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Socio-demographic characteristics of investors in the Warsaw Stock Exchange – How they influence the investment decision

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Abstract

The aim of the study was to investigate how age, gender, experience and education influence the investment decisions of individual investors in the Warsaw Stock Exchange. The source of data were two surveys sent to individual investors through the Polish Association of Individual Investors. In order to assess the significance of the given characteristics, we estimated a series of ordered logit regression models. Based upon the obtained answers and our estimations, we conclude, inter alia, that the Polish female investors typically have higher risk aversion and they trust the expert opinion, while the men are more likely to take risk. Less educated investors are also more eager to take higher risk, while the less experienced ones are more risk-averse. Unlike the more experienced market participants, they tend to estimate the risk of their portfolio through standard deviation or expected shortfall and use technical analysis more often.

Keywords: Warsaw Stock Exchange, individual investment, investment style

JEL: G11, G02, D12

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1. Introduction

The goal of this paper is to analyse how age, gender, education and experience influence the investment decisions of individual investors in the Warsaw Stock Exchange (further: WSE). The WSE is the largest in Central Europe and behaves quite differently to the other stock exchanges (for instance – it seems to be more integrated with the US market than other Central-European stock exchanges, see, e.g. Egert, Koubaa 2004 or Adam, Bańbuła, Markun 2015). The differences can be linked to the condition of fundamentals, to the exchange rate system, the share of foreign investors, etc. (Wang, Moore 2009). The main investors in the WSE are institutional and their investment decisions affect the movements of the indices the most. In our study we focus, however, on individual investment decisions.

The literature on emerging stock exchange markets concentrates mainly on volatility analysis and integration of the markets with EU, while the literature on investment decisions of individual investors is devoted to the developed economies (Nguyen, Schuessler 2012; De Bondt, Zurstrassen, Arzeni 2001). Up to our knowledge only a few papers concentrate on the aspect of individual investment in the WSE. Goodfellow, Bohl and Gebka (2009) focus on herd behaviour of individual investors in Poland and infer the investment decisions based upon the fluctuations of daily prices in the WSE, combined with the institutional framework. Kalinowski and Krzykowski (2012) examine the rationality of individual investors in the Warsaw Stock Exchange. Osińska, Pietrzak and Żurek (2011) verified the belief perseverance biases (i.e. the biases that are related to the mental discomfort that humans experience when the current information contradicts the previously held one) among Polish investors. The authors confirmed their presence, especially the illusion of control and excessive optimism. Rzeszutek, Czerwonka and Walczak (2015) demonstrated that susceptibility to the certainty effect depended on the level of expertise in stock market investing. Surprisingly, professional investors were not only susceptible to the certainty effect while making decisions, but the degree of susceptibility was even stronger in this group than among those who were only casually engaged in investing.

The main sources of knowledge about individual investors in Poland are the WSE's reports and the National Investors' Surveys (further: NIS). The WSE's reports are based on surveys run among national brokerage offices and focus on participation of different groups of investors in turnover on the Warsaw Stock Exchange. The NIS has been conducted annually since 2002 by the Polish Association of Individual Investors (AII). The association is the largest organization that unites stock investors in Poland, operating since 1999 and belonging to the World Federation of Investors Corporation (WFIC). The NIS results provide the broad characteristics of the WSE: their demographics, portfolio information, motivations to invest, sources of information and also opinions about the WSE. In order to supplement the information from this survey, we have prepared questionnaires about portfolio choices and focused on the investors' criteria and preferences.

We decided to investigate the behavioural patterns of individual investors in Poland for several reasons. First of all, as the leader of the region, the Polish market differs from the remaining CEE markets. Secondly, the market is still emerging – according to the classification created by MSCI (Morgan Stanley Capital International) and the IMF – and thus, the investors' behaviour should differ from the behaviour of the investors in the developed ones. From the previous research (Goodfellow, Bohl, Gebka 2009) we know that individual investors in Poland prefer the auction system (as opposed to continuous trading), similarly to the developed stock exchange players they trade infrequently and their portfolios are much less diversified than the portfolios of institutional investors. Moreover, during

the period 1996–2000, the investors engaged in herd behaviour during the market downswings, while there was little sign of such behaviour during the bullish market (Goodfellow, Bohl, Gebka 2009). Additionally, over the last five years the number of individual investors has fallen to the lowest level in the WSE history (according to statistics published by the WSE: share of investors in trading on the exchange, http://www.gpw.pl/analizy).

An essential element of the survey was the part containing the questions about the most important socio-demographic characteristics of the investors. When analysing the results, we found interesting relationships between the answers and demographics. Based upon the data collected in our surveys, we estimated a set of models to investigate how such factors as age, gender, experience and education influence the investment decisions of an individual investor in the Warsaw Stock Exchange. The estimated model was the logistic regression for ordered data (proportional and non-proportional odds models). The choice of this model is the standard approach for this type of data.

The results of the estimation suggest that such characteristics as gender and experience indeed differentiate investors. In general, women are more risk-averse than men, use expert opinion and believe in portfolio theory more frequently than men. When it comes to experience and age: the experienced investors are less likely to believe in expert opinion and do not consider technical analysis nor standard deviation as useful tools to assess the risk level of their portfolio. In contrast, the inexperienced and young investors do utilize these methods. Moreover, the less educated investors are more eager to take risk than the educated ones.

The remainder of the paper is organised as follows. First, we briefly describe Polish individual investors. Next, a brief overview of behavioural aspects in investors' decision-taking models is presented. In Section 4 we present the survey (including the methodology) and the model. Subsequently, we analyse in detail the impact of socio-demographic factors on the decision-making processes, utilizing descriptive statistics based on surveys' results and the logistic regressions (the models were estimated using the information from the 2013 survey only). Data analysis is supported by contingency tables, chi-squared tests and logistic regression. The analyses concentrate on the criteria taken into account by the investors, the usefulness of risk information, attitude to gain and risk including value function for losses and gains. In the last section we discuss the obtained results.

2. Individual investors – an overview

The characteristics of individual investors and their influence on the market vary depending on the country. For example, the New York Stock Exchange (NYSE) has become more institutionalized – buyers and sellers are largely institutions. In 1950 retail investors owned over 90% of the stock of US corporations, while in 2009 it is less than 30%, representing only 2% of the NYSE trading volume (Davis 2009). On the other hand, most transactions in the Chinese stock market are made nowadays by individual retail investors rather than institutional ones. More than 30 million new trading accounts were opened in the first five months of 2015 – three times as many as in the whole of 2014 according to the data from the China Securities Depository and Clearing Corporation Limited. In Poland, during the period of boom (2006–2007) individual investors' transactions accounted for over 30% of the turnover in the main market. In 2009 the number fell to 27% and a year later, to 20%. Starting from 2009, their share in the turnover of the main market gradually decreased, to reach 12% in first half

of 2015. Individual investors are still the main group in the NewConnect market,[1] but the share of their accounts has also declined: from 92% in 2007, when the market was opened, to 79% in the first half of 2015.

As mentioned above, the main source of knowledge about individual investors in Poland (apart from the WSE reports) is the National Investors' Survey. In 2014, the NIS covered 7,023 questionnaires, completed by investors from across Poland (15.6% of the respondents were members of AII). Men make up the vast majority of the NIS's respondents (82.6%). However, since 2010 the percentage of women has been systematically increasing, starting from 10.8% in 2010, 11.5% in 2011, 12% in 2012, 14.9% in 2013 up to 17.4% in 2014. The largest group of female investors are those between 46–55 years old, and there is a positive relationship between investment frequency and age. Compared to previous years, a slight increase in the average age of overall investors (since 2010) has been noticed. The largest number of investors are the ones between 26–34 years old (33.3%). The fraction of investors younger than 35 decreased to 44.1%. Currently, the percentage of people between 36–45 years old has increased from 26.9% to 28.1% and those over 46 from 23.7% to 27.8%. In line with this trend, the number of surveyed investors of short experience has been steadily decreasing. Less than a half of the respondents were people of a maximum five years' internship experience in investing. Currently, the average holding period for the market is 8 years. Among the respondents, 73% had higher education (slightly more than 28% – a background in economics), less than 15% – a secondary education and only less than 2% – an elementary and vocational education. The vast majority of the NIS's respondents (9/10) invest independently, using their own investment account. The percentage of investors declaring that they invest through investment funds declined slightly and amounted to 35.0%. Compared to the western stock exchanges, there are still very few long-term investors in Poland. 18% of the respondents declared that the period of their investment was equal to one month, 40% – one year, while only 32% – to more than a year. Up to 97% of investors do not participate in general meetings. Every fifth respondent was the owner of a portfolio of a value up to PLN 10,000, and another 20% of respondents – of a value in the range of PLN 10–30,000. The average Polish investor does not spend a lot of time on investing. 30% of respondents devote up to 1 hour per day on analysis, nearly one in four: up to several hours a week, and roughly as many (approx. 19%) – a few hours a month. Almost the same number of respondents (19.4%) spend many hours a day on investing. It can be observed that the time devoted to analysis increases together with the value of the portfolio.

Unfortunately, it is difficult to find similar studies for other countries. Global surveys of individual investors have been conducted by Natixis Global Asset Management since 2012 and Franklin Resources, Inc. The last online survey of Natixis was conducted in February 2015 and is a global study of 7,000 investors from 17 countries of Asia, Europe, the Americas, the Middle East, and Australia. Natixis Global Asset Management surveyed individual investors globally to understand their investment prospects, investing strategies and how they measure their progress toward financial goals (see: http://ngam.natixis.com/global/1396983606714/Individual+Investor+Survey). The Franklin Templeton Global Investor Sentiment Survey, conducted by ORC International from 12 February to 2 March 2015 included responses from 11,500 individuals in 23 countries: Brazil, Chile and Mexico in Latin America; Australia, China, Hong Kong, India, Japan, Malaysia, South Korea and Singapore in Asia Pacific; France, Germany, Greece, Italy, Poland, Spain, Sweden and the UK in Europe, South Africa, the UAE, and

[1] NewConnect is the Polish alternative stock exchange, created on the basis of the London AIM (Alternative Investment Market). It is conducted outside the regulated market. See: http://www.newconnect.pl.

the US and Canada in North America. This research focuses on the study of opinion about investing, optimism and investment sentiment (see: http://www.franklinresources.com/corp/pages/generic_content/news_center/GISS-2015.jsf).

3. How the investors make their decisions – behavioural aspects and models

Over the years scientists have developed many models to describe the investors' decision-making processes based upon behavioural criteria, other than the ones postulated in the classical models of financial mathematics.[2] Behavioural theory is especially useful to analyse individual investment. As the institutional investors are expected to apply financial models to construct and manage their portfolios, the individual investors can follow other rules and behave irrationally according to the formal models. The aspects that can influence the decision-making process of an individual investor are, for instance, the attitude to risk and loss, confidence in expert opinion, benchmark construction, ability to diversify the portfolio, etc. Below, we present briefly the role of these aspects in behavioural models. In our study we will concentrate how they are affected by socio-demographic aspects of investors (gender, age, education, experience, etc.).

3.1. Risk aversion, loss aversion and ambiguity aversion

The term 'loss aversion' is attributed to Kahneman and Tversky's (1979) work, in which the prospect theory was introduced. The authors proposed a value function that should explain the "irrational" behaviour of the investors. The function that passes through the reference point is *s*-shaped and asymmetrical. The following features of the function can be noticed:

– is defined on gain and losses rather than on total wealth,
– is concave in domain of gains and convex in domain of losses,
– considerably steeper for losses than for gains.

The value function illustrates an interesting and empirically observed phenomenon. People tend to prefer a smaller gain, which is almost certain, to a large gain, which is less probable. In the case of losses, people tend to prefer a higher loss, which is less probable, to a smaller loss, which is almost certain. Thus, risk aversion in the positive domain is accompanied by risk seeking in the negative domain.

The term 'ambiguity' aversion addresses the fact that the investors do not know the probability distribution of the (expected) return rates. Empirical studies show that most people try to avoid games of unknown probability distribution (see Ellsberg 1961; Rode et al. 1999; Borowski 2014).

Risk aversion is a well-known characteristic of investors, applied also in classical finance. The behavioural finance analysts also link risk aversion to emotion. The researchers show that investors in a good mood are less risk averse and value the market situation mode optimistically. On the other hand, depressed investors would be more cautious and show higher risk aversion (see Dowling, Luccey 2005). The effect of risk perception on the investment decision is included for instance in the Shefrin and Statman (2000) model. According to the model, the portfolio of the investor resembles a layered pyramid. In the lower layers, the investors allocate less risky assets, while on the upper ones – the risky assets. The layers are associated with aspirations.

[2] This subsection is mostly based on Borowski (2014).

3.2. The role of expert opinion

Apart from the psychological aspects, the investor decision-making process is also influenced by the expert opinion or opinions of other participants of the financial market. Schachter et al. (1991) claim that the investors tend to be less influenced by the opinion of experts during the bull market, while during the bear market they are more prone to the suggestions of experts, other investors or the press. The effect of macro-announcements on the behaviour of the dynamics of prices in stock exchanges has already been widely studied (see for instance Andersen et al. 2003; Będowska-Sójka 2010 and many others), as well as the impact of forecasts made by analysts on the behaviour of capital markets (Ivkovic, Jegadeesh 2004).

3.3. The role of benchmark

In order to assess the effectiveness of their portfolio management, both individual and institutional investors compare their results to some benchmarks. Such a benchmark can be, for instance, a portfolio created by another manager. Sharfstein and Stein (1990) argue that the strategy of following the benchmark can contribute to the herd behaviour in the market and result in panics in the case of loss. Such herd behaviour is observed when the list of the benchmark index is changed. When the change is announced, the positive returns are observed, while over one or two weeks after a company is incorporated into the index abnormal ones are observed. This phenomenon is a result of the excess demand of institutional investors, and as a consequence of it, the asset is overpriced. In a short time, the situation stabilizes and the demand diminishes (see also: Lakonishok, Shleifer, Vishny 1992).

Brown, Harlow and Starks (1996) also showed that when a fund manager assesses the effectiveness of his portfolio by comparing it with the benchmark, then he tends to manage the risk of the portfolio by comparing the current results with his previous results. Thus, if in the previous period the return from the investment was higher than the return from the benchmark, the manager would be eager to prolong the results. Thus, he would change the shares of the assets in such a way that the risk would be minimized and the correlation of the portfolio with the benchmark – maximized up to the end of the period. In this way the excess return (over the benchmark) could be prolonged to the end of the assessment period. On the other hand, if the rate of return from the portfolio is lower than the one from the benchmark in the first period, the manager would be eager to increase the risk of the fund, expecting a higher return in the next period ("chasing the benchmark"). The findings are consistent with the prospect theory, i.e. that the managers who obtain a positive excess return would be risk averse, while those who obtain a negative return – risk seeking.

3.4. Portfolio diversification

Institutional investors tend to diversify their portfolios. According to studies, the degree of diversification of an individual investor's portfolio is, however, smaller (e.g. Szyszka 2007). First of all, the degree of international diversification is minor, resulting in the so-called home bias (e.g. Cooper, Kaplanis 1994; Huberman 2001; Karlsson, Norden 2007 and many others). Individual investors prefer also to allocate their wealth in companies that they know. This behaviour is explained in psychology by the already

mentioned ambiguity aversion. It is also observed that the employees of listed companies tend to buy or hold for long term stocks of the companies they work for. In many cases their portfolios consist of only this one asset. This phenomenon is explained in literature by the so called familiarity bias (Bernatzi 2001; Borkowski 2014). In consequence, individual investors rarely use the classical portfolio theory, instead investing in the familiar.

3.5. Fundamental or technical analysis

Most of the behavioural finance models assume that the investors utilize either technical or fundamental analysis. For instance, DeLong et al. (1990) proposed a model where the investors were divided into two groups: the first one utilized the fundamental data, while the second (noise traders) took into account the informational noise. They assumed that the noise traders tend to under- or overestimate the fair value of risky assets. All of these factors affected the prices of the assets.

In the model of Hong and Stein (1999) there are also two groups of investors: the newswatchers (utilizing the fundamental analysis) and speculators. The latter take decisions through analysing short--term trends (momentum traders). The authors show that the dynamics of prices in the market depends on what group of investors dominate (see also: Szyszka 2009). We refer the Reader to the book of Borowski (2014) for a detailed review of the behavioural models distinguishing between the investors applying technical or fundamental analysis.

3.6. Socio-demographic aspects of investment

Most of the abovementioned characteristics are used in different behavioural models. In our study we aimed to check whether these aspects of the investment style of the Polish individual investor can be determined by such characteristics as age, gender, experience and education. More and more studies confirm that gender has a significant influence on the investment style, especially risk assessment and degree of portfolio diversification. For instance, Barber and Odean (2001) show that men tend to trade more frequently than women and that women tend to hold less risky positions than men, while Vaarmets, Liivamägi and Talpsepp (2014) show that in the case of Estonia, people with higher mental abilities are more likely to participate in the stock market. Czerwonka and Rzeszutek (2012) ran an experiment among Polish investors and students of different fields and showed that significantly more men than women succumbed to the effect of certainty in investment decisions. Moreover, the results of a survey conducted by Szyszka (2007) proved that Polish students of fine arts and music were less susceptible to overconfidence and were more accurate in their estimates of the probability of market events than a group of stock market traders and educated investors.

4. The survey and the model

We verify whether gender, age, education and experience influence the risk assessment, degree of portfolio diversification, attitude to gain (benchmark), type of analysis used and self-confidence (following expert opinion or intuition) with respect to the Polish investor.

4.1. Survey methodology

The study is based on the results of two surveys conducted via the AII. Surveys were carried out through the website of the AII over the period from July to September 2013 and from March to May 2015. In the first survey we obtained 332 responses, while in the second one – 394. According to the National Depository for Securities, in the first half of 2014 the total number of brokerage accounts exceeded 1.5 million (in the first half of 2013 there were more than 1.48 milion of them). However, it is worth keeping in mind that some of them were inactive accounts, and the number of active ones is estimated to be about 14% of all the accounts (i.e. about 204,000). The first survey covered 14 closed questions. The questions concerned the investment decision of the respondents: applied analysis, risk assessment methods and expected return. Another group of questions investigated how the respondents assessed the usefulness of various types of information and how satisfied they were with the results of the investment. The entire first survey and its results can be found in the doctoral dissertation (Rutkowska 2014) and questions selected for the study are presented in Appendix. The second survey covered 16 closed questions. The main part of the questionnaire consisted of sentences to be evaluated in a five-point Likert scale. They concerned a different approach to investing, the economic situation and general statements about the stock market. In both surveys there were also questions about age, gender, education and the number of years of investment.

4.2. The sample description

It should be remembered that the study sample was not purely random and should be treated rather as an occasional sample than a representative one. Information about the study was provided through the AII sites, newsletters, and during meetings and conferences. Thus, the respondents were the active investors who took active part in a range of AII activities, including expanding their knowledge about investing. This may suggest that their investment knowledge was higher than the actual average. The largest group of respondents (44% in 2013 and 30% in 2015)[3] were from 26 to 35 years old. Almost every fourth person was between the age of 36–45 years (30% in 2015), people up to 25 years accounted for 19% of respondents, while those between 46–55 and those over 55 years accounted for 6% and 13% respectively. When it comes to education, 85% (81% in 2015) of the respondents were people with higher education. Among them, nearly 36% (35% in 2015) had a degree in economics, while nearly 30% had a technical education (27% in 2015). 14% (17% in 2015) of respondents completed only secondary education. Among the youngest investors (up to 25 years) there dominated people with secondary and higher economic education: 41.27% (70% in 2015). Among the oldest investors (above 55 years old), the majority had higher technical education (65% in 2013 and 50% in 2015). Among people with higher economic education, more than 95% (85% in 2015) were younger than 46 years old. Nearly half of respondents – 45.8% (36% in 2015) were investors with 1–5 years' experience, and every fourth (27%) with 5–10 years' experience. People investing longer than 10 years accounted for 16.4% (30%) of the total respondents, and those with experience of less than one year – 13% (7%). In the first survey only 23 women took part, amounting to less than 7% of the sample (9% in 2015).

[3] The values in brackets present the values from the second survey carried out in 2015 not on the same sample group.

4.3. Methodology

For the purpose of our study, we use the most popular approach for ordered data – logistic regression. Ordinal logit models that consider the ordinal structure of the dependent variable are used when the dependent variable has at least three categories and the categories are ordinally arranged (see e.g. Ari, Yildiz 2014). A review of the models for ordinal response analysis can be found, among others, in Ananth and Kleinbaum (1997), Agresti (2002) and Gruszczyński (2012).

Consider a variable Y with categorical outcomes denoted by $1, 2, \ldots k$ and let $\boldsymbol{X}$ denote p-dimensional vector of covariates. The dependence of Y on $\boldsymbol{X}$ for the proportional odds model (McCullagh 1980) has the following form:

$$\Pr\left(Y \le y_j \,|\boldsymbol{X} = \boldsymbol{x}\right) = \frac{\exp\left(\alpha_j + \boldsymbol{x}'\boldsymbol{\beta}\right)}{1 + \exp\left(\alpha_j + \boldsymbol{x}'\boldsymbol{\beta}\right)'} \tag{1}$$

or equivalently in logit form:

$$\operatorname{logit}\Pi_j = \log\frac{\Pi_j}{1-\Pi_j} = \log\left(\frac{\Pr\left(Y \le y_j \,|\boldsymbol{X} = \boldsymbol{x}\right)}{\Pr\left(Y > y_j \,|\boldsymbol{X} = \boldsymbol{x}\right)}\right) = \alpha_j + \boldsymbol{x}'\boldsymbol{\beta} \tag{2}$$

where α_j (known as thresholds or cut-points) are unknown parameters satisfying condition $\alpha_1 \le \alpha_2 \le \ldots \le \alpha_{k-1}$ and $\boldsymbol{\beta} = (\beta_1, \ldots, \beta_p)'$ is a vector of unknown regression coefficients corresponding to $\boldsymbol{X}, j = 1, \ldots, k-1$.

In the proportional odds model the effect of each predictor remains the same across each $k-1$ logits. This restriction follows from the assumption of the proportional odds. The log cumulative odds ratio is proportional to the distance between $\mathbf{x}_1$ and $\mathbf{x}_2$:

$$\log\frac{\Pr\left(Y \le y_j \,|\boldsymbol{X} = \boldsymbol{x}_1\right)/\Pr\left(Y > y_j \,|\boldsymbol{X} = \boldsymbol{x}_1\right)}{\Pr\left(Y \le y_j \,|\boldsymbol{X} = \boldsymbol{x}_2\right)/\Pr\left(Y > y_j \,|\boldsymbol{X} = \boldsymbol{x}_2\right)} = \boldsymbol{\beta}'\left(\boldsymbol{x}_1 - \boldsymbol{x}_2\right) \tag{3}$$

A model that relaxes the assumption of proportional odds is referred to as a non-proportional odds model. The more general non-proportional odds model has the following form:

$$\Pr\left(Y \le y_j \,|\boldsymbol{X} = \boldsymbol{x}\right) = \frac{\exp\left(\alpha_j + \boldsymbol{x}'\boldsymbol{\beta}_j\right)}{1 + \exp\left(\alpha_j + \boldsymbol{x}'\boldsymbol{\beta}_j\right)'} \tag{4}$$

$$\operatorname{logit}\Pi_j = \log\frac{\Pi_j}{1-\Pi_j} = \log\left(\frac{\Pr\left(Y \le y_j \,|\boldsymbol{X} = \boldsymbol{x}\right)}{\Pr\left(Y > y_j \,|\boldsymbol{X} = \boldsymbol{x}\right)}\right) = \alpha_j + \boldsymbol{x}'\boldsymbol{\beta}_j \tag{5}$$

where $\boldsymbol{\beta}_j = (\beta_{j1}, \ldots, \beta_{jp})'$ is a vector of unknown regression coefficients corresponding to $\boldsymbol{X}$.

The parameter vector for the non-proportional odds model is $\boldsymbol{\phi} = (\boldsymbol{\phi}_1', \ldots, \boldsymbol{\phi}_p')'$, where $\boldsymbol{\phi}_j = (\alpha_j, \beta_{j1}, \ldots, \beta_{jp})'$ is a vector consisting of an intercept α_j and p slope parameters $\beta_{j1}, \ldots, \beta_{jp}$. The score test of proportional odds assumption examines the equality of separate slope parameters under the null hypothesis: $H_0: \boldsymbol{\beta}_1 = \boldsymbol{\beta}_2 = \ldots = \boldsymbol{\beta}_{k-1}$. Then under H_0, there is a single common slope parameter for each of the p explanatory variables. Let $\beta_1, \ldots, \beta_p$ be the common slope parameters. Let $\hat{\alpha}_1, \hat{\alpha}_2, \ldots, \hat{\alpha}_{k-1}$ and $\hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_p$ be the maximum likelihood estimates (MLEs) of the intercept parameters and the common slope parameters. Then, if the null hypothesis is true, the MLE of $\boldsymbol{\phi}$ is $\boldsymbol{\phi}_{H_0} = \left(\hat{\boldsymbol{\phi}}_1', \ldots, \hat{\boldsymbol{\phi}}_p'\right)'$, where $\hat{\boldsymbol{\phi}}_j' = \left(\hat{\alpha}_j, \hat{\beta}_1, \ldots, \hat{\beta}_p\right)$ for $1 \le j \le k-1$.

Let $\boldsymbol{g}(\boldsymbol{\phi})$ be the gradient vector of the first partial derivatives of the log likelihood with respect to the parameter vector $\boldsymbol{\phi}$ and let $H(\boldsymbol{\phi})$ be the Hessian matrix of the second partial derivatives with respect to $\boldsymbol{\phi}$ Let $\boldsymbol{I}(\boldsymbol{\phi})$ be the expected value of $-H(\boldsymbol{\phi})$. The score test statistic

$$\boldsymbol{S} = \boldsymbol{g}'\left(\hat{\boldsymbol{\phi}}_{H_0}\right)\boldsymbol{I}^{-1}\left(\hat{\boldsymbol{\phi}}_{H_0}\right)\boldsymbol{g}\left(\hat{\boldsymbol{\phi}}_{H_0}\right) \tag{6}$$

has an asymptotic χ^2 distribution with $p(k-2)$ degrees of freedom.

If a general model (4) fits better, the simple and less parametrized model might be preferable (Agresti 2002). Even if model (1) has lack of fit because of small p-value in test of proportional odds, it may usefully summarize the effect of explanatory variables and is easier to interpret.

All calculations for proportional odds models were performed using the SAS statistical software 9.3. The estimates of non-proportional odds model were obtained using R package VGAM. To estimate the models we used the data from the 2013 survey only.

5. Investment decision aspects – empirical results

5.1. Methods of investment analysis

According to the survey of 2013 (question 1, Appendix), the most popular method of analysis used by investors was the technical analysis (*always* used by 31% of the respondents, and *often* by 35%) and the fundamental one (*always* used by 28%, and *often* by 38%).[4] However, intuition played an important role as well. When selecting a portfolio, less than 5% of the respondents completely avoid decisions based on intuition, one in four respondents admitted to use it *often*, and 39%, *sometimes*. Every fourth respondent bases his or her decisions on expert predictions *often*, and nearly 30% trusts them *sometimes*. The least popular appeared to be the modern portfolio theory. Only 6% of the respondents try to use it *always* and more than 15% have *never* used it. In the second survey we asked respondents what would convince them to use portfolio optimization models. The two most common answers were *models should be intuitive and easy to use* (75% agree and strongly agree) and *models should be more realistic* (73%). Nearly 60% of the respondents consider the two requirements as *important* and *very important*. However, nearly 66% claim that they do not have enough time to utilize the models, and half of respondents admit to having too little economic knowledge (the latter answer was given by the respondents of background

[4] A similar result was presented in the NIS.

other than economics). Moreover, almost 67% agree and strongly agree with the sentence that they prefer to have in their portfolio shares of several companies that they know, rather than many which they do not know. Slightly more than 5% did not know how to evaluate the sentence and less than 9% of respondents did not agree with it.

The estimates of proportional odds models 1–3 (see Table 1) suggest there is a relationship between the frequency of use of expert opinion and the investors' age, education, gender and experience. Taking into account the sign of the β_{age} parameter and the significance test results, we conclude that older and better educated investors believe in expert opinion more often. Let us explain these conclusions more explicitly with the following example: the odds that the investor with a higher education uses predictions of experts *always* or *often* (instead of *never*, *rarely* or *sometimes*) is almost three times (exp(1.0244) = 2.7854) higher than the odds of a similar choice by an investor with a secondary education. Women are more likely to trust the expert opinion than men.

The small p-value of proportional odds test suggests that a more general non-proportional odds model may better describe the pattern of dependence between the frequency of use of expert opinion and the investor's experience. Indeed, the estimates of non-proportional odds model 3b are consistent with the results of proportional odds model 3a calculations (the signs of parameters $\beta, \beta_1, \ldots \beta_4$ are the same). Using the estimates of model 3a and 3b we conclude that more experienced investors are less likely to believe in expert opinion.

The estimates of the proportional odds model 4 (see Table 1) suggest that gender has an impact on the frequency of using portfolio analysis: women are more likely than men to use this criterion. The results of proportional odds models 5 and 6 suggest that less experienced and younger investors trust technical analysis more than any other group. For other models most of the coefficients are insignificant.

5.2. Usefulness of information of different types of risk measures

In question 5 (survey 2013) respondents assessed the usefulness of information carried by the particular risks measure. Some of the respondents found that the standard deviation is not a useful measure of risk (12% assessed its usefulness as *very little* and more than 17% as *little*). However, 28% and 32% of respondents respectively indicated its suitability as *average* and *large*. Only slightly more than 8% found this information to be *very important*. In the case of information carried by semivariance, also approx. 12% found it to be of *very little* use and about one in five respondents found it to be of *little* use. More than 37% of respondents consider semivariance suitability as *average*, 23% as *large* and only less than 4% as *very important*. The measure of conditional value at risk is similarly assessed: more than 30% found it of *small* and *very small* importance, and just over 7% indicated a *very large* suitability. The information carried by value-at-risk is estimated slightly higher. Only 8% of respondents found its relevance to be *very little*, while 12% found it to be *little* relevant. The impact of this information is assumed *average* by every fourth respondent, *large* by nearly 36% and *very large* by more than 15%.

The logistic regression for a relationship between the evaluation of different types of information and the age, experience, education, and gender of the investor (see Table 2) shows interesting results in four cases. There is a relationship between the evaluation of usefulness of standard deviation as a risk measure and other variables. The estimates of models 7a, 7b and 8 suggest that for younger and less

experienced investors, standard deviation is a more useful risk measure than for older or experienced ones. There are similar patterns of the relationships between evaluation of semideviation information and experience (model 9) or Value at Risk and age (model 10). The estimates of proportional odds model 11 suggest that there is a relationship between the evaluation of the Expected Shortfall as a risk measure and education and experience. Less educated and experienced investors tend to evaluate it as more useful.

These results may suggest that the investors prefer more straightforward measures of risk. It seems that they lose confidence in any of the risk measures as they get older, better educated and more experienced or – perhaps – utilize some other measures, based on experts' judgments or intuition. Another possibility is that together with age, education or experience the so-called judgmental overconfidence bias develops (overestimating the precision of ones' judgement, see e.g. Fellner, Kruegel 2012). However, the latter hypothesis would require additional testing.

5.3. Attitude to gain

The next group of questions in the 2013 survey (questions: 4, 6, 8, Appendix) were designed to examine the method of determining the expectations of return on investment and the evaluation of the obtained results. Over 60% of respondents admitted that their expectations of returns vary over time and depend on current conditions and sentiment in the market. Nearly 14% formulate them based on interest rates of deposits and other instruments and less than 9% on acquired experience. Only 4.5% of people have some constant expectations, and 9% are not able to assess what influences their expectations. Only 6% of respondents say that they formulate their expectations as a crisp number. Half of the respondents express their expectations by infinite range, specifying the minimum acceptable rate of return, and 42% by finite interval, not including the profits above a certain improbable level.

When evaluating their investment, more than 39% compare the result with the planned profit, over 25% with interest rate of deposits/bonds, and one in five persons with the score of a selected index. Only 10% of investors compared the achieved return rate with the best results in a given period, and only 1.5% indicated that they compared it with the worst result. Among the *other* answers, 3 people (1.8%) do not use any benchmark, one compares the results with the previous results, and one with the three most popular answers at the same time.

In the case of people who declared that they compare the results with a selected index, more than 75% make their expected rate of return dependent on the conditions and market sentiment. Among the people determining their expected rate of return based on their experience, more than 65% compared the result with the planned profit. Over 60% of those, who formulated their expectations based on interest on deposits or other instruments, compared the results with them. However, among investors comparing their results with the planned profit, more than half (57%) conditioned their expected rate of return based on moods and conditions on the market. There was no significant effect of age, experience, or education on how the respondents assess the investment according to chi-squared tests.

5.4. Attitude to risk

More than half of the respondents of the 2013 survey stated that they preferred to risk less even if the possibility of a lower return was higher. Slightly more than 42% would take more risk looking forward to get a higher return, while less than 5% prefer not to risk at all and avoid any risky investments. Assessing their attitude to risk on a five-point scale, more than a half identified it as *average*, and 30% as *high*. These responses were further examined through the question in which the respondents had to choose one of three portfolios, each of the same median value but with a different range of possible outcomes. The results were consistent with the results of the direct question about the attitude to risk. In the group of people with a *low* and *very low* risk attitude, there was almost no one of over 10 years' experience. Among the risk averse investors (who chose *low* in the scale) more than 70% were ones of less than 5 years' experience. Among those with a *high* tendency (57%), investors of 1–5 years' experience dominated, while more than one in four had experience of 5–10 years. This may indicate that risk tolerance increases with experience or that the risk-averse investors resign from investment. More than half of the respondents with a positive attitude to risk were the ones with a higher technical education. 40% of the *average* risk-taking respondents had higher education in economics, and every fifth – technical and higher education (or equivalent). In the sample, no dependence between the investors' age and risk attitude was observed. The answers to the question requiring respondents to select one of the three portfolios with the same median value and various projections confirmed the attitude of the respondents to risk. Almost half of the respondents from the 2015 survey admitted that at that moment they accepted higher risk than a few years ago, while 38% disagreed with this statement.

The estimates of proportional odds model 12 (based on the survey from 2013) for the relationship between willingness to take risk and the education and gender of the investor (see Table 3) shows that investors' willingness to take risk is smaller for better educated market participants. Women are less risk-takers than men.

Based on the average responses to questions 10 and 11 (survey 2013), the value function for losses and gains can be sketched. The empirical value function derived from our survey for groups varying in age, experience and education looks very similar. It is worth taking a look at the value function grouped in gender, because only on the profit side (positive part of the *x*-axis) the curves are the same (see Figure 1). When it comes to losses, women are characterized by lower loss acceptance (positive part of the *x*-axis), which is also confirmed by their higher risk aversion. Significant differences in value function are only observed for groups varying in risk aversion level (see Figure 2). Investors with high risk aversion react *more strongly*, they assign greater value to the same return rate than those with lower risk aversion and much smaller value for losses. Investors of average risk aversion react in the same way to both losses and gains. Investors with low risk aversion feel less satisfied than investors with high risk aversion with the same level of return. However, if we consider the same level of loss, investors of very low risk aversion have higher loss acceptance, while those of the highest risk aversion – the lowest.

5. Summary

In the article we analyse the investment style of an average Polish individual investor trading on the WSE, based upon his or her socio-demographic characteristics, i.e. age, education, experience and

gender. The sources of our data were the results of the survey designed by Rutkowska and published in her doctoral dissertation, as well as an additional survey conducted in 2015. Based upon the collected data in the 2013 survey, we estimated a series of ordered logistic regression models.

We found that such characteristics as age, gender and experience differentiate investors. In general, women are more risk-averse than men, use expert opinion and trust portfolio theory more frequently than men. When it comes to experience and age, experienced investors are less likely to believe in expert opinion and do not consider technical analysis nor standard deviation as useful tools to assess the risk level of their portfolio. On contrary, the inexperienced and young investors do utilize these methods. Moreover, the less educated investors are more eager to take risk than the educated ones.

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Appendix

Selected questions from the questionnaires

1. Please rate on a scale: 1–5 (1 – never, 2 – rarely, 3 – sometimes, 4 – often, 5 – always).
   When you select your portfolio, how often do you use the following techniques:

a) intuition	1	2	3	4	5
b) current predictions of experts	1	2	3	4	5
c) portfolio analysis	1	2	3	4	5
d) technical analysis	1	2	3	4	5
e) fundamental analysis	1	2	3	4	5

4. Is your expected rate of return:
   a) solid,
   b) variable:
      – depending on the conditions and sentiment in the stock market,
      – depending on the interest rates for deposits and other instruments,
      – depending on the acquired experience,
      – other: .....
   c) it is difficult to say.

5. Please rate on a scale: 1–5 (1 – very small, 2 – small, 3 – average, 4 – high, 5 – very high) usefulness of the information: *The average rate of return is 10%, and…*

a) the standard deviation from the average result is 15%	1	2	3	4	5
b) the average deviation of the results below average is 12%	1	2	3	4	5
c) probability of loss greater than 10% is 5%	1	2	3	4	5
d) the average loss of 5% of the maximum loss is 11%	1	2	3	4	5

6. Is your expected rate of return expressed by:
   a) a single (crisp) number, e.g. *I expect the rate of return of 12%*,
   b) an interval, e.g. *I expect the rate of return from 10% to 15%*,
   c) an infinite interval, e.g. *expected rate of return at least 10%*.

8. Do you compare your investment results with:
   a) the best of results in the current period,
   b) the score of a selected index,
   c) the worst results in the current period,
   d) the planned profit,
   e) the interest rate on deposits/bonds,
   f) other: .....

9. What is your approach to risk?
   a) I prefer not to risk at all, even if I could gain more.
   b) I prefer small risk over the possibility of higher profit.
   c) I prefer to risk more, hoping to achieve more profit.

10. Please assess your level of satisfaction if after half a year of investment you receive the following rate of return (1 – very low, 2 – low, 3 – average, 4 – high, 5 – very high):

a) 5%	1	2	3	4	5
b) 10%	1	2	3	4	5
c) 15%	1	2	3	4	5
d) 20%	1	2	3	4	5
e) 25%	1	2	3	4	5

11. To what extent are you able to accept the following declines in invested capital after half a year from the start of the investment (1 – lack of acceptance, 2 – low, 3 – average, 4 – high, 5 – very high):

a) 5%	1	2	3	4	5
b) 10%	1	2	3	4	5
c) 15%	1	2	3	4	5
d) 20%	1	2	3	4	5
e) 25%	1	2	3	4	5

12. Please rate yours willingness to take risk:
   a) very low,
   b) low,
   c) average,
   d) high,
   e) very high.

13. Please evaluate the sentences in the following scale: strongly agree (2), agree (+1), do not know (0), do not agree (-1) strongly disagree (-2):
   a) I prefer to invest in a few companies that I know, than to invest in a lot of unknown companies;
   b) I accept a higher risk level than I used to accept a few years ago.

14. Please rate the sentences in the following scale: strongly agree (2), agree (+1), do not know (0), do not agree (-1), strongly disagree (-2):
   a) portfolio optimization models should be more intuitive and easy to make me use them;
   b) portfolio optimization models should be more realistic to make me use them;
   c) I would have to have more time to analyse investments to use the portfolio optimization models;
   d) I would have to have more economic knowledge to use the portfolio optimization models.

Table 1
Relationship between the type of analysis used and the age, experience, education, gender of investor – logistic regression results

Model 1: usefulness of expert opinion ~ age
Wald test of joint significance:
H_0: It does not depend on the age of the investors how they value the usefulness of experts opinion ($\beta_{age} = 0$).
H_1: $\beta_{age} \neq 0$
$\chi^2(1) = 6.2523$, $p = 0.0124$
Score test for the proportional odds assumption: $\chi^2(3) = 5.9804$, $p = 0.1126$

	Value	Std. error	Wald χ^2	p-value
β_{age}	-0.2526	0.1010	6.2523	0.0124
α_1	-1.8991	0.3058	38.5668	< 0.0001
α_2	0.0821	0.2584	0.1009	0.7507
α_3	1.4501	0.2723	28.3539	< 0.0001
α_4	4.1213	0.4247	94.1908	< 0.0001

Model 2: usefulness of expert opinion ~ education + gender
Wald test of joint significance:
H_0: It does not depend on the education nor gender of the investors how they value the usefulness of experts opinion ($\beta_{edu} = 0$, $\beta_{sex} = 0$).
H_1: $\beta_{edu} \neq 0$ or $\beta_{sex} \neq 0$.
$\chi^2(2) = 22.7494$, $p < 0.0001$
Score test for the proportional odds assumption: : $\chi^2(3) = 4.3833$, $p = 0.6249$

	Value	Std. error	Wald χ^2	p-value
β_{edu}	-1.0244	0.3134	10.6826	0.0011
β_{gender}	1.4685	0.4393	11.1755	0.0008
α_1	0.0359	1.2885	0.0008	0.9777
α_2	2.0694	1.2997	2.5352	0.1113
α_3	3.4374	1.3084	6.9019	0.0086
α_4	6.2082	1.3381	21.5245	< 0.0001

Model 3a: usefulness of expert opinion ~ experience
Wald test of joint significance:
H_0: It does not depend on the experience of the investors how they value the usefulness of experts opinion ($\beta_{exp} = 0$).
H_1: $\beta_{exp} \neq 0$
$\chi^2(1) = 2.8149$, $p = 0.0934$
Score test for the proportional odds assumption: $\chi^2(3) = 15.5520$, $p = 0.0014$

	Value	Std. error	Wald χ^2	p-value
β_{exp}	0.1901	0.1133	2.8149	0.0934
α_1	-2.9317	0.3562	67.7521	< 0.0001
α_2	-0.9613	0.3020	10.1353	0.0015
α_3	0.3688	0.2974	1.5374	0.2150
α_4	3.0412	0.4282	50.4344	< 0.0001

Model 3b: usefulness of expert opinion ~ experience
Wald test of joint significance:
H_0: It does not depend on the experience of the investors how they value the usefulness of experts opinion ($\beta_{exp,1} = \beta_{exp,2} = \beta_{exp,3} = \beta_{exp,4} = 0$).
H_1: ~ H_0
$\chi^2(4) = 14.1874$, $p = 0.0067$

	Value	Std. error	Wald χ^2	p-value
$\beta_{exp,1}$	0.3654	0.2266	2.6003	0.1068
$\beta_{exp,2}$	0.2392	0.1289	3.4446	0.0635
$\beta_{exp,3}$	0.0129	0.1355	0.0090	0.9245
$\beta_{exp,4}$	1.7328	0.5979	8.3988	0.0038
α_1	-3.3930	0.6459	27.5939	< 0.0001
α_2	-1.0878	0.3400	10.2362	0.0014
α_3	0.7926	0.3510	5.0979	0.0240
α_4	0.3781	0.9434	0.1606	0.6886

Model 4: usefulness of portfolio analysis ~ gender
Wald test of joint significance:
H_0: It does not depend on the gender of the investors how they value the usefulness of portfolio analysis ($\beta_{gender} = 0$).
H_1: $\beta_{gender} \neq 0$
$\chi^2(1) = 7.0627$, $p = 0.0079$
Score test for the proportional odds assumption: $\chi^2(3) = 1.2059$, $p = 0.7516$

	Value	**Std. error**	**Wald χ^2**	***p*-value**
β_{gender}	1.1491	0.4324	7.0627	0.0079
α_1	-2.6433	0.4424	35.7012	< 0.0001
α_2	-1.2896	0.4256	9.1806	0.0024
α_3	-0.2071	0.4191	0.2444	0.6211
α_4	1.6478	0.4473	13.5734	0.0002

Model 5: usefulness of technical analysis ~ age
Wald test of joint significance:
H_0: It does not depend on the age of the investors how they value the usefulness of technical analysis ($\beta_{age} = 0$).
H_1: $\beta_{age} \neq 0$
$\chi^2(1) = 2.8225$, $p = 0.0929$
Score test for the proportional odds assumption: $\chi^2(3) = 1.6286$, $p = 0.6529$

	Value	**Std. error**	**Wald χ^2**	**p-value**
β_{age}	0.1646	0.0980	2.8225	0.0929
α_1	-3.6339	0.3806	91.1568	< 0.0001
α_2	-2.0256	0.2823	51.4705	< 0.0001
α_3	-1.1847	0.2639	20.1499	< 0.0001
α_4	0.3617	0.2554	2.0044	0.1568

Model 6: usefulness of technical analysis ~ experience
Wald test of joint significance:
H_0: It does not depend on the experience of the investors how they value the usefulness of technical analysis ($\beta_{exp} = 0$).
H_1: $\beta_{exp} \neq 0$
$\chi^2(1) = 6.5900$, $p = 0.0103$
Score test for the proportional odds assumption: $\chi^2(3) = 0.9583$, $p = 0.8113$

	Value	Std. error	Wald χ^2	p-value
β_{exp}	0.2900	0.1130	6.5900	0.0103
α_1	-3.9753	0.4160	91.3051	< 0.0001
α_2	-2.3557	0.3264	52.0814	< 0.0001
α_3	-1.5035	0.3083	23.7768	< 0.0001
α_4	0.0406	0.2954	0.0189	0.8907

Note: respondents' answers were treated as ordinal variables.
Age: 1 – less than 25 years, 2 – from 25 to 35 years, 3 – from 36 to 45 years, 4 – from 46 to 55 years, 5 – over 55 years.
Education: 1 – elementary, 2 – vocational, 3 – secondary, 4 – higher.
Gender: 1 – male, 0 – female.
A Wald test with the null hypothesis H_0: $\theta = 0$ against the alternative H_1: $\theta \neq 0$ is used to evaluate the statistical significance of each coefficient (θ) in the model.

Table 2
Relationship between the evaluation of different type of information and the age, experience, education, gender of investor – logistic regression results

Model 7a: evaluation of the standard deviation information ~ age
Wald test of joint significance:
H_0: It does not depend on the age of the investors how they evaluate the usefulness of the standard deviation as a risk measure ($\beta_{age} = 0$).
H_1: $\beta_{age} \neq 0$
$\chi^2(1) = 9.0607$, $p = 0.0026$
Score test for the proportional odds assumption: $\chi^2(3) = 7.8255$, $p = 0.0498$

	Value	Std. error	Wald χ^2	p-value
β_{age}	0.2959	0.0983	9.0607	0.0026
α_1	-2.7101	0.3014	80.8407	< 0.0001
α_2	-1.5837	0.2691	34.6390	< 0.0001
α_3	-0.3643	0.2540	2.0564	0.1516
α_4	1.6796	0.2915	33.1971	< 0.0001

Model 7b: evaluation of the standard deviation information ~ age
Wald test of joint significance:
H_0: It does not depend on the age of the investors how they evaluate the usefulness of the standard deviation as a risk measure ($\beta_{age,1} = \beta_{age,2} = \beta_{age,3} = \beta_{age,4} = 0$).
H_1: ~ H_0
$\chi^2(4) = 16.8952$, $p = 0.0020$

	Value	**Std. error**	**Wald χ^2**	***p*-value**
$\beta_{age,1}$	0.2626	0.1550	2.8703	0.0902
$\beta_{age,2}$	0.2399	0.1163	4.2550	0.0391
$\beta_{age,3}$	0.2468	0.1144	4.6541	0.0310
$\beta_{age,4}$	1.0180	0.2727	13.9356	0.0002
α_1	-2.6235	0.4329	36.7271	< 0.0001
α_2	-1.4417	0.3094	21.7125	< 0.0001
α_3	-0.2393	0.2860	0.7001	0.4028
α_4	0.3191	0.5056	0.3983	0.5280

Model 8: evaluation of the standard deviation information ~ experience
Wald test of joint significance:
H_0: It does not depend on the experience of the investors how they evaluate the usefulness of the standard deviation as a risk measure ($\beta_{exp} = 0$).
H_1: $\beta_{exp} \neq 0$
$\chi^2(1) = 5.9535$, $p = 0.0147$
Score test for the proportional odds assumption: $\chi^2(3) = 3.7104$, $p = 0.295$

	Value	**Std. error**	**Wald χ^2**	**p-value**
β_{exp}	0.2699	0.1106	5.9535	0.0147
α_1	-2.6577	0.3308	64.5653	< 0.0001
α_2	-1.5195	0.3027	25.2021	< 0.0001
α_3	-0.3228	0.2904	1.2351	0.2664
α_4	1.7080	0.3234	27.8881	< 0.0001

Model 9a: evaluation of the semideviation information ~ experience
Wald test of joint significance:
H_0: It does not depend on the experience of the investors how they evaluate the usefulness of the semideviation as a risk measure ($\beta_{exp} = 0$).
H_1: $\beta_{exp} \neq 0$
$\chi^2(1) = 3.0976$, $p = 0.0784$
Score test for the proportional odds assumption: $\chi^2(3) = 7.3276$, $p = 0.0622$

	Value	Std. error	Wald χ^2	p-value
β_{exp}	0.1952	0.1109	3.0976	0.0784
α_1	-2.4060	0.3268	54.2140	< 0.0001
α_2	-1.1417	0.2997	14.5154	0.0001
α_3	0.4713	0.2935	2.5790	0.1083
α_4	2.6979	0.3841	49.3329	< 0.0001

Model 9b: evaluation of the semideviation information ~ experience
Wald test of joint significance:
H_0: It does not depend on the experience of the investors how they evaluate the usefulness of the semideviation as a risk measure ($\beta_{exp,1} = \beta_{exp,2} = \beta_{exp,3} = \beta_{exp,4} = 0$).
H_1: ~ H_0
$\chi^2(4) = 10.8682$, $p = 0.0281$

	Value	Std. error	Wald χ^2	p-value
$\beta_{exp,1}$	0.3998	0.1802	4.9230	0.0265
$\beta_{exp,2}$	0.1679	0.1289	1.6975	0.1926
$\beta_{exp,3}$	0.0970	0.1373	0.4996	0.4797
$\beta_{exp,4}$	0.9269	0.3660	6.4123	0.0113
α_1	-2.9538	0.5142	32.9953	< 0.0001
α_2	-1.0799	0.3419	9.9754	0.0016
α_3	0.7063	0.3534	3.9958	0.0456
α_4	1.1515	0.7298	2.4897	0.1146

Model 10: evaluation of the VaR information ~ age
Wald test of joint significance:
H_0: It does not depend on the age of the investors how they evaluate the usefulness of VaR as a risk measure ($\beta_{age} = 0$).
H_1: $\beta_{age} \neq 0$
$\chi^2(1) = 3.3931$, $p = 0.0655$
Score test for the proportional odds assumption: $\chi^2(3) = 2.1444$, $p = 0.5430$

	Value	**Std. error**	**Wald χ^2**	**p-value**
β_{age}	0.1790	0.0972	3.3931	0.0655
α_1	-2.8194	0.3130	81.1465	< 0.0001
α_2	-1.7408	0.2730	40.6617	< 0.0001
α_3	-0.5392	0.2553	4.4612	0.0347
α_4	1.2566	0.2679	21.9958	< 0.0001

Model 11: evaluation of the ES information ~ education + experience
Wald test of joint significance:
H_0: It does not depend on the experience and education of the investors how they evaluate the usefulness of the standard deviation as a risk measure ($\beta_{edu} = 0,\ \beta_{exp} = 0$).
H_1: $\beta_{edu} \neq 0$ or $\beta_{exp} \neq 0$.
$\chi^2(2) = 12.0672$, $p = 0.0024$
Score test for the proportional odds assumption: : $\chi^2(6) = 7.7933$, $p = 0.2536$

	Value	**Std. error**	**Wald χ^2**	***p*-value**
β_{edu}	0.7046	0.3046	5.3520	0.0207
β_{exp}	0.2509	0.1148	4.7771	0.0288
α_1	-5.1528	1.1888	18.7884	< 0.0001
α_2	-4.0639	1.1789	11.8838	0.0006
α_3	-2.8001	1.1672	5.7549	0.0164
α_4	-0.7957	1.1621	0.4688	0.4935

Table 3
Relationship between willingness to take risks and age, experience, education, gender of investor – logistic regression results

Model 12: willingness to take risk ~ education + gender
Wald test of joint significance:
H_0: Willingness to take risk does not depend on gender and education of the investors ($\beta_{edu} = 0,\ \beta_{gender} = 0$).
H_1: $\beta_{edu} \neq 0$ or $\beta_{gender} \neq 0$.
$\chi^2(2) = 12.0672$, $p = 0.0024$
Score test for the proportional odds assumption: $\chi^2(6) = 6.8757$, $p = 0.3325$

	Value	**Std. error**	**Wald χ^2**	***p*-value**
β_{edu}	0.6662	0.3103	4.6091	0.0318
β_{gender}	-1.1620	0.4453	6.8081	0.0091
α_1	-5.9448	1.3842	18.4454	< 0.0001
α_2	-3.7526	1.3055	8.2619	0.0040
α_3	-0.8891	1.2943	0.4719	0.4921
α_4	1.4528	1.3002	1.2485	0.2638

Figure 1
Value function by gender

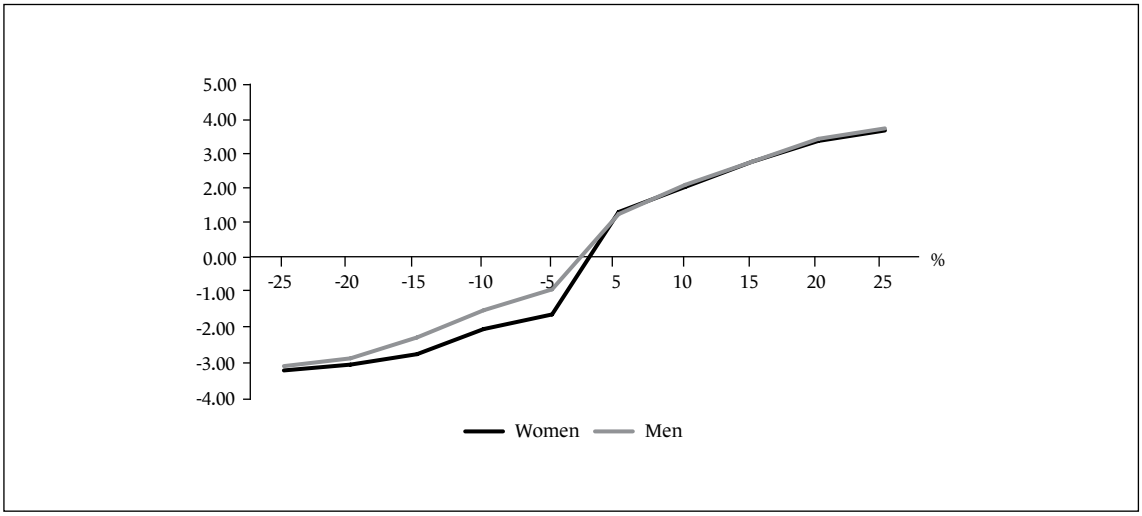

Figure 2
Value function group by risk aversion