# The brilliant mind of investors[1]

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# The brilliant mind of investors

**Abstract**

We study how investors' educational path and characteristics affect market participation, performance and risk taking in the stock market. To investigate such effects, we use educational performance measured by standardized exams and the type and specialty of a university degree obtained. The data covers one complete business cycle and includes detailed transactions and performance on the national stock exchange for all Estonian individual investors along with their past educational records from a national registry. The main contribution of the paper is a substantial step forward in determining how education and mental abilities influence stock market participation, risk taking and performance. We offer strong evidences that people with higher mental abilities are more likely to participate in the stock market and investors also outsmart other people in every field. Controlling for trading style, wealth, experience and a variety of demographic and educational characteristics, we provide empirical evidence that investors with overall high intellectual ability, as well as investors holding higher university degrees or degrees in certain fields, outperform market and achieve higher risk-adjusted returns. Investors holding a master's or doctoral degrees are more risk averse and those holding a university degree in economics or finance are more risk seeking.

***Keywords*****:** behavioral finance, stock market participation, risk-adjusted performance, portfolio risk, educational characteristics, individual investors

***JEL classification:*** G02, G11, I22, J24

## 1. Introduction

The discussion about why some people are financially in better shape than others is probably one of the key debates in advanced society. Even though the question why some have become richer than others is very complicated, important answers seem to be connected to financial know-how - the understanding of the money making game together with its different possibilities and risks. Rooij, Lusardi, and Alessie (2012) provide evidence that financial literacy is essential for making good money-related decisions, which means that better financial literacy increases wealth. They also note that one of the important financial decisions - the decision about investing into the stock market is dependent on the financial literacy. They bring out that people, who are participating in the stock market have a possibility to benefit from the equity premiums. The low financial knowledge[2] may be one reason why stock market participation rates are so low[3].

Financial literacy and stock market participation seems also to increase with overall education. Campbell (2006) found that more educated people are investing more in stocks and they also make less investment mistakes as less educated people tend to avoid stock markets as they do not have a proper knowledge about investing. In addition cognitive abilities or potential to obtain a good education and financial literacy has found to be an important factor, which determine the participation in stock market as argued by Grinblatt, Keloharju, and Linnainmaa (2011). They used data from the Finnish Armed Forces, who conduct tests for young men typically at the age of 19 or 20 and proved that all the three tested components - logical, verbal and mathematical – are influencing the stock market participation. However having the data only for men may not give us the complete picture about how cognitive abilities are influencing decisions connected to the stock market.

It seems that due to the insufficient data availability so far studies, which concentrate on the influence of educational characteristics and abilities to the stock market participation have been more or less limited by the level of the education or generalized measurements of investors' sophistication. Also many of researchers have used survey questions to determine connections between stock market participation and different characteristics. Grinblatt, Keloharju, and Linnainmaa (2011) express their doubts about fairness of these kind of studies

[2] Please see Lusardi and Mitchell (2008) and Hilgert, Hogarth, and Beverly (2003).

[3] Please see Hong, Kubik, and Stein (2004); Grinblatt, Keloharju, and Linnainmaa (2011). They bring out that only about the half of the households in U.S. are participating in the stock market directly or indirectly. This means that direct participation rates are even lower.

as the main shortcoming of survey data is that they involve response bias. This means that studies based on responses to different questions may be not fully objective and they are carrying humanity factor, which in this case is not wanted.

Several studies have concluded that the overall educational level is one factor affecting the financial behavior of investors. Hong, Kubik, and Stein (2004) and Kumar (2009) show that investors with a university degree have a higher propensity to invest in stocks compared to less educated investors. Christiansen, Joensen, and Rangvid (2008) demonstrate that financial decisions do not only depend on education level, but are influenced also by the type of the education. Individuals having a university degree in economics are more likely to participate in the stock market and hold stocks than otherwise comparable investors. Grable (1998) provides clear empirical evidence that educational level is the most significant factor affecting investor`s risk tolerance in the stock market and concludes that education appears to encourage risk taking. On the other hand, Grinblatt, Keloharju, and Linnainmaa (2011) provide empirical evidence that investors with higher IQ are more likely to hold mutual funds and larger number of stocks, which contributes to better portfolio diversification and lower risk. Grinblatt, Keloharju, and Linnainmaa (2012) provide evidence that individuals with higher IQ are attaining better performance but they were not able to include educational characteristics. Gottesman and Morey (2006) have demonstrated that fund managers holding MBAs from top ranked schools exhibit superior performance, but their sample includes only mutual fund managers. Guiso, Haliassos, and Jappelli (2003) assert that the overall education level is affecting the financial behavior, but they have not considered how educational characteristics influence investor’s risk-adjusted performance in the stock market. This question has stayed unanswered, in large part because an absence of appropriate data.

We do not use survey questions, which makes our data free of human biases. Instead of that we are combining complete dataset from Nasdaq OMX Tallinn with data obtained from Estonian Ministry of Education and Science. Our full stock market data includes all stockholdings and transactions made in the Estonian stock exchange from January 1, 2004 until December 31, 2012. This means we have detailed data about stockholdings and transactions for this nine year period. We use the full business cycle data to avoid any biases that could arise from using only either bull market or bear market periods and to include changes in investor`s perceptions, trading and risk taking behavior during the 2008–2009 financial crises as noted e.g. by Hoffmann, Post, and Pennings (2013). Our educational data includes high school grades, educational levels together with university degrees and type of education. In addition to that we have also final high school exam results for all the people, who took national high school final exams between the years 1997, when Estonian state started to centrally administrate these exams, until the year 2012.

This integrated unique dataset allows us to make a strong contribution to the literature. We make a substantial step forward in determining how educational characteristics and abilities are influencing stock market participation. In fact we are able to give answers to the questions about how level of skills and knowledge in all the main scientific disciplines are influencing stock market participation. In addition we are also able to determine wide range of educational characteristics, which are common to stockholders.

Moreover, this paper is also the first empirical documentation of comprehensive educational characteristics, which influence investor`s risk-adjusted returns in stock market during the full business cycle, including the bull and bear market. Christiansen, Joensen, and Rangvid (2008) draw attention to one of the still unsolved questions - whether economists also perform better on the stock market. We are able to compare the results of a wide range of investors with different educational background and take into account their skills in mathematics and other subjects by classifying investors by the results that they have obtained in state administered exams after high school.

We hypothesize that people participating in the stock market achieve better results in all the main educational disciplines compared to the people, who do not trade in the stock market. This means that stock market participation depends on the level of knowledge of all these main disciplines. Another hypothesis is that investors with higher state national exam result, higher educational level and with university degree in economics demonstrate better risk-adjusted performance in the stock market than investors and are more risk averse.

Our results expand the knowledge reflected in previous literature. We show that the driver for investing is not only higher educational level as for example brought out by Calvet, Campbell, and Sodini (2007) and Guiso, Haliassos, and Jappelli (2003) nor type of education as suggested by Christiansen, Joensen, and Rangvid (2008), but also the ability to solve very different problems. Similarly to Grinblatt, Keloharju, and Linnainmaa (2011) we find that participation in stock market can be assessed already before the actual trading takes place and is connected to the brighter mind. This means that investors tend to be not only more educated as found in previous studies, but investors are also outsmarting other people in every field, including both so called soft and hard sciences.

We offer empirical evidence that investors with higher mathematical skills combined with high overall intellectual ability and higher educational level (meaning bachelor, masters or doctors degree) are more successful in the stock market in terms of risk-adjusted performance and they hold less riskier portfolios due to higher portfolio diversification. We demonstrate that good performance in state national exams alone is not sufficient to achieve highest performance in stock market, but one must have also corresponding degree from university to master the stock market.

Second section of our paper is dedicated to the findings in the previous literature. We give an overview of our data used for the study in the third section. The fourth section describes the methodology used and sections 5-7 discuss the findings in detail.

## 2. Pervious literature

The desire to understand the factors behind the complicated financial decision making process has pushed many researchers to dig into surrounding questions and study them from different angles. One of these questions is what makes people to enter to the stock market? Who are these people, who are trading on the stock market?

Kaustia and Torstila (2011) concentrate on personal values in their study and find the relationship between political views and stock market participation. They show that there is a lower probability to buy stocks for left-wing voters and politicians than other people.

Guiso, Sapienza, and Zingales (2008) argue that people, who invest in stocks are more trusting in their nature. In addition, trust in stock market seems to be related to the knowledge about the stock markets. The latter has found support by other researchers. For example based on household survey Van Rooij, Lusardi, and Alessie (2011) conclude that financial literacy makes the difference, which means that people with higher financial literacy tend to invest more in stocks. The general lack of knowledge about finance and financial markets is also consistent with reported figures, which show that participation in stock markets is very modest (Bricker et al. (2012)). In Europe the rate of direct participation in the stock market varies across countries, but on average tend to be even smaller than in U.S. (Guiso, Haliassos, and Jappelli (2003)).

Stock market awareness can be improved in different ways. For example Hong, Kubik, and Stein (2004) propose that social activity makes people to participate more in stock markets. This means that individuals, who are socially active, meaning that they communicate with their neighbors and go to church, tend to invest more in stocks. Reason may be that learning from friends and neighbors probably reduces fixed participation costs. However this shows that stock market awareness can travel from mouth to mouth and is not only studied at school. Similarly financial literacy can be also improved through the workplace. Bernheim and Garrett (2003) argue that financial education in the workplace significantly increases the probability of savings in general. They also find that households, who were exposed to financial curricula during high school have higher savings rates than others. The same findings can be seen in the study of Bayer, Bernheim and Scholz (2009), who conclude that financial education at workplace increases participation in retirement plans.

Traditional education still matters. Educational level and wealth are other drivers, which have proved to make people to participate in the stock market. For example, Guiso, Haliassos, and Jappelli (2003) find strong connection between stock market participation and the level of education and wealth[4]. These findings are also supported by Campbell (2006), who conclude that less educated and less wealthy households tend to avoid investing in stocks. He also proposes that this kind of behavior may be reasonable, because less educated and less wealthy people also tend to make more investment mistakes. Therefore it should not be a surprise that financial knowledge and participation in the stock market is increasing together with the overall education level and household resources (Guiso and Jappelli (2005)).

The type of education seems to play a role in people's wish to buy stocks as well. In fact Christiansen, Joensen, and Rangvid (2008) propose that financial decisions do not only depend on education level, but they are also influenced by the type of the education. They show that people, who are more involved in economic science, meaning that people, who have obtained university degree in economics, have also higher tendency to hold stocks.

In addition to directly obtained education, there seems to be a connection also between out-of-box mindset or natural intelligence and participating in stock market. Based on the data of Finnish young males, Grinblatt, Keloharju, and Linnainmaa (2011) proved that men with higher IQ tend to participate in the stock market more than men with lower IQ. The measured IQ consisted of logical, verbal and mathematical subcomponents and they all played a role in participation. As young men in the sample were tested by the Finnish Armed Forces typically at the age of 19 or 20, it can be assumed that they were still quite a beginning of the road to improve their financial literacy. They also find that the IQ-effect on participation is monotonic and notably larger than the effect of income[5].

Some parallels can be drawn between the study about IQ by Grinblatt, Keloharju, and Linnainmaa (2011) and the research of Barnea, Cronqvist, and Siegel (2010), who are digging

[4] Same conclusion can be made from the figures presented in the study by Bricker et al. (2012).
[5] Even though we are unable to control wealth as a driver for stock market participation, we expect the wealth effect to be non-existent or small in our sample as mental abilities are measured in very early in life, when accumulation of wealth has not been started yet.

even deeper, when starting point is considered. By using data of Swedish identical and fraternal twins, they show that many factors influencing our financial behavior are affected by our genetics. This means that our financial behavior is greatly determined already before we are born. Still consistent with studies of the stock market awareness[6], they also show that similar or family environment have a significant effect on the investment behavior of young individuals, but this effect disappears as an individual gains own experiences.

Additionally, we can find several researches concentrating on different factors influencing investor behavior and performance is the stock market. For example Kumar (2009) finds that investors with lower income and lower education level are more likely to gamble in the stock market. Stock market gamblers are also rather younger and unemployed. Their portfolio performance is usually worse than average. This is consistent also with evidences that financial decisions are influenced by age – older investors outperform younger investors. Additionally female investors tend to experience better performance than male investors as they hold stocks longer and trade less noted by e.g. Barber and Odean (2001) and Talpsepp (2010).

Barber and Odean (2007) provide evidences that individual investors tend to buy stocks, which grab their attention through unusual events. This kind of behavior does not generate superior returns. Odean (1998) has also focused on the influence of trading frequency to the stock performance and found that most investors do not benefit from active trading. On average, the stocks investors buy subsequently underperform those they sell. In addition most active traders underperform those who trade less (Barber and Odean (2000)). Furthermore there are also evidences that foreign investor and investors with the larger portfolio (sophisticated, institutional investors) do better in stock market than domestic investors and investors with small portfolio (less sophisticated, households). Sophisticated institutional foreign investors tend to hold winners and sell losers, while less sophisticated domestic households tend to do the opposite as found by Grinblatt and Keloharju (2000). This view is shared by Talpsepp (2011). Grinblatt and Keloharju (2001) find that investors are reluctant to realize losses and that past returns and historical price patterns affect trading. Feng and Seasholes (2005) added trading experience to their research and proved that more sophisticated and more experienced investors are less influenced by the disposition effect and therefore act more rational. According to Dhar and Zhu (2006) the wealth is also connected to

[6] For example Hong, Kubik, and Stein (2004)

the investor behavior – wealthier individuals tend to be less influenced by the disposition effect.

While previous researchers have used indirect measure of sophistication, Grinblatt, Keloharju, and Linnainmaa (2012) have proved that directly measured IQ really does influence trading behavior and portfolio performance. Investors with higher IQ have better stock-picking skills and market timing; therefore their portfolios are also experiencing better performance. Gottesman and Morey (2006) showed that fund managers who hold MBAs from top schools have superior performance. They conclude that other education variables, such as whether the manager attained a CFA designation or holds either a non-MBA master's level graduate degree or Ph.D., are generally unrelated to mutual fund performance. We on the other hand provide clear empirical evidence that individual investors holding a bachelor, masters or doctoral degree achieve higher risk-adjusted returns in the stock market than investors with no such degree.

Hoffmann, Post, and Pennings (2013) demonstrate that individual investor perceptions have changed and driven trading and risk taking behavior during the recent financial crisis. Investor perceptions have fluctuated significantly during the crisis, with risk tolerance and risk perceptions have been less volatile than return expectations. Additionally, Weber, Weber, and Nosic (2012) give an insight of investors behavior during the crisis and the changes of risk. The time period of our dataset enables to cover the whole business cycle, which helps to avoid any biases that could arise from using only either bull market or bear market periods and any changes in investors trading behavior. Malmendier and Nagel (2011) present evidence that macroeconomic shocks influence financial risk taking. They report that individuals who have experienced low stock market returns throughout their lives so far show lower willingness to take financial risk, are less likely to participate in the stock market, and are more pessimistic about future stock returns. Furthermore, Amromin and Steven (2009) find that expected risk and return are strongly influenced by economic prospects. Dwyer, Gilkeson, and List (2002) show that women take less risk with a reasoning that men are more risk seeking because of generally better financial knowhow. Also Barber and Odean (2001) agree that women are more risk averse then men. Goetzmann and Kumar (2008) find that investors holding under diversified stock portfolios experience higher volatility and risk in stock market. Grable (1998) concludes that education appears to encourage risk taking, because increased level of attained academic training allows individuals to assess risk and benefits more carefully then someone with less education. The findings confirmed conclusions from Haliassos and Bertaut (1995), who have found that individuals less then college degree were less likely to hold risky assets, compared to individuals with at least a college degree. On the other side many researchers claim the opposite. As we take higher level of education as proxy for higher IQ, Grinblatt, Keloharju, and Linnainmaa (2011) provide clear empirical evidence that investors with higher IQ are more likely to hold mutual funds and larger number of stocks, which contributes to better portfolio diversification and lower risk.

We can conclude from literature that there are many factors influencing participation in the stock market – in addition to personal values, trusting nature, social activity, and wealth – both natural intelligence and traditional education determines whether people buy or avoid stocks. Investors IQ, sophistication, experience are expected also to affect various biases in investment decisions as well as performance and risk taking.

## 3. Data

We combine two different datasets in order to study the educational effects on the stock market participation. Firstly we have detailed unique dataset obtained from the Estonian Ministry of Education and Science, which includes all high school grades, results of high school final exams and information about individual's educational level, which means university degrees and types of education. This detailed educational data is integrated with complete dataset form Tallinn stock exchange provided by Nasdaq OMX Tallinn. Nasdaq OMX Tallinn is the only stock exchange in Estonia. The period covers full business cycle and stock market data consists of all transactions made with a total of 23 listed Estonian companies in period of nine years starting form 01.01.2004 until 31.12.2012 as well as all stockholdings from same period. We are not able to calculate returns for positions opened before January 2004 and thus such transactions are discarded from our sample which is a common practice in the literature. Prices are adjusted for stock splits and dividends. The market capitalization of Nasdaq OMX Tallinn is about 2 billion euros as of 31.12.2013. Due to its small size there can be some liquidity constraints for active trading in the Estonian stock market.

The combination of these two datasets enables to determine educational characteristics of investors. In addition, we also have high school final exam results for the whole population, who took these exams starting from implementation of the national final exam system in 1997 until 2012. High school final exams are identical for all high school graduates and are essential for graduation. They also serve as entry exams to Estonian universities, which is additional motivation for students to get the best result possible. Exams are taken in history, mother tongue, English, German, French, Russian as second language, Mathematics, Physics, Chemistry, Biology, Geography and Social studies. The level of difficulty of the exams is aimed to be the same throughout the years as exams taken at different years are equally regarded as university entry exams at the same year. These properties allow us to compare investor's and non-investor's final exam results and study how level of knowledge in different subjects are connected to participation.

We are able to extract information about every stock market individual investor, including one's age, gender, nationality (domestic or foreign), experience, portfolio size, stocks allocation in portfolio, average stocks holding period, number of transactions and transaction size. We are also able to identify investors by the level of education (high school, bachelor, master, doctor), by education type (mathematics, statistics, economics, medicine, law, information technology, public administration, chemistry, physics, psychology etc.) and by high school ranks. In total we are able to construct a very large number of control variables in four main categories (demographic, experience, level of wealth, trading style).

The total number of different investors who have made at least one purchase trade during our sample period is 33 843, of which 27 859 are individual investors. Of those investors, we are able to obtain official educational characteristics for 8 277 investors and that forms our main sample for cross sectional analysis. For panel analysis we are able to use 35 904 investor-year observations for investors that we have educational characteristics available. As not all the investors with educational data have all data points for various research question setups, some of the sample may be slightly smaller, e.g. market participation dataset consists of 6 811 investors and 214 963 non-investors who all have necessary detailed information available (see Table 1).

For analysis, we mostly use binary and ordinal setup required for the use of different probability models. Thus, we divide the dependent variables into equally distributed deciles or quartiles. Most of the independent variables are binary. For robustness checks, we also use different distributions for segmentation. Deciles and quartiles of the constructed variables are adjusted so that none of the result appears simultaneously in two groups within these categories and we construct divide observations into categories on a year to year basis to make each year's results directly comparable.

Foundation data of our research are described high school final exam results, which means that investors' mental abilities are measured early in life (mostly at the age of 18), when very few are already entered into stock market. This also means that people at this young age do not have accumulated wealth yet – usually they still live with their parents and do not have jobs. Based on these properties we assume that in our case wealth plays rather limited role in process of making a participation decision.

Still consistent with previous literature investors participating in Nasdaq OMX Tallinn stock exchange tend to be wealthier than non-participants according to their educational level and specialties[7] (which are obtained several years after the mental abilities are measured). In our sample 80% of the all investors have higher education[8] – from this over half (54.5%) have a degree in finance, business, management or in economics, 8.6% have a degree in IT and 6.0% have degree in law. Average salary earned by people with higher education is 1.7 times bigger than for these Estonians, who have only graduated high school. Moreover top salaries in Estonia are earned by people working in finance and IT sector[9]. Statistics refers clearly that Estonian investors tend to be wealthier than average Estonian.

## 4. Methodology

First we are interested in comparing stock market participants average high school final exam results to exam results obtained by the individuals, who did held stocks during our sample period (please see Table 2). For determining the significances of these differences we employ simple two sample t-tests with equal variances. In addition to testing the significances of the differences, we also compute the effect size by using Cohen's *d* and Hedges's *g*. Cohen's *d* and Hedges's *g* are similar metrics, which indicate the standardized difference between two means. Even though there is no universal value for small or large effect size, the rule of thumb is that value of 0.2 for Cohen's *d* and Hedges's *g* is considered to be small, value of 0.5 indicates medium effect size and value of 0.8 and higher can be considered as large effect size.

Dependence between stock market participation and exam results or knowledge level in different subjects is found by using probit regression models. Due to the dependent binary variable, probit model is suitable choice for addressing participation question and has found broad support in the previous participation literature. For example probit model has been used

[7] Wealth has been found to be one factor influencing stock market participation for example by Guiso and Jappelli (2005) and Campbell (2006)

[8] This compares with 34% figure for all Estonians, who are older than 20 years, based on Estonian Population and Housing Census conducted in 2011.

[9] Statistics Estonia. http://www.stat.ee/72318 (2014).

by Grinblatt, Keloharju, and Linnainmaa (2011), who studied relationship between IQ and stock market participation, also by Hong, Kubik, and Stein (2004), who found connection between participation and social activity. In addition probit model has been the key method also in several other relevant papers and used for example by Christiansen, Joensen, and Rangvid (2008), Guiso, Sapienza, and Zingales (2008) and Bogan (2008). As said, we are using similar approach and we have models for two cases – for actual exam results and grouped exam results, where related or independent variables are dummies. Our models can be described as follows:

$$Probit(Investor_i) = \beta_0 + \beta_1 Examresult_{\,ij} + \sum_{k=2}^{K} \beta_k controls_{\,ik} + \epsilon_i$$

$$Probit(Investor_{\,i}) = \beta_0 + \beta_1 Examresultgroup_{\,ijl} + \sum_{k=2}^{K} \beta_k controls_{\,ik} + \epsilon_i$$

where $Investor_{\,i}$ is dependent variable for person *i*, which takes a value 1, if person *i* was trading in the stock market during our sample period and equals 0, if person is considered as non-investor; $Examresult_{\,ij}$ represents person $i$'s actual exam result for exam $j$ and $\sum_{k=2}^{K} \beta_k controls_{\,ik}$ are control variables (gender, age). $Examresultgroup_{\,ijl}$ represent a dummy variable for adjusted deciles and quartiles and takes value of 1, if person *i* exam *j's* result was included in group *l*.

In addition to described general models, we are also re-estimating the models using exam results and exam results group variables individually together with control variables. For example we are building the model, where only exam result variable is mathematics exam result variable or lowest adjusted quartile variable for mathematics exam results. This serves a dual purpose – it acts as a robustness check and also avoids possible misleading conclusions caused by multicollinearity in general model, where all exam result variables are included. This means that as there are many explanatory variables in general model, some of them can be statistically not significant with high standard errors, because of the multicollinearity problem.

For easier interpretation of the results of described probit regression models we use post estimated marginal analysis and calculate average marginal effects as well as marginal effects for males and females separately.

To study the impact of education on investor's performance, we use aggregate data to have an indicator for the average return during the observed period for every investor type. As investors can also trade foreign stocks and increase or decrease amount invested, which has an effect to performance, we calculate portfolio return as an annual money-weighted return. We do calculate and compare the results for time-weighted returns to money-weighted returns in case there is any significant variance in the outcome of the method selected.

In order to measure risk-adjusted performance, we use three different methods: RAP (Risk-Adjusted Performance of Modigliani and Modigliani (1997)), Sharpe ratio (Sharpe (1966)) and Jensen alpha model (Jensen (1968)). As a proxy for a risk we use standard deviation of portfolio return as suggested by Markowitz (1991) and Modigliani and Modigliani (1997). We mainly present results or the RAP model where the basic idea is to use the market opportunity cost of risk, or trade-off between risk and return, to adjust all portfolios to the level of risk in the unmanaged market benchmark (e.g., the S&P 500), thereby matching a portfolio's risk to that of the market, and then measuring the returns of this risk-matched portfolio and ranks portfolios the same way the Sharpe ratio does. It should be noted that the choice of risk adjusted performance metric does not change the results which remain consistent regardless of using the RAP model, Sharpe ratio or Jensen alpha.

For analyzing the effect of educational characteristics on the performance, we use probability models. As we divide investors either in quartiles or deciles by their performance, we have ordinal outcomes if we want to analyze the effect on each performance group. For this kind of data analysis the ordered logistic regression model has been used and suggested by Coval and Shumway (2005), Greene (1997), Gelman and Hill (2007) and van Dijk and Pellenbarg (2000). The reason for this model comes from our data categorization. We have divided the investor into quartiles and deciles, based on the risk-adjusted return, starting from the lowest and ending with the highest category as suggested by Coval and Shumway (2005). We conclude the ordered logistic regression model to be most appropriate statistical model to perform this type of analysis and present the results of the ordered logit model. We also use binary logit model to study the effect of educational and other characteristics on different performance groups separately and to confirm the results of ordered logit model. Both models, ordered logit and binary logit, are also utilized for panel data analysis. To conduct panel data analysis, we construct all performance and risk related variables on a yearly basis.

We measure the risk as standard deviation of portfolio`s return as suggested by Markowitz (1991) and Modigliani and Modigliani (1997). As a proxy for a risk we use standard deviation of portfolio return.

## 5. Results of market participation

Our exam results data includes 784 757 observations including 221 774 unique individuals; 6 811 of them are considered as investors as they have owned stocks in the Estonian stock market during the period of 2004 until 2012. Due to establishment of the new national high school final exam system at 1997 and therefore availability of data, the average age of our sample is rather low – 29.18 for investors and 26.77 for non-investors. Still investors, who trade in the Nasdaq OMX Tallinn tend to be quite young also in general as presented by Talpsepp (2010), who also brings out that Estonian stock market is dominated by male investors. The same conclusions can be made from the Table 1[10]. As shown by Talpsepp (2010) total number of investors in Estonian stock market was less than 21 000 as of 2008, which means that our sample of investors with high school exam results covers about one third of the total number of stockholders.

[10] In our sample 73,2% of the investors are male investors, which is comparable with a 67,9% figure presented by Talpsepp (2010).

## Table 1.

## Descriptive Statistics

Table 1 reports descriptive statistics of the investor and non-investor subsamples used to study the relationship between mental abilities (high school final exam results) and stock market participation. In Panel A general statistics of age and gender is presented. In panel B subsamples are divided by age group. Age is calculated as of year 2012 (end of the sample period).

**Panel A. General statistics of investors and non-investors**

| | Investors | | | | | Non-investors | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | Std. Dev | Min | Max | N | Mean | Std. Dev | Min | Max |
| **Age** | 6 811 | 29.18 | 4.41 | 17 | 55 | 214 963 | 26.77 | 4.92 | 16 | 70 |
| **Females** | 1 827 | 1 | 0 | 1 | 1 | 123 634 | 0 | 0 | 0 | 0 |
| **Males** | 4 984 | 1 | 0 | 1 | 1 | 91 329 | 0 | 0 | 0 | 0 |

**Panel B. Investors and non-investors by age group**

| | Investors | | | | Non-investors | | | |
|---|---|---|---|---|---|---|---|---|
| Age Group | N | Cumulative | Percent | Cumulative percent | N | Cumulative | Percent | Cumulative percent |
| **16-20** | 206 | 206 | 3.02 | 3.02 | 23 501 | 23 501 | 10.93 | 10.93 |
| **21-25** | 1 185 | 1 391 | 17.40 | 20.42 | 68 276 | 91 777 | 31.76 | 42.69 |
| **26-30** | 2 570 | 3 961 | 37.73 | 58.16 | 70 807 | 162 584 | 32.94 | 75.63 |
| **31-35** | 2 505 | 6 466 | 36.78 | 94.93 | 45 819 | 208 403 | 21.31 | 96.95 |
| **36-40** | 293 | 6 759 | 4.30 | 99.24 | 5 256 | 213 659 | 2.45 | 99.39 |
| **over 41** | 52 | 6 811 | 0.76 | 100.00 | 1 304 | 214 963 | 0.61 | 100.00 |
| **over 16** | 6 811 | | 100 | | 214 963 | | 100 | |

## Table 2.

## Descriptive Statistics of the National High School Final Exam Results

Table 2 reports descriptive statistics, number of observations, mean, standard deviation, min and max of the high school final exam results taken by investors and non-investors. In addition mean difference of these subsamples is presented. Mean difference shows how much investors' results on average are relatively higher than non-investors' results. Maximum possible result for every exam is 100 and minimum is 0.

| | Investors | | | | | Non-investors | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Exam | N | Mean | Std. Dev | Min | Max | N | Mean | Std. Dev | Min | Max | Mean Difference (%) |
| **Mathematics** | 4 483 | 55.94 | 25.47 | 0 | 100 | 88 127 | 49.69 | 24.84 | 0 | 100 | 12.58 |
| **Physics** | 801 | 64.55 | 23.15 | 8 | 100 | 11 180 | 56.74 | 24.26 | 0 | 100 | 13.76 |
| **Chemistry** | 1 517 | 62.21 | 22.33 | 0 | 100 | 36 836 | 58.43 | 22.42 | 0 | 100 | 6.47 |
| **Biology** | 1 499 | 62.77 | 18.86 | 5 | 98 | 57 624 | 57.29 | 19.62 | 0 | 100 | 9.57 |
| **Geography** | 1 262 | 69.07 | 14.03 | 21 | 98 | 54 998 | 59.31 | 16.01 | 0 | 100 | 16.46 |
| **Mother tongue** | 6 653 | 61.63 | 20.33 | 0 | 100 | 191 739 | 57.51 | 20.51 | 0 | 100 | 7.16 |
| **English** | 5 406 | 71.31 | 16.82 | 0 | 100 | 133 961 | 66.35 | 17.46 | 0 | 100 | 7.48 |
| **German** | 644 | 72.14 | 18.60 | 0 | 100 | 16 133 | 68.55 | 18.71 | 0 | 100 | 5.24 |
| **History** | 2 573 | 60.69 | 19.27 | 6 | 98 | 54 102 | 54.26 | 21.02 | 0 | 100 | 11.85 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Social studies** | 1 088 | 67.39 | 13.81 | 24 | 97 | 48 595 | 61.92 | 14.93 | 0 | 99 | 8.83 |

The main conclusion from data presented in Table 2 is that investors are outsmarting non-investors as their high school final exam results are on average remarkably higher. For example, people who are trading on the stock markets have achieved on average 55.94 points out of 100 in mathematics final exam. This is 12.6% higher result than average outcome for people, who do not participate in the stock market. The difference between results of stockholders and non-stockholders is biggest in case of Geography exam (16.5%), but also notable in the case of chemistry and language exams like Mother tongue, English and German. As French exam and Russian as foreign language was taken only by 36 and 131 investors respectively they have left out from the table and further analysis.

These insights are also reflected in high school rank data. We divided all Estonian high schools based on the average exam results into deciles and quartiles. It means that high schools with highest average exam results belong to the top decile (10%) and top quartile (25%). Based on the sample including 1615 investors with high school data, we find that only 0.7% of investors studied in high schools belonging to the lowest decile, 5.8% studied in high schools belonging to the second decile. At the same time 18.2% of investors graduated high schools, which were in penultimate or ninth decile based on average final exam results and 29.5% of investors' high schools were in top 10%. Similarly only 9.04% of investors graduated from high schools, which can be found in the bottom 25% of all Estonian high schools, but at the same time more than a half of investors studied at high schools belonging to the top 25% in Estonia. Thus, we can conclude that investors tend to study in best high schools in Estonia, if level of knowledge is considered. This means that environment, where investor is acquiring her or his general education favors top class results.

For all exams much lower proportion of the investors subsample can be seen in lower groups than proportion of non-investors. For example 9.68% of all Geography exam results are in lowest or first adjusted decile, but only 2.22% of all exam results taken by investors are falling into this group (and 9.85% of results taken by non-investors). Similarly the highest adjusted quartile includes 25.00% of total number of Geography exam results, but at the same time 46.41% of stockholder's exam results and 24.51% non-stockholder exam results are in this group. In general, proportionally there are fewer exam results falling into the first 5-6 adjusted deciles than non-investor results and in many cases biggest proportions are in highest adjusted deciles and quartiles.

In order to study relationship between mental abilities or high school final exam results and stock market participation, we define our dependent, endogenous variable $y_i^*$ as *investor*, which takes value 1, if person has held stocks in Estonian stock market and value 0, if she/he has not traded or held stocks in Estonian stock market during the period of 2004-2012. In total there are 221 774 observations used for our main models (for more information please see Table 1). From our total investors' sample 80.0% have higher education[11], which in turn is divided so that 15.52% of them have a degree in natural and exact sciences, 6.45% have a degree in humanities, 61.23% are holding a degree in social sciences and 16.80% in applied and other sciences. Large proportion of social studies degree holders is consistent with a data presented and conclusions made by Christiansen, Joensen, and Rangvid (2008). Exam results are again divided into deciles and quartiles with one difference – as we are interested only in investors, exam results groups are constructed also among investors.

### 5.1. Are investors smarter than non-investors?

In this section we provide empirical evidences to our hypothesis that people, who participate in the stock have higher mental abilities than those people, who do not invest their money in the stock market. We also prove that this higher mental capability is absolute as investors are showing their higher intelligence in all the scientific areas studied.

There have been several studies, which have concentrated on education and found that more educated people tend also to participate more in the stock market. For example Kumar (2009) found that longer education path means also higher probability to buy stocks and make better investment decisions, also studies by Calvet, Campbell, and Sodini (2007) and Guiso, Haliassos, and Jappelli (2003) show that education matters. Christiansen, Joensen, and Rangvid (2008) developed this question further and proved that not only level of education matters, but also type of education plays a role in stock market participation. Still these previous studies have been unable to present evidences that investors are also mentally more capable than non-investors until Grinblatt, Keloharju, and Linnainmaa (2011) found the relationship between IQ and stock market participation. We are able to shed even a brighter light on this question as we are able to present broad evidence that investors are for example better mathematicians as well as historians or philologists.

To prove our hypothesis also presented in section 4, we are using simple t-tests as described in previous section. We show that differences between the high school final exam

[11] Even though our sample is rather young as shown in Table 1, this figure is still remarkably higher than Estonian average - as suggested by Estonian Population and Housing Census conducted in 2011, 34% of all Estonians, who are older than 20 years have obtained higher education.

results achieved by stock market participants and non-participants are statistically significant in every case studied.

The results are actually already reflected in Table 2, where we can see that on average investors achieved 5.24% (German exam) until 16.45% (Geography exam) higher results than non-investors. In Table 3, we add the proof that these differences are big enough to be statistically significant. From Table 3 we can see that on average investors are getting 6.25 percentage points higher scores for mathematics exam, 7.89 percentage points higher scores in physics exam etc. As all these differences between investors' and non-investors' exam results are remarkable, it should be no surprise that according to the t-tests results all these differences are also statistically significance at 0% level. In other words there is no doubt that based on our sample investors' attainments in every subjects are from a higher league compared to non-investors. These results are consistent with findings by Grinblatt, Keloharju, and Linnainmaa (2011).

**Table 5.**

**Differences between Investors and Non-investors Exam Results**

Table 5 reports differences between means of exam results achieved by investors and non-investors, also differences in standard errors has reported together with 95% confidence interval of the these differences. In addition t-values and degrees of freedom has shown and also the significance levels. In all cases differences in exam results were statistically significant at 0% level, which is represented by three stars ***. To measure the size of the difference Cohen's d and Hedges' g has been used and reported. The value of 0.2 can be considered as small effect size, value of 0.5 medium effect size and value over 0.8 can be considered has a large effect size.

| | Group Differences | | | | | | | Effect size |
|---|---|---|---|---|---|---|---|---|
| | | | 95% Confidence Interval of the Difference | | | | | |
| Group | Mean | Std. Error Mean | Lower | Upper | t | Df | Significance | 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 |
| **Geography** | 9.760 | 0.455 | 8.869 | 10.652 | 21.462 | 56 258 | *** | 0.611 |
| **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 |
| **German** | 3.592 | 0.752 | 2.118 | 5.065 | 4.778 | 16 775 | *** | 0.192 |
| **History** | 6.428 | 0.423 | 5.599 | 7.256 | 15.212 | 56 673 | *** | 0.307 |
| **Social studies** | 5.474 | 0.457 | 4.578 | 6.370 | 11.976 | 49 681 | *** | 0.367 |

We can also see that effect sizes are quite considerable in most cases. As all the sample sizes are rather large then Cohen's d and Hedges' g are equal in sense of presented accuracy. For Geography exam both metrics are 0.611 which can be understood as there is a above medium difference between investors' knowledge about Geography and non-investors knowledge about the same subject. In most cases effect sizes are between 0.2 and 0.4, which can be understood as there is above small difference between stock market participants' and non-participants' mental abilities in corresponding areas. For German and Chemistry we can interpret these effect sizes as small ones.

### 5.2. Does stock market participation depend on mental abilities in different areas?

In previous section we presented a proof that investors' are smarter than non-investors. In this section we will add another proof and show that stock market participation is also dependent on the mental abilities in all fields we studied. This means that people with a higher competence in any of the subjects analyzed (achieved better results in all high school final exams) are also participating in the stock market more likely.

For finding the relationship between stock market participation and mental abilities, we used probit regression model as also described in section 4 (methodology section)[12]. We have estimated the model for stock market participation for all exams and control variables, but as one of the explanatory variables in the general model is statistically not significant, it can be because of multicollinearity. Therefore, we have also re-estimated the model using all the exam variables independently together with control variables.

The results are presented in Table 4. We have left out the exams, which were taken by less than 5% of investors from total investor population (French exam and Russian as foreign language), because in these cases results may be not so reliable (French exam was taken only by 36 investors and Russian as foreign language by 131 investors).

From results reported in Table 4, we can conclude that all the high school national exam results and control variables are statistically significant at 0% level. This applies in both cases– for actual exam results and for model, where adjusted deciles and quartiles variables were used. All the coefficients presented in the panel A  (the model with actual exam results) are positive, meaning that an increase in any of studied exam results leads to an increase in predicted probability of stock market participation. In other words – people with a better knowledge in all the different subjects studied are also more likely to buy stocks.

[12] For robustness check also logit regression model was used, but as conclusions are same for both type of models, only results from probit regressions are presented in the paper.

## Table 4.

## National High School Final Exam Results and Stock Market Participation

Table 6 reports coefficients together with significance level, pseudo $R^2$ and number of observations from probit regressions in which the dependent variable takes the value of one, if individual has held stocks or traded in stock market during our sample period. In addition post estimated average marginal effects as well as marginal effects for males and females separately are shown. All the coefficients in panel A and panel B are significant at 0% 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 together with control variables was tested. In Panel A outcome of the probit model for actual exam results are presented, in panel B exam results are divided into two categories - adjusted deciles and adjusted quartiles. Deciles and quartiles were adjusted in the case where the cutoff point of the decile or quartile was in the middle of some specific result and the boundary was lifted so that every result stayed only in one group. Only the lowest and highest adjusted deciles and quartiles are reported. Results for control variables gender and age shown in panel A are from general model, where all the actual exam results were included (in which case all the exam results coefficients were also very similar to these reported in the table). For keeping the table as simple as possible results for control variables in panel B has not shown. Data in the table is based on national high school final exams taken from 1997 until 2012 and on Estonian stock market data from 2004 until 2012.

| | | | | | Marginal Effects (%) | | |
|---|---|---|---|---|---|---|---|
| **Independent Variables** | **Coefficients** | **z-values** | **Pseudo $R^2$** | **N** | **Average** | **Male** | **Female** |
| **Panel A. Probit regressions with actual exam result variables** | | | | | | | |
| **Mathematics exam result** | 0.00765*** | 25.37 | 0.0853 | 92 610 | 0.071 | 0.105 | 0.038 |
| **Physics exam result** | 0.00993*** | 11.99 | 0.0744 | 11 981 | 0.120 | 0.144 | 0.045 |
| **Chemistry exam result** | 0.00642*** | 11.14 | 0.0815 | 38 353 | 0.051 | 0.084 | 0.028 |
| **Biology exam result** | 0.01016*** | 16.32 | 0.0841 | 59 123 | 0.056 | 0.104 | 0.033 |
| **Geography exam result** | 0.01761*** | 20.21 | 0.0950 | 56 260 | 0.086 | 0.138 | 0.043 |
| **Mother tongue exam result** | 0.00784*** | 27.73 | 0.0842 | 198 392 | 0.054 | 0.089 | 0.029 |
| **English exam result** | 0.01107*** | 27.92 | 0.0956 | 139 367 | 0.085 | 0.138 | 0.046 |
| **German exam result** | 0.00853*** | 8.04 | 0.0845 | 16 777 | 0.066 | 0.115 | 0.035 |
| **History exam result** | 0.00944*** | 19.09 | 0.0773 | 56 675 | 0.084 | 0.137 | 0.048 |
| **Social studies exam result** | 0.01463*** | 14.83 | 0.0897 | 49 683 | 0.071 | 0.127 | 0.035 |
| **Age (general model)** | 0.06062*** | 41.79 | 0.1186 | 221 774 | 0.377 | 0.593 | 0.212 |
| **Gender (general model)** | 0.58184*** | 46.37 | 0.1186 | 221 774 | 3.623 | | |
| **Panel B. Probit regressions with exam result lowest and highest group variables** | | | | | | | |
| **Mathematics exam result groups** | | | | | | | |
| lowest adjusted decile | -0.3704*** | -13.53 | 0.0727 | 92 610 | -3.48 | -5.18 | -1.84 |
| highest adjusted decile | 0.3522*** | 16.51 | 0.0741 | 92 610 | 3.31 | 4.92 | 1.74 |
| lowest adjusted quartile | -0.3485*** | -18.56 | 0.0773 | 92 610 | -3.26 | -4.84 | -1.72 |
| highest adjusted quartile | 0.3059*** | 18.95 | 0.0768 | 92 610 | 2.86 | 4.26 | 1.51 |
| **Physics exam result groups** | | | | | | | |
| lowest adjusted decile | -0.6328*** | -7.43 | 0.0607 | 11 981 | -7.74 | -9.31 | -2.87 |
| highest adjusted decile | 0.4041*** | 7.71 | 0.0586 | 11 981 | 4.96 | 5.95 | 1.85 |
| lowest adjusted quartile | -0.4444*** | -8.90 | 0.0637 | 11 981 | -5.42 | -6.51 | -2.02 |
| highest adjusted quartile | 0.3650*** | 8.96 | 0.0625 | 11 981 | 4.46 | 5.35 | 1.67 |

*Continues*

**Table 4 – Continued**

| Independent Variables | Coefficients | z-values | Pseudo $R^2$ | N | Marginal Effects (%) Average | Male | Female |
|---|---|---|---|---|---|---|---|
| **Chemistry exam result groups** | | | | | | | |
| lowest adjusted decile | -0.4054*** | -8.16 | 0.0776 | 38 353 | -3.23 | -5.33 | -1.80 |
| highest adjusted decile | 0.2562*** | 7.14 | 0.0754 | 38 353 | 2.04 | 3.38 | 1.14 |
| lowest adjusted quartile | -0.2371*** | -7.70 | 0.0765 | 38 353 | -1.89 | -3.12 | -1.05 |
| highest adjusted quartile | 0.2273*** | 8.23 | 0.0768 | 38 353 | 1.81 | 2.99 | 1.01 |
| **Biology exam result groups** | | | | | | | |
| lowest adjusted decile | -0.4804*** | -9.59 | 0.0724 | 59 123 | -2.67 | -4.96 | -1.59 |
| highest adjusted decile | 0.2953*** | 8.74 | 0.0693 | 59 123 | 1.64 | 3.06 | 0.98 |
| lowest adjusted quartile | -0.3240*** | -10.92 | 0.0736 | 59 123 | -1.80 | -3.34 | -1.07 |
| highest adjusted quartile | 0.3096*** | 12.33 | 0.0748 | 59 123 | 1.81 | 3.20 | 1.02 |
| **Geography exam result groups** | | | | | | | |
| lowest adjusted decile | -0.5561*** | -8.00 | 0.0652 | 56 260 | -2.81 | -4.48 | -1.37 |
| highest adjusted decile | 0.4639*** | 15.04 | 0.075 | 56 260 | 2.32 | 3.70 | 1.14 |
| lowest adjusted quartile | -0.4991*** | -12.41 | 0.0738 | 56 260 | -2.50 | -3.99 | -1.22 |
| highest adjusted quartile | 0.4195*** | 16.57 | 0.0799 | 56 260 | 2.09 | 3.33 | 1.03 |
| **Mother Tongue exam result groups** | | | | | | | |
| lowest adjusted decile | -0.3451*** | -14.32 | 0.0748 | 198 392 | -2.41 | -3.98 | -1.30 |
| highest adjusted decile | 0.2517*** | 15.05 | 0.0744 | 198 392 | 1.76 | 2.90 | 0.95 |
| lowest adjusted quartile | -0.3162*** | -19.80 | 0.0782 | 198 392 | -2.20 | -3.63 | -1.19 |
| highest adjusted quartile | 0.2536*** | 19.89 | 0.0774 | 198 392 | 1.76 | 2.92 | 0.95 |
| **English exam result groups** | | | | | | | |
| lowest adjusted decile | -0.3898*** | -14.98 | 0.0832 | 139 367 | -3.04 | -4.91 | -1.65 |
| highest adjusted decile | 0.3316*** | 18.44 | 0.0845 | 139 367 | 2.58 | 4.17 | 1.40 |
| lowest adjusted quartile | -0.3416*** | -19.81 | 0.0869 | 139 367 | -2.65 | -4.28 | -1.44 |
| highest adjusted quartile | 0.3014*** | 21.67 | 0.0876 | 139 367 | 2.34 | 3.78 | 1.27 |
| **German exam result groups** | | | | | | | |
| lowest adjusted decile | -0.2054*** | -3.07 | 0.0739 | 16 777 | -1.60 | -2.80 | -0.86 |
| highest adjusted decile | 0.2362*** | 4.11 | 0.075 | 16 777 | 1.84 | 3.22 | 0.98 |
| lowest adjusted quartile | -0.2695*** | -5.77 | 0.0786 | 16 777 | -2.09 | -3.66 | -1.12 |
| highest adjusted quartile | 0.2759*** | 6.71 | 0.0801 | 16 777 | 2.14 | 3.74 | 1.14 |
| **History exam result groups** | | | | | | | |
| lowest adjusted decile | -0.4478*** | -10.71 | 0.0656 | 56 675 | -4.03 | -6.57 | -2.27 |
| highest adjusted decile | 0.2902*** | 9.99 | 0.0636 | 56 675 | 2.61 | 4.27 | 1.48 |
| lowest adjusted quartile | -0.3363*** | -13.35 | 0.0684 | 56 675 | -3.02 | -4.92 | -1.71 |
| highest adjusted quartile | 0.3055*** | 14.55 | 0.0690 | 56 675 | 2.74 | 4.47 | 1.55 |
| **Social Studies exam result groups** | | | | | | | |
| lowest adjusted decile | -0.4449*** | -7.37 | 0.0737 | 49 683 | -2.18 | -3.91 | -1.09 |
| highest adjusted decile | 0.3557*** | 9.59 | 0.0754 | 49 683 | 1.74 | 3.12 | 0.87 |
| lowest adjusted quartile | -0.3377*** | -9.33 | 0.0766 | 49 683 | -1.65 | -2.96 | -0.83 |
| highest adjusted quartile | 0.3299*** | 11.61 | 0.0798 | 49 683 | 1.61 | 2.88 | 0.80 |

In panel B individuals were divided into adjusted deciles (about 10% of total population) and adjusted quartiles (about 25% of total population) based on their exam scores.

Results for the lowest and highest adjusted deciles and quartiles are presented. In every case coefficients for lowest groups are negative and coefficients for highest groups are positive. This means that change from 0 to 1 in lowest groups decreases the predicted probability of stock market participation and change from 0 to 1 in highest groups increases the predicted probability of stock market participation. As already seen from the results in panel A – individuals with high intelligence tend to participate in the stock market more likely and individuals, who fail to prove their high intelligence tend to participate less likely.

In order to make more precise conclusions, we have also performed marginal analysis of the coefficients. As interpreting results of marginal analysis is straightforward for categorical variables, which take value of zero or one, we are concentrating on results presented in panel B (the model with adjusted deciles and quartiles).

People in lowest adjusted decile for mathematics exam result have on average 3.5% smaller probability to participate in the stock market than people, who do not belong into this group. At the same time the probability is 5.2% smaller for males and 1.8% smaller for females. Similarly, people with highest mathematical skills (belonging to highest adjusted decile) have on average 3.3% higher probability to buy stocks than others (for males probability is higher 4.9% and for females 1.7%). In this sense results of the physics exam tend to be the best predictor of stock market participation – people in the lowest adjusted decile have on average 7.7% smaller probability to buy stocks than others (for males probability is 9.3% lower and for females 2.9% lower). Men, who perform best in physics have also 6.0% higher probability to be a stockholder than those men, who does not perform so well in physics. On average people, who achieve highest results in physics are participating in stock market with 5.0% higher probability than other people according to our sample. In general we can conclude that impact of mathematics and physics exam results on stock market participation is somewhat stronger than in a case of language exams for example. The explanation may be that for people, who have better skills in mathematics and physics have also higher interest in stock markets, because for them it is easier to understand the stock market, which is also largely based on different mathematical operations and calculations (in other words associated participation costs are lower)[13]. This view is supported by the fact that stock market participation rate is highest for mathematics and physics exam – 4.8% of the people, who took the mathematics exam and 6.7% of the people, who took a physics exam,

[13] This explanation is consistent with research by Vissing-Jørgensen (2003), who argue that fixed costs are the reason why U.S. households tend to not participate in the stock market. Similar arguments are also made by Hong, Kubik, and Stein (2004).

were also involved in the stock market in studied period. In contrast in all other cases the participation rate was under 4% with only one exception – for history exam participation rate was 4.5%, but still lower than for mathematics or physics. Also results of marginal analysis show that after mathematics and physics, history exam results have better predictive power in sense of stock market participation than other exams.

We can also conclude that better results in any of our studied national high school final exams tend to increase the probability of stock market participation. This means that investors are outsmarting other people from every angle – they are better mathematicians, better historians, better biologists, they are better with languages etc. The conclusion is stronger for men as their probabilities to participate in the stock market are much more dependent on their mental abilities than in case of women. In general this is consistent also with conclusions made by Grinblatt, Keloharju, and Linnainmaa (2011), who proved the connection between men's general mental abilities and stock market participation. Still as we showed the picture for men and women is not so homogeneous and therefore conclusions made by Grinblatt, Keloharju, and Linnainmaa (2011) cannot be exactly also generalized for females.

Still the explanation behind so broad better performance by investors on average may be that people with better knowledge and better skills are also more ambitious, therefore they are continuing their studies after the high school and as they get better jobs and salaries they try to find ways also to financially secure themselves. This is supported by the studies, which prove the relationship between education and stock market participation[14].

For getting even more complete picture we also compare marginal effects of second until tenth adjusted decile group to the lowest adjusted decile. We find that in almost every case probabilities to buy stocks are increasing monotonically, when moving from second adjusted decile to the highest or tenth adjusted decile. For example for mathematics exam men, whose results fell into second decile are participating in stock market with 1.1% higher probability than men, who scored worst in mathematics exam. For the third adjusted decile the same probability is 1.4% higher, for fourth decile it is 3.0% higher etc. Men, who achieved best results are participating in stock market with 9.4% higher probability than men, who performed worst in mathematics exam. On average people with best results have 6.4% higher probability to buy stocks compared to people with lowest mental abilities in mathematics.

[14] For example Calvet, Campbell, and Sodini (2007) and Guiso, Haliassos, and Jappelli (2003), but also Lusardi (2003).

# Table 5.

## Dynamics of Stock Market Participation

Table 7 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 lowest adjusted decile, which serve as a benchmark group and therefore is not included in the table. Probit regression models are constructed so that dependent variable or investor dummy took the value of 0, if person has not held stocks in our sample period and value of 1, if person has had stocks in observed period. Independent variable representing specific exam result groups took the value from 1 to 10 according to the exam results. Weakest exam results fall into first deciles and were coded as 1, highest exam results were included in tenth decile and took value of 10. Control variables gender and age were also included in all models, but in order to keep the table as simple as possible estimated values for these control variables are not reported (except marginal effects for males and females). Three stars represent 1% significance level, two stars 5% and one star 10% significance level. Results reported in the table are based on national high school final exams taken from 1997 until 2012 and on Estonian stock market data from 2004 until 2012.

| Independent Variables | Adjusted deciles | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 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 | 0.007 | 0.009 | 0.020 | 0.024 | 0.031 | 0.031 | 0.035 | 0.045 | 0.064 | | |
| Marginal effects for males | 0.011 | 0.014 | 0.030 | 0.037 | 0.047 | 0.047 | 0.054 | 0.067 | 0.094 | | |
| Marginal effects for females | 0.003 | 0.004 | 0.009 | 0.012 | 0.015 | 0.015 | 0.018 | 0.023 | 0.034 | | |
| **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 | 0.022 | 0.035 | 0.040 | 0.048 | 0.051 | 0.058 | 0.068 | 0.078 | 0.109 | | |
| Marginal effects for males | 0.026 | 0.042 | 0.048 | 0.058 | 0.061 | 0.070 | 0.081 | 0.093 | 0.129 | | |
| Marginal effects for females | 0.007 | 0.012 | 0.014 | 0.018 | 0.019 | 0.022 | 0.026 | 0.031 | 0.046 | | |
| **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 | 0.016 | 0.016 | 0.017 | 0.025 | 0.027 | 0.022 | 0.031 | 0.032 | 0.046 | | |
| Marginal effects for males | 0.027 | 0.028 | 0.029 | 0.042 | 0.045 | 0.037 | 0.053 | 0.054 | 0.075 | | |
| Marginal effects for females | 0.008 | 0.008 | 0.009 | 0.013 | 0.014 | 0.011 | 0.017 | 0.018 | 0.026 | | |

*Continues*

## Table 5 – Continued

| Independent Variables<br>Estimated values | Adjusted deciles 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Highest | N | Pseudo $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **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 | 0.008 | 0.009 | 0.014 | 0.015 | 0.017 | 0.023 | 0.024 | 0.034 | 0.037 | | |
| Marginal effects for males | 0.016 | 0.019 | 0.028 | 0.030 | 0.033 | 0.045 | 0.047 | 0.065 | 0.070 | | |
| Marginal effects for females | 0.004 | 0.005 | 0.007 | 0.008 | 0.009 | 0.012 | 0.013 | 0.019 | 0.021 | | |
| **Geography** | | | | | | | | | | | |
| Coefficients | 0.009 | 0.362*** | 0.324*** | 0.392*** | 0.446*** | 0.608*** | 0.631*** | 0.767*** | 0.925*** | 56 260 | 0.096 |
| z-values | 0.090 | 4.460 | 3.940 | 4.770 | 5.680 | 7.750 | 8.180 | 10.100 | 12.490 | | |
| Average marginal effect | 0.000 | 0.009 | 0.008 | 0.010 | 0.012 | 0.020 | 0.022 | 0.031 | 0.045 | | |
| Marginal effects for males | 0.000 | 0.015 | 0.013 | 0.017 | 0.020 | 0.033 | 0.035 | 0.049 | 0.070 | | |
| Marginal effects for females | 0.000 | 0.004 | 0.003 | 0.005 | 0.006 | 0.010 | 0.011 | 0.016 | 0.024 | | |
| **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 | 0.005 | 0.009 | 0.011 | 0.014 | 0.021 | 0.021 | 0.028 | 0.032 | 0.037 | | |
| Marginal effects for males | 0.008 | 0.016 | 0.020 | 0.024 | 0.036 | 0.037 | 0.049 | 0.055 | 0.063 | | |
| Marginal effects for females | 0.002 | 0.004 | 0.005 | 0.006 | 0.010 | 0.010 | 0.014 | 0.016 | 0.018 | | |
| **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 | 0.007 | 0.009 | 0.015 | 0.018 | 0.020 | 0.029 | 0.034 | 0.034 | 0.050 | | |
| Marginal effects for males | 0.012 | 0.015 | 0.026 | 0.029 | 0.033 | 0.048 | 0.055 | 0.056 | 0.081 | | |
| Marginal effects for females | 0.003 | 0.004 | 0.008 | 0.009 | 0.010 | 0.015 | 0.017 | 0.018 | 0.027 | | |

*Continues*

**Table 5 - Continued**

| Independent Variables<br>Estimated values | Adjusted deciles<br>2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Highest | N | Pseudo $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **German** | | | | | | | | | | | |
| Coefficients | -0.026 | 0.032 | 0.031 | 0.160* | 0.110 | 0.333*** | 0.352*** | 0.396*** | 0.414*** | 16 777 | 0.086 |
| z-values | -0.280 | 0.350 | 0.340 | 1.840 | 1.180 | 4.020 | 4.160 | 4.680 | 4.900 | | |
| Average marginal effect | -0.001 | 0.002 | 0.002 | 0.010 | 0.007 | 0.025 | 0.027 | 0.031 | 0.033 | | |
| Marginal effects for males | -0.003 | 0.003 | 0.003 | 0.019 | 0.012 | 0.045 | 0.048 | 0.056 | 0.059 | | |
| Marginal effects for females | -0.001 | 0.001 | 0.001 | 0.005 | 0.003 | 0.013 | 0.014 | 0.016 | 0.017 | | |
| **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 | 0.010 | 0.017 | 0.018 | 0.026 | 0.028 | 0.036 | 0.040 | 0.049 | 0.058 | | |
| Marginal effects for males | 0.017 | 0.029 | 0.032 | 0.044 | 0.047 | 0.060 | 0.068 | 0.081 | 0.094 | | |
| Marginal effects for females | 0.005 | 0.008 | 0.009 | 0.013 | 0.014 | 0.019 | 0.022 | 0.027 | 0.032 | | |
| **Social Studies** | | | | | | | | | | | |
| Coefficients | 0.225*** | 0.248*** | 0.321*** | 0.304*** | 0.445*** | 0.508*** | 0.539*** | 0.620*** | 0.751*** | 49 683 | 0.089 |
| z-values | 2.930 | 3.230 | 4.430 | 4.060 | 6.200 | 7.140 | 7.480 | 8.930 | 10.920 | | |
| Average marginal effect | 0.006 | 0.007 | 0.009 | 0.009 | 0.015 | 0.018 | 0.020 | 0.025 | 0.036 | | |
| Marginal effects for males | 0.011 | 0.013 | 0.018 | 0.016 | 0.028 | 0.034 | 0.037 | 0.046 | 0.063 | | |
| Marginal effects for females | 0.003 | 0.003 | 0.004 | 0.004 | 0.007 | 0.009 | 0.010 | 0.012 | 0.018 | | |

Again, in addition to mathematics, also physics skills tend to be a strong predictor of stock market participation as people with highest physics' intelligence are holding stocks with 10.9% higher probability compared to people, whose abilities in physics are weakest. For men with best results in physics the same probability is even 12.9% higher compared to men, who tend to perform weakest in physics. These and all other probit regressions and post estimated marginal effect results are reported in Table 5.

### 5.3. Is there a difference in participation effects between men and women?

The answer is "yes" – there are remarkable differences between male and female investors' probabilities to participate in stock market, at least when this participation is dependent on mental abilities. This phenomena is hard to explain and may be one of the question to be solved by further research.

The results are presented in tables 4 and 5. Looking at the mathematics exam, we see that males and females in the lowest decile have respectively 5.2% and 1.8% smaller probability to buy stocks than people, who do not belong into this group. At the same time males showing the highest mathematical abilities have 4.9% higher probability to buy stocks than rest of the males. This compares with a 1.7% higher probability for females. The differences in these participation effects for males and females are obvious, but reason behind is difficult to find. It is impossible to explain this phenomena by the differences in exam results – on average male graduates 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 explain the multiple difference in mentioned probabilities for males and females.

Same conclusions can be made for other exams as well. For example on average male students achieve 53.7 points for their history exam (standard deviation 20.8), while females get 54.6 points for the same exam (standard deviation 21.2). Regardless the probabilities depending on mental abilities in history are still very different for males and females. Males, who fail to prove their intelligence in history tend to buy stocks with a 6.6% lower probability than these males, who are not belonging to lowest adjusted decile. Similarly same figure for females is 2.3%. When studying highest adjusted decile, we see that males in this group have 4.3% and females 1.5% higher probability to participate in the stock markets than other people. Again these differences cannot be explained by the results achieved in history exam by male and female students.

As concluded in previous chapter – on average investors are outsmarting non-participants in every field. At same time the conclusion is clearly stronger for men as their probabilities to participate in the stock market are much more dependent on their mental abilities than in case of women. In general this is also consistent with Grinblatt, Keloharju, and Linnainmaa (2011), who proved the connection between men's general mental abilities and stock market participation. Still as we showed, the picture for men and women is not so homogeneous and therefore findings by Grinblatt, Keloharju, and Linnainmaa (2011) cannot be exactly generalized also for females.

Of course the same conclusions about this interesting phenomena is also reflected in table 5, where marginal effects of higher adjusted deciles are compared to the lowest decile. We can see that in every case marginal effects for male are increasing faster than same effects for females, when moving from second adjusted decile to the highest or tenth adjusted decile. If we compare effect of mental abilities in Physics, we can see that males belonging to second adjusted decile have 2.6% higher probability to participate in the stock market than males in the first (lowest) adjusted decile. This compares to 0.7% higher probability for females. For the third adjusted decile the probabilities are 4.2% higher for males and 1.2% higher for females. Men, who achieving top results in their Physics exam tend to buy stocks with 12.9% higher probability compared to men with lowest intelligence in Physics. Same figure for women is 4.6%.

So the question remains – why the effect of mental abilities to stock market participation is lot stronger for men than for women? We are currently able to explain that just with a conclusion that men and women are different in nature.

### 5.4. Do smarter investors enter the market and trade at a "better time"?

We showed that investors tend to be clearly smarter than non-investors and given the generally positive returns of the stock market (average annual return of 11.04% for the studied period), it pays off. But the question remains, do mental abilities affect the decision when to enter the market.

Recording the first trade of each investor, we construct a heat map showing the relative proportion of investors entering the market each quarter (see Figure 1). As there are clearly proportionally more investors belonging to top academic deciles, we calculate the average participation rate for each investor decile and compare the proportion of investors belonging to a particular decile to the average proportion of that investor decile. The result gives us a heat map, which shows with darker colors the quarters for which market participation for a particular decile is relatively high and with lighter colors for which market participation is relatively low.

The overall results indicate that there is not much difference in timing the market participation (making the first trade) for investor groups with different mental abilities. We see that relative market participation has been slightly higher for the smartest decile (number 10) for the first two quarters of 2004. We basically do not see much difference between the investor groups during the boom years till the first quarter of 2007. Some difference can be noted during the second quarter of 2007 which follows the first quarter of 2007 with a very rapid growth and even a faster decline in asset prices. This scared away the smarter investors but basically didn't affect investors in the lower deciles. Although the results are not that clear, we see that new smarter investors (higher deciles) were more prone to enter the market during the crisis years and afterwards.

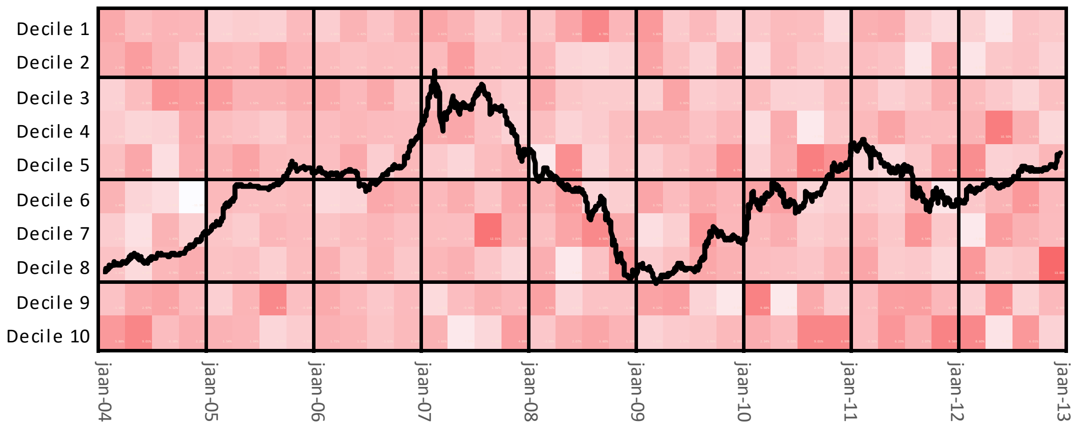


Figure 1. Dark line shows Nasdaq OMXT index movement for the period 2004-2012. Darker colors indicate the quarters for which market participation for a particular investor decile is relatively high and lighter colors indicate quarters for which market participation is relatively low. Investor deciles 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.

The overall result seems to be that there is not much difference between the investor groups during the middle and late bull market (like 2005 and 2006). It seems that smart investors had lower relative market entry probabilities during the worst times (Q1 and Q2 of 2007) but are more willing to enter the market during the later bear market and earlier bull market. It should be noted that current analysis takes into account only the first trade date and not subsequent trading. So the results do not show very clear overall differences in investor groups and clear superior timing of market entry for smarter individuals. However, analysis of overall trading activities of smarter and less smart investors presented in Figure 2 show more clearly that smarter investors did not trade that much during times which turned out to be not beneficial to their investment returns in retrospect.

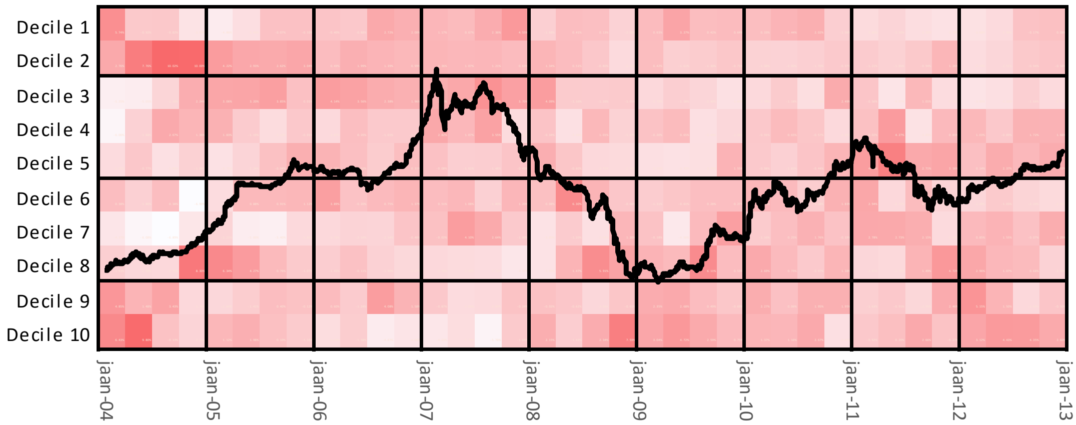


Figure 2. Dark line shows Nasdaq OMXT index movement for the period 2004-2012. Darker colors indicate the quarters for which stock trading for a particular investor decile is relatively high and lighter colors indicate quarters for which stock trading is relatively low. Investor deciles are constructed 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.

Trading activity of investor groups (presented in Figure 2) shows that smarter investors (higher deciles) were less prone to trade during the volatile times and peak of the stock market during the second half of 2006 till almost the end of 2008. However, smart investors were the ones starting to buy at the bottom of the stock market starting from the second half of 2008 till the beginning of 2010. The opposite has happened for investors with lower mental abilities (lower deciles). We see more trading activity during boom times and clearly less trading activity during the period when the market started to come out of the crisis. We also studies the proportion of sales vs the proportion of buys for all investor deciles. There is not too big differences in the proportion of sales between investor deciles. Still, we observe higher proportion of sales during the times when market fell in 2007 and clearly lower proportions after that in 2008 and 2009 when market was rebounding. The proportions indicate more or less reasonable behavior for all investor groups depending on the market movement but such proportions might also be affected by liquidity issues and trading activity of institutional investors, which we do not study in the current paper.

Still the overall conclusion is that smarter investors trade at a better time in retrospect. Studying the trading activity in combination with the proportion of sales and buys, the results show that smarter investors are more likely to buy stocks when stock prices turned out to be cheap. They are not necessarily selling stocks at the highest prices but they do not buy at times when stocks turned out to be overvalued either. Investors with lower mental abilities tend to be buying more at higher valuation and not so much when stocks are cheaper after the market has significantly fallen.

## 6. Results of portfolio performance

### 6.1. Are top academics better investors?

We study how academic factors affect the probability of being among best performing investors and test the hypothesis that investors with superior intellectual abilities can lead to outperformance. In general, the conclusion is clearly that superior intellectual abilities come with a higher probability of being among more successful investors. Still, there are certain abilities and combination of abilities that give a higher edge than others.

We start with a hypothesis that higher score in mathematics exam (which should be an indication of math abilities as there is a strong motivation for all students aspiring to go to university, to perform well at those exams) or in any other more relevant exam (mother tongue, foreign language) increases the probabilities being among outperforming investors.

To test the hypothesis, we use an ordered logistic regression model. We run the model with risk adjusted performance groups as a dependent variable and different educational factors as independent variables. We start with simple regressions to study the isolated effects of educational variables on performance and then introduce a number of control variables (demographic, wealth, experience, trading style). Finally we combine the relevant factors in multifactor models. We report the results of the most relevant factors amongst national exam results and specialties (see Table 6 for regression results and Table 7 for marginal analysis results). We have used slightly different setups for the regressions, using robust standard errors and using both logit (see Appendix C and D) and ordered logit models.

The results indicate that investors do not necessarily need to be in the top decile to have the highest marginal effect on the probability of being among the most successful investors but being in the top quartile is highly beneficial. We can see clear correlation that being in the top quartile of basically any exam performer increases the probability of being among the best investors and decreases the probability of being among worst investors. The effect is the opposite for the lowest quartile academic performers, who have relatively higher probability being among worst performing investors. It should be noted that in absolute terms, worst quartile exam results tend to have a greater effect than top quartile exam results. This means that high intellectual abilities do not help so much, but low intellectual abilities tend to be clearly undesirable as the effect is greater on the negative side.

The size of marginal effects can be quite big for certain exams. The probability of being among the best investors is about 2% higher for top quartile than for low quartile academics when considering only individual exam factors. The magnitude is the same among the worst performing investors with slightly higher marginal difference. It should be noted that "baseline" probabilities of being among our adjusted equally distributed deciles and quartiles is about 1/10 and 1/4 respectively. Under different setups (see Table 7), marginal effects can reach 6% for top quartile and 5% for bottom quartile.

The results indicate that mathematics exam results have the greatest impact on the stock market performance (top quartile odds-ratio of 1.27 and low quartile odds-ratio of 0.79). Other popular exams as mother tongue, English as a foreign language and history also have similar signs in the coefficients but slightly lower odd-ratios. Besides mathematics, other real science exams are not that popular among students and for example physics and chemistry exam results turn out to be relevant only at the 10% significance level or even worse and such effects disappear completely in other setups.

Including different control variable groups into regressions do not change the sign or magnitude of the educational factors. The choice of control variables was made based on previous literature (e.g. Grinblatt and Keloharju (2000), Dhar and Zhu (2006), Ivković, Sialm, and Weisbenner (2008), Talpsepp (2011), Grinblatt, Keloharju, and Linnainmaa (2012)) Such literature shows that demographic variables, wealth, experience and portfolio allocation affects influence trading decisions and portfolio performance.

When including continuous control variables (such as total number of transactions, average portfolio size, number of stock in the portfolio, average holding period or portfolio turnover rate), both educational factors and control variables remain significant, but the odds-ratios for control variables remains qualitatively very near to 1. The real story behind the control variables is slightly more complicated.

Feng and Seasholes (2005) suggest to use the total number of transactions as a measure of investor experience. The general positive coefficient for that indicates that more experience tends to increase success probability. On the other hand, the same variable can be considered as a proxy for trading too much (Barber and Odean (2000)). We also use the number of years an investor has been active as a proxy for experience. As for the other control variables, we divide investors into categories by the number of transactions they have made. This reveals that a very low number of transactions as well as a very high number of transactions decreases the probability of being among successful investors. To a certain point, a larger number of trades increase the success probability but the fall after that is rapid. Such a finding seems to be consistent with both of the mentioned references. The importance of experience can also been seen from the statistically significant variable which captures the number of years an investor has been active. This control variable remains significant in almost all of our different model setups. As the focus of the current study is mainly on educational factors, the description of the behavior of control variables under different model setups is kept to minimum.

Another controversy may arise from the trading frequency variable which seems to indicate that higher frequency increases success probabilities which contradicts previous literature. Current results are based on the assumption of pure effects of stock selection and thus do not take transaction costs into account, which starts to affect especially the most active investors. Our sample does not include only long term investors but also shorter term speculators.

A general conclusion from studying the type of trades the most successful investors make, is that some of the shorter term investors have been able to outperform longer term investors. This comes from the fact that investors who entered the market during the boom and were able to exit before the meltdown, made good returns and the used money-weighted-return methodology doesn't penalize those short term investors. The other contingent of successful investors comprised of those who participated in IPO offerings during the boom years and sold their positions relatively fast. Those IPOs increased significantly the number of total market participants but the following price patterns turned out to be classical post IPO returns with short term outperformance and long term underperformance. All of that affects the coefficients of the used control variables under different setups but even here the indication is that being among the most active investors is not the path to success.

The level of wealth seems to be clearly an important factor. We use average portfolio size as a proxy for wealth. When introducing the quartiles of average portfolio size in the regressions, the number of stocks in the portfolio and total number of transactions become insignificant. This is an expected result. Still, all of our educational variables remain significant in the regressions. The demographics of investors seem to favor slightly older female investors among our quite young sample.

Currently we have talked about the effect of different exam results separately. But in reality, each high school graduate has to take 3-5 state exams. Our current approach has a slight drawback, namely, when we include more than one exam in our regression model, multicollinearity starts to affect the results and most of the exams become statistically insignificant. It can be easily be assumed that students who are good at certain subject, can, in fact, be also successful at other subjects, thus the multicollinearity. To tackle the problem, we construct a new variable called “egghead”. We use the variable to represent a student who has been among top quartile for at least 2 different exams.

Next, we study two different subsamples: the smaller egghead subsample and the larger ordinary student subsample. The results are interesting: mother tongue exam (which actually means essay writing) is relevant in the egghead subsample at the 5% and mathematics exam at the 10% significance level. In the non-egghead subsample, only mathematics exam is statistically significant factor but marginal effects become clearly larger from previous 2% difference to 7% difference between the math wizards and others. Essay writing results indicate an additional 2% marginal effect difference for top quartile writers and others. Belonging to the egghead group adds about 2% marginal effect. If we require 3 or 4 top quartile exams to gain egghead membership, every other exam variable except mathematics exam become statistically insignificant in the subsample models. The highest marginal effect difference we can get is about 6%, regardless whether the egghead group member had 3 or more top quartile exams. Surprisingly, the egghead membership has stronger effect on the positive side than negative.

To simplify interpretation of the results, we also calculate annual average money-weighted returns for different type of investors. Top quartile math performers’ gain on average 14.47% (10.26% risk adjusted), bottom quartile 6.38% (5.39%) annually during the viewed period from 2004-2012. The respective gains for English exams are 15.3% (11.89%) and 6.82% (5.89%). The market index (OMX Tallinn) had annual average return of 11.05% for the period.

There could be several reasons why investors with higher mathematical abilities show good performance in the stock market. Probably the key element present among math top performers is stronger analytical skills. That can help them to better understand and analyze financial information and make more accurate analysis by having deeper understanding of the numbers. Investors with good math skills can make more rational investment decisions, decreasing the emotional component in investment decisions. However, as our subsample of eggheads shows, good math skills are not enough. To increase the probability of being among top investors, overall high mental abilities (high IQ) is needed. Under different setups, both mathematics and mother tongue (essay writing) are still significant factors among eggheads and the models imply that combining math skills with some sort of social science skills (especially mother tongue or English exam), yield the highest probability to be among best investors. As essay writing requires also constructive thinking to express one's thoughts clearly and such skills can also be considered analytical. Thus, our results seem to indicate that not only math, but also other forms of analytical abilities are greatly helpful for investors. Given the overall good exams scores required, we can clearly conclude, that high IQ is an important factor for investment success and low IQ can lead to poor stock market performance. Such findings are consistent with Grinblatt, Keloharju, and Linnainmaa (2012).

As mathematics results remain the only significant factor helping non-eggheads, math seem to be the most influential skill required. However, subsequently presented results of university degree and specialty effects show that pure mathematicians do not do as well in the stock market as more broadly equipped economics or even information technology majors.

### 6.2. Does a Ph.D. help to outperform?

We test how university degree and specialty affect performance. From single regressions, which are supported by different multiple regressions, we find that the higher the degree, the better the chances of being among top investors. It should be noted, that we combine having a master's degree with doctoral degree in the same category because of relatively small number of investors with Ph.D. degrees. Still, having a bachelor degree (or equivalent) is better than having no degree at all.

Highly intelligent people are usually more likely to pursue higher education which makes such findings not surprising. We use the same controls (demographic, experience, wealth, trading style) in the regressions for university degree and also introduce the newly formed control for eggheads (actually we also try both top and bottom quartiles of different exams as well). In all the cases university degree variables remain significant in the regressions. The only exception is when including dummies for various portfolio size categories at the same time, which turns bachelor degree insignificant. This is not the case for using a continuous variable for portfolio size. Such exception seems to be caused by the fact that one of our portfolio size dummies has higher correlation with the bachelor degree variables as university degrees are usually associated with higher income and wealth.

# Table 6.

## Ordered logistic regression model for risk-adjusted return and educational characteristics

Table 6 reports coefficients and z-values from an ordered logit regression with robust standard errors in which the dependent variable takes the value 1-4, depending on which quartile the investor belongs. We present the odds ratios to simplify interpretation. In the first column independent dummy variables are presented. The other columns present multiple regression results. Coefficients denoted with *, ** and *** are respectively significant at the 10%, 5% and 1% level.

| Independent variables | Individual variables | | High school exam results and control variables | | | | Educational level and control variables | | Education type and control variables | | All educational and control variables | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value |
| Math exam top quartile | 1.27*** | 4.58 | 1.21*** | 2.93 | | | | | | | 1.16** | 2.20 |
| Math exam bottom quartile | 0.79*** | -2.74 | | | 0.77*** | -2.59 | | | | | | |
| Physics exam top quartile | 1.20* | 1.74 | | | | | | | | | | |
| Physics exam bottom quartile | 1.25 | 0.86 | | | | | | | | | | |
| Mother tongue exam top quartile | 1.18*** | 3.71 | 1.13** | 2.14 | | | | | | | 1.12** | 2.07 |
| Mother tongue exam bottom quartile | 0.91 | -1.38 | | | 0.97 | -0.30 | | | | | | |
| English exam top quartile | 1.16*** | 3.00 | | | | | | | | | | |
| English exam bottom quartile | 0.81*** | -2.85 | | | 0.79** | -2.52 | | | | | | |
| History exam top quartile | 1.14** | 1.99 | | | | | | | | | | |
| History exam bottom quartile | 0.79** | -1.96 | | | 0.89 | -0.82 | | | | | | |
| Eggheads (high IQ top academics) | 1.21*** | 4.14 | | | | | | | | | | |
| Master’s or doctoral degree | 1.22** | 2.39 | | | | | 1.47*** | 3.97 | | | 1.43*** | 3.53 |
| Bachelor or equivalent degree | 1.17*** | 3.86 | | | | | 1.21*** | 3.92 | | | 1.13** | 2.24 |
| Degree in economics or business | 1.10** | 2.13 | | | | | | | 1.19*** | 3.08 | 1.11* | 1.83 |
| Degree in business administration | 1.40** | 2.24 | | | | | | | 1.70*** | 3.31 | 1.55*** | 2.68 |
| Degree in finance | 1.01 | 0.05 | | | | | | | 0.97 | -0.18 | | |
| Degree in information technology | 1.37*** | 3.99 | | | | | | | 1.34*** | 3.32 | 1.26** | 2.47 |
| Degree in math or statistics | 1.14 | 0.37 | | | | | | | 1.07 | 0.20 | | |
| Degree in phys. or chem. or biology | 0.95 | -0.31 | | | | | | | 0.85 | -0.87 | | |
| Degree in law | 1.03 | 0.35 | | | | | | | 1.13 | 1.08 | | |
| Degree in medicine | 1.18 | 1.09 | | | | | | | 1.19 | 1.08 | | |
| Degree in psychology | 0.82 | -0.84 | | | | | | | 1.12 | 0.44 | | |
| Male (dummy) | | | 0.92 | -1.42 | 0.93 | -1.31 | 0.93 | -1.21 | 0.93 | -1.26 | 0.93 | -1.29 |
| Birth year | | | 0.99** | -2.50 | 0.99 | -1.52 | 0.99 | -1.52 | 0.99* | -1.92 | 0.99* | -1.80 |
| Total number of transactions | | | 0.99*** | -3.41 | 0.99*** | -3.42 | 0.99* | -1.70 | 0.99*** | -3.40 | 0.99*** | -3.30 |
| Number of years active | | | 1.28*** | 9.32 | 1.28*** | 9.30 | 1.28*** | 9.11 | 1.29*** | 9.26 | 1.29*** | 9.19 |
| Average portfolio size | | | 1.01*** | 3.09 | 1.01*** | 3.00 | 1.01*** | 2.97 | 1.01*** | 3.04 | 1.01*** | 3.04 |
| Avg. number of stocks in the portfolio | | | 1.05*** | 2.42 | 1.05*** | 2.60 | 1.05*** | 2.63 | 1.05*** | 2.61 | 1.05*** | 2.32 |
| Portfolio turnover rate | | | 1.02*** | 3.37 | 1.01*** | 3.38 | 1.02*** | 3.44 | 1.02*** | 3.37 | 1.02*** | 3.30 |
| Average holding period | | | 0.99*** | -16.41 | 0.99*** | -16.70 | 0.99*** | -16.68 | 0.99*** | -16.70 | 0.99*** | -16.58 |

## Table 7.

## Marginal effect analysis for risk-adjusted return categories

Table 7 reports coefficient probabilities and z-values from a ordered logit regression marginal analysis for the discrete change in dummy variable from 0 to 1. The category y=1 represents the lowest and the category y=4 the highest risk-adjusted performance in the stock market. Coefficients denoted with *, ** and *** are respectively significant at the 10%, 5% and 1% level.

| Independent variables | y = Pr(Quartile=1) | | y = Pr(Quartile =2) | | y = Pr(Quartile =3) | | y = Pr(Quartile =4) | |
|---|---|---|---|---|---|---|---|---|
| | Coefficients (dy/dx) | z-values | Coefficients (dy/dx) | z-values | Coefficients (dy/dx) | z-values | Coefficients (dy/dx) | z-values |
| **Marginal effect for high school exam results and control variables** | | | | | | | | |
| Math exam top quartile | -3.51%*** | -3.03 | -1.25%*** | -2.72 | 1.00%*** | 3.13 | 6.35%*** | 2.85 |
| Math exam bottom quartile | 5.31%** | 2.46 | 1.32%*** | 3.30 | -1.87%** | -2.25 | -4.78%*** | -2.76 |
| Mother tongue exam top quartile | -2.26%** | -2.17 | -0.76%** | -2.06 | 0.68%** | 2.24 | 2.34%** | 2.11 |
| English exam bottom quartile | 4.68%** | 2.41 | 1.21*** | 3.06 | -1.62%** | -2.22 | -4.28%*** | -2.66 |
| **Marginal effect for education level and control variables** | | | | | | | | |
| Master’s or doctoral degree | -6.71%*** | -4.38 | -2.81%*** | -3.48 | 1.54%*** | 6.98 | 7.98%*** | 3.72 |
| Bachelor or equivalent degree | -3.70%*** | -3.87 | -1.13%*** | -3.99 | 1.18%*** | 3.73 | 3.65%*** | 3.96 |
| **Marginal effect for education type and control variables** | | | | | | | | |
| Degree in economics or business | -3.20%*** | -3.15 | -1.10%*** | -2.97 | 0.94%*** | 3.32 | 3.36%*** | 3.02 |
| Degree in business administration | -8.78%*** | -3.87 | -4.10%*** | -2.87 | 1.55%*** | 9.30 | 11.33%*** | 3.03 |
| Degree in information technology | -5.29%*** | -3.48 | -2.09%*** | -2.87 | 1.34%*** | 4.65 | 6.03%*** | 3.07 |

## Table 8.

## Ordered logit regression model for standard deviation and educational characteristics

Table 8 reports coefficients and z-values from an ordered logit regression with robust standard errors in which the dependent variable takes the value 1-4, depending on which quartile the investor belongs. We present the odds ratios to simplify interpretation. In the first column independent dummy variables are presented. The other columns present multiple regression results. Coefficients denoted with *, ** and *** are respectively significant at the 10%, 5% and 1% level.

| Independent variables | Individual variables | | High school exam results and control variables | | Educational level and control variables | | Education type and control variables | | All educational and control variables | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value |
| Math exam top quartile | 0.90** | -1.96 | | | | | | | | |
| Math exam bottom quartile | 1.05 | 0.53 | | | | | | | | |
| Physics exam top quartile | 0.79** | -2.23 | | | | | | | | |
| Physics exam bottom quartile | 0.97 | -0.14 | | | | | | | | |
| Mother tongue exam top quartile | 0.88*** | -2.79 | | | | | | | | |
| Mother tongue exam bottom quartile | 1.07 | 1.01 | | | | | | | | |
| English exam top quartile | 0.86*** | -3.11 | | | | | | | | |
| English exam bottom quartile | 1.05 | 0.60 | | | | | | | | |
| History exam top quartile | 0.87** | -2.19 | | | | | | | | |
| History exam bottom quartile | 1.04 | 0.31 | | | | | | | | |
| Geography exam top quartile | 0.64*** | -5.19 | 0.72*** | -3.27 | | | | | | |
| Geography exam bottom quartile | 1.09 | 0.40 | | | | | | | | |
| Eggheads (high IQ top academics) | | | 0.87** | -2.48 | | | | | 0.84*** | -3.20 |
| Master's or doctoral degree | 0.80*** | -2.76 | | | 0.75*** | -2.97 | | | 0.75*** | -3.02 |
| Bachelor or equivalent degree | 1.03 | 0.69 | | | 0.94 | -1.21 | | | | |
| Degree in economics or business | 1.12** | 2.41 | | | | | 1.05 | 0.92 | | |
| Degree in business administration | 0.88 | -0.86 | | | | | 0.79 | -1.27 | | |
| Degree in finance | 1.42*** | 2.68 | | | | | 1.38** | 2.06 | 1.42** | 2.31 |
| Degree in information technology | 0.89 | -1.49 | | | | | 0.91 | -1.03 | | |
| Degree in math or statistics | 1.07 | 0.21 | | | | | 0.79 | -0.63 | | |
| Degree in phys. or chem. or biology | 0.75 | -1.64 | | | | | 0.74 | -1.61 | | |
| Degree in law | 0.96 | -0.44 | | | | | 0.91 | -0.88 | | |
| Degree in medicine | 0.84 | -1.16 | | | | | 1.07 | 0.40 | | |
| Degree in psychology | 0.84 | -0.74 | | | | | 0.77 | -1.06 | | |
| Male (dummy) | | | 1.09 | 1.57 | 1.06 | 0.98 | 1.09 | 1.59 | 1.09 | 1.50 |
| Birth year | | | 1.00 | 1.30 | 0.99 | -0.29 | 1.00 | 0.91 | 1.00 | 0.28 |
| Total number of transactions | | | 0.99 | -0.46 | 0.99 | -0.46 | 0.99 | -0.41 | 0.99 | -0.38 |
| Number of years active | | | 1.71*** | 16.54 | 1.72*** | 16.84 | 1.72*** | 16.77 | 1.72*** | 16.79 |

| Independent variables | Individual variables | High school exam results and control variables | | Educational level and control variables | | Education type and control variables | | All educational and control variables | |
|---|---|---|---|---|---|---|---|---|---|
| Average portfolio size top quartile | | 0.84** | -2.46 | 0.87* | -1.89 | 0.85** | -2.25 | 0.86** | -2.04 |
| Avg. number of stocks in the portfolio | | 0.83*** | -8.92 | 0.82*** | -9.15 | 0.82*** | -9.08 | 0.82*** | -9.07 |
| Portfolio turnover rate | | 1.02* | 1.90 | 1.02* | 1.87 | 1.02* | 1.86 | 1.02* | 1.83 |
| Average holding period | | 1.01*** | 16.28 | 1.01*** | 16.48 | 1.01*** | 16.29 | 1.01*** | 16.35 |

# Table 8.

## Marginal effect analysis for portfolio risk categories

Table 7 reports coefficient probabilities and z-values from a ordered logit regression marginal analysis for the discrete change in dummy variable from 0 to 1. The category y=1 represents the lowest and the category y=4 the highest portfolio risk in the stock market. Coefficients denoted with *, ** and *** are respectively significant at the 10%, 5% and 1% level.

| **Independent variables** | **y = Pr(Quartile=1)** | | **y = Pr(Quartile =2)** | | **y = Pr(Quartile =3)** | | **y = Pr(Quartile =4)** | |
|---|---|---|---|---|---|---|---|---|
| | Coefficients (dy/dx) | z-values | Coefficients (dy/dx) | z-values | Coefficients (dy/dx) | z-values | Coefficients (dy/dx) | z-values |
| **Marginal effect for high school exam results and control variables** | | | | | | | | |
| Eggheads (high IQ top academics) | 2.57%** | 2.44 | 0.81%*** | 2.63 | -0.75%** | -2.34 | -2.62%** | -2.53 |
| Geography exam top quartile | 6.45%*** | 3.08 | 1.55%*** | 4.69 | -2.07%*** | -2.82 | -5.93%*** | -3.53 |
| **Marginal effect for education level and control variables** | | | | | | | | |
| Master’s or doctoral degree | 5.78%*** | 2.81 | 1.44*** | 4.03 | -1.83*** | -2.58 | -5.39%*** | -3.17 |
| **Marginal effect for education type and control variables** | | | | | | | | |
| Degree in finance | -5.57%** | -2.25 | -2.45%* | -1.79 | 1.22%*** | 3.46 | 6.80%* | 1.94 |

Interesting results start to reveal when conducting marginal analysis. There is about 4% marginal effect difference for master's or doctoral degree owner on both the top and bottom quartile. Depending on the model setup and when keeping different controls at their means, such effect can rise to 8% on the positive side and 7% on the negative side (see Table 7). This means that the probability of being among top performers is about 7% higher for master's and doctoral degree holder than for other investors. The probability of being among the bottom quartile of investors is about 5% lower.

We collected all available data of university degree types earned by investors. We generalized and grouped them into different categories according to the names of university programs. Given the large number of such programs, this approach can yield slight misclassifications but we are definitely able to distinguish between different fields. Our results show that economics (either economics, finance, business administration or those combined) seems to be good for stock market performance. Another specialty being immune to any other controls in the various regressions and showing very clear positive effect is information technology.

Neither mathematics; physics; law; medicine; and any of the other social science specialties seem to be significant. Even pure finance programs did not turn out to be significant in the models as we use risk adjusted performance and finance majors turn out to be among the highest risk takers who do not fully get compensated for risk[15]. The general tendency seems to be that certain social science specialties can even have slightly negative statistically significant effect but those specialties are not well represented among our investors and thus we do not present such results.

We also calculate nominal and risk adjusted returns in absolute terms. Holding bachelor degree; master's or doctoral degree; or degree in economics; information technology; or business administration, results in annual average return of 14.28%, 15.33%, 15.92%, 18.08% and 13,11% respectively. Corresponding risk-adjusted returns are 12.39%, 11.32%, 12.57%, 13.68% and 12.68% compared to 11.05% of market index.

The coefficients of the abovementioned specialties remain significant in most of the regressions. Robustness of the effect of information technology and business administration is especially clear, although economics variable is not that robust to some of the setups probably because of its heterogeneous consistence. We study separately the educational choices of investors from high school to university to find that the choices are rational and investors with

[15] We provide risk related results in the next section.

higher IQ-s have the highest probability of being among information technology or any of the economics related specialties. Clearly students from science-oriented high schools move to real sciences at the universities as well, but it does not seem to favor their future path to the stock market nor success there. Still, when using the subsample of eggheads and non-eggheads; and using various setups that include controls for intellectual abilities and exam results, the specialties: economics or business and information technology seem to positively affect the probability of being among the top investors. Those results confirm our findings that even high intellectual abilities alone are not sufficient to give the biggest push to achieving top returns in stock market.

The reason why investors holding a university degree achieve higher risk-adjusted returns in the stock market can be connected with their higher intellectual abilities which are further enhanced during their university student years, regardless of what specifically they study. Higher intellectual abilities come with potential for analyzing financial markets and company's financial performance. We draw a conclusion that higher level of education helps investors to make more rational investment decisions. The same view is supported by Grinblatt, Keloharju, and Linnainmaa (2012).

We present clear results that performance in the stock market is not only affected by the level of education, but also the type of the education. We conduct a detailed review of the curriculum of the most popular economics and business programs and it shows that investors graduating from those majors are educated more in micro- and macroeconomics, investment analysis, business management and financial markets. It should all contribute to the deeper understanding of the financial markets and investment decisions and improve financial analysis skills. They should be less affected by behavioral biases and emotional decisions and are more aware of the investment and portfolio management concepts. This view is supported by Nguyen and Schuessler (2012), who argue that higher level of education reduces significantly behavioral biases.

It is interesting that individuals holding a degree in information technology achieve higher risk-adjusted returns than investors with no such degree. Their discipline forces them to systematic and analytical every-day thinking which should be beneficial for investing. Students of information technology get some advanced math and statistics courses which can help them, although pure mathematicians and statisticians do not seem to benefit from such knowledge. Given the higher education choice of the best high school students and previous results, where the combination of math skills and some social science or constructive thinking skills were required to perform well, the benefits of studying information technology might not be that surprising. Higher income of such investors might be one of the reasons as our proxy for income and wealth is not perfect. On the other hand, medicine and law both attract talented students and come with higher income, but neither of them turn out to be significant in any of the models. This seems to support our story that math skills are very important, but going into too quantitative grounds does not help individual investors.

### 6.3. Robustness checks

To verify the robustness of our results and used proxies, we have taken a number of steps. We estimate the ordered logistic regression models also for Jensen alpha and Sharpe ratio, which could be seen as alternative measures of risk-adjusted performance. We use the same model setup as for the RAP model and the results confirm our prior findings of the importance of math skills and overall high intelligence.

We also use logit regressions (see Appendix C and D) instead of ordered logit although the latter should be preferred for the task. The results of logit regressions confirm the presented results. In case of using logit regressions, we need to run a regression separately for every performance group and can compare the obtained coefficients along with standard errors. For example, one could expect that overall intelligence decreases monotonically the probability of being among below average performing investors when moving from the middle categories to the bottom categories and increasing probability when moving to the opposite direction. In most cases, that is exactly what comes out of the regressions, but when using deciles (see Appendix D) the results can be more mixed because of relatively narrow groups and using equally divided groups. When using quartiles, the results are more robust and thus we present mostly quartile results in this paper.

The covered time span includes a full business cycle with changing bull and bear market periods. The question remains, whether better educated highly intelligent investors are able to perform well during both the bull market and bear market. We utilize a panel data approach to deal with that. We calculate the required metrics now for each of the years in our sample and run random effects ordered panel logit model for that (see Appendix A). As the same results are still there, we conclude that the choice of periods and methodology does not change the main findings presented in this section. The main difference is that the effects of higher education become statistically weaker.

When using control variables, we use continuous variables and also divided certain controls (e.g. total number of trades made) into categories. This approach helps to reveal some of the otherwise hidden characteristics, such as that low number of trades probably means less experience but too high number of trades is already overtrading. To not to let us fooled by the prioritized proxy variables alone (e.g. we controlled for other trading frequency related variables such as portfolio turnover), different proxies are also used (e.g. average holding period, number of purchases made, number of sales made, total stock days in the portfolio etc). In addition to total portfolio size, we could control for average transaction size of both the purchases and sales. To capture experience, we tried other proxies such as whether the investor has ever faced large realized or paper gains or losses or how many years of experience an investor has. Our final choice of control variables is very similar to Grinblatt, Keloharju, and Linnainmaa (2012).

## 7. Results of risk-taking

### 7.1. Are more intelligent investors more risk averse?

We test the hypothesis that more intelligent investors are more risk averse in the stock market. We calculate portfolio level standard deviation for each investor for the viewed period and divide investors into deciles and quartiles based on their portfolio level risk. The top quartile (decile) contains investors with the highest and the bottom quartile (decile) with the lowest level of risk. This enables us to use methodologically the same approach as for studying portfolio performance. Risk level groups become dependent variable in the ordered logistic regressions and educational characteristics are used as independent variables along with the same choice of control variables (demographic, experience, wealth, trading style).

We run a number of single regressions with different exam results as independent variables (see Table 8). The results are similar for all major exams - the best performing academics tend to be among investors who take less risk. Odds ratios for top quartile academics are less than 1 and statistically significant. The same is true also for investors who belong to our “egghead” assembly (defined in the previous section), irrelevant of how high we set the hurdle to be in that group.

When studying marginal effects of different exams (see Table 9), the results are usually in the same magnitude as for performance results. This means that the probability of top quartile academics being among low quartile risk takers is about 3% higher than for less academically equipped investors. The probability being among high risk takers is in the same magntitude lower. The only outlier here seems to be geography top performers who have clearly increased probability (marginal effect difference of about 9% which decreases to about 6% in the presented setup) of being among low risk takers and similarly decreased probability of being among high risk takers. Similar anomaly (the same sign but higher effect than the rest of the sample) seemed to be present for geography exam takers when studying market participation for the same sample. We have hypothesized about possible special properties of those 937 geography exam takers but have not found any fundamental plausible reason what could make them special among the rest of the sample. The most plausible reason could be that geography exam takers are the ones, who possess natural curiosity in the world around us. We would not emphasize the effect of geography exam.

To give a picture what the educational effects mean in absolute terms, we calculated average annual standard deviations for different investor groups. Given the relatively small market and including also volatile periods, average standard deviation of investors' portfolios is around 46%, which is a quite high number. For the best academics, this figure is mostly between 42-44%. Those figures confirm the results obtained from marginal analysis that the high school exam top performers are more risk averse.

Introducing controls in the exam results related regressions does not change the sign or magnitude of the previously mentioned effects. As expected, investors with larger portfolios seem to take less risk, higher turnover and more trading yields higher risk. The main difference from performance results is that only the largest quartile of portfolio is significant in the regressions. Usually larger portfolio is associated with larger number of investments and we also control for that. When including both portfolio size and number of investments in the portfolio, only the latter is statistically significant. Closer investigation reveals that only investors with the largest portfolio seem to take less risk when controlling for diversification. This could be caused by the relatively small size of an average investor which means that the portfolio grown larger in absolute terms only in the largest quartile.

Diversifying portfolio with more different stocks reduces risks. Once again, demographic variables do not turn out to be significant in our models. One of the reasons for that can be the fact that although generally women tend to outperform and take less risk than men (Barber and Odean (2001); Dwyer, Gilkeson, and List (2002); and Talpsepp (2010) for the same market), our descriptive statistics and market participation results already show that women achieve better results in the exams. Thus, when including a gender dummy in the regressions is outweighed by the use of educational characteristics, which already contain some of that information. As our sample is quite young, age differences tend to be still relatively small regardless whether we use continuous control variable of discrete age groups.

Many of our findings confirm prior results noted by different authors. We see from the control variables that investors having higher portfolio diversification of stock are experiencing lower standard deviation. Additionally, we present empirical evidence that investors trading very actively (having the total number of transactions over 100 and belonging to highest portfolio turnover rate quartile) are experiencing higher risk, which is in line with the findings of Odean (1998). In addition, we show that investors having a larger portfolio, which is proxy for wealth, are more risk averse compared to investors with smaller portfolio. Those findings confirm the findings of Goetzmann and Kumar (2008) and Grinblatt, Keloharju, and Linnainmaa (2011).

The reasons behind the lower risk level of investors with higher intellectual abilities can be better portfolio diversification as our analysis confirmed that academically best performing investors hold more diversified portfolios. Our findings are in line with Goetzmann and Kumar (2008), who suggest that investors holding under diversified stock portfolios experience higher volatility and risk in stock market. As higher high school exam results can be seen as proxy for higher intelligence then those findings are also in in line with the conclusion of Grinblatt, Keloharju, and Linnainmaa (2011), who found that with higher IQ are more likely to hold large number of stocks and experiencing lower risk.

### 7.2. Do universities teach risk taking?

We also test how university degree and specialty affect risk taking in the stock market. Some of our results are similar to the findings of the stock market performance but we are able to offer some interesting insights.

There seems to be a negative effect of a higher university degree on risk taking. Our results show that investors with master's or doctoral degree are more likely to belong among investors with lower level of risk. But we do not see any statistically significant effect of holding a bachelor degree or equivalent. Marginal effects of such characteristics are alightly larger than the effects of exam results (6% difference in probabilities for both the top and the bottom quartile). As obtaining master's and doctoral degree compared to bachelor degree probably require more effort, as well as mental abilities and intelligence, the findings support our hypothesis that investors with higher IQ can be associated with less risky portfolio. Those findings are in line with conclusion by Grinblatt, Keloharju, and Linnainmaa (2011) who demonstrate that investors with higher IQ are more likely to hold mutual funds and large number of stocks and therefore experiencing lower risk. They add that low IQ-investors are likely to experience excess volatility, because of poor diversification or poor choice of factor exposure.

More interesting results are revealed when analyzing the effects of university specialties. Only two of the large number of specialties turns out to be statistically significant and both have a positive effect on risk taking. Our results show that investors who have studied economics or business (including financial economics and management) and finance tend to take higher risks in the stock market. Finance specialty is significant at the 1% significance level and economics specialty at the 5% level. Marginal effects of especially finance are clear and strong (reaching 7%). This means that investors holding finance degrees have 7% higher probability of being among highest quarter of risk takers than others or 6% decreased probability of being among risk averse investors. Once again, adding different controls into the regressions does not change the results.

In absolute terms it means an average annual portfolio standard deviation of about 44% for master's or doctoral degree holders; 47.3% for economics majors; and 49% standard deviation for finance majors.

It is an interesting finding that investors holding a university degree in economics or finance are more risk seeking in the stock market. Those investors should have a better understanding of the financial markets and portfolio risk concept and therefore they might intentionally take more risk to achieve greater returns in the stock market.

To get a better picture of the connections between risk taking and performance, we analyze relations between risk taking behavior and risk-adjusted performance. We find that investors holding a degree in economics show an average of 15.92% annual return and 12.57% risk adjusted return. The benchmark index return is 11.05%. Investors holding a finance degree show a stunning 20.69% annual return but because of riskier portfolios, their risk adjusted return is 11.93%. It should be noted that those figures are averages over the investor groups and have not been adjusted for transaction costs.

Those nominal and risk-adjusted returns show clearly that the investors holding degree in economics and finance outperform market benchmark index during the full business cycle. This means that it is not just pure luck, but deliberate portfolio management and stock picking, which contributes to the superior performance. Based on this, we conclude that investors holding a degree in economics and finance intentionally take more risk in the stock market to achieve greater nominal returns compared to investors with no such university degree. The reason behind is deeper and better knowledge of the financial markets as well as better understanding of risk and portfolio management concepts. This finding also explains the results found by Grable (1998), who concludes that education appears to encourage risk taking, because increased level of attained academic training allows individuals to assess risk and benefits more carefully then someone with less education. The conclusion is also in line with the finding of Dwyer, Gilkeson, and List (2002), who argue that better financial knowledge contributes to the higher risk taking. Our results help to fill the gap in literature where higher intellectual abilities are associated with less risk taking (e.g. Grinblatt, Keloharju, and Linnainmaa (2011)) and higher education with more risk taking (e.g. Grable (1998) and Dwyer, Gilkeson, and List (2002)). Our results show that in fact higher university degrees (master's and doctoral) can be associated with less risk taking but higher education in finance specialized fields clearly encourages risk taking.

### 7.3. Robustness checks

In addition to the presented ordered logit model, we estimate logit model for robustness check purpose. Results on individual level as well as with control variables do not differ from ordered logit regression model results (see Appendix E). Besides quartile categorization of dependent variables we use decile categorization for standard deviation. The results from decile categorization do not differ on individual as well on combined model with control variables from the quartile grouped ordered logit regression model and thus are even clearer than performance related results.

We also run random effects panel ordered logit model on risk metrics calculated based on yearly periods (see Appendix B). Those results are also in line with our presented results, although coefficients of exam related variables are not statistically significant in our model, higher levels of education and finance specialty are still statistically significant with the similar effect as previously described.

## 8. Conclusion

Previous literature points to the conclusions that investors are smarter than non-investors in sense of better education and cognitive abilities. Due to the lack of appropriate data, these conclusions remain somewhat perfunctory and it is not clear how the level of skills in different areas influences stock market participation, performance and risk taking. We are decreasing this gap with the current study.

We find strong and broad evidence that stock market participation depends on mental abilities in very different areas. Investors are better mathematicians, better historians, better philologists and they have also better understanding of natural sciences. We also find clear evidence that people with higher mental abilities tend to participate more likely in the stock market. We find that basically in all cases probabilities to buy stocks increases monotonically together with mental abilities. The effect of mental abilities on stock market participation is much stronger for males than for females. This is an important finding and again improves the knowledge offered by previous literature.

Our results show that investors with higher mental abilities generally have higher risk adjusted return in the stock market. Better mathematical skills are clearly beneficial to be more successful investor, but combining math skills with good results in other fields (meaning overall high achievement or IQ) are even more beneficial. In addition, we find that investors holding higher degrees (master’s or doctoral) outperform investors with lower degrees (bachelor and equivalent) who in turn outperform others. We demonstrate that a university degree in economics and business administration or in information technology seem to increase the probability of being among the most successful investors.

We find that investors with top performance in national exam high school exams and high mental abilities are more risk averse. The same is true for investors with master’s or doctoral degree. The finding that investors holding a university degree in economics or finance are more risk seeking helps to shed more light on how higher mental abilities and university degree explains risk taking. We conclude that in general higher IQ and university degree reduce risk taking but specialized finance or economics related degrees encourage intentional risk taking to achieve higher nominal returns.

## References


1. Amromin, Gene, and Sharpe Steven, 2009, *Expectations of Risk and Return among Household Investors: Are Their Sharpe Ratios Countercyclical?* (Board of Governors of the Federal Reserve System Working Paper.).
2. Barber, B. M., and T. Odean, 2007, All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors, *Review of Financial Studies* 21, 785–818.
3. Barber, BM, and T Odean, 2001, Boys will be boys: Gender, overconfidence, and common stock investment, *The Quarterly Journal of Economics* 116, 261–292.
4. Barber, BM, and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *Journal of Finance* 55, 773–806.
5. Barnea, Amir, Henrik Cronqvist, and Stephan Siegel, 2010, Nature or nurture: What determines investor behavior?, *Journal of Financial Economics* 98, 583–604.
6. Bayer, Patrick J., B. Douglas Bernheim, and John Karl Scholz, 2009, The Effects of Financial Education in the Workplace: Evidence From a Survey of Employers, *Economic Inquiry* 47, 605–624.
7. Bernheim, B.Douglas, and Daniel M Garrett, 2003, The effects of financial education in the workplace: evidence from a survey of households, *Journal of Public Economics* 87, 1487–1519.
8. Bogan, Vicki, 2008, Stock Market Participation and the Internet, *Journal of Financial and Quantitative Analysis* 43, 191–212.
9. Bricker, Jesse, Arthur B. Kennickell, Kevin B. Moore, and John Sabelhaus, 2012, Changes in US family finances from 2007 to 2010: Evidence from the Survey of Consumer Finances, *Federal Reserve Bulletin* 98.
10. Calvet, Laurent E., John Y. Campbell, and Paolo Sodini, 2007, Down or Out: Assessing the Welfare Costs of Household Investment Mistakes, *Journal of Political Economy* 115, 707–747.
11. Campbell, John Y., 2006, Household finance, *The Journal of Finance* 61, 1553–1604.
12. Christiansen, C., J. S. Joensen, and J. Rangvid, 2008, Are Economists More Likely to Hold Stocks?, *Review of Finance* 12, 465–496.
13. Coval, JD, and Tyler Shumway, 2005, Do behavioral biases affect prices?, *Journal of Finance* 60, 1–34.
14. Dhar, Ravi, and Ning Zhu, 2006, Up close and personal: Investor sophistication and the disposition effect, *Management Science* 52, 726–740.
15. Dijk, Jouke van, and Piet H. Pellenbarg, 2000, Firm relocation decisions in The Netherlands: An ordered logit approach, *Papers in Regional Science* 79, 191–219.
16. Dwyer, Peggy D., James H. Gilkeson, and John a. List, 2002, Gender differences in revealed risk taking: evidence from mutual fund investors, *Economics Letters* 76, 151–158.
17. Feng, Lei, and Mark S. Seasholes, 2005, Do Investor Sophistication and Trading Experience Eliminate Behavioral Biases in Financial Markets?, *Review of Finance* 9, 305–351.
18. Gelman, Andrew, and Jennifer Hill, 2007, *Data Analysis Using Regression and Multilevel/Hierarchical Models (Google eBook)* (Cambridge University Press).

19. Goetzmann, W. N., and a. Kumar, 2008, Equity Portfolio Diversification, *Review of Finance* 12, 433–463.
20. Gottesman, AA, and MR Morey, 2006, Manager education and mutual fund performance, *Journal of Empirical Finance* 13, 145–182.
21. Grable, JE, 1998, Investor risk tolerance: Testing the efficacy of demographics as differentiating and classifying factors, *Financial Counseling and Planning* 9, 61–74.
22. Greene, William, 1997, Econometric analysis, 3rd ed., 672–676.
23. Grinblatt, Mark, and Matti Keloharju, 2000, The investment behavior and performance of various investor types: a study of Finland's unique data set, *Journal of Financial Economics* 55, 43–67.
24. Grinblatt, Mark, and Matti Keloharju, 2001, What Makes Investors Trade?, *Journal of Finance* 56, 589–616.
25. Grinblatt, Mark, Matti Keloharju, and Juhani T. Linnainmaa, 2011, IQ and stock market participation, *The Journal of Finance* 66, 2121–2164.
26. Grinblatt, Mark, Matti Keloharju, and Juhani T. Linnainmaa, 2012, IQ, trading behavior, and performance, *Journal of Financial Economics* 104, 339–362.
27. Guiso, L, M Haliassos, and T Jappelli, 2003, Household stockholding in Europe: where do we stand and where do we go?, *Economic Policy* 18, 127–170.
28. Guiso, Luigi, and Tullio Jappelli, 2005, Awareness and stock market participation, *Review of Finance* 9, 537–567.
29. Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2008, Trusting the stock market, *The Journal of Finance* 63, 2557–2600.
30. Haliassos, M, and CC Bertaut, 1995, Why do so few hold stocks?, *Economic Journal*, 1110–1129.
31. Hilgert, Marianne A, Jeanne M Hogarth, and Sondra G Beverly, 2003, Household financial management: the connection between knowledge and behavior, *Federal Reserve Bulletin*, 309–322.
32. Hoffmann, Arvid O.I., Thomas Post, and Joost M.E. Pennings, 2013, Individual investor perceptions and behavior during the financial crisis, *Journal of Banking & Finance* 37, 60–74.
33. Hong, Harrison, JD Kubik, and JC Stein, 2004, Social interaction and stock-market participation, *Journal of Finance* 59, 137–163.
34. Ivković, Zoran, Clemens Sialm, and Scott Weisbenner, 2008, Portfolio Concentration and the Performance of Individual Investors, *Journal of Financial and Quantitative Analysis* 43, 613–655.
35. Jensen, Michael C., 1968, The performance of mutual funds in the period 1945-1964, *The Journal of Finance* 23, 389–416.
36. Kaustia, Markku, and Sami Torstila, 2011, Stock market aversion? Political preferences and stock market participation, *Journal of Financial Economics* 100, 98–112.
37. Kumar, A, 2009, Who gambles in the stock market?, *The Journal of Finance* 64, 1889–1933.
38. Lusardi, Annamaria, 2003, Saving and the effectiveness of financial education, *Journal of Financial Transformation*, 159–169.
39. Lusardi, Annamaria, and Olivia S. Mitchell, 2008, Planning and Financial Literacy: How Do Women Fare?, *American Economic Review* 98, 413–417.
40. Malmendier, U., and S. Nagel, 2011, Depression Babies: Do Macroeconomic Experiences Affect Risk Taking?, *The Quarterly Journal of Economics* 126, 373–416.
41. Markowitz, HM, 1991, Foundations of portfolio theory, *The Journal of Finance* 46, 469–477.

42. Modigliani, Franco, and Leah Modigliani, 1997, Risk-Adjusted Performance, *The Journal of Portfolio Management* 23, 45–54.
43. Nguyen, Tristan, and Alexander Schuessler, 2012, Investment Decisions and Socio-demographic Characteristics – Empirical Evidence from Germany, *International Journal of Economics and Finance* 4, 1–12.
44. Odean, Terrance, 1998, Do Investors Trade Too Much?, *American Economic Review* 89, 1279–1298.
45. Rooij, Maarten Van, Annamaria Lusardi, and Rob Alessie, 2011, Financial literacy and stock market participation, *Journal of Financial Economics* 101, 449–472.
46. Rooij, van Maarten, Annamaria Lusardi, and Rob Alessie, 2012, Financial Literacy, Retirement Planning and Household Wealth, *The Economic Journal* 122, 449–478.
47. Sharpe, WF, 1966, Mutual fund performance, *Journal of Business* 39, 119–138.
48. Talpsepp, Tõnn, 2010, Does Gender and Age Affect Investor Performance and the Disposition Effect?, *Research in Economics and Business: Central and Eastern Europe* 2, 76–93.
49. Talpsepp, Tõnn, 2011, Reverse Disposition Effect of Foreign Investors, *Journal of Behavioral Finance* 12, 183–200.
50. Weber, M., E. U. Weber, and a. Nosic, 2012, Who takes Risks When and Why: Determinants of Changes in Investor Risk Taking, *Review of Finance* 17, 847–883.
51. Vissing-Jørgensen, Annette, 2003, Perspectives on Behavioral Finance : Does " Irrationality " Disappear with Wealth ? Evidence from Expectations and Actions, *NBER Macroeconomics Annual 2003* 18, 139–194.

**Appendix A.** Panel ordered logit for performance and educational characteristics.

Table reports odds ratios and z-values for panel ordered logit regressions. Dependent variable is risk adjusted portfolio return, which is divided into four equally sized adjusted quartiles. Odds ratio > 1 means that factor affects the probability of being among best performers positively; odds ratio < 1 means negative effect. Frequency of observations is 1 year. Coefficients denoted with *, ** and *** are respectively significant at the 10%, 5% and 1% level.

| | Educational individual variables and control variables | | | | | | | | | | | | Education level and control variables | | Education type and control variables | | All educational and control variables | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value |
| Math exam top quartile | 1.09** | 2.38 | | | | | | | | | | | | | | | 1.07** | 1.98 |
| M. tongue exam top quartile | | | 1.05* | 1.76 | | | | | | | | | | | | | | |
| M. tongue exam bottom quartile | | | | | 0.91** | -2.05 | | | | | | | | | | | | |
| English exam top quartile | | | | | | | 1.08** | 2.27 | | | | | | | | | | |
| English exam bottom quartile | | | | | | | | | 0.92* | -1.68 | | | | | | | | |
| Eggheads (high IQ top academics) | | | | | | | | | | | 1.07** | 2.23 | | | | | | |
| Master's or doctoral degree | | | | | | | | | | | | | 1.08* | 1.65 | | | 1.06 | 1.12 |
| Bachelor or equiv. degree | | | | | | | | | | | | | 1.05* | 1.74 | | | 1.02 | 0.64 |
| Degree in economics | | | | | | | | | | | | | | | 1.06** | 1.98 | 1.05* | 1.79 |
| Degree in business | | | | | | | | | | | | | | | 0.91 | -1.2 | | |
| Degree in IT | | | | | | | | | | | | | | | 1.13** | 2.46 | 1.12** | 2.25 |
| Male | 0.99 | -0.55 | 0.99 | -0.33 | 0.99 | -0.25 | 0.99 | -0.43 | 0.99 | -0.35 | 0.99 | -0.44 | 0.99 | -0.36 | 0.99 | -0.55 | 0.99 | -0.52 |
| Birth year | 1.00** | -2.4 | 1.00** | -2.24 | 1.00* | -1.89 | 1.00** | -2.36 | 1.00* | -1.9 | 1.00** | -2.4 | 1.00* | -1.9 | 1.00* | -1.9 | 1.00* | -1.7 |
| Average portfolio size | 1.00** | 2.34 | 1.00** | 2.33 | 1.00** | 2.32 | 1.00** | 2.32 | 1.00** | 2.32 | 1.00** | 2.33 | 1.00** | 2.27 | 1.00** | 2.28 | 1.00** | 2.24 |
| Avg. num. stocks in portfolio | 1.04*** | 3.91 | 1.04*** | 3.98 | 1.04*** | 3.96 | 1.04*** | 4 | 1.04*** | 3.97 | 1.04*** | 3.93 | 1.04*** | 3.95 | 1.04*** | 3.98 | 1.04*** | 3.88 |
| Portfolio turnover rate | 1.00*** | 3.52 | 1.00*** | 3.5 | 1.00*** | 3.53 | 1.00*** | 3.54 | 1.00*** | 3.52 | 1.00*** | 3.51 | 1.00*** | 3.54 | 1.00*** | 3.43 | 1.00*** | 3.48 |
| Average holding period | 1.00*** | 7.29 | 1.00*** | 7.29 | 1.00*** | 7.27 | 1.00*** | 7.26 | 1.00*** | 7.29 | 1.00*** | 7.28 | 1.00*** | 7.27 | 1.00*** | 7.27 | 1.00*** | 7.24 |

**Appendix B.** Panel ordered logit for risk taking and educational characteristics.

Table reports odds ratios and z-values for panel ordered logit regressions. Dependent variable is portfolio risk, which is divided into four (ten) equally sized adjusted quartiles (deciles). Odds ratio > 1 means that factor affects the probability of being among more risk takers positively; odds ratio < 1 means negative effect. Frequency of observations is 1 year. Coefficients denoted with *, ** and *** are respectively significant at the 10%, 5% and 1% level.

| | High school exam results and control variables | | | | Educational level and control variables | | | | Education type and control variables | | | | All educational and control variables | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Quartile | | Deciles | | Quartile | | Deciles | | Quartile | | Deciles | | Quartile | | Deciles | |
| | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value | Odds ratio | z-value |
| Eggheads (high IQ top academics) | 0.96 | -1.12 | 0.95 | -1.34 | | | | | | | | | 0.95 | -1.31 | 0.94 | -1.53 |
| Master's or doctoral degree | | | | | 0.77*** | -4.26 | 0.78*** | -4 | | | | | 0.77*** | -4.26 | 0.78*** | -4.02 |
| Bachelor or equivalent degree | | | | | 0.95 | -1.39 | 0.96 | -1.17 | | | | | 0.96 | -1.15 | 0.97 | -0.89 |
| Degree in economics | | | | | | | | | 1.01 | 0.33 | 1.02 | 0.44 | | | | |
| Degree in finance | | | | | | | | | 1.21** | 1.96 | 1.21* | 1.95 | 1.20** | 1.98 | 1.21** | 1.99 |
| Degree in Business Administration | | | | | | | | | 0.87 | -1.23 | 0.88 | -1.12 | | | | |
| Degree in information technology | | | | | | | | | 0.96 | -0.67 | 0.96 | -0.7 | | | | |
| Male | 1.05 | 1.23 | 1.05 | 1.24 | 1.03 | 0.83 | 1.03 | 0.86 | 1.05 | 1.43 | 1.06 | 1.45 | 1.04 | 1.12 | 1.04 | 1.16 |
| Birth year | 1.00 | 1.16 | 1.00 | 1.59 | 1.00* | 1.68 | 1.00*** | 2.6 | 1.00 | 1.24 | 1.00* | 1.72 | 1.00 | 1.55 | 1.00** | 2.3 |
| Number of years active | 1.07*** | 3.77 | 1.09*** | 4.53 | 1.07*** | 3.87 | 1.09*** | 4.62 | 1.07*** | 3.78 | 1.09*** | 4.54 | 1.07*** | 3.87 | 1.09*** | 4.62 |
| Average portfolio size top quartile | 0.88*** | -2.95 | 0.88*** | -2.99 | 0.90** | -2.43 | 0.90** | -2.48 | 0.88*** | -2.88 | 0.88*** | -2.92 | 0.90** | -2.47 | 0.90** | -2.54 |
| Avg. number of stocks in the portfolio | 0.86*** | -12.09 | 0.86*** | -12.07 | 0.86*** | -12.19 | 0.86*** | -12.18 | 0.86*** | -12.17 | 0.86*** | -12.17 | 0.86*** | -12.19 | 0.86*** | -12.16 |
| Portfolio turnover rate | 1.00*** | 3.89 | 1.00*** | 4.28 | 1.00*** | 3.84 | 1.00*** | 4.24 | 1.00*** | 3.89 | 1.00*** | 4.29 | 1.00*** | 3.86 | 1.00*** | 4.25 |
| Average holding period | 1.00*** | 11.02 | 1.00*** | 11.11 | 1.00*** | 11.17 | 1.00*** | 11.26 | 1.00*** | 11.01 | 1.00*** | 11.11 | 1.00*** | 11.14 | 1.00*** | 11.23 |

**Appendix C.** Logit regressions by quartile for the period 2004-2012: performance and educational characteristics.

Table reports odds ratios for logit regressions run for every risk-adjusted performance quartile. Quartile 1 is associated with the lowest risk and quartile 10 with the highest portfolio risk. Dependent variable takes the value of 1 if investor belongs to the specified quartile. If odds ratio > 1, it means increased probability of belonging to the particular group because of the factor. Coefficients denoted with *, ** and *** are respectively significant at the 10%, 5% and 1% level.

| | Quartile 1 | Quartile 2 | Quartile 3 | Quartile 4 | Quartile 1 | Quartile 2 | Quartile 3 | Quartile 4 |
|---|---|---|---|---|---|---|---|---|
| | With controls | | | | Without controls | | | |
| Math exam top quartile | 0.80*** | 0.87 | 1.14* | 1.17** | 0.83*** | 0.82*** | 1.17** | 1.20*** |
| Master's or doctoral degree | 0.66*** | 0.98 | 1.18 | 1.44*** | 0.58*** | 1.12 | 1.24* | 1.20 |
| Bachelor or equivalent degree | 0.87** | 0.95 | 1.07 | 1.19*** | 0.80*** | 1.03 | 1.12** | 1.09 |
| Degree in economics | 0.92 | 1.00 | 0.95 | 1.15* | 0.93 | 1.04 | 0.93 | 1.11* |
| Degree in information technology | 0.86 | 0.87 | 0.99 | 1.31** | 0.80** | 0.74*** | 1.22** | 1.28** |
| Male | 1.09 | 0.90 | 1.17** | 0.90 | | | | |
| Birth year | 1.00 | 1.00 | 1.01 | 1.00 | | | | |
| Total number of transactions | 0.97*** | 1.02*** | 1.01*** | 0.98*** | | | | |
| Number of years active | 0.75*** | 0.70*** | 1.15*** | 1.77*** | | | | |
| Average portfolio size | 1.00* | 1.00** | 1.00* | 1.00** | | | | |
| Avg. number of stocks in the portfolio | 0.84*** | 1.07** | 1.13*** | 1.00 | | | | |
| Portfolio turnover rate | 1.07*** | 0.95*** | 0.97*** | 1.03*** | | | | |
| Average holding period | 1.00** | 1.00*** | 1.00*** | 1.00*** | | | | |

**Appendix D.** Logit regressions by deciles for the period 2004-2012: performance and educational characteristics.

Table reports odds ratios for logit regressions run for every risk-adjusted performance decile. Decile 1 is associated with the lowest risk and decile 10 with the highest portfolio risk. Dependent variable takes the value of 1 if investor belongs to the specified quartile. If odds ratio > 1, it means increased probability of belonging to the particular group because of the factor. Coefficients denoted with *, ** and *** are respectively significant at the 10%, 5% and 1% level.

| **Panel A** | With control variable | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Decile 1 | Decile 2 | Decile 3 | Decile 4 | Decile 5 | Decile 6 | Decile 7 | Decile 8 | Decile 9 | Decile 10 |
| Math exam top quartile | 0.71*** | 1.10 | 0.75** | 0.88 | 0.92 | 1.06 | 1.12 | 1.19 | 1.05 | 1.10 |
| Master's or doctoral degree | 0.65* | 0.70 | 0.77 | 1.35 | 0.91 | 0.81 | 1.48** | 1.28 | 1.84*** | 1.14 |
| Bachelor or equivalent degree | 0.94 | 0.89 | 0.84* | 1.17 | 0.90 | 1.10 | 1.08 | 1.25** | 1.15 | 1.05 |
| Degree in economics | 0.98 | 0.98 | 0.92 | 0.86 | 1.06 | 1.00 | 0.86 | 1.02 | 1.19* | 1.14 |
| Degree in information technology | 0.74* | 1.05 | 0.99 | 1.21 | 0.62** | 0.95 | 0.92 | 1.10 | 1.39** | 1.24 |
| Male | 1.37*** | 0.91 | 0.81** | 0.94 | 0.97 | 1.09 | 1.10 | 1.22* | 0.89 | 0.88 |
| Birth year | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.03*** | 1.02*** | 0.98*** |
| Total number of transactions | 0.96*** | 0.98** | 0.99 | 1.01** | 1.02*** | 1.01 | 1.01*** | 1.01 | 1.00 | 0.96*** |
| Number of years active | 1.03 | 0.69*** | 0.70*** | 0.76*** | 0.72*** | 1.12** | 1.06 | 1.33*** | 1.58*** | 1.79*** |
| Average portfolio size | 1.00*** | 1.00*** | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00** | 1.00** | 1.00*** |
| Avg. number of stocks in the portfolio | 0.84*** | 0.97 | 0.92 | 1.13*** | 1.00 | 1.09** | 1.08** | 1.13*** | 1.09** | 0.88** |
| Portfolio turnover rate | 1.09*** | 1.05** | 1.01 | 0.96*** | 0.94*** | 0.99 | 0.97*** | 0.98 | 1.00 | 1.10*** |
| Average holding period | 1.00*** | 1.00*** | 1.00*** | 1.00*** | 1.00*** | 1.00*** | 1.00** | 1.00* | 1.00*** | 1.00*** |

| **Panel B** | Without control variables | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Decile 1 | Decile 2 | Decile 3 | Decile 4 | Decile 5 | Decile 6 | Decile 7 | Decile 8 | Decile 9 | Decile 10 |
| Math exam top quartile | 0.77** | 1.07 | 0.77** | 0.76** | 0.90 | 1.05 | 1.12 | 1.37*** | 1.22** | 0.99 |
| Master's or doctoral degree | 0.39*** | 0.74* | 0.93 | 1.64*** | 0.88 | 0.97 | 1.52*** | 1.14 | 1.24 | 1.06 |
| Bachelor or equivalent degree | 0.76*** | 0.85** | 0.97 | 1.25** | 0.89 | 1.12 | 1.17* | 1.16* | 1.01 | 0.99 |
| Degree in economics | 0.95 | 1.02 | 0.97 | 0.89 | 1.11 | 1.00 | 0.85* | 0.94 | 1.10 | 1.23** |
| Degree in information technology | 0.74* | 0.90 | 0.81 | 0.93 | 0.65** | 1.15 | 1.06 | 1.23 | 1.26* | 1.30* |

**Appendix E.** Logit regressions by quartile for the period 2004-2012: risk taking and educational characteristics.

Table reports odds ratios and z-values for logit regressions run for every risk quartile. Quartile 1 is associated with the lowest risk and quartile 4 with the highest portfolio risk. Dependent variable takes the value of 1 if investor belongs to the specified quartile. If odds ratio > 1, it means increased probability of belonging to the particular group because of the factor. Coefficients denoted with *, ** and *** are respectively significant at the 10%, 5% and 1% level.

| Independent variables | Quartile 1 | | Quartile 2 | | Quartile 3 | | Quartile 4 | |
|---|---|---|---|---|---|---|---|---|
| Eggheads (high IQ top academics) | 1.26*** | 3.21 | 0.96 | -0.54 | 0.93 | -0.97 | 0.89 | -1.62 |
| Master's or doctoral degree | 1.47** | 2.44 | 1.58*** | 3.77 | 0.80 | -1.5 | 0.57*** | -3.72 |
| Bachelor or equivalent degree | 1.08 | 1.24 | 1.01 | 0.14 | 1.06 | 0.84 | 0.89* | -1.74 |
| Degree in finance | 0.70 | -1.6 | 0.62** | -2.19 | 1.58** | 2.39 | 1.22 | 1.06 |
| Male | 0.90 | -1.39 | 1.01 | 0.15 | 1.00 | 0.06 | 1.12* | 1.69 |
| Birth year | 1.00 | 1.53 | 1.00** | -2.49 | 1.00 | 0.5 | 1.00 | 0.74 |
| Number of years active | 0.64*** | -7.3 | 1.17*** | 3.99 | 0.79*** | -5.81 | 1.48*** | 9.97 |
| Average portfolio size top quartile | 1.70*** | 4.87 | 1.02 | 0.26 | 0.68*** | -3.87 | 0.91 | -1.02 |
| Avg. number of stocks in the portfolio | 1.41*** | 10.03 | 1.22*** | 7.65 | 0.92*** | -2.66 | 0.70*** | -10.87 |
| Portfolio turnover rate | 0.96*** | -3.23 | 0.99** | -2.51 | 1.00 | 1.06 | 1.01*** | 3.12 |
| Average holding period | 1.00*** | -21.79 | 1.00* | 1.75 | 1.00*** | 18.37 | 1.00*** | 9.23 |