7.05	−1.32%***	−2.02%***	−0.72%***	***
Skilled agricultural, forestry and fishery workers	0.115	1.28	0.96%	1.46%	0.55%	
Craft and related trades workers	−0.379***	−13.21	−2.27%***	−3.6%***	−1.13%***	***
Plant and machine operators, and assemblers	−0.325***	−7.60	−1.96%***	−3.06%***	−1.02%***	***
Elementary occupations	−0.285***	−5.38	−1.76%***	−2.73%***	−0.93%***	***
Gender	0.59***	37.89	4.53%			
Age	0.01***	7.05	0.10%	0.12%***	0.09%***	***
Income	0.10***	31.08	0.79%	1.05%***	0.50%***	***
Higher Education	0.39***	25.88	3.02%	4.91%***	1.11%***	***

The table reports the coefficients, z-values, and significance levels from probit regressions together with post estimated average marginal effects. Probit regression models are constructed so that the dependent variable or investor dummy takes the value 0 if the person has not held shares in our sample period and the value 1 if the person has had shares in the period observed. The independent variable representing the specific economic activity takes the value 1 if the individual is involved in this economic activity. Control variables for gender, age, income and higher education were also included. The results for the control variables are from the general model, where all the variables were included. Column "Diff." shows statistical significance of the difference of marginal effects between male and female. Three stars indicate the 1% significance level, two stars 5%, and one star the 10% significance level. The income variable reflects annual average social tax paid to the government in the period 2004–2010 and is multiplied by 1000, making the marginal effect more meaningful (marginal effects show how probability increases when annual average social tax paid increases by 1000 EUR per year).

The results of socio-economic status (see Table 7) support the conclusion that the stock market attracts individuals with ambition and leadership skills more and individuals who are ready to take risks in general. Entrepreneurs and employers tend to have a higher probability of participating in the stock market than others do, and the average probability of participation for entrepreneurs after controlling for income is 3.8% higher than that for the unemployed for example. Individuals who are willing to take risks as entrepreneurs and employers are also more likely to buy shares than others are. Entrepreneurs and self-employed individuals are more eager to search for new opportunities and for ways of increasing wealth, and are more used to doing so, which may explain why they have decided to invest in the stock market. Baron (1998) argues that entrepreneurs are less likely to engage in counterfactual thinking, but are more likely to show overconfidence in their judgments and are better at adapting to new situations. Given that stock market participation requires constant reaction to new situations and overconfidence has been associated with more trading (Barber and Odean, 2001), the positive effect of entrepreneurial traits such as tenacity and self-efficacy (Baum and Locke, 2004) on market participation should not be surprising. As the unemployed have a lower probability of participating in the stock market than others even when we control for income, the results may reflect their low willingness to seek new opportunities.

Analysing individuals from the number of their subordinates supports these conclusions. Having more subordinates reflects having more ambition and better leadership skills, which increase the probability of a person participating in the stock market, but the effect disappears when income is included as a control variable.

We also study the effect of socio-economic characteristics and perceived socio-economic status. Status might become important

Table 9
Alternative definitions of stock market participation.

	Investor		Investor (minimum of 3 trades)		Investor (portfolio over 900 EUR)	
Independent variables	Coef.	Marginal effects	Coef.	Marginal effects	Coef.	Marginal effects
Mathematics exam, quartile 2	0.050*	0.50%	0.058	0.31%	0.041	0.18%
Mathematics exam, quartile 3	0.089***	0.92%	0.075**	0.41%	0.095**	0.43%
Mathematics exam, quartile 4	0.179***	1.97%	0.171***	1.03%	0.151***	0.72%
Mother tongue exam, quartile 2	0.045	0.46%	0.055	0.30%	0.116**	0.46%
Mother tongue exam, quartile 3	0.103***	1.10%	0.096**	0.55%	0.188***	0.80%
Mother tongue exam, quartile 4	0.095***	1.01%	0.121***	0.70%	0.218***	0.96%
English exam, quartile 2	0.071**	0.68%	0.020	0.11%	0.006	0.03%
English exam, quartile 3	0.149***	1.52%	0.097**	0.56%	0.078*	0.36%
English exam, quartile 4	0.222***	2.38%	0.122***	0.72%	0.122***	0.58%
Control variables						
Male	0.642***	6.81%	0.737***	4.00%	0.663***	2.92%
Age	0.022***	0.24%	0.015***	0.09%	0.027***	0.13%
Income	0.000***	0.00%	0.000***	0.00%	0.000***	0.00%
Higher education	0.278***	3.06%	0.272***	1.63%	0.258***	1.24%
Proportion of persons with stocks identified as investors	100%		72%		47%	

The table reports the coefficients and significance levels from the probit regressions together with post estimated average marginal effects. The probit regression models are constructed so that the dependent variable or investor dummy takes the value 1 if the person is classified as an investor and 0 otherwise. Persons are classified if they have had shares in their portfolio in the period observed. Additional restrictions are shown in parenthesis i.e. in the second regression persons are classified as investors only if they have made at least 3 trades and in the third regression only when their average portfolio is over 900 euros. Three stars indicate the 1% significance level, two stars 5%, and one star the 10% significance level.

when individuals see themselves as being of lower status or feel less confident about their abilities, or are discriminated against because of their status or any other socio-economic characteristics.

Grinblatt and Keloharju (2001) show that distance and language affect stock market participation, and we conclude that nationality and citizenship also play a role. Individuals from the majority tend to be significantly more likely to participate in the stock market than other groups. We distinguish between the minority group[25] and other nationalities, since the minority group has a different cultural background and exhibits a lower level of integration in society and the stock market, both of which are dominated by the majority group.

A low level of integration in society can lead to the perceived socio-economic status being lower, which is also reflected in lower average salaries for the minority group. This can in turn lead to lower self confidence in the relatively complex question of whether to participate in the stock market. As our results show, this can have a clearly negative effect, especially on males, who have been generally culturally seen as the breadwinners of the family. However, lower participation by the minority group can also be caused by a cultural effect that our sample does not allow us to test for properly because of the heterogeneity and the small sample size of other minority nationalities. Cultural differences could be a factor that explains why religious individuals have a lower probability of participating in the stock market in our sample. In the prevailing culture of the sample, religious people usually follow more rules and have more restrictions in their lives than the rest of the sample, which mainly classifies as non-religious.

Legal marital status indicates a certain stability in personal life and the positive effect of combined wealth could result in a higher level of market participation. Our results show that being legally married has a slight positive effect on stock market participation, but if we include controls for income, this effect disappears. Thus our results show that married individuals have more resources to buy shares with but the status itself does not increase the probability that they will participate in the stock market.

4.3. Differences between men and women

Our results show a remarkable difference in the probability of participation in the stock market for male and female investors when the participation is dependent on mental abilities. This phenomenon is hard to explain and may be one of the questions that needs to be solved by further research. Currently we can argue that such differences can mostly be explained by choice.

The mathematics exam (see Table 4) shows that men in the lowest decile are 1.6% less likely to buy shares than people who not in this group and women in that decile are 0.9% less likely. At the same time, men with the highest mathematical abilities are 3.8% more likely to buy shares than the rest of the men, while the probability for women is 1.5% higher. The differences in these participation effects for men and women are clear, but the reason for them is difficult to find. It is impossible to explain this phenomenon by the differences in exam results, as male graduates on average achieve 49.2 points out of 100 with a standard deviation of 25.4% and female graduates score 50.8 points with a standard deviation of 24.4%. These figures are too similar to

[25] Russians or Russian citizens

explain the difference in the observed probabilities of participation. The same conclusion can be reached for other exams as well.

As shown, investors on average do better than non-participants in every subject, but this conclusion is clearly stronger for men as the probabilities of them participating in the stock market are more dependent on their academic abilities than are those of women. This is generally consistent with Grinblatt et al. (2011), who showed the connection between men's general mental abilities and stock market participation. However, the picture for men and women is not so homogeneous. Halko et al. (2012) and Almenberg and Dreber (2015) suggest that risk aversion should be considered which is not possible for our large sample.

Marginal effects (see Table 3) for men increase faster than those for women when moving from the second adjusted decile to the highest or tenth adjusted decile. We believe that non-cognitive abilities could be a factor can partly explain that difference as several studies[26] report significant differences in personality traits of men and women.

A similar tendency can be observed for factors related to occupation, as women tend to be less affected by either the mental abilities or occupation. We cannot completely rule out the possible explanation that financial decisions within a household are made by men and women distance themselves from such decisions, but when variables related to legal status such as marriage are used, they do not turn out to be significant in the regressions when additional controls such as income are included.

We can only draw some parallels with the majority and minority nationalities for our sample. Individuals from minority nationalities participate less in the stock market. It can be assumed that one of the reasons could be perceived and actual disadvantage because of limited language and cultural knowledge, which yields lower self-confidence when investments are made in such an environment. Similar reasons could apply for women; their training should be as good as that of men but a lower level of self-confidence could be a reason. If we measure self-confidence in a similar way to Barber and Odean (2001), stock market trading data for the same sample as ours show that women clearly trade less than men (Liivamägi et al., 2017) and so are not as confidant or overconfident.

We also study how the further educational path is dependent on previous academic results such as exams. The findings show[27] that both men and women choose their further educational path such as going to university with reference to their academic abilities but men tend to choose exact and natural sciences more frequently even though they do not seem to possess stronger abilities in those subjects. Like with stock market participation, men seem to be more influenced by their abilities in pursuing their educational path. Given that we are able to control for a large number of factors and the difference in the effects of market participation between men and women still exists, the difference can be explained either by non-cognitive abilities, which we are able to test only partially, or by a choice that is dependent on other factors or values.

5. Discussion of policy measures

We provide results of possible factors that influence stock market participation in an emerging market where participation rates are clearly lower[28] than in developed markets. We believe that our documented effects can be generalized for developed markets as well,[29] despite income and wealth gap, because trading and other characteristics of investors (as discussed before) and the effect of intelligence on market participation (Grinblatt et al., 2011) are very similar to investors of developed markets. Further cross-country studies should be conducted when detailed data becomes available to confirm that.

The level of income and wealth is lower[30] in our sample than for more developed markets, which means that participation in the stock market can affect the living standard during retirement even more than in developed countries. At the end of the sample period,[31] Estonian households had 68% of their assets in cash or deposits. An average interest on time deposits was about 2.4% during the sample period (approaching zero by the end of the period) and about 60% of deposits were demand deposits earning very little interest. At the same time, the annual average return of the Nasdaq Tallinn stock market index was 11.05% and the average inflation rate about 4.4%. It is evident that encouraging stock market participation is clearly important for the society to help to raise the standard of living in such a setting.

Guiso et al. (2003) argue that market participation is affected by participation costs related to obtaining information and the ability to process information. Our results are in line with previous studies confirming the positive effect of education and intelligence. Moreover, we identify specific components of general intelligence, such as quantitative skills and crystallized intelligence, which have the largest effect on market participation.

As in many other studies,[32] we are able to measure only direct stock market participation. It is possible that some investors choose indirect market participation by investing into mutual funds. However, direct domestic stock ownership during the observed period

[26] See e.g. Schmitt et al. (2008).

[27] See Vaarmets (2018) for further details.

[28] The Household Finance and Consumption Network (HFCN) reports direct stock market participation rate to be 3.6% in Estonia (our sample of younger individuals has participation rate of 3.1%). For example, Greece, Latvia, Hungary and Slovakia have even a lower participation rate; Italy and Poland have a similar participation rate and Belgium, Germany, France, Ireland and Spain have a participation rate near or slightly over 10%; and Finland and Cyprus have a participation rate over 20%. The Euro area average is 8.8%.

[29] Cultural differences can have an effect, but for example survey results of Statman (2008) indicate quite similar risk preferences for people in Estonia and in the United States.

[30] The HFCN reports that the median gross income per household in Estonia is 38% of the average of the median gross income in the EU and the median net wealth is 42% of the average of the median net wealth in the EU.

[31] Data is provided by the Bank of Estonia.

[32] For example Campbell (2006), Guiso et al. (2008), Grinblatt et al. (2011), etc.

would have yielded in clearly higher returns than investing into other regions or asset classes.[33] The average annual return of MSCI World during the period is 5.55% and the same figure for Nasdaq Tallinn is 11.05%. There were no mutual funds nor index funds offered during the period which invested purely in the domestic stock market. The closest alternatives were emerging market funds with lower returns (with various levels of risk depending on the fund) than achieved in the domestic stock market on average. It is also plausible that investors prefer to invest into the real estate market which lagged behind the stock market during the period and offered only slightly lower returns during the first bull market phase but clearly underperformed after the crisis. In any case, domestic stock market participation represents investments into an important asset class which would help to raise living standard and income during retirement in the long run and thus should be generally encouraged.

How do our results help to increase market participation? First, we see that education helps and our results help to identify the subject areas which are the most important ones. It is debated whether education can at least slightly increase e.g. quantitative or crystallized knowledge, but currently prevalent view seems to be that increasing such abilities is limited. Still, correlations between academic results and intelligence decrease with age (Pind et al., 2003) which once again still favours the effects of education as a possible policy measure in the context of our results. Exam results are not pure measures of components of intelligence but are also clearly related to possessing knowledge. Thus, another question is whether better schooling can improve the results. The administering body of exams in our sample has conducted research[34] whether schools contribute positively, neutrally or negatively compared to expected contribution in helping to obtain good exam results.[35] On average, schools do not seem to contribute positively nor negatively to the exam results but certain schools seem to have a positive[36] effect. This implies that “good schooling” could help. Unfortunately our data does not allow to check for the impact of good schooling directly but people from good schools are more likely to continue education and earn higher income later in their life, which are the factors that we are able to control for.

Our results clearly show that familiarity with the operations of the stock market can boost participation. Thus, introducing assignments related to the operations of the stock market (e.g. calculation exercises in mathematics, information gathering in computer classes etc.) at school and having personal finance or investment courses at different levels of education can also increase familiarity with financial markets. Not being familiar with the operations of financial markets and the discomfort of gathering relevant information to make investment decisions, can be one of the larger barriers to participate in the stock market in an emerging market. Our results show that increased familiarity can help to increase participation rates but the effect is strongest for the most intelligent people. It means that difference investment courses are likely to help but not everyone has an equal learning capacity.

Higher risk aversion or absence of trust can also discourage stock market participation. But as the results of Statman (2008) or Rieger et al. (2014) show, risk tolerance or trust indicators in Estonia are quite similar to countries which have clearly higher participation rates. Our results show that e.g. professions associated with higher risk aversion (such as people working in the educational sector or involved in activities related to health and social work) tend to participate less.

We run correlations of possible external factors with the number of new participants of the stock market. Apart from the economic and income growth,[37] we find the strongest correlation between new IPOs and new participants. Short time series and the example of one country does not allow to make any far-reaching conclusions. Still, it seems that offering more choice for investment opportunities and strongly advertising those in mainstream media (which happens during IPOs in Estonia), does seem to help to improve participation rates. Privatization or partial privatization of state owned companies and listing the shares on the stock exchange or introducing regulations encouraging the listing of private companies could be steps that can be undertaken.

The impact of new IPOs raises a question how timing of the IPOs (generally more IPOs occur during economic booms) and higher participation rates are connected with academic abilities or intelligence. Proportionally more investors belong to top academic deciles,[38] thus we calculate the average participation rate for each investor decile and compare the proportion of investors who belong to a particular decile to the average proportion of that investor decile. The result gives us a heat map (see Fig. 1) which shows with darker (lighter) colors the quarters for which market participation for a particular decile is relatively high (low). There does not seem to be much difference in when groups of investors with different academic abilities enter the market. Some variance can be noted during the second quarter of 2007 which follows a sudden fast decline in asset prices. This scared away smarter investors but basically didn't affect investors in the lower deciles (the active IPO period still continued at that time). This indicates that any policy measures or promotional activities have to take into account the phase of the market cycle and are potentially more effective during the expansion phase.

Differences participation rates of men and women can be addressed by even small nudges. Bock (2015) describes a successful experiment of sending female employees evidence of gender inequality at school and workplace, at the same reminding them about time to nominate themselves for promotion. Similar approach of acknowledging gender differences and providing encouragement in educational or promotional measures addressed to women, can have a positive effect on market participation as well.

[33] When comparing domestic stock market and real estate market in terms of risk and return, results can vary depending on the period viewed. However, during our sample period, the worst year in domestic stocks resulted in a drawdown of −63% and it took less than 2 years to recover such a loss. In domestic real estate market the biggest drawdown was −43% and it took about 6 years to recover. The average annual return of the domestic real estate market during the period is 5.54%

[34] Statistics about the results is available from http://www.haridussilm.ee

[35] Non-controllable factors such as socioeconomic factors and factors related to the abilities and previous academic results are factored out.

[36] The statistics are available for 3–4 years starting from 2014 which do not allow to make statistically significant conclusions about the consistency of the effect for a particular school.

[37] Real estate price are also very highly correlated with economic growth, which has a similar effect.

[38] We group investors into deciles according to their average exam scores.

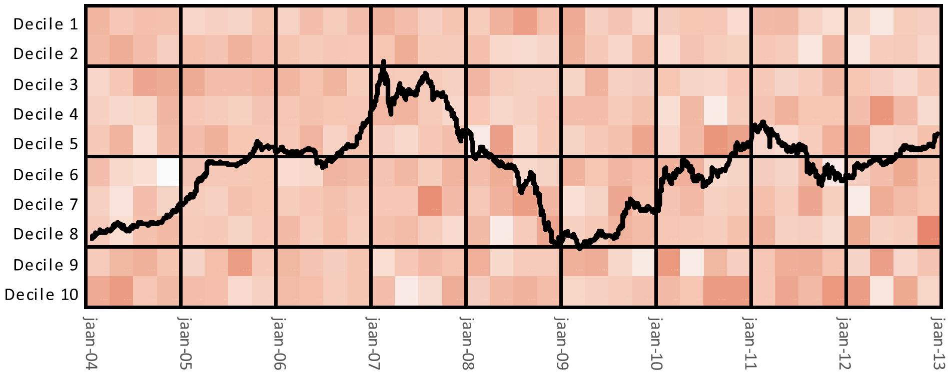

Fig. 1. Heat map of entering the market by academic deciles.
Dark line shows Nasdaq Tallinn index movement for the period 2004–2012. Darker colors indicate the quarters for which market participation for a particular investor decile is relatively high and lighter colors indicate quarters for which market participation is relatively low. Investor deciles are constructed based on mathematics national exam results. Similar heat maps where classification of investors was based on different exam results were not notably different and showed the same tendencies. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

6. Conclusion

We conclude that economic activity, occupation, socio-economic status, religious affiliation, nationality and citizenship influence stock market participation. We find broad evidence that a brighter mind, a higher level of education and better quantitative and language skills help to increase the probability of a person participating in the stock market. We offer empirical evidence that stock market participation depends on mental abilities in very different areas. We also conclude that the impact of mathematics and physics exam results on stock market participation is stronger than those of results in other subjects.

We find that the effect of mental abilities on stock market participation is much stronger for men than for women. These differences cannot be explained by the differences in academic results achieved by men and women because the average level and standard deviations of comparable results are very similar for men and women.

Involvement in entrepreneurial activities or managerial positions tend to increase participation rates. The common traits based on occupation or socioeconomic status (which have been previously identified in psychological literature) are ambition, readiness to take risks, or openness to new experiences and intelligence which can lead individuals to buy shares. Differences in non-cognitive abilities or other currently unidentifiable factors can also affect participation, which is implied by the varying effects of mental abilities on the stock market participation of men and women. Familiarity with or a certain exposure to how the stock market operates can also play a role.

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Appendix 3. Paper III

HOW DOES LEARNING AND EDUCATION HELP TO OVERCOME THE DISPOSITION EFFECT?

Publication:

Vaarmets, T.; Liivamägi, K.; Talpsepp, T. 2018. How Does Learning and Education Help to Overcome the Disposition Effect? *Review of Finance*, vol. 23, issue 4, pp. 801–830. https://doi.org/10.1093/rof/rfy006. (ETIS 1.1).

Draft as conference proceedings:

Vaarmets, T., Liivamägi, K., Talpsepp, T. 2016. *How Does Learning and Education Help to Overcome the Disposition Effect?* World Finance & Banking Symposium, December 14–15, 2016, Dubai, United Arab Emirates.

Vaarmets, T., Liivamägi, K., Talpsepp, T. 2016. *How Does Learning and Education Help to Overcome the Disposition Effect?* 2016 Annual Meeting of the Financial Management Association International, Las Vegas, USA, October 19–22, 2016.

Vaarmets, T., Liivamägi, K., Talpsepp, T. 2016. *How Does Learning and Education Help to Overcome the Disposition Effect?* 8th International Conference "Economic Challenges in Enlarged Europe", Conference Proceedings, June 19–21, 2016, Tallinn: Tallinn University of Technology.

Review of Finance, 2018, 1–30
doi: 10.1093/rof/rfy006

How Does Learning and Education Help to Overcome the Disposition Effect?*

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Abstract

The paper assesses how intelligence, education, and learning affect the disposition effect using our exhaustive NASDAQ OMX Tallinn dataset. We employ survival analysis to show that higher intelligence and stronger learning abilities as measured by education level and the type of education lessen the disposition effect. More highly educated and intelligent investors also learn faster by trading. We find that mathematical abilities are beneficial for overcoming the disposition effect and propose that learning ability is one of the most important components of intelligence in affecting the disposition effect.

JEL classification: G02, G11

Keywords: Disposition effect, Learning, Education, Intelligence, Mental abilities

Received December 30, 2015; accepted May 27, 2016 by Editor Burton Hollifield.

1. Introduction

The ability of investors to learn from their own mistakes is an important factor that can help prevent them taking short-sighted or biased investment decisions. There has been a lot of discussion about the importance of educating investors in how to avoid unnecessary volatility in the financial markets. One bias that is still prevalent in the financial markets is the overall tendency of investors to hold on to underwater positions and to give up winning

* We would like to thank Burton Hollifield and an anonymous referee. We are grateful to Kalle Viks and Nasdaq OMX Tallinn Stock Exchange, Marko Mölder and Estonian Ministry of Education and Science, Lauri Veski and Innove, and Aime Lauk and Statistics Estonia for the data and their supportive attitude and efforts for processing our data requests. We thank Karsten Staehr, Merike Kukk, Laivi Laidroo, Karin Jõeveer, and participants of various seminars and conferences for helpful suggestions. This work was supported by the Tallinn University of Technology [B45] and the European Union through the European Regional Development Fund.

positions too early. This well-known phenomenon is the disposition effect,[1] and it has been scrutinized intensively since the 1990s.

Most of the literature on the disposition effect uses the prospect theory developed by Kahneman and Tversky (1979) to explain the tendency to hold losers and sell winners. This view has been challenged since the end of 2000s though, and Barberis and Xiong (2009), Kaustia (2010), and Hens and Vlcek (2011) argue that the prospect theory cannot always explain the disposition effect.[2] The results of recent theoretical studies imply that there are in all likelihood still unexplored reasons and explanations behind the disposition effect.

A better understanding of the disposition effect can help to reduce the cost of the bias for investors.[3] One of the reasons why the effect still needs investigation is that more detailed data become available only when more time has passed from the first identification of the bias.

An important part of the recent disposition effect literature has focused on the learning process as one of the possible explanations. Feng and Seasholes (2005) were among the first to show that experience affects the disposition effect and later studies such as, for example, Seru, Shumway, and Stoffman (2010) distinguish between "learning from experience" and "learning about one's ability" to trade, and they emphasize the importance of the latter. Even so, the characteristics of investors in the form of their abilities, knowledge, and skills can contribute positively or negatively to the disposition effect. The current literature has not studied in detail how education, intelligence, and innate cognitive abilities affect the disposition effect.

Our contribution to the literature is to provide empirical insights into how education, intelligence, and certain mental abilities affect the disposition effect. We also show that learning abilities and the speed of learning can vary greatly and affect the disposition effect, even though we do not identify any strong effects from "learning about one's abilities." Our dataset allows us to measure intelligence and certain mental abilities in an educational setting before investors enter the stock market and to observe their subsequent behavior in the stock market.

The study combines complete detailed transaction records from 2004 to 2012 from Nasdaq OMX Tallinn with data from the Estonian Ministry of Education and Science that gives information on individuals' high school grades, examination results, university

1 First documented by Shefrin and Statman (1985) with prominent work by Odean (1998), Grinblatt and Keloharju (2001), Feng and Seasholes (2005), Dhar and Zhu (2006), etc.

2 Barberis and Xiong (2009) show that prospect theory is more likely to fail to explain the disposition effect when the expected risky asset return is high (once the expected return exceeds a certain level) and when the number of trading periods is low (in contrast to when the number of trading periods is high and the expected risky asset return is relatively low). Kaustia (2010) argues that the propensity to sell a stock jumps when the return exceeds zero, but it is approximately constant over a wide range of losses and increasing or constant over a wide range of gains (prospect theory predicts that the propensity to sell the stock declines as its price moves away from the purchase price in either direction). Hens and Vlcek (2011) conclude that the explanation based on prospect theory is sound *ex post*, assuming that the investment was made, but would not hold *ex ante* because investors who are affected by the disposition effect would not have made the investment in the first place.

3 Being influenced by the disposition effect has been identified as a costly bias, see, for example, Goulart *et al.* (2015).

degrees, and subjects. The use of Estonian data provides a unique opportunity to work with a complete dataset which is not affected by subsample selection biases.

We show how the performance of investors in terms of the disposition effect depends on their education level and standardized high school final examinations. We use the education level, education type, and examination results as proxies for intelligence. A higher level of education and certain types of education indicate higher intelligence and especially learning abilities as a component of intelligence. Although particular final examinations are a matter of choice, the choice of examinations is not arbitrary, because most university courses require certain basic examinations in the mother tongue, mathematics, and a foreign language, though there are exceptions, especially for humanities subjects.

Combining the effect of education and intelligence with "learning by doing" allows us to ascertain how different abilities affect the disposition effect in a detail that has not been possible before. In addition, we can answer the question of whether the speed and importance of "learning by doing" depends on education and intelligence.

We find support for the hypothesis that "baseline learning abilities"[4] play an important role in affecting the disposition effect. One of our main findings is that investors with higher academic degrees or more challenging academic paths, which can serve as an indication of higher intelligence, are less influenced by the disposition effect and also learn faster by doing. We conclude that learning abilities are one of the most important components of intelligence in affecting the disposition effect. Such knowledge can help in designing more effective educational and training programs for investors.

The remainder of the paper is organized as follows. Section 2 reviews the findings in the previous literature. We give an overview of our data in Section 3. Section 4 describes the methodology and Section 5 discusses the findings. The conclusion is presented in Section 6.

2. Related Literature

The disposition effect has been one of the central topics in behavioral finance since the early days of the discipline, starting with the work of Shefrin and Statman (1985). Using prospect theory (Kahneman and Tversky, 1979), Shefrin and Statman (1985) argue that investors frame all choices in terms of potential gains and losses relative to a fixed reference point, and they employ an "S-shaped" valuation function. The effect is that the investor is risk averse in the gain region and risk seeking in the loss region. Parts of the recent literature reason that the explanation based on prospect theory can only partly explain the disposition effect. Studies by Barberis and Xiong (2009), Kaustia (2010), and Hens and Vlcek (2011), for example, argue that explanations based on prospect theory can only apply to a

4 We also focus on learning ability as one of the constructs of intelligence. We use the term "baseline learning abilities" to indicate the capacity to learn in a general fashion. Some people are able to learn new things faster than other people, by mastering more difficult concepts, processing, and memorizing more information, etc. We use overall learning abilities as a synonym for "baseline learning abilities" without explicitly distinguishing between the sources or means of learning. Learning can occur in many different ways, such as reading information from books, which is a more abstract way of learning, or alternatively by personally experiencing the world. We distinguish "learning by doing" in our paper as one particular type of learning where an investor is able to learn only by making trades themselves. "Learning about one's abilities" is used for a more abstract way of learning in which an investor has to be able to make generalizations about their ability to trade and then adjust by stopping or continuing their trading accordingly.

small number of cases and can yield both the disposition effect and the reverse of the disposition effect. Even though there are different approaches to explaining[5] the disposition effect, empirical literature[6] does not question the existence of the phenomenon and recent literature[7] shows that some investors can be affected by the reverse disposition effect.

The presence of the disposition effect is very strongly documented by many prominent authors. Using a stock market dataset from the USA, Odean (1998) shows that individual investors experience the disposition effect at the aggregate level. These findings are confirmed by numerous authors for many markets. Shapira and Venezia (2001) use Israeli data to show that both individual and professional investors exhibit the disposition effect, and the view is shared by Grinblatt and Keloharju (2001), who find that investors tend to be reluctant to realize their losses except in the tax-selling month of December.

These findings are generally consistent with the study by Dhar and Zhu (2006). Dhar and Zhu (2006) argue, however, that there are differences at the individual level and almost 20% of individual investors are not influenced by the disposition effect and can even behave contrary to its predictions. Investors who are immune to the phenomenon tend to have higher trading frequency, higher income, and financial sector jobs. The latter two are proxies of investors' sophistication, and Feng and Seasholes (2005) also emphasize the importance of investor sophistication and trading experience and argue that those characteristics together can eliminate the reluctance to realize losses. They contend that even though trading experience alone weakens the disposition effect, it does not eliminate it entirely. Kaustia, Alho, and Puttonen (2008) and da Costa *et al.* (2013) confirm that higher experience leads to a reduction of the disposition effect. Seru, Shumway, and Stoffman (2010) also find that investors' performance improves as they become more experienced; investors who make more trades, and thus have the opportunity to learn from their mistakes, are less influenced by the disposition effect.[8]

The results of various empirical studies indicate that other factors that influence the disposition effect are gender, age, and portfolio diversification. Having a gain or loss at the portfolio level does not seem to contribute to the disposition effect (Talpsepp, Vlcek, and Wang, 2014) but the current performance and past price movement of individual stocks affect the disposition effect instead (Kubiska, Markiewicz, and Tyszka, 2012).

The learning process that occurs in the financial markets is an important aspect that can also reduce the disposition effect. Learning can occur in different forms in the financial markets as discussed by Fenton-O'Creevy *et al.* (2012); Nicolosi, Peng, and Zhu (2009);

5 Barberis and Xiong (2009) develop an alternative implementation of explanations based on the prospect theory of the disposition effect. Some of the alternative explanations of the disposition effect include the Barber and Odean (1999) hypothesis that investors have a belief that all stocks revert to the mean, which is related to the contrarian strategy and assumes that past winners tend to underperform past losers. Lakonishok and Smidt (1986) propose another explanation that investors restore previous diversifications by rebalancing their portfolios after large price fluctuations. Ferris, Haugen, and Makhija (1988) hypothesize that trading costs play a substantial role in investors not selling stocks at lower prices.

6 Including, for example, Odean (1998), Shapira and Venezia (2001), Grinblatt and Keloharju (2001), Coval and Shumway (2005), Locke and Mann (2005), and Feng and Seasholes (2005).

7 Including Talpsepp (2011) and Cici (2012).

8 Bachmann and Hens (2015) argue that learning from one's own mistakes may not be very effective, and indeed they point out that learning by doing is irrational and it is more effective to seek advice in order to avoid investment mistakes like the disposition effect.

and others. Some earlier studies have focused mostly on "learning from experience," like Feng and Seasholes (2005), who show that more trading experience reduces the disposition effect. However, Seru, Shumway, and Stoffman (2010) emphasize the role of "learning about one's ability to trade." They find that investors who trade regularly suffer less from the disposition effect but have a lower speed of learning. The effects of "learning about one's ability to trade" are not strong for the market under investigation in the current paper (Muhl and Talpsepp, 2016).

The linkage between mental or academic abilities and the disposition effect has received little attention in the literature before now. One of the main reasons is the lack of good data. Many researchers use various proxies to measure sophistication, but these proxies do not strongly relate to mental and academic abilities. Even so, Goo *et al.* (2010) show that the disposition effect is dependent on education as investors with a higher level of education and a higher academic degree experience a lower disposition effect.

3. Data

Our sample combines two different datasets. The stock market dataset is obtained from Nasdaq OMX Tallinn and contains detailed information about all transactions by all market participants for 2004–2012. We have information about the age, gender, and domicile (domestic or foreign) of every investor and can calculate their portfolio size, stock allocations in the portfolio, trading activity, experience of participation in the market or in making trades, average stock holding period, number of transactions, and transaction size, among various other metrics. There may be some liquidity constraints for active trading as the Estonian stock market is small and had only twenty-three different companies listed during the period. The total number of individuals and institutions active during the period was 33,843.

Our second dataset contains exhaustive educational data provided by the Estonian Ministry of Education and Science. We have education information for 10,555 investors. Integrating these two datasets gives us a quite unique combination for our study. We are able to identify investors by whether their level of education is high school, bachelor, master, or doctor, and by their subject background, such as mathematics, statistics, economics, medicine, law, information technology, public administration, chemistry, physics, or psychology. Moreover, we have all the high school grades and all the national high school final examination results for each individual investor. These examinations are identical for all high school graduates and as examinations are used for admission to university, the level of difficulty is aimed to be the same throughout the years. With the detailed information about investors' educational and academic results, we can draw conclusions about their academic abilities that are closely correlated with mental abilities (Deary and Johnson, 2010) and give a picture about their natural or baseline learning abilities.

The people in our sample are relatively young, with an average age of 32.6 years, because the national examinations are taken around the age of 18 years and our educational data start from 1997. However, the sample is in line with the overall market as the average Estonian investor is also relatively young because the history of Estonia's capital markets is short. The age distribution of our sample is presented in Figure 1.

The typical investor in Nasdaq OMX Tallinn is quite similar to an investor in developed markets like those in the USA or Finland in terms of the proportion of male and female investors, and their trading frequency, relative portfolio diversification, and overall

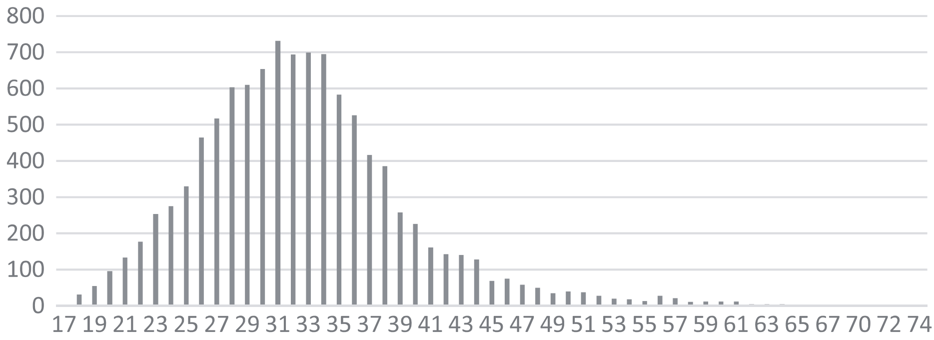

Figure 1. Age distribution. The graph shows the age distribution of investors in our sample. Most investors in our sample are in their late 20s and early 30s as at December 31, 2012.

disposition effect. Barber and Odean (2001) document that 78.7% of all stock market investors are male in the sample from the USA, which is comparable with the figures in our sample where 73.7% of investors are male (presented also in Table I).

Altogether, we have 6851 investors with at least one examination result in our sample. As mother tongue, English and mathematics examinations may be considered as compulsory examinations[9] they are also the most popular.

Of the 10,555 investors in our sample, 64.3%, or almost two-thirds, had completed higher education by 2012.[10] The number of investors with a master's or doctoral degree is 608, which is 5.8% of the total sample and 9.0% of those with higher education. A further 1521 investors have completed vocational training, and 2244 investors, or 21.3% of the total sample, have only finished high school. Figure 2 shows the distribution of investors by education type.

The most popular discipline among university subjects for investors is social sciences, a result which is consistent with the findings of Christiansen, Joensen, and Rangvid (2008). At 23.8%, nearly one quarter of the total sample and 37.0%, or over one-third, of investors with higher education have a degree in economics or a related field. The corresponding figures for investors with a business degree are 17.5% of the total and 27.2% of graduates. This means that about 40% of the investors in our total sample have a degree in economics or business, which is not that surprising given the knowledge needed for participating in the stock market. There is a strong representation of investors with a degree in IT in our sample as well, with 716 investors or 6.8% of the total sample. A smaller number of investors have graduated from law or medicine or hold a degree in natural and exact sciences.

4. Methodology

The main three methods used for measuring the disposition effect are PGR–PLR analysis, logit regressions, and survival analysis. PGR–PLR analysis was proposed by Odean (1998) and it counts each realized gain, realized loss, paper gain, and paper loss for each day a

9 Mother Tongue, English, and Mathematics are required examinations for admission to most courses at Estonian universities.

10 This compares to 34% for the whole population according to the 2011 Census. Thus, investors tend to be significantly better educated than the average person within the same age bracket.

Table I. Number of investors with national high school examination results and with education data

The table reports statistics for investors whose results from the national high school examinations are available. The total number of investors who had taken their national high school examinations by 2012 is shown together with the number of male and female investors separately. Statistics are presented for 10 different examinations. The proportions of the total for male and female investors are reported. The total sample size is also shown at the bottom of the table. The total sample includes investors with national examination results data together with investors about whom we also have education type or level data.

Sample	Total	Male	Proportion (%)	Female	Proportion (%)
National high school examination sample	6,851	5,346	78.0	1,505	22.0
Mother Tongue examination	6,438	5,016	77.9	1,422	22.1
English examination	5,449	4,284	78.6	1,165	21.4
Mathematics examination	4,648	3,794	81.6	854	18.4
History examination	2,600	1,993	76.7	607	23.3
Chemistry examination	1,553	1,197	77.1	356	22.9
Biology examination	1,502	1,065	70.9	437	29.1
Geography examination	1,223	1,007	82.3	216	17.7
Social science examination	1,086	859	79.1	227	20.9
Physics examination	866	814	94.0	52	6.0
German examination	669	519	77.6	150	22.4
Total sample (investors with education data)	10,555	7,779	73.7	2,776	26.3

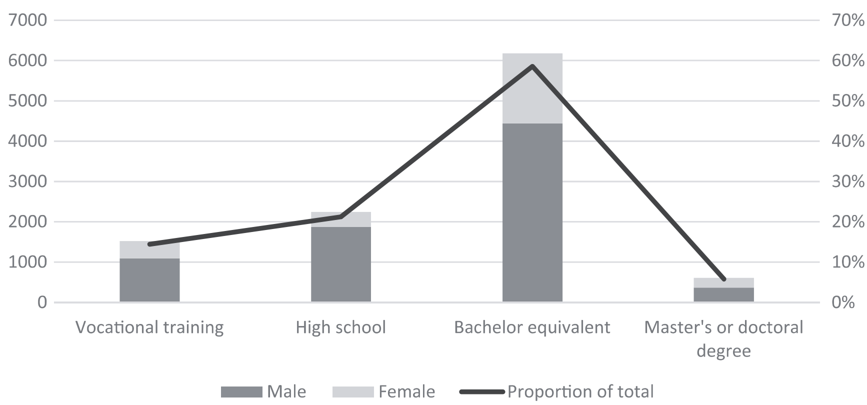

Figure 2. Sample distribution by education level. The graph shows the number of investors with the breakdown between male and female investors in each education group on the left axis. The corresponding proportions are shown on the right axis.

position is sold. The counts are then used to calculate the proportion of gains realized, labeled PGR, and the proportion of losses realized, labeled PLR.[11] Logit regressions are

11 PGR–PLR analysis is also used by Frazzini (2006), Dhar and Zhu (2006), Chen *et al.* (2007), and Kumar and Lim (2008).

employed by Grinblatt and Keloharju (2001) among others, and survival analysis was proposed by Feng and Seasholes (2005), who present the advantages of the method over alternative approaches.

Following the suggestions of Feng and Seasholes (2005) and the later use of survival analysis by Seru, Shumway, and Stoffman (2010) and others, we choose survival analysis as our main method for measuring the disposition effect. As a robustness check, we also run logit regressions, and they confirm the findings in all cases. We use a Cox proportional hazard model to measure the probability that an investor will sell a current stock position. To interpret the results we calculate the hazard rate, which is the probability of selling at time t conditional on holding a stock until time $t-1$. The hazard rate h and the vector of coefficients β for the covariates are obtained by maximum-likelihood estimation of the following equation:

$$h(t, p, X) = \ p\lambda t^{p-1} + \exp(X\beta + \epsilon_t), \tag{1}$$

where $p\lambda t^{p-1}$ indicates the baseline hazard and X is the vector of fixed and time-varying covariates. One advantage of the survival analysis is that it allows for censored observations, which suits our setup as not all positions are closed by the end of the sample period and the data contain partial liquidation as well.

Our independent variables include different educational characteristics such as education type and level and academic results, together with control variables such as gender, investor type, number of trades made, experience, and so forth. We divide the national examination results into deciles and quartiles, so that the weakest results are in the lowest decile or quartile and investors with the highest scores are in the top decile or quartile, and we construct dummy variables for this.

We use interaction terms of the covariates with the trading loss indicator (TLI) or gain indicator (TGI) variables in the regressions to capture how particular covariates for characteristics affect the disposition effect. We can do this by multiplying the dummy variable for the top mathematics examination decile by the TLI or TGI dummy variable to identify those investors who have the best academic results in mathematics and whose stock position is in loss or gain. All regressions also include TLI and TGI variables without interaction terms to capture the overall tendency of investors to hold on to or sell positions depending on whether they are in loss or gain.

The captured hazard ratios for covariates describe a relative probability for how the hazard varies in response to explanatory covariates. Interpreting the coefficient's hazard ratio is actually relatively easy as the hazard rate changes when an independent variable changes from zero to one. For brevity, we only present results for covariates that are of interest, on occasion giving only the interaction terms, and we omit from the tables control variables like gender, age, trading experience, etc., or if we present only the interaction terms, in most cases we also show the education-related controls but do not present the coefficient for the TLI/TGI alone (as the TLI/TGI coefficients remain unchanged in different regression setups). The baseline level of the disposition effect measured by the TLI or TGI variable as presented in Section 5.1 remains the same for all regressions and the overall probability change of the position being sold dependent on whether it is in loss or gain can be calculated by multiplying the hazard ratios of all the relevant covariates.

Running the regressions requires an appropriate data setup. Like Feng and Seasholes (2005) and Seru, Shumway, and Stoffman (2010) we discard any stock purchases that occurred before January 1, 2004 and any resulting sales. We compute whether a position is in loss or gain for every day, for every stock position, and for every investor. This gives us a total of 19 million observations for the sample of 10,555 investors. We use the volume-weighted average purchase price as the reference price for the position and record a gain or a loss for each position if the reference price is lower or higher than the daily low price. The TLI or TGI indicator takes the value 1 if the position is in loss and 0 if it is in profit.

5. Results

5.1. The Aggregate Disposition Effect

The characteristics that our sample shows are very closely comparable to the results presented in earlier empirical studies in terms of the magnitude of the general disposition effect. Our results confirm that there is a tendency for investors to sell winners too early and hold losers too long. The results of the survival analysis are presented in Table II. The hazard ratio of 0.793 from the TLI regression indicates that the investors' propensity to sell is 20.7% lower when the position is in loss than in the baseline probability[12] for selling the stock. Similarly, investors' propensity to abandon their stocks increases by 24.9%, with a hazard ratio of 1.249, when a stock is trading above the purchase price.[13]

Our results (see Table II) show that male investors tend to be less affected by the disposition effect and female investors more affected, which is in line with Feng and Seasholes (2005) and the experimental study of Rau (2014). One reason is that relatively young men generally trade clearly more, which lowers the disposition effect, as also noted by Feng and Seasholes (2005), who find that men are 30% more likely to realize a loss than women. That is supported by Rau (2014) who shows that men sell a higher proportion of capital losses but a lower proportion of capital gains than women.

After studying the selling behavior of local and foreign investors (see Table II), we conclude that foreign investors, who may be considered more sophisticated[14] than domestic investors and who do not suffer from the home bias, exhibit the reverse disposition effect. Local investors tend to hold their losers longer, with a hazard ratio of 0.817, and are more likely to sell their winners, with a hazard ratio of 1.225. This is consistent with the results in Talpsepp (2011) and also with several other studies that ascertain the relationship between investors' sophistication and the disposition effect.[15]

12 The Cox proportional hazard model allows the coefficients for covariates to be estimated without the baseline hazard being estimated. The following example running the Cox proportional hazard model on our sample illustrates the interpretation of the hazard ratios. The estimated survivor function shows that 7% of positions still open after 30 days will be sold during the next 5 days, and this can be considered the baseline hazard. If those positions are in loss, only $7\% \times 0.79 = 5.5\%$ of positions will be sold during the same period.

13 Feng and Seasholes (2005) find that the hazard rate of a sale decreases by 36.8% if a stock is in loss. At the same time, Grinblatt and Keloharju (2001) conclude that Finnish households are 21% less likely to sell their positions with a moderate loss and 32% less likely to do so with an extreme loss.

14 As argued by Talpsepp (2011), investing in a foreign market usually requires more knowledge, capital, and experience, as the first steps in the investment world are usually made in the domestic market.

15 For example, Grinblatt and Keloharju (2001) and Dhar and Zhu (2006).

Table II. Aggregate disposition effect

The table reports the results of the survival analysis—the hazard ratios, *z*-values, and significance levels. TLI represents the total loss indicator, taking the value 1 if a position is in loss and the value 0 otherwise. Similarly TGI is the total gain indicator, which takes the value 1 if a stock is trading above the purchase price and zero otherwise. Investor-specific variables are interacted with TLI and TGI to capture the disposition effect. These investor-specific variables are also dummy variables, which take the value 1 if an investor is identified by a specific variable (e.g., the male variable takes the value 1 if an investor is a male) and zero otherwise.

Variable	Hazard ratio	*z*-Statistic	Variable	Hazard ratio	*z*-Statistic
TLI	0.793***	−25.62	Total gain indicator (TGI)	1.249***	24.64
Male×TLI	1.190***	6.75	Male×TGI	0.838***	−6.87
Foreign investor×TLI	1.224**	1.92	Foreign investor×TGI	0.816**	−1.93

***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

In terms of experience as measured by "learning by doing," our results are once again in line with the earlier literature such as Feng and Seasholes (2005). The results presented in Table III show that the disposition effect starts to decrease when an investor has made at least 10 trades.

5.2. How Does the Education Level Affect the Disposition Effect?

So far we have shown that the investors in our sample are very similar to investors in previous studies in the disposition effect and also in factors affecting the disposition effect. Although the time spent at an educational institution may give the investor very little specific knowledge about how to avoid the disposition effect, it can give a direct indication of an investor's overall intelligence, including academic and learning abilities. Thus, we can assume that an investor who has spent more time studying is probably more intelligent than an investor whose educational path has been shorter or conducted at a lower level.

Our results (presented in Table IV) show that investors with a master's or doctoral degree tend to be less affected by the disposition effect. The probability of investors with a master's or doctoral degree selling a losing position is 8.6% higher, with a hazard ratio of 1.086, and the probability of them selling a winning position is 7.2% lower, with a hazard ratio of 0.928. It should be noted that on average such investors hold on to their positions with hazard ratios of 0.769 and 0.831, which means that they generally trade less and their overall probability of selling a position is lower than for other investors regardless of the effect of having a winning or losing position.

The hazard ratio showing the disposition effect for investors with vocational training is also statistically significant in our regressions. In the Estonian educational system, vocational training either replaces the last 3 years of high school or follows high school. It can be considered academically less challenging than going to high school and afterward continuing at a university. In contrast to the experience in some countries, vocational training was clearly out of favor for students during the sample period. Our data indicate that investors with this kind of education are prone to the disposition effect as they tend to hold losing positions for longer, with a hazard ratio of 0.913, and to sell winning positions more easily, with a hazard ratio of 1.089. These results are consistent with Goo *et al.* (2010),

Table III. The effects of "learning by doing"

The table reports results from the survival analysis—the hazard ratios, *z*-values, and significance levels. TLI represents the total loss indicator, taking the value 1 if the position is in loss and the value 0 otherwise. TGI is the total gain indicator, which takes the value 1 if a stock is trading above the purchase price and zero otherwise. The results are reported only for variables showing experience (how many trades an investor has made) and for interacted variables. Experience-related variables are interacted with TLI and TGI to capture the disposition effect. Experience-related variables are dummy variables. The trading data cover the period from 2002 to 2012. The table summarizes the results of individually run regressions.

Variables	Hazard ratio	z-Statistic	Variables	Hazard ratio	z-Statistic
Number of trades: 1–5×TLI	0.938**	–2.18	Number of trades: 1–5×TGI	1.061**	2.02
Number of trades: 1–5	0.597***	–24.86	Number of trades: 1–5	0.560***	–27.79
Number of trades: 6–10×TLI	0.940**	–2.05	Number of trades: 6–10×TGI	1.067**	2.13
Number of trades: 6–10	0.667***	–20.63	Number of trades: 6–10	0.626***	–20.23
Number of trades: 11–20×TLI	1.077***	2.85	Number of trades: 11–20×TGI	0.927***	–2.94
Number of trades: 11–20	0.715***	–20.93	Number of trades: 11–20	0.772***	–12.75
Number of trades: 21–50×TLI	1.152***	6.74	Number of trades: 21–50×TGI	0.869***	–6.69
Number of trades: 21–50	0.813***	–16.24	Number of trades: 21–50	0.937***	–3.93
Number of trades: 51–100×TLI	1.148***	5.44	Number of trades: 51–100×TGI	0.870***	–5.53
Number of trades: 51–100	1.199***	11.90	Number of trades: 51–100	1.377***	15.86
Number of trades: over 100×TLI	1.161***	7.36	Number of trades: over 100×TGI	0.863***	–7.27
Number of trades: over 100	2.541***	75.12	Number of trades: over 100	2.945***	65.27

***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table IV. Education level and disposition effect

The table reports results from the survival analysis—the hazard ratios, *z*-values, and significance levels. TLI represents the total loss indicator, taking the value 1 if the position is in loss and the value 0 otherwise. Similarly, TGI is the total gain indicator, which takes the value 1 if a stock is trading above the purchase price and zero otherwise. Results are reported only for education level variables and for interacted variables in the regressions. Education level variables are interacted with TLI and TGI to capture the disposition effect. Education level variables are also dummy variables. Trading data cover the period from 2002 to 2012; educational data are taken as of 2012.

Variables	Hazard ratio	*z*-Statistic	Variables	Hazard ratio	*z*-Statistic
Vocational training×TLI	0.913***	−3.52	Vocational training×TGI	1.089***	3.32
Vocational training	1.069***	4.19	Vocational training	0.980	−1.00
High school×TLI	1.036	1.54	High school×TGI	0.967	−1.49
High school	1.070***	4.65	High school	1.107***	5.79
Bachelor's degree×TLI	0.996	−0.20	Bachelor's degree×TGI	1.004	0.24
Bachelor's degree	0.987	−1.16	Bachelor's degree	0.983	−1.19
Master's or doctoral degree×TLI	1.086**	1.99	Master's or doctoral degree×TGI	0.928*	−1.81
Master's or doctoral degree	0.769***	−10.43	Master's or doctoral degree	0.831***	−5.62

***Significant at 1% the level; **significant at the 5% level; *significant at the 10% level.

who document that investors with a higher level of education exhibit a lower disposition effect.

Another interesting result is that even though the higher level of education given by a bachelor's or higher degree tends to reduce the disposition effect, investors with higher education are more reluctant to sell their positions in general. For example, investors who have only high school education or vocational training tend to have a higher probability than other investors of selling their positions if the effects of being in gain or loss are discounted (see the hazard ratios of the control variables). This means that more highly educated investors trade less frequently than less educated investors. This can have positive effects on their returns from the transaction cost point of view as they are not trying to outsmart the market by believing in their ability always to choose the best stocks. As they are also less influenced by the disposition effect, they let their profits run slightly more. The finding is consistent with Barber and Odean (2000), who show that trading too much can have negative effects on the portfolio performance and the same is true for the same sample we use (Liivamägi, Vaarmets, and Talpsepp, 2014).

All in all, we can conclude that intelligence plays a role in affecting investor behavior for the disposition effect. The effect is present at the bottom and top ends of the educational path for investors with vocational training and those with Master's or Doctoral degrees. We can see that the disposition effect is greater for investors with vocational training. These are investors who have chosen a less challenging educational path and are thus likely to exhibit lower learning abilities as well. We do not find any clearly distinguishable effects for the majority of investors, but we see an effect once again for investors who have taken the longest educational path and gained a master's or doctoral degree, and who thus probably have the highest intelligence, resulting in the disposition effect being reduced.

We present the robustness checks along with explanations in Appendix A for all of the results presented in the main sections of the paper. The effects presented in this subsection are also found with statistically significant coefficients when survival models are run with many different covariates for control variables and education level variables at the same time. When experience-related variables are added to the same model, the statistical significance of the education level variables starts to suffer, though the signs of the coefficients remain the same.

5.3. How Does the Type of Education Affect the Disposition Effect?

In addition to intelligence that can be signaled by the level of education, other more specific cognitive abilities can also be revealed by the type of higher education. People who have chosen different subjects for study may have clearly different cognitive abilities that may also affect their trading behavior. Of course they also possess different sets of knowledge after the university but we do not find proof that the knowledge taught in university is of great importance in reducing the disposition effect. We test the effects of possible differences in cognitive abilities by studying how the disposition effect is affected by the choice of courses in the broader sense of humanities, social studies or natural sciences, or the narrower sense of particular subjects.

Our results (see Table V) show that investors with a degree in humanities exhibit the disposition effect and investors with a degree in natural sciences tend to be more immune to it. Investors with a humanities degree have a hazard ratio of 0.782, meaning a 21.8% lower probability of selling their losing stock, and they have a 28.3% higher probability than the sample average of selling their winning stock.

These results stand in contrast to those for investors with a degree in natural sciences, whose probability of selling their losing stock is 8.3% higher than the sample average and probability of selling their winning stock is 7.5% lower. Given that the probability of selling a losing position is about 20% smaller than that of selling a winning position in general, this alone does not completely eliminate the disposition effect, but it clearly reduces it when other factors like experience, which can have a combined bigger effect, are not considered.

Once again we do not find a significant effect for the majority of the sample, as 74% of the investors with higher education and 49% of the total sample have a degree in social science. However, there are clear differences between investors at the different ends of the education scale of natural sciences and humanities. There are two main sources from which such differences can originate.

A possible explanation of the differences between the results for investors with degrees in humanities and natural sciences is that the latter possess more skills for dealing with numbers by analyzing and calculating. This can make them more pragmatic as they can analyze stock market situations better and reach more rational conclusions. We cannot completely exclude the explanation that investors who feel more comfortable with numbers are more interested in stock markets and therefore have more experience, which tends to decrease the disposition effect according to the earlier literature.[16] Nor are we able to

16 For example, Feng and Seasholes (2005) and Dhar and Zhu (2006).

Table V. Disposition effect for specialty groups

The table reports results from the survival analysis—the hazard ratios, *z*-values, and significance levels. TLI represents the total loss indicator, taking the value 1 if the position is trading with a loss and the value 0 otherwise. Similarly, TGI is the total gain indicator, which takes the value 1 if a stock is trading above purchase price and zero otherwise. The results are reported for specialty groups' variables as well as for interacted variables. Specialty groups are interacted with TLI and TGI to capture the disposition effect. Specialty groups' variables are also dummy variables, which take the value 1 if an investor has a degree in a specific discipline and the value 0 otherwise. Trading data cover the period from 2002 to 2012; educational data are taken as of 2012.

Variables	Hazard ratio	*z*-Statistic	Variables	Hazard ratio	*z*-Statistic
Humanities×TLI	0.782***	−6.37	Humanities×TGI	1.283***	6.48
Humanities	1.226***	9.16	Humanities	0.957	−1.39
Natural science×TLI	1.056**	2.20	Natural science×TGI	0.913***	−3.81
Natural science	0.992	−0.49	Natural science	1.070***	3.42
Social science×TLI	0.995	−0.29	Social science×TGI	1.005	0.26
Social science	0.943***	−5.37	Social science	0.938***	−4.54

***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

measure any non-cognitive skills[17] that may also play an important role in any investment activities, and we cannot conclude that investors who have studied natural sciences are more intelligent in general.

It may be argued[18] that studying natural sciences requires more effort as there is less room for relative interpretations and more skills need to be mastered before a student can graduate. Higher dropout rates from natural sciences courses indicate the same, so investors graduating from natural sciences may also possess higher learning abilities or problem-solving abilities, which are certain components of intelligence.

We do not find a degree in social sciences to have a statistically significant effect on selling behavior, but we are able to break investors with degrees in social sciences into smaller groups by subject and study those groups in more detail (the results are presented in Table VI).

Surprisingly, a degree in finance and or in any field related to economics including finance does not give an advantage as investors with this type of higher education tend to be even more prone to the disposition effect, and the hazard ratio for selling losing positions is 0.943 for investors with a degree in any field of economics and 0.773 for investors with a degree more narrowly in finance. This unexpected finding may be a result of overconfidence as investors with education in finance and economics may see themselves as better educated about the foundations of the stock market, and so they may lose the necessary focus or try to outsmart the market. Although we can classify business graduates separately and we do not find any statistically significant effect for them, it is very difficult to find major differences between the curricula of various economics and business subjects at

17 See, for example, Heckman and Rubinstein (2001) for emphasis of the importance of non-cognitive skills.

18 See, for example, Hofer and Pintrich (1997) for an overview of epistemological beliefs.

Table VI. University degrees and the disposition effect

The table presents hazard ratios associated with an individual investor's decision to sell or hold stocks at a loss or gain based on the investor's degree. The hazard ratios together with the *z*-value and the level of statistical significance are reported for subject group variables and also for interacted variables. This means that we interact each subject variable with the trading loss indicator (TLI) and with the TGI in order to measure cross-sectional differences in investors' propensities to sell losers and winners. TLI takes the value 1 if a stock is trading below its purchase price, and 0 otherwise. Similarly, the TGI variable takes the value 1 if a stock is trading above its purchase prize and 0 otherwise. The trading data cover the period from 2002 until 2012; educational data are taken as of 2012.

Variables	Hazard ratio	*z*-Statistic	Variables	Hazard ratio	*z*-Statistic
Maths or statistics×TLI	0.994	−0.04	Maths or statistics×TGI	1.015	0.10
Maths or statistics	0.919	−0.89	Maths or statistics	0.908	−0.87
Chemistry, physics, or biology×TLI	1.177**	2.11	Chemistry, physics, or biology×TGI	0.844**	−2.21
Chemistry, physics, or biology	0.937*	−1.41	Chemistry, physics, or biology	1.107*	1.67
IT×TLI	1.101***	−24.95	IT×TGI	0.905***	−3.18
IT	1.172***	8.67	IT	1.294***	10.10
Economics related×TLI	0.943**	−2.85	Economics related×TGI	1.066***	3.13
Economics related	0.808***	−17.23	Economics related	0.759***	−16.93
Finance×TLI	0.773***	−4.23	Finance×TGI	1.302***	4.34
Finance	1.085**	2.36	Finance	0.836***	−3.60
Law×TLI	1.184***	4.07	Law×TGI	0.845***	−4.06
Law	0.885***	−4.70	Law	1.046	1.42
Medicine×TLI	1.248**	2.38	Medicine×TGI	0.799**	−2.42
Medicine	0.748***	−5.12	Medicine	0.935	−0.92

***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

undergraduate level, and classifying them into different groups can be somewhat arbitrary. Thus, when we group all economics subjects together, we still see a slightly increased disposition effect for investors with an economics background.

Conclusions about investors with a background in natural sciences are confirmed by the results for investors with degrees in chemistry, physics, biology, and IT. The hazard ratios for those subjects indicate a higher probability of selling losing stocks and a lower probability of selling winning stocks. We are able to distinguish some additional subjects but most of them do not have a large enough number of observations to give statistically significant results, so for example we do not find any relevance for a psychology degree. Even so, we see that investors with a degree in law or medicine tend to be affected less by the disposition effect in our sample. One explanation for this finding could be that people graduating from law or medicine tend to have higher academic results when they are admitted to university, but, as will be seen in the next subsection, this cannot be the major reason. Very high drop-out rates from medicine courses also indicate that those who graduate may possess other possibly non-cognitive traits such as persistence, which we cannot directly control for.

5.4. How Do Academic Abilities Affect the Disposition Effect?

A natural question that emerges from the results presented so far is whether smarter investors are less influenced by the disposition effect. As our results show, better academic results, which should indicate higher intelligence, may reduce the disposition effect but there is no straightforward linkage. Examination results can indicate the strengths of various mental abilities because the skills and knowledge required for the examinations differ from examintion to examination.

We divide investors in our sample into quartiles and deciles depending on their national high school final examination results in a particular examination. As the examination results are an important factor for university admissions for students and school rankings for high school teachers, motivation to do well in the examinations is generally high. All the investors in our sample took their final examinations at around the age of 18 years, so before they entered the stock market. Although success in those examinations requires a clear learning effort, overall intelligence along with high mental and academic abilities clearly plays an important role. Those examinations are more of a one-time effort requiring preparation and high mental abilities. Thus, we regard those examinations mostly as an indicator of intelligence and academic abilities.[19]

Grouping investors into quartiles or deciles (we report results for quartiles only) thus gives us the smartest investors in the top group, the fourth quartile, and the academically weakest in the bottom or first, group. Not every investor has taken all the examinations shown in Table VII but 94% took the mother tongue examination, 80% took the English language examination, and 68% took the mathematics examination. Those three examinations are the most important, as most of the university courses require two or all three of those three examinations as part of their admission criteria. Some of the natural sciences courses also require the chemistry, biology, or physics examination, and some social sciences and humanities require the history examination. There are also other possible choices for the national examinations but we present the results of three examinations for natural sciences and three examinations for humanities.

19 See, for example, Deary and Johnson (2010) for discussion of the correlation between intelligence and academic abilities.

Table VII. Trading losses, gains, and academic results

The table presents hazard ratios associated with an individual investor's decision to sell or hold stocks based on the investors' national high school examination results. High school examination results are divided into deciles and quartiles for each examination, meaning that the related variable takes the value of 1 if the investors' examination result is in a specific decile or quartile and zero otherwise. The results for six different examinations are reported. The hazard ratios together with the *z*-value and the level of statistical significance are reported for interacted variables. This means that each examination group variable is interacted with the TLI or TGI in order to measure cross-sectional differences in investors' propensities to sell losers. TLI takes the value 1 if a stock is trading below its purchase price, and zero otherwise, and TGI takes the value 1 if a stock is trading above its purchase price, and zero otherwise. The trading data cover the period from 2002 to 2012; the national high school examination results data are from the period 1997 to 2012.

	Regressions with TLI		Regressions with TGI		Regressions with TLI		Regressions with TGI	
Variables	Hazard ratio	*z*-Statistic	Hazard ratio	*z*-Statistic	Hazard ratio	*z*-Statistic	Hazard ratio	*z*-Statistic
Quartiles	Maths examination		Maths examination		Mother tongue		Mother tongue	
1st×TLI (TGI)	0.936**	−2.10	1.071*	2.19	0.998	−0.06	1.000	−0.02
2nd×TLI (TGI)	0.943*	−1.88	1.058*	1.80	0.952	−1.51	1.050	1.50
3rd×TLI (TGI)	1.051	1.58	0.946*	−1.78	1.011	0.46	0.993	−0.31
4th×TLI (TGI)	1.066**	2.05	0.944*	−1.85	1.019	0.73	0.979	−0.79
Quartiles	Chemistry examination		Chemistry examination		English examination		English examination	
1st×TLI (TGI)	0.878**	−2.42	1.131**	2.30	1.009	0.30	0.995	−0.17
2nd×TLI (TGI)	0.953	−0.93	1.055	1.03	1.012	0.42	1.048	1.58
3rd×TLI (TGI)	0.923	−1.35	1.083	1.35	0.962	−1.30	0.977	−0.78
4th×TLI (TGI)	1.267***	4.30	0.791***	−4.27	1.013	0.44	0.995	−0.15
Quartiles	Physics examination		Physics examination		History examination		History examination	
1st×TLI (TGI)	0.970	−0.42	1.024	0.33	0.887***	−2.91	1.132***	2.99
2nd×TLI (TGI)	0.952	−0.71	1.042	0.59	1.031	0.76	0.973	−0.70
3rd×TLI (TGI)	1.011	0.19	0.997	−0.06	1.126***	2.75	0.892***	−2.67
4th×TLI (TGI)	1.086	1.09	0.923	−1.05	0.972	−0.74	1.020	0.51

***Indicates the significance at the 1% level, **5% level, and *10% level.

We test how national high school final examination results, which we take to indicate investors' intelligence, are related to the disposition effect. No similar tests have so far been presented in the literature due to the lack of data, though there are a number of studies about the relationships between investor sophistication and the disposition effect. The studies conclude that more sophisticated investors are less prone to the disposition effect.

The examination results used do not directly measure how sophisticated the investors in our sample are, but they can act as a general proxy of intelligence, which can be connected with an investor's sophistication as well. In general, our results for the impact of mental abilities on the disposition effect are mixed (see Table VII).

The results of the survival analysis for the losing positions (TLI = 1) cover six different examinations. The picture is clearer for examinations in the natural or exact sciences. For example, investors with higher score in the mathematics examination in the fourth quartile seem to be less influenced by the disposition effect, with hazard ratios above 1 in Table VII. We also see that being less successful and in the bottom quartile in maths or chemistry seems to increase the disposition effect. We do not find statistically significant effects for the physics examination but at least for quartile results, the magnitude of the effects is the same, with hazard ratios <1 for the 1st and 2nd quartiles and above 1 for the 3rd and 4th quartiles. It should be noted that only 13% of investors for whom we have examination data took the examination in physics, and that is 8% of our total sample.

The results for the softer sciences are more mixed. We show the results for the mother tongue, English, and history examinations, which are the three most popular examinations in that category. We do not find any statistically significant results by quartiles for the mother tongue and English examinations, which are the two most popular examinations. We do find some statistically significant coefficients for decile regressions but we basically end up with quite random results, which we do not consider meaningful. Being among the top performers in those examinations clearly requires high intelligence, but it might not require such an effort in preparation. It is very hard to become a top performer in those examinations only by studying hard and doing practice exercises, as it is very difficult to master the art of writing essays or speaking a foreign language without having an innate talent for it.[20] We do find some statistically significant coefficients for the history examination but the indication from that is also mixed, as both doing really well and doing quite poorly in the history examination seem to decrease the disposition effect and all in all, we cannot draw any meaningful conclusions about the mental abilities that are manifest in the results of humanities examinations.[21]

Such effects emerge much more clearly from study of the effect of mental abilities on market participation and stock portfolio performance[22] using the same proxies. Thus, we conclude that maths skills may be among the abilities that help to attenuate the disposition effects, but skills in humanities do not play an important role. The stronger effect in natural sciences is more in line with the effects that we see when we compare the effect of different subjects, where natural sciences also played a bigger role. As the top performers in most of the natural science examinations have a lower probability of being affected by the disposition effect, we conclude that certain mental abilities such as being good at numbers help in defeating the disposition effect. But we do not find support for the argument that all areas of intelligence can contribute to reducing the disposition effect.

20 At least according to popular belief (Horwitz, 1988).

21 The same applies to the examination results for social sciences and other foreign languages, which we do not present here.

22 See Vaarmets, Liivamägi, and Talpsepp (2014) for market participation and Liivamägi, Vaarmets, and Talpsepp (2014) for performance results.

5.5. What Affects the Speed of Learning?

As we argue that the learning abilities of investors are different, we should also see the effects in our trading data. As presented in Section 5.1, learning by doing appears to take place for the investors in our sample, because the investors become less influenced by the disposition effect when they have made more trades. If the level of education and the type of education can be used as proxies for intelligence and learning abilities, we should at least see some differences in the magnitude and speed of learning by doing for different groups as well. And that is indeed the case.

We run regressions with different subsamples of the level or field of education. The results (see Figure 3 and Table VIII) confirm our previous findings and show that the disposition effect fades faster for investors with higher education such as master's or doctoral degrees than for others. The hazard showing the probability of an investor selling a stock position that is in loss shows a 32.7% higher probability for an investor who has made at least 11 trades than for one who has made fewer than 5 trades. The same figure reaches that high for investors with a bachelor's degree only when they have made over 100 trades, meaning their speed of learning by doing is clearly slower. It would be expected that the more trades an investor has made, the less that investor is influenced by the disposition effect, and we can see such a linearly increasing trend for most groups.

However, we observe that investors with a master's or doctoral degree seem not to have learnt anything when they have made over 100 trades, as the corresponding hazard ratio is not statistically different from 1. The explanation for this could be that investors with high academic degrees trade less than other investors and given a smaller number of such investors, our sample just does not contain enough investors with high academic degrees to draw any conclusions about how a very large number of trades affects their bias. The same applies for the same variables for certain subject-based subsamples.

We do not find any statistically significant effect of learning by doing for investors with vocational training. This supports our previous conclusion that such investors may have a lower level of intelligence. The increasing effect of learning by doing is present for investors holding a bachelor's or equivalent degree.

The picture is quite similar for different subjects of study. We do observe a statistically significant and monotonically increasing effect for investors with a background in social sciences, who clearly become less influenced by the disposition effect when they have made more trades. Given that those investors mostly hold degrees in economics and finance and surprisingly are prone to the disposition effect in general, their learning by doing effect is to be expected. We also observe a similar increasing effect for investors with a background in natural sciences, who are able to learn faster than investors with a social sciences background. This is once again consistent with our previous hypothesis that having a natural science background can be beneficial in the stock market environment. We find a statistically significant learning effect for humanities graduates only when they have made over 100 trades.

We run similar regressions for all the top and bottom quartiles for different final examination results. We find a consistent effect only for the mathematics examination, where people with high skills in maths learn relatively fast by trading but investors in the bottom quartile exhibit basically no notable improvement for the disposition effect. The results for all other examinations—which indicate different types of mental abilities—do not show any other meaningful pattern or type of skillset that can be beneficial for an investor to learn faster than the average.

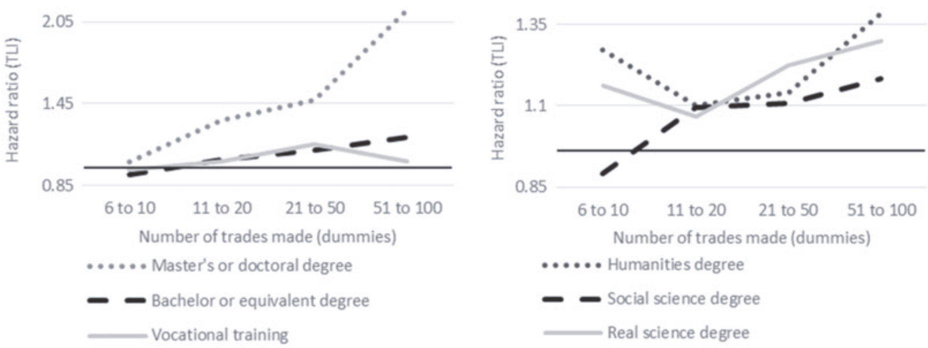

Figure 3. The speed and magnitude of learning by doing for different education groups. The graph shows the speed and magnitude of learning by doing. The *X*-axis shows the number of trades made (interacted trade dummy variables with TLI) and the *Y*-axis shows the corresponding hazard ratios. A hazard ratio over 1 (marked by the black dotted horizontal line) indicates that investors in the subgroup are less influenced by the disposition effect. The higher the hazard ratios, the less investors are influenced by the disposition effect given that they have made a particular number of trades. The slopes of the lines show the speed of learning.

All in all, we conclude that the learning by doing effect occurs faster for investors with higher intelligence and is almost absent for investors with lower intelligence. We find consistent effects of learning faster by doing for all the groups whom we expect to exhibit educational characteristics that help to reduce the disposition effect.

5.6. Discussion

We would like to highlight the importance of intelligence and certain mental abilities, especially maths, which influence trading behavior and the speed of cognitive learning in the financial markets.

When we consider cognitive learning through gaining investment experience by trading, we face a process of a Bayesian expectation revision mechanism (Grossman, Kihlstrom, and Mirman, 1977). Investors have to deal with a large amount of information and must update their beliefs accordingly. Updating beliefs means asking a large number of questions about the investment decision, which are all part of the belief revision mechanism. By repeating the process multiple times, investors gain a better ability to estimate probabilities for Bayesian inference and are thus more successful. However, people are not inherently good at estimating probabilities and the learning process is not easy. It would be safe to assume that some people are able to learn faster than others in that setting.

So far the previous literature has mainly focused on various socioeconomic characteristics and different forms of learning but has partly neglected intelligence, mostly because of the lack of appropriate data. The sample that we use lets us distinguish between different mental abilities and after testing different sets of mental abilities we find that intelligence plays an important role. When we consider the constructs of "complex problem solving knowledge acquisition," "complex problem solving system control," "learning abilities," and "intellectual status" [as identified by Beckmann and Guthke (1995)] as cognitive mental abilities or components of overall intelligence, we find the strongest effect is for long-term learning

Table VIII. Learning by doing by education level and field of studies

The table reports the results of the survival analysis—the hazard ratios, *z*-values, and significance levels. TLI represents the total loss indicator, taking the value 1 if a position is in loss and the value zero otherwise. TGI represents the total gain indicator, taking the value 1 if a position is in gain and the value 0 otherwise. Trade dummies (the number of trades made) are interacted with TLI and TGI to capture the disposition effect. Control variables are omitted from the table.

	Master's or doctoral degree		Bachelor equivalent		Vocational training	
Variables	Hazard ratio	*z*-Statistic	Hazard ratio	*z*-Statistic	Hazard ratio	*z*-Statistic
Number of trades: 6–10×TLI	1.026	0.13	0.932	−1.33	0.964	−0.35
Number of trades: 11–20×TLI	1.327*	1.67	1.040	0.80	1.030	0.31
Number of trades: 21–50×TLI	1.475***	2.68	1.108**	2.33	1.151	1.59
Number of trades: 51–100×TLI	2.135***	4.49	1.201***	3.87	1.028	0.29
Number of trades: over 100×TLI	1.095	0.60	1.253***	5.23	1.143	1.50
	Natural and real science		Social sciences		Humanities	
Number of trades: 6–10×TLI	1.161	1.60	0.890**	−2.03	1.270	1.20
Number of trades: 11–20×TLI	1.066	0.72	1.096*	1.71	1.101	0.55
Number of trades: 21–50×TLI	1.223**	2.46	1.108**	2.15	1.140	0.84
Number of trades: 51–100×TLI	1.300***	2.84	1.182***	3.26	1.383*	1.79
Number of trades: over 100×TLI	1.171*	1.73	1.304***	5.65	1.331**	1.97
	Master's or doctoral degree		Bachelor equivalent		Vocational training	
Variables	Hazard ratio	*z*-Statistic	Hazard ratio	*z*-Statistic	Hazard ratio	*z*-Statistic
Number of trades: 6–10×TGI	0.975	−0.13	1.072	1.31	1.067	0.61
Number of trades: 11 to 20×TGI	0.750*	−1.70	0.956	−0.93	0.986	−0.15
Number of trades: 21 to 50×TGI	0.675***	−2.71	0.898**	−2.44	0.891	−1.30
Number of trades: 51 to 100×TGI	0.469***	−4.48	0.827***	−4.04	0.996	−0.04
Number of trades: over 100×TGI	0.908	−0.65	0.795***	−5.32	0.896	−1.23
	Natural and real science		Social sciences		Humanities	
Number of trades: 6–10×TGI	0.869	−1.51	1.125**	2.05	0.788	−1.20
Number of trades: 11–20×TGI	0.948	−0.61	0.912*	−1.72	0.908	−0.55
Number of trades: 21–50×TGI	0.830**	−2.29	0.898**	−2.25	0.874	−0.86
Number of trades: 51–100×TGI	0.777***	−2.72	0.838***	−3.45	0.710*	−1.90
Number of trades: over 100×TGI	0.867	−1.56	0.762***	−5.78	0.748**	−2.00

***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

abilities. As we cannot use the results of standard intelligence tests, and our measures of complex problem-solving activities emerge from the academic setting such as maths and physics examiantions, we can only suggest a direction from which the effect mostly comes. We cannot rule out other possible sources, as mathematics skills played some role in our dataset as a part of complex problem solving for example, although some other components of traditional intelligence testing[23] like academic results and the examination results that we could use did not become significant in affecting the disposition effect.

Our results concerning the importance of intelligence do not rule out any other possible cognitive abilities and learning. Nor do our results contradict any current studies. In combination with financial market research on IQ, such as Grinblatt, Keloharju, and Linnainmaa (2012), we are able to add to the growing amount of literature on how different aspects of mental abilities and intelligence affect investment and trading decisions.

If we generalize our results, intelligence be an important reason why only a small proportion of investors are able to learn fast enough to eliminate the emergence of behavioral biases in the financial markets, as learning by doing is not very efficient (Bachmann and Hens, 2015).

6. Conclusion

The disposition effect is a well-researched area of finance. We are able to contribute by studying the effects of intelligence and education on the disposition effect.

We conclude that educational characteristics and intelligence play an important role in affecting investor behavior. We show that the disposition effect is stronger for investors with lower intelligence by using different proxies to measure their mental abilities in the academic setting. We find a stronger effect at both ends of the education scale. Highly educated investors who have master's or doctoral degrees are less influenced by the disposition effect and investors who have chosen vocational training instead, which may signal they are less able to cope with more challenging academic tasks than others in our sample, or have only high school education are more influenced by the disposition effect. Moreover, highly educated investors are able to learn faster by doing and by actually making trades, and investors with lower intelligence do not improve their trading even when they become more experienced. We find some beneficial effects for mathematical abilities, as better number skills can be associated with lower levels of the disposition effect.

As investors with financial education are clearly affected by the disposition effect despite their supposedly better knowledge, we cannot emphasize the importance of knowledge as a policy measure when trying to avoid behavioral biases. Even good abilities in knowledge memorization, as shown by the results of certain final examinations, do not help. Thus, any one-time campaigns to increase investor awareness and knowledge are probably of low impact, but are not completely useless. Domain knowledge can help investors learn a little faster when they enter the market. However, educating investors must be seen as a long process and it will be inevitable that some investors will just not be able to learn despite the efforts made.

23 See, for example, Guthke and Stein (1996).

Appendix A: Robustness Checks

This appendix reports robustness checks for the results presented in the main text of the paper. The robustness checks presented here are obtained by running logit regressions for the same model setups that were used for the survival analysis. To help in comparing the results of the hazard models with the results of the robustness checks, all the tables in this Appendix use the same numbers (though in Arabic form) as the corresponding tables in the main text with the prefix "A."

Table AI. Aggregate disposition effect (in the logit regressions)

The table reports the results of the logit regressions—the coefficients, *z*-values, and significance levels. TLI is the total loss indicator, taking the value 1 if a position is in loss and the value 0 otherwise. Similarly, TGI is the total gain indicator, which takes the value 1 if a stock is trading above its purchase price and zero otherwise. Investor-specific variables are interacted with TLI and TGI to capture the disposition effect. These investor-specific variables are also dummy variables and take the value 1 if an investor is identified by a specific variable (e.g., the male variable takes the value 1 if an investor is a male) and zero otherwise.

Variable	Coefficient	*z*-Statistic	Variable	Coefficient	*z*-Statistic
Total loss indicator (TLI)	−1.169***	−47.82	Total gain indicator (TGI)	1.159***	47.47
Male×TLI	0.137***	5.22	Male×TGI	−0.144***	−5.5
Foreign investor×TLI	0.232**	2.15	Foreign investor×TGI	−0.244**	−2.27

***Significant at the 1% level; **significant at the 5% level; and *significant at the 10% level. All of the regressions in Table AI confirm exactly the results of the survival analysis regressions presented in Table II. The coefficients are slightly different but the magnitude of the effects is similar.

Table AII. The effects of "learning by doing" (in the logit regressions)

The table reports results from the logit regressions—the coefficients, *z*-values, and significance levels. TLI taking the value 1 if the position is in loss and the value 0 otherwise. TGI is the total gain indicator, which takes the value 1 if a stock is trading above its purchase price and zero otherwise. The results are reported only for the variables showing experience (how many trades an investor has made) and for interacted variables. Experience-related variables are interacted with TLI and TGI to capture the disposition effect. Experience-related variables are dummy variables. The trading data cover the period from 2002 to 2012. The table summarizes the results of individually run regressions.

Variables	Coefficient	*z*-Statistic	Variables	Coefficient	*z*-Statistic
Number of trades: 1–5×TLI	0.041	1.40	Number of trades: 1–5×TGI	−0.046	−1.56
Number of trades: 1–5	−0.694***	−33.42	Number of trades: 1–5	−0.653***	0.02
Number of trades: 6–10×TLI	−0.046	−1.52	Number of trades: 6–10×TGI	0.053*	1.76
Number of trades: 6–10	−0.704***	−35.91	Number of trades: 6–10	−0.756***	0.02
Number of trades: 11–20×TLI	0.011	0.42	Number of trades: 11–20×TGI	−0.019	−0.74
Number of trades: 11–20	−0.537***	−33.50	Number of trades: 11–20	−0.521***	−25.59
Number of trades: 21–50×TLI	0.208***	9.88	Number of trades: 21–50×TGI	−0.207***	−9.85
Number of trades: 21–50	−0.242***	−18.93	Number of trades: 21–50	−0.034**	−2.01
Number of trades: 51–100×TLI	0.180***	7.09	Number of trades: 51–100×TGI	−0.181***	−7.15
Number of trades: 51–100	0.420***	27.47	Number of trades: 51–100	0.601***	29.84
Number of trades: over 100×TLI	0.393***	19.27	Number of trades: over 100×TGI	−0.39***	−19.15
Number of trades: over 100	1.616***	132.16	Number of trades: over 100	2.008***	123.44

***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level. All of the regressions in Table AII confirm exactly the results of the survival analysis regressions presented in Table III. The results of survival analysis are statistically more significant and clearer for some regressions (e.g., Number of trades: 11–20 × TLI).

Table AIII. Education level and disposition effect (in the logit and OLS regressions)

The upper panel of the table reports results from the logit regressions and the lower panel of the OLS regressions—the coefficients, *z*-values, and significance levels. TLI is the total loss indicator, taking the value 1 if the position is in loss and the value 0 otherwise. Similarly, TGI is the total gain indicator, which takes the value 1 if a stock is trading above its purchase price and 0 otherwise. Results are reported only for education level variables and for interacted variables in the regressions. Education level variables are interacted with TLI and TGI to capture the disposition effect. Education level variables are also dummy variables. Trading data cover the period from 2002 to 2012; educational data are taken as of 2012.

Logit regressions

Variables	Coefficient	*z*-Statistic	Variables	Coefficient	*z*-Statistic
Vocational training×TLI	−0.032	−1.25	Vocational training×TGI	0.021	0.84
Vocational training	0.106***	6.64	Vocational training	0.080***	4.02
High school×TLI	0.100***	4.37	High school×TGI	−0.098***	−4.29
High school	0.166***	11.38	High school	0.264***	15.04
Bachelor's degree×TLI	−0.040**	−2.18	Bachelor's degree×TGI	0.042**	2.30
Bachelor's degree	−0.046***	−4.02	Bachelor's degree	−0.087	−6.06
Master's or doctoral degree×TLI	−0.0670	−1.61	Master's or doctoral degree×TGI	0.077*	1.86
Master's or doctoral degree	−0.415***	−16.47	Master's or doctoral degree	−0.488***	−14.86

OLS regressions

Variables	Coefficient	*t*-statistic	Variables	Coefficient	*t*-statistic
Vocational training×TLI	−0.00053***	−5.37	Vocational training×TGI	0.00048***	4.87
Vocational training	0.00069***	8.72	Vocational training	0.00018***	3.11
High school×TLI	−0.00047***	−5.20	High school×TGI	0.00047***	5.12
High school	0.00110***	14.95	High school	0.00063***	11.67
Bachelor's degree×TLI	0.00010	1.50	Bachelor's degree×TGI	−0.00009	−1.30
Bachelor's degree	−0.00029***	−5.28	Bachelor's degree	−0.00019***	−4.69
Master's or doctoral degree×TLI	0.00133***	10.68	Master's or doctoral degree×TGI	−0.00129***	−10.30
Master's or doctoral degree	−0.00218***	−21.77	Master's or doctoral degree	−0.00086***	−11.61

***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level. For the results shown in Table AIII, which are comparable to those in Table IV, we run the logit regressions as well as OLS regressions for the robustness checks. Given the signs of the coefficients in the logit regressions, the results support survival analysis results in most of the cases. The only difference comes in the variables for Master's or Doctoral degrees. To address this issue we also run OLS regressions, which confirm our survival results. In addition, when we consider the statistical significance of the variables connected with the Master's or Doctoral degree and also vocational training, the OLS regressions results support our survival analysis results. The problem with logit regressions is that with the setup where we use the level of education as an explanatory variable, the regressions do not converge in some cases (we report the results obtained with just a small number of iterations to obtain the coefficients) and thus the results obtained are not reliable. This unreliability of the logit regressions due to convergence issues is the reason why we also employ OLS regressions. The OLS regressions match the results of the survival analysis even in cases when the results of logit regressions differed (e.g., Master's or doctoral degree × TLI).

Table AIV. Disposition effect for specialty groups (in the logit regressions)

The table reports results from the logit regressions—the coefficients, *z*-values, and significance levels. TLI is the total loss indicator, taking the value 1 if the position is trading with a loss and the value 0 otherwise. Similarly, TGI is the total gain indicator, which takes the value 1 if a stock is trading above its purchase price and 0 otherwise. The results are reported for course group variables and for interacted variables. Course groups are interacted with TLI and TGI to capture the disposition effect. Course group variables are also dummy variables, which take the value 1 if an investor has a degree in a specific discipline and the value 0 otherwise. Trading data cover the period from 2002 to 2012; educational data are taken as of 2012.

Variables	Coefficient	*z*-Statistic	Variables	Coefficient	*z*-Statistic
Humanities×TLI	−0.336***	−8.72	Humanities×TGI	0.343***	8.91
Humanities	0.221***	9.91	Humanities	−0.119***	−3.80
Natural science×TLI	0.071***	2.71	Natural science×TGI	−0.076***	−2.91
Natural science	−0.037**	−2.26	Natural science	0.037*	1.82
Social science×TLI	−0.025	−1.40	Social science×TGI	0.027	1.50
Social science	−0.118***	−10.74	Social science	−0.144***	−10.27

***Significant at the 1% level; **significant at the 5% level; and *significant at the 10% level. All of the regressions in Table AIV confirm exactly the results of the survival analysis presented in Table V. All of the signs and the statistical significance of the coefficients correspond to the hazard ratios reported in Table V.

Table AV. University degrees and the disposition effect (in the logit regressions)

The table presents coefficients associated with an individual investor's decision to sell or hold stocks at a loss or gain based on the investor's degree. The coefficients together with the *z*-value and the level of statistical significance are reported for subject group variables and also for interacted variables. This means that we interact each subject variable with the TLI and with the TGI in order to measure cross-sectional differences in investors' propensities to sell losers and winners. TLI takes the value 1 if a stock is trading below its purchase price, and 0 otherwise. Similarly, the TGI variable takes the value 1 if a stock is trading above its purchase prize and 0 otherwise. The trading data cover the period from 2002 until 2012; educational data are taken as of 2012.

Variables	Coefficient	*z*-Statistic	Variables	Coefficient	*z*-Statistic
Maths or statistics×TLI	0.374**	2.55	Maths or statistics×TGI	−0.358**	−2.44
Maths or statistics	−0.408***	−4.26	Maths or statistics	−0.0440	−0.40
Chemistry, physics, or biology×TLI	0.026	0.33	Chemistry, physics, or biology×TGI	−0.0330	−0.43
Chemistry, physics, or biology	−0.030	−0.64	Chemistry, physics, or biology	0.0010	0.01
IT×TLI	0.069**	2.18	IT×TGI	−0.072**	−2.28
IT	0.253***	13.76	IT	0.325***	12.72
Economics related×TLI	−0.065***	−3.17	Economics related×TGI	0.071***	3.450
Economics related	−0.17***	−13.69	Economics related	−0.238***	−14.650
Finance×TLI	−0.385***	−6.32	Finance×TGI	0.395***	6.48
Finance	0.003	0.09	Finance	−0.388***	−7.76
Law×TLI	0.121***	2.92	Law×TGI	−0.117***	−2.83
Law	−0.152	−5.82	Law	−0.0330	−1.04
Medicine×TLI	0.058	0.62	Medicine×TGI	−0.0590	−0.63
Medicine	−0.497***	−8.75	Medicine	−0.439***	−5.98

***Significant at the 1% level; **significant at the 5% level; and *significant at the 10% level. The regressions in Table AV confirm the results of the survival analysis results presented in Table VI. The only difference is that the results of logit regressions show that the investors with a mathematics background (variable Maths or Statistics × TLI/TGI) are less affected by the disposition effect, which confirms our conclusion that being good at maths helps to reduce the disposition effect. The results of the survival analysis for the effect of the same variable were statistically not significant and had an unexpected sign. However, logit regression results do not show a statistically significant coefficient (variable Chemistry, Physics, or Biology × TLI/TGI) for the investors with a chemistry or physics or biology background, which the results for the survival analysis did, although the sign is the same as for the results of the survival analysis.

Table AVI. Trading losses, gains, and academic results (in the logit regressions)

The table presents coefficients associated with an individual investor's decision to sell or hold stocks and the investors' national high school examination results. High school examination results are divided into deciles and quartiles for each examination, meaning that the related variable takes the value of 1 if the investor's examination result is in a specific decile or quartile and zero otherwise. The results for two different examinations are reported. The coefficients together with the *z*-value and the level of statistical significance are reported for interacted variables. This means that each examination group variable is interacted with the TLI or TGI in order to measure cross-sectional differences in investors' propensities to sell losers. TLI takes the value 1 if a stock is trading below its purchase price, and 0 otherwise, and TGI takes the value 1 if a stock is trading above its purchase price, and 0 otherwise. The trading data cover the period from 2002 to 2012; the national high school examination results data are from the period 1997 to 2012.

	Regressions with TLI		Regressions with TGI		Regressions with TLI		Regressions with TGI	
Variables	Coefficient	*z*-Statistic	Coefficient	*z*-Statistic	Coefficient	*z*-Statistic	Coefficient	*z*-Statistic
Quartiles	Maths examination				Chemistry examination			
1st×TLI (TGI)	−0.018	−0.59	0.024	0.77	0.011	0.05	−0.019	−0.35
2nd×TLI (TGI)	0.030	0.96	−0.038	−1.22	−0.160***	−3.06	0.166***	3.18
3rd×TLI (TGI)	−0.070**	−2.22	0.062**	1.98	−0.080	−1.35	0.080	1.36
4th×TLI (TGI)	0.037	1.21	−0.028	−0.9	0.205***	3.73	−0.203***	−3.7

***Indicates the significance at the 1% level, **5% level, and *10% level. Logit regressions with variables related to examination results mainly confirm our survival analysis results presented in Table VII. We present the results of the robustness checks of the mathematics and chemistry examination in Table AVI as they affect the disposition effect the most in our survival analysis regressions. Chemistry examination results are clearly in line with the conclusion that the natural science-related thinking and the maths-related skills are beneficial for reducing the disposition effect. The maths examination results are more mixed but the coefficients obtained for the bottom and top quartiles have the expected signs that correspond to the results of the survival analysis, though the coefficients are not statistically significant. The coefficients of the results of the other examinations, with the small exception of the history examination, turned out to be not statistically significant in the logit regressions either.

Table AVII. Learning by doing education level and field of studies (in the logit regressions)

The table reports the results of the logit regressions—the coefficients, *z*-values, and significance levels. TLI is the total loss indicator, taking the value 1 if a position is in loss and the value 0 otherwise. TGI represents the total gain indicator, taking the value 1 if a position is in gain and the value 0 otherwise. Trade dummies (the number of trades made) are interacted with TLI and TGI to capture the disposition effect. Control variables are omitted from the table.

	Master's or doctoral degree		Bachelor equivalent		Vocational training	
Variables	Coefficient	*z*-Statistic	Coefficient	*z*-Statistic	Coefficient	*z*-Statistic
Number of trades: 6–10×TLI	−0.078	−0.40	−0.165***	−3.10	−0.053	−0.51
Number of trades: 11–20×TLI	−0.078	−0.47	−0.144***	−2.95	−0.071	−0.74
Number of trades: 21–50×TLI	0.328**	2.28	0.068	1.54	−0.026	−0.29
Number of trades: 51–100×TLI	0.271*	1.62	0.205***	4.34	−0.400***	−4.22
Number of trades: over 100×TLI	0.300**	2.02	0.347***	8.05	0.383***	4.29
	Natural and real science		Social sciences		Humanities	
Number of trades: 6–10×TLI	0.018	0.13	−0.162***	−2.81	−0.015	−0.07
Number of trades: 11–20×TLI	0.010	0.09	−0.147***	−2.76	0.184	1.06
Number of trades: 21–50×TLI	0.254**	2.24	0.051	1.07	0.010	0.06
Number of trades: 51–100×TLI	0.109	0.92	0.146***	2.86	0.257	1.43
Number of trades: over 100×TLI	0.566***	5.14	0.398***	8.46	0.276**	1.93
	Master's or doctoral degree		Bachelor equivalent		Vocational training	
Variables	Coefficient	*z*-Statistic	Coefficient	*z*-Statistic	Coefficient	*z*-Statistic
Number of trades: 6–10×TGI	0.078	0.40	0.165***	3.10	0.096	0.91
Number of trades: 11–20×TGI	0.052	0.31	0.132***	2.70	0.083	0.87
Number of trades: 21–50×TGI	−0.333**	−2.32	−0.077*	−1.75	0.058	0.65
Number of trades: 51–100×TGI	−0.271*	−1.62	−0.216***	−4.58	0.436***	4.59
Number of trades: over 100×TGI	−0.307**	−2.06	−0.354***	−8.22	−0.349***	−3.91
	Natural and real science		Social sciences		Humanities	
Number of trades: 6–10×TGI	−0.043	−0.32	0.166***	2.89	0.015	0.07
Number of trades: 11–20×TGI	−0.047	−0.38	0.142***	2.66	−0.183	−1.06
Number of trades: 21–50×TGI	−0.287**	−2.53	−0.058	−1.20	−0.024	−0.15
Number of trades: 51–100×TGI	−0.121	−1.02	−0.158***	−3.09	−0.287	−1.60
Number of trades: over 100×TGI	−0.576***	−5.23	−0.407***	−8.65	−0.286**	−2.00

***Significant at the 1% level; **significant at the 5% level; and *significant at the 10% level. The regressions in Table AVII confirm the results of the survival analysis results presented in Table VIII. In both cases, investors with a higher academic degree (who can be considered to be more intelligent) or with a natural sciences background (who are stronger in maths) learn faster. Less intelligent investors and investors with a background in humanities seem to start to learn how to avoid the disposition effect only when they have made over 100 trades. It should be noted that though the survival analysis didn't give a statistically significant effect for experience of over 100 trades for holders of Master's and Doctoral degrees, the expected effect is clearly present and is statistically significant in the logit regressions.

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Curriculum Vitae

1. Personal data

Name	Tarvo Vaarmets
Date and place of birth	24.01.1982, Kuressaare, Estonia
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2. Education

Educational institution	Graduation/ Study year(s)	Education (Field of study/ degree)
Tallinn University of Technology	(2019)	Financial economics / Doctor of Philosophy
Tallinn University of Technology	2010	Economics / Master of Business Administration
Reims Management School	2008–2009	Master studies in France
Tallinn University of Technology	2004	Computer Systems / Diploma

3. Language competence/skills (fluent, average, basic skills)

Language	Level
Estonian	Native
English	Fluent
Russian	Average
German	Basic skills

4. Special courses

Period	Course	Educational or other organisation
08.2012	Doctoral course in behavioural finance	Helsinki School of Economics, Finland
01.2007	Business & Economics Journalism Course	TOL / Dow Jones
2006	Folk High School studies	Odder Højskole, Denmark

5. Professional employment

Period	Organisation	Position
2019– ...	Estonian Financial Supervision and Resolution Authority	Financial Auditor, Prudential Supervision Division
2013– …	Tallinn University of Technology	Visiting Lecturer, Department of Economics and Finance
2015–2019	Swedbank	Credit Analyst, Department of Credit Research
2012–2015	Estonian Ministry of Finance	Financial analyst, Department of State Assets

2010–2012	Swedbank	Financial analyst, Baltic Restructuring and Financing Unit
2006–2010	Äripäev	Analyst-editor, Stock Exchange Department

6. Research activity, including honours

2019 – DoRa Plus 1.1. scholarship for presentation of the article "Academic Abilities, Trading and Performance in the Stock Market" at the World Finance Conference, Santiago de Chile, Chile on July 24–26, 2019.

2018 – Doctoral School in Economics and Innovation scholarship for presentation of the article "How do cognitive and non-cognitive abilities influence stock market participation?" at the World Finance Conference, Mauritius on July 25–27, 2018.

2016 – Bank of Estonia research award for the article "How Does Learning and Education Help to Overcome the Disposition Effect" (co-authors Kristjan Liivamägi and Tõnn Talpsepp).

2016 – DoRa Plus 1.1. scholarship for presentation of the article "How Does Learning and Education Help to Overcome the Disposition Effect?" at the World Finance & Banking Symposium, Dubai, United Arab Emirates on December 14–15, 2016.

2016 – Kristjan Jaak scholarship for presentation of the article "How Does Learning and Education Help to Overcome the Disposition Effect?" at the 2016 Annual Meeting of the Financial Management Association International, Las Vegas, USA on October 19–22, 2016.

2015 – Kristjan Jaak scholarship for presentation of the article "Mental Abilities, Specialty Choice and Gender Differences among Investors" at the World Finance & Banking Symposium, Hanoi, Vietnam on December 17–18, 2015.

2015 – DoRa 8 scholarship for presentation of the article "The brilliant mind of investors" at the World Finance Conference, Buenos Aires, Argentina on July 22–24, 2015.

2014 – Bank of Estonia research award for the article "Brilliant mind of investors: how does education affect market participation, performance and risk taking" (co-authors Kristjan Liivamägi and Tõnn Talpsepp).

Publications

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Working Papers

Talpsepp, T., Liivamägi, K., Vaarmets, T. 2018. Academic Abilities, Trading and Performance in the Stock Market.

Conference presentations / Conference proceedings

Talpsepp, T., Vaarmets, T. 2019. *Academic Abilities, Trading and Performance in the Stock Market*. World Finance Conference, July 24–26, 2019, Santiago de Chile, Chile. (ETIS 5.2).

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Vaarmets, T. 2015. *Mental Abilities, Specialty Choice and Gender Differences among Investors.* World Finance & Banking Symposium, December 17–18, 2015, Hanoi, Vietnam. (ETIS 5.2).

Vaarmets, T., Liivamägi, K., Talpsepp, T. 2015. *The brilliant mind of investors.* World Finance Conference, July 21–24, 2015, Buenos Aires, Argentina. (ETIS 5.2).

Liivamägi, K., Vaarmets, T., Talpsepp, T. 2015. *Investor Education and Risk Taking Behaviour in the Stock Market*. The 7th international conference "Economic Challenges in Enlarged Europe" Conference Proceedings, June 14–16, 2015, Tallinn: Tallinn University of Technology. (ETIS 3.4).

Vaarmets, T., Liivamägi, K., Talpsepp, T. 2015. *The brilliant mind of investors*. INFINITI Conference on international finance, Ljubljana, Slovenia, June 8–9, 2015. (ETIS 5.2).

Vaarmets, T., Liivamägi, K., Talpsepp, T. 2014. *The brilliant mind of investors.* The 6th International Conference "Economic Challenges in Enlarged Europe", Conference Proceedings, June 15–17, 2014, Tallinn: Tallinn University of Technology. (ETIS 3.4).

Liivamägi, K., Vaarmets, T., Talpsepp, T., 2014. *Masters of the stock market*. The 6th International Conference “Economic Challenges in Enlarged Europe”, Conference Proceedings, June 15–17, 2014, Tallinn: Tallinn University of Technology. (ETIS 3.4).

7. Theses defended

2010: *The Forecast Accuracy by Estonian Stock Analysts and Its Determinants*. Master Thesis. Supervisor Tõnn Talpsepp. Tallinn University of Technology.

2004: Raising the test quality of digital systems by improving traceability, Diploma Thesis. Supervisor Raimund Ubar. Tallinn University of Technology.

8. Main research topics

Behavioural finance, the disposition effect, stock market participation, investment decisions, education

9. Additional information

2014–2015 Member of the supervisory board of the Balti Innovation Fund, Eesti Kaardikeskus AS and AS Teede Tehnokeskus

2014–2015 Member of supervisory board of Saaremaa Arenduskeskus SA

2011– … Member of the working group of doctoral studies at TSEBA

2011– … Advanced Open Water Diver Licence

2002– … Member of the fraternity “Vironia”

Elulookirjeldus

1. Isikuandmed

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2. Hariduskäik

Õppeasutus (nimetus lõpetamise ajal)	Lõpetamise/ õppimise aeg	Haridus (eriala/kraad)
Talllinna Tehnikaülikool	(2019)	Finantsökonoomika / doktor
Talllinna Tehnikaülikool	2010	Majandus / Ärikorralduse magister
Reims Management School	2008-2009	Majandus, magistriõpingud
Talllinna Tehnikaülikool	2004	Infotehnoloogia / Arvutisüsteemide diplom

3. Keelteoskus (alg-, kesk- või kõrgtase)

Eesti keel	Emakeel
Inglise keel	Kõrgtase
Vene keel	Kesktase
Saksa keel	Algtase

4. Täiendusõpe

Õppimise aeg	Täiendusõpe	Täiendusõppe korraldaja nimetus
08.2012	Doktorikursus käitumuslikus rahanduses	Helsinki School of Economics, Soome
01.2007	Äri- ja majanduse ajakirjanduskursus	TOL / Dow Jones, Tšehhi
2006	Rahvaülikooliõpingud	Odder Højskole, Taani

5. Teenistuskäik

Töötamise aeg	Tööandja nimetus	Ametikoht
2019– ...	Finantsinspektsioon	Finantsaudiitor, Kapitalijärelvalve divisjon
2013– ...	Tallinna Tehnikaülikool	Tunnitasuline lektor, Majandusanalüüsi ja rahanduse instituut
2015–2019	Swedbank	Võlakirjade analüütik, Võlakirjade analüüsi üksus
2012–2015	Rahandusministeerium	Finantsanalüütik, Riigivara osakond
2010–2012	Swedbank	Finantsanalüütik, Balti Restruktureerimise ja Finantseerimise osakond
2006–2010	Äripäev	Analüütik-toimetaja, Börsitoimetus

6. Teadustegevus, sh tunnustused

2019 – DoRa Plus 1.1. stipendium artikli “Academic Abilities, Trading and Performance in the Stock Market” presenteerimiseks konverentsil World Finance Conference, Santiago de Chile, Tšiili 24–26 juuli, 2019.

2018 – Majandusteaduse ja innovatsiooni doktorikooli rahaline toetus artikli “How do cognitive and non-cognitive abilities influence stock market participation?” presenteerimiseks konverentsil World Finance Conference, Mauritius 25–27 juuli, 2018.

2016 – Eesti Panga teaduspreemia artikli "How Does Learning and Education Help to Overcome the Disposition Effect" eest (kaasautorid Kristjan Liivamägi and Tõnn Talpsepp).

2016 – DoRa Plus 1.1. stipendium artikli “How Does Learning and Education Help to Overcome the Disposition Effect? ” presenteerimiseks konverentsil World Finance & Banking Symposium, Dubai, Araabia Ühendemiraadid 14–15 detsember, 2016.

2016 – Kristjan Jaak stipendium artikli “How Does Learning and Education Help to Overcome the Disposition Effect?” presenteerimiseks konverentsil 2016 Annual Meeting of the Financial Management Association International, Las Vegas, USA 19–22 oktoober, 2016.

2015 – Kristjan Jaak stipendium artikli “Mental Abilities, Specialty Choice and Gender Differences among Investors” presenteerimiseks konverentsil World Finance & Banking Symposium, Hanoi, Vietnam 17–18 detsember, 2015.

2015 – DoRa 8 stipendium artikli “The Brilliant Mind of Investors” presenteerimiseks konverentsil World Finance Conference, Buenos Aires, Argentiina 22–24 juuli, 2015.

2014 – Eesti Panga teaduspreemia artikli “The Brilliant Mind of Investors: how does education affect market participation, performance and risk taking” eest (kaasautorid Kristjan Liivamägi and Tõnn Talpsepp).

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7. Kaitstud lõputööd

Eesti aktsiaanalüütikute prognooside täpsus ja seda mõjutavad tegurid, magistritöö, juhendaja Tõnn Talpsepp, Tallinna Tehnikaülikool.

Digitaalskeemide testimiskvaliteedi tõstmine jälgitavuse parandamise abil, diplomitöö, juhendaja Raimund Ubar, Tallinna Tehnikaülikool.

8. Teadustöö põhisuunad

Käitumuslik rahandus, dispositsiooniefekt, investeerimisotsused, haridus

9. Lisainfo

2014–2015 Balti Innovatsiooni Fondi, Eesti Kaardikeskus ASi ja ASi Teede Tehnokeskus nõukogude liige

2012–2015 Saaremaa Arenduskeskus SA nõukogu liige

2011– … Majanduse doktoriõppe töörühma liige

2011– ... PADI edasijõudnud avavee sukeldumislitsents (AOWD)

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