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Abstract

We study the relationship between personal traits and trading outcomes in continuous double auction asset markets. There are mixed theoretical predictions about this relationship followed by similarly mixed empirical evidence. We examine the correlation of cognitive skills, willingness to speculate, risk attitude, willingness to compete, and overconfidence with trading activity in a very simple experimental market with one asset and no uncertainty about the fundamental value. We build on a market setting very close to the canonical one of Smith, Suchanek and Williams (1988) with a constant fundamental value. We conclude that willingness to speculate is the main driver of trading activity. Willingness to speculate and cognitive skills are the only significant predictors for achieved profits from trading. Our experimental results could provide a benchmark for trading activity outcomes in more complicated, real world asset market environments.

Keywords: experimental economics, asset market, trading activity, personal traits

JEL Classification: G41, C91, D91, D53

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1 Introduction

Asset markets are supposed to be a tool for achieving efficiency through redirecting money flows to more profitable investment opportunities. According to the Federal Reserve's survey of consumer finances, 54% of US households owned stocks in 2017 (either directly or through investment funds).[1] The European Securities and Markets Authority Report (2019) claims that households in the EU owned over EUR 27 trillion in financial assets, and 25% of this amount is attributed either to investment fund shares or equity. However, trading in the financial markets is not always profitable for traders. Barber et al. (2008) provide evidence from the Taiwan Stock Market in which individual investors lose almost 3% of their income annually. Barber and Odean (2000) provide evidence that more active individual traders underperform the market even more than average individual traders. Surprisingly, little is known about the characteristics of these traders. Knowing more about the characteristics and behavior of asset market traders is the first step in helping them avoid suffering such losses. Complexity and lack of information about underlying fundamental processes often prevents the study of important economic questions using only observational data. Therefore, the much simplified environment of experimental asset markets provides a toolbox for testing various hypotheses about trading decisions in asset markets.

This paper examines the relationship between personal traits and trading outcomes in continuous double auction asset markets. Although many studies link personal traits with overall market outcomes (mostly size or duration of price bubbles), there is little in previous literature about this relationship at the individual level. We examine the relationship in an experimental market with one asset and no uncertainty about the fundamental value. However, an effort to relate personal traits to individual market outcomes creates problems that are difficult to bypass. Trading in the asset market can be influenced, for example, by complex interactions among the traders, previous history of trading, trading strategies, beliefs about fundamental values, or beliefs about other players. We attempt to minimize these confounds by our experimental design. Although we cannot remove them completely, we contribute to the literature by providing a useful insight into the relationship between personal traits and trading outcomes in asset

[1] Bricker et al. (2017)

markets. A more general contribution of our paper is in the potential identification of traders who suffer serious financial loses by trading in asset markets and who would benefit from relevant policies or educational campaigns.

Many studies use an experimental approach in investigating asset markets. The most robust and consistent finding (comparable with real asset markets) is the rise and subsequent crash of asset price bubbles.[2] Powell and Shestakova (2016) provide an overview of the current state of the literature on market bubbles in experimental markets. However, the majority of studies investigate aggregate market outcomes rather than individual trading behavior, while studies that do analyze individual outcomes have focused on the association with one or only several personal characteristics or traits. The current literature identifies five personal traits or characteristics that affect behavior in the (mainly experimental) asset markets: overconfidence, risk attitudes, willingness to compete, cognitive abilities, and willingness to speculate. We investigate the role of each trait for individual market outcomes. The conclusions of current studies are often mixed for most of these traits, as we summarize in the following paragraphs.

Beliefs about having better trading skills than other traders, i.e. overconfidence, may lead to excessive trading and consequently to different profit compared to when trading is not driven by this trait. Odean (1998) introduces a theoretical model in which traders are overconfident. He proposes more versions of the model depending on the access to information and its cost. In general, overconfidence affects the way traders seek and react to new information. The model predicts higher trading volumes for overconfident traders and lower expected profits for traders who trade more. *Barber and Odean (2000)* examine the trading results for a large data set of traders trading in real asset markets. Controlling for the transaction cost and type of assets, they conclude that higher overconfidence is associated with higher trading volumes and lower resulting profits. Conversely, Kourtidis et al. (2011) provide non-experimental evidence that traders with greater overconfidence perform better than traders with lower overconfidence in the stock markets. Fiedler (2011) obtains a similar result for experimental markets. In examining experimental asset markets, Cueva and Rustichini (2015) find no effect of overconfidence on the size of the bubbles, but they do not investigate its connection with individual outcomes.

One of the main characteristics of an asset market is uncertainty about the realized out-

[2] This result has also been observed in an environment without speculations (Lei et al., 2001).

comes. Therefore, if the potential outcomes are associated with subjective or objective probabilities, it is natural to incorporate risk attitudes into the decision making of the traders. Fellner and Maciejovsky (2007) examine the effects of the risk attitude on experimental market activities. Their results show a correlation of trading activity with one of their risk attitude measures (lottery choices) and no correlation with the other measure (certainty equivalents). Eckel and Füllbrunn (2015) find lower mispricing if the experimental market consists of more risk-averse traders, while Holt et al. (2017) find no correlation between risk attitude and peak price in their experimental markets.

Financial markets may be perceived by traders as a strongly competitive environment (e.g. Cueva and Rustichini, 2015) and therefore decisions in these markets can resemble tournaments. There is some accumulated evidence (e.g. Gneezy et al., 2003, Niederle and Vesterlund, 2007, Kamas and Preston, 2012) that women are less likely to engage in competition even if there are no differences in underlying skills (Buser et al., 2014).[3] Eckel and Füllbrunn (2015) find higher bubbles for the experimental markets with more competitive traders.

It is also natural to believe that success or failure in asset markets depends on one's ability to correctly process all the available information. Cognitive skills are probably the mostly studied personal characteristic associated with individual trading outcomes. The most common tasks for the elicitation of cognitive skills are the Cognitive Reflection Test (CRT) used by Frederick (2005) or the Raven's matrices (Raven, 2000). The results for this measure are unambiguous and suggest that higher cognitive skills are associated with lower market bubbles and, more importantly for our study, higher achieved profits in experimental asset markets Shestakova et al., 2019, Breaban and Noussair, 2015, Cueva and Rustichini, 2015, Noussair et al., 2014.

The last personal trait associated with asset market outcomes is the willingness to speculate, which reflects one's eagerness to be involved in speculative behavior that might turn out to be profitable. This trait is measured by the Speculation Elicitation Task Score (SET) introduced by Janssen et al. (2018). They show that the SET-score is a strong predictor for bubble creation and individual trading activity and that there is no statistically significant relationship between decisions in this task and the results of the Cognitive Reflection Test (CRT) or risk measures (using the approach of Holt and Laury,

[3]For a more detailed overview on the willingness to compete, see Chapter 8 in Kagel and Roth (2016).

2002).

Thus, all five personal traits are found to have a certain impact, at least at the aggregate level, on outcomes in asset markets. However, at the individual level, the evidence is sparse or non-existent for most traits. The only robust finding from the above mentioned studies is positive correlation between cognitive skills and achieved profits (Noussair et al., 2014).

Therefore, we use an experimental design that allows us to investigate the relationship between personal traits and trading outcomes at the individual level and broaden our understanding in this area. Our results suggest that only willingness to speculate is significantly associated with both trading activity and achieved profits. Additionally, higher cognitive skills are associated with higher profits. However, other personal traits are, quite surprisingly, neither statistically (at the 5% level in most specifications) nor economically significant for the individual trading outcomes.

2 Experimental design

We divide the entire experiment into two phases in order to minimize interaction between individual traits elicitation and trading decisions. We measure willingness to speculate, cognitive abilities, overconfidence, willingness to compete, and risk attitude (in this order) in the first phase. A standard socio-demographic questionnaire then follows. The first phase is concluded with cash payments in Czech Korunas (CZK) for decisions made by subjects. The second phase consists of only the experimental financial market. The second phase takes place exactly one week after the first phase.[4] It concludes with cash payments for trading and a show-up fee for both phases. The first reason for dividing the experiment into two phases is to prevent cognitive depletion, which could influence decision-making in later tasks.[5] The second reason is to minimize the mutual influence of one task on decisions made in a subsequent task.[6]

[4]For an example of this kind of two-phase experiment, see Bosch-Rosa et al. (2018).

[5]For more details on the effects of cognitive depletion, see O'Dhaniel et al. (2015) or Boksem et al. (2005).

[6]One example would be interaction of CRT with other tasks described in Brañas-Garza et al. (2012).

The first phase

The first phase starts with printed general instructions in which the subjects are informed about the basic rules and procedures of the experiment. They are then informed that this phase will consist of four tasks and a questionnaire. They are informed that they will be paid only for their decisions made in one of the tasks, which is determined at the end of the session by a public random draw of a token (a strategy method introduced by Selten, 1967).[7] The subjects are further informed that they will not be receiving any feedback on other subjects' decisions or on anyone's payoffs until the feedback stage. Subjects are then asked to read printed instructions for the first task and to answer a comprehension quiz, which is checked by experimenters. In the event of incorrect answers, this is privately explained by assistants and subjects are asked to correct their answers. After all subjects answer the quiz correctly the experiment starts with all additional instructions displayed on the screen.

The first task is a Speculation Elicitation Task (SET) used by Janssen et al. (2018). This task is in the form of a game based on the bubble game by Moinas and Pouget (2013) and it is essentially "finding-a-greater-fool" task. Three randomly-selected subjects form an ordered group. Each subject is asked to decide whether to buy or refuse to buy a worthless asset from a preceding group member for an exogenously given price. If you buy and then sell the asset to a subsequent group member, you earn CZK 300.[8] If you buy it and the next player does not buy it, you earn zero. If you do not buy the asset, you earn a fixed amount, CZK 100. [9] Nobody knows his or her exact position in the group. However, you can infer probabilities of being in each of the three positions from the price you are offered.

The second task is to answer a set of 15 questions, which includes the three original Cognitive Reflection Test (CRT) used by Frederick (2005) and another 12 similar questions.[10] The reason for adding more than the original three questions was to use the answers in the subsequent overconfidence measure and because of the possibility that the answers to the original CRT questions might be well known. The subjects can earn CZK 20 for each

[7]See Brandts and Charness (2011) for a comparison of the strategy method and direct-response method.

[8]CZK 300 was equal to approximately EUR 11.1 or USD 12 at the time of the experiment.

[9]Approximately EUR 3.7 or USD 4.

[10]The questions are attached in Appendix 1.

correct answer (if the second task is relevant for payoff). The CRT score is correlated with decisions in many tasks and domains. Toplak et al. (2011) conclude that the CRT score is a good predictor of performance on various heuristic-and-biases tasks. We also elicit beliefs about the number of correct answers and their position in the group in order to have a measure for two types of overconfidence (see, e.g. Grieco and Hogarth, 2009, for an overview of methods to elicit overconfidence measures). This elicitation is incentivized and subjects are paid CZK 80 for a correct guess (if the second task is payoff-relevant).

The third task measures a willingness to compete. The subject is asked to make choice between competition and a lottery. Competition means that the subject will be matched with another randomly chosen subject and their scores from the previous tasks will be compared. The subject with the higher achieved score is a winner and receives CZK 440, the loosing subject receives CZK 40. The lottery can yield payoffs of CZK 440 and CZK 40. Each subject is presented with menu of 10 choices for which the probability of winning CZK 440 in the lottery changes from 0 to 0.9 (by steps of 0.1). The task is based on the endogenous selection of payment scheme used by Niederle and Vesterlund (2007), but due to the choice between a lottery or a tournament (not a piece-rate or a tournament) it is robust to the variation of risk preferences among the subjects.

The fourth task elicits a subject's risk attitude. We base our approach on the task used by Dohmen et al. (2010) and Schubert et al. (1999).[11] The subjects are presented with a menu of 10 choices between a lottery and sure amount. The lottery is fixed at two potential outcomes of CZK 40 or CZK 440 with equal probabilities. The sure amount increases from CZK 0 up to CZK 360 (with multiple switching points allowed).

Subjects are then asked to complete a short demographic questionnaire and the payoff-relevant task is drawn. After collecting their cash reward for the first phase of the experiment, they sign in for one of the sessions for the second phase, which are scheduled one week after the first phase (more time slots possible for some sessions).

The second phase

The second phase of the experiment consists of an experimental asset market based on the Smith et al. (1988) approach with a constant fundamental value (e.g. Noussair et al.,

[11]More on the risk elicitation methods and their comparison can be found in Abdellaoui et al. (2011) or Crosetto and Filippin (2016).

2001, Bostian et al., 2005). Kirchler et al. (2012) find that a constant fundamental value causes less confusion among the subjects. The subjects read the printed instructions that describe the trading mechanism and the layout of the trading screen. Each subject starts with 3 assets and 300 experimental currency unit (ECU). The asset market consists of 15 trading periods, each lasting 90 seconds. The redemption value of each asset at the end of the experiment (after 15 periods) is ECU 100. Each asset yields a dividend at the end of each period. This dividend is the same for all assets in a given period and has one of these values: 0, 2, 6, or 12 and each value is equally likely to occur. Thus, the expected value of the dividend is ECU 5 at the end of each period. ECUs held at the end of each period yield interest of 5%. The combination of dividends and interest on cash leads to the constant fundamental value of ECU 100 for each asset. Information about the fundamental value is explicitly mentioned in the instructions in order to minimize heterogeneity of beliefs about the knowledge and understanding of other traders. The same information about the fundamental value is repeated by an experimenter when summarizing the instructions.

Each subject can create or accept either bids to buy or offers to sell in real time. No borrowing is allowed. The subjects see the history of average prices in all previous periods, the history of all prices (for concluded trades) in the current period, and the amount of their ECUs and assets available for trading. A screenshot of the trading screen is in *Appendix 3*. After each period, the subjects are informed about the dividend for that period.[12] After 15 periods, the assets held are bought back for 100 ECUs each and then the payoffs are rescaled in such that average earnings from the second phase is CZK 200. The subjects are then paid a fixed show-up fee of CZK 150 in cash on top of their trading payoffs.

Logistics

All sessions were conducted at the *Laboratory of Experimental Economics* (LEE) at the University of Economics in Prague in three waves from February 2017 until March 2019. Additional waves were run in order to increase the statistical power of our analysis. The experiment was conducted using a computerized interface programmed in zTree (Fischbacher, 2007). Subjects were recruited using the Online Recruitment System for Eco-

[12] To prevent the potential influence of different dividend streams across the sessions, we generated a random stream of dividends which were used for all trading sessions.

nomic Experiments (Greiner, 2015) from a subject database of the LEE. The first phase consisted of 10 session with a total of 191 subjects. The average payoff for the first phase was CZK 151 (approx. EUR 5.9). Of 191 subjects, 182 actually participated in the second phase, which consisted of the 10 sessions, and we perform our analysis on these 182 subjects.[13] The average payoff for the second phase, including a fixed show-up fee, was CZK 377 (approx. EUR 14.7). There was not exactly one-to-one correspondence between the first phase and the second phase sessions, and subjects could choose the preferred time on the second phase day. Therefore, the number of traders in our experimental market varies from 14 to 23 traders. Our subjects are mostly students from various universities in Prague, most of whom from the University of Economics. Around 72% of the subjects report "Economics or Business" as their field of study, with the remaining subjects reporting other fields. Of the 182 subjects, 92 are females and 90 are males. Using the Kruskal-Wallis test for equality of populations, there are no statistical differences in any demographic characteristics across the experimental markets (p-values ranging from 0.317 to 0.939).

3 Results

In this section, we analyze our results. First, we briefly compare decisions and results from both phases of the experiment with the previous literature, and then we investigate the role traits in trading activity. In the last part of this section, we establish the relationship between the traits and resulting profits in the experimental asset markets.

The decisions of the subjects lead to an average SET-score of 3.53, which is in line with the score of 3.42 from Janssen et al. (2018), with 4 also being a modal choice. However, the distribution of the values is "flatter" in our case, with more subjects (relatively speaking) being categorized into the extreme values category. A histogram of the SET-score can be found in *Appendix 2* of this paper.[14]

[13] The subjects who did not participate in the second stage are not statistically different in their decisions from the first phase from other subjects. They share very similar demographic characteristics except for the gender composition, but again there are no statistical differences.

[14] We cannot exclude confounding of the behavior in this task by preference for an activity driven either by beliefs about the experimenter's expectations (more on experimenter demand effects in Zizzo, 2010) or by an inherent willingness to be active in the experiment. However, we believe that dispersion of payoffs, and the fact that payoff maximizing decisions (given the beliefs about actions of other players) already require several actions, minimize this incentive. Moreover, if this preference is orthogonal to the

The outcome of the original CRT questions (mean = 1.75, SD = 1.06) is slightly higher than the overall mean in the initial study by Frederick (2005) but lower than the best scoring subsample in that study.

Our two overconfidence measures show that 66.5% of the subjects estimate their result in the quiz part to be higher than their actual score by more than one. Further, 58.8% of the subjects overestimate their actual position by more than one place. There are no statistical gender differences in these measures. There is also a suggestion from the Dunning-Kruger effect that worse performing subjects suffer from a relatively higher overconfidence (Kruger and Dunning, 1999).[15] We reduce our two overconfidence measures to one measure of overconfidence using a principal component approach for the purpose of further analysis (Anderson et al., 1963, Jackson, 2005).[16]

We measure willingness to compete as the number of competitive choices in the fourth task. This translates to a mean belief about the probability of winning the tournament to be in the range between 50% and 60%. Even though there is a slight and statistically significant difference between males and females (males more competitive, p-value of 0.076 using the M-W ranksum test), it is driven by different beliefs about one's own performance. If we control for these beliefs, there are no significant gender differences in willingness to enter competition.

For risk elicitation, the mean of risky choices is 5.28, with females being significantly more risk averse (p-value of 0.01 using M-W ranksum test). Assuming the CRRA[17] utility function, 53.9% of the subjects exhibit behavior consistent with r parameter higher or equal to 0.38 and less than 16% of the subjects fall into the category of risk-lovers. These findings are consistent with results from the previous literature (e.g. Dave et al., 2010).

These 5 examined traits are not statistically different across the trading sessions at the 5% significance level.[18] There is a statistically significant difference at the 10% level regarding risk measure and overconfidence about the achieved score. However, each of these differences is driven by one slightly outlying session (not the same session for both

willingness to speculate, it does not change the interpretation of our analysis.

[15]For more discussion about this effect and its alternative explanation see, for example, Ryvkin et al. (2012) or Feld et al. (2017).

[16]We also conduct the entire the analysis with either (or both) of the overconfidence measures for a robustness check. There were no qualitative and negligible qualitative differences in the results compared to the principal component approach.

[17]Constant Relative Risk Aversion

[18]Using the Kruskal-Wallis rank test

traits). Thus, all our measures of traits are in line with previously established results and we intend to use them for our analysis. Our elicited traits exhibit mostly no or weak correlations among each other.[19] The highest correlation coefficient (in absolute value) is of the size -0.41 (between the CRT score and overconfidence about the position in the group).

We checked for potential confusion in decision making in risk- or competition choices (making more than one switch in their choices) or who buy for the highest price in the SET task. There are 32 subjects who could be potentially labeled as confused or at least inconsistent in their choices. Most of this behavior comes from multiple switching points in the willingness to compete elicitation; only 3 subjects made multiple switches in the risk elicitation task and 5 subjects were buying for the highest price in the SET task. However, there are 5 outlying subjects who made inconsistent choices in two or all three tasks (all multiple switchers in the risk elicitation and 3 of 5 subjects making odd decisions in the SET task). We can only speculate that these subjects are confused by the experiment. We analyzed these results even with these 5 subjects. There is no qualitative difference in conclusions. However, in some cases, adding these 5 potentially confused subjects leads to inflation of the estimated coefficients. In order to err on the side of caution with our conclusions, we exclude these 5 subjects from our final analysis. Henceforth, if we refer to the full sample, we refer to 177 subjects (182-5).[20] If we refer to "consistent" subjects, we refer to 150 subjects with no "mistake" in their choices. If we refer to "inconsistent" subjects we refer to 27 subjects with exactly one inconsistent decision.[21]

Trading results

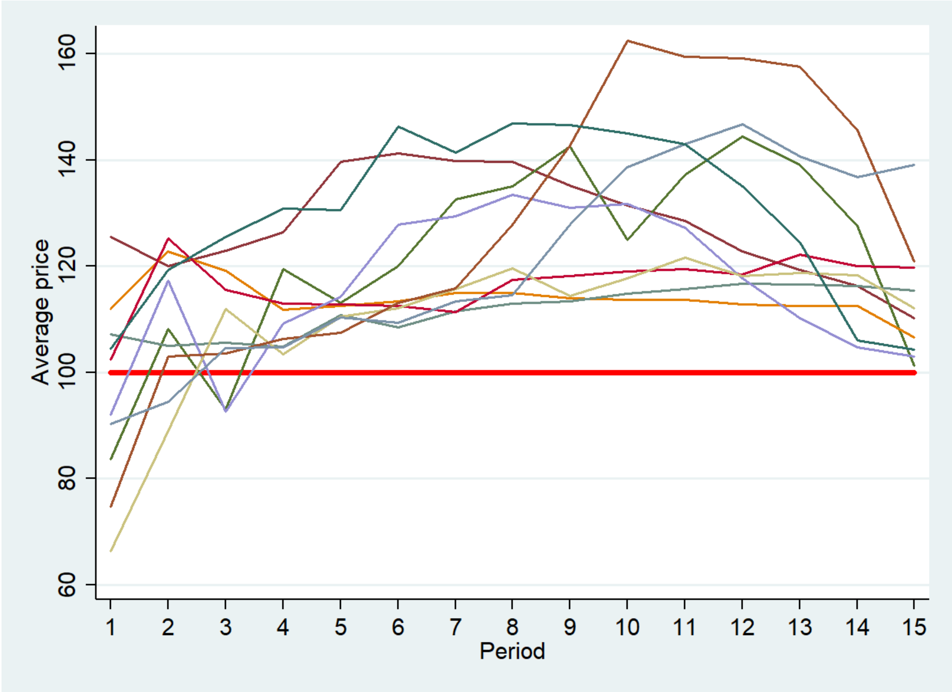
Figure 1 presents the average price in each of the 15 trading periods for each of the 10 experimental asset markets. After the third period, the average price of the concluded trades was above the fundamental value of the asset (thick red line) in each market. Thus, we observe substantial price bubbles in each asset market even though the fundamental

[19]This is in line with Breaban and Noussair (2015), who also found weak correlations among the traits they use.

[20]This sample size allows us to detect an effect of medium size (0.3 x SD) at the 1% significance level with power (1-β) at least 0.86 for intended specification with the highest number of control variables (lowest number of degrees of freedom) . Calculations performed using G*Power software Faul et al. (2018).

[21]Using the Kruskal-Wallis rank test, these 27 subjects are not statistically different from consistent subjects with respect to any demographic characteristics.

Figure 1: Average prices of the asset in experimental markets



value was explicitly emphasized in the instructions. Quantifying the size of the bubble using either measures of geometric (absolute) deviations proposed by Powell (2016) or relative (absolute) deviations proposed by Stöckl et al. (2010), we find these measures in the range from 0.09 to 0.29 for the G(A)D and in the range from 0.117 to 0.3 for the R(A)D, which is in the lower range of values found by previous studies (see e.g. Stöckl et al., 2010, for an overview). We speculate that slightly smaller bubbles are caused by the explicit information about the fundamental value provided in the instructions, which is also consistent with the findings of Cheung and Coleman (2014).

We also analyze the correlation of personal traits with aggregate market measures to contribute additional evidence to the existing literature. In particular, we examine the relationship between the level of mispricing and personal traits, and between the aggregate number of concluded trades and personal traits. Following Breaban and Noussair (2015), we weight each personal trait by the market power of each individual, because the impact of the personal traits of someone holding relatively more assets or cash on the market outcome is larger. The market power of each individual measure is computed as the mean of two shares: the average share of owned assets on the total number of assets in the market and the average share of cash on the total number of cash in the market.

For the level of mispricing in each market, we use the geometric deviation measure. The strongest correlations of this measure (in absolute value) are with the weighted CRT score (-0.381) and weighted SET score (-0.314). However, these correlations are not statistically significant (p-value 0.276 for CRT and 0.378 for SET). Other personal traits have much lower correlation coefficients with this measure (below 0.2 in absolute value). There is no qualitative or sizable quantitative change when using other measures of mispricing. Figure 3 depicts these relationships with added linear fitted values. Conducting a similar analysis with the number of concluded trades in each market, we find that the correlations are statistically significant at the 5% level for willingness to compete (0.603, p-value 0.065) and overconfidence measure (0.553, p-value 0.098). Risk attitude is also highly correlated with the number of trades (-0.517), but this relationship is not statistically significant. Other traits are weakly correlated with the number of trades. Figure 4 depicts these relationships with added linear fitted values.

Traits and trading activity

We study the relationship between the elicited potential traits and the trading activity of individuals in experimental markets. We measure trading activity as the total number of concluded trades in all periods of the experimental asset market. We use robust standard errors and, in most of the specifications, we control for the session fixed effects.[22]Table 1 presents the results of the OLS estimation in four specifications.

The only individually statistically significant trait of the trading activity across all specifications, when using the full sample of subjects, is the SET score. One additional choice to buy in the SET task translates, on average, into an increase in the number of trades by approximately 6% (depending on specification). Risk attitude is statistically significant at the 10% level, but this is not robust across specifications. We do not exclude other traits from the specifications as they are jointly statistically significant in some statistical specifications at the 5% level. None of the demographic controls is statistically significant for prediction of the trading activity. Another interesting result from this analysis is the very high number of trades by the subjects who made inconsistent decisions in at least

[22]An alternative approach would be clustering at the session level, as the trading activity of the subjects is inherently correlated within the same session. However, with a low number of clusters, and as shown by Abadie et al. (2017), it is enough to control for session fixed effects. In fact, the correlation coefficient (intrasession correlation) of trading activity at the session level in our dataset is 0.113.

Table 1: Traits and trading activity

	Number of trades			
SET score	1.290**	1.336**	1.010*	1.070
	(0.527)	(0.572)	(0.601)	(0.693)
CRT score	-0.825	-0.939	-1.210	-0.857
	(1.099)	(1.068)	(1.182)	(1.333)
Overconfidence	0.656	0.153	0.290	0.166
	(0.853)	(0.956)	(1.010)	(1.300)
Risk	0.898	1.232*	1.184	1.47*
	(0.712)	(0.670)	(0.777)	(0.853)
Willingness to compete	0.729	0.382	0.423	0.161
	(0.518)	(0.490)	(0.526)	(0.551)
Session FE	no	yes	yes	yes
Demographic controls	no	no	yes	yes
Constant	yes	yes	yes	yes
R^2	0.062	0.193	0.236	0.256
Observations	177	177	177	150[23]

Notes: Robust standard errors in parentheses.
Statistically significant in two-tailed tests at: * 10%, ** 5%, *** 1%.

one task in the first phase of the experiment. The mean number trades of this group is 22.77, while it is 18.19 for the consistent subjects.

Alternatively, we can use other measures of trading activity used by Shestakova et al. (2019). Measuring trading activity by the number of placed orders, we find no significant relationship of placed asks with any of the studied traits. Using the number of bids placed, we find a significant relationship between this measure and willingness to compete at any conventional level for the whole sample. Risk attitude is also statistically significant at either the 1% or 5% level (depending on the specification). Other traits are statistically not significant and this also holds for all the traits when looking at the consistent subjects only. We are primarily interested in the actual trades and thus we do not further explore other measures because those measures could reflect differences mainly in strategies regarding how to buy or sell the asset. One can create many orders in the hope of being accepted by mistake (for an extreme price) or some subjects could employ the strategy of only accepting created offers.[24]

So far, the analysis has focused on the quantity of trades. However, this does not reflect the characteristics of these trades. For example, one could accumulate a high number of trades for our measure by trading around the market price with almost no impact on the overall profits. On the other hand, one can be involved only in several trades during the experiment that dramatically change one's earnings. To explore this dimension of trading, we analyze achieved profits in the next section.

Traits and profits

In this section, we investigate the relationship between traits and achieved profits. All the experimental markets start with the same amount of shares and cash per subject. We use the same stream of randomly-chosen dividends for all the experimental markets repeatedly. This leads to the same total amount of cash at the end of each trading period in each market. It also leads to the same number of shares per subject at the end of the experiment in each market. Therefore, we normalize the achieved final profits into a number expressing the profit of each subject relative to the average profit in the session.[25]

[24] Correlation coefficient between the concluded trades and the number of offers created is 0.45.

[25] One potential drawback of using the same stream of dividends could be the spillover effect that the subjects in the later markets will know this from their friends. However, that would require noting down

Table 2: Traits and profits

	Relative profit			
SET score	-0.025**	-0.027**	-0.031**	-0.31**
	(0.010)	(0.012)	(0.012)	(0.013)
CRT score	0.070***	0.074***	0.058***	0.065***
	(0.018)	(0.019)	(0.020)	(0.021)
Willingness to compete	0.014	0.016*	0.016*	0.015*
	(0.009)	(0.010)	(0.009)	(0.008)
Overconfidence	0.020	0.023	0.015	0.021
	(0.016)	(0.018)	(0.018)	(0.015)
Risk	-0.007	-0.006	-0.012	-0.027*
	(0.017)	(0.017)	(0.017)	(0.015)
Female dummy	—	—	-0.125***	-0.143***
			(0.041)	(0.041)
Session FE	no	yes	yes	yes
Other demographic controls	no	no	yes	yes
Constant	yes	yes	yes	yes
R^2	0.181	0.194	0.269	0.379
Observations	177	177	177	150[26]

Notes: Robust standard errors in parentheses.
Statistically significant in two-tailed tests at: * 10%, ** 5 %, *** 1%.

In this way, the results are easier to interpret. Table 2 presents the results of the OLS estimation in three specifications with a full sample of the subjects and one specification with the consistent subjects only (see the definition of a consistent subject at the beginning of Section 3). We use robust standard errors, and in most of the specifications, we control for session fixed effects.

The traits that are statistically significant across all specifications are the SET score and CRT score. One additional choice to buy in the SET task translates to a drop in profits by approximately 3%. One additional correct answer in the original CRT score translates to profits higher by approx. 6.5%. Willingness to compete is statistically significant at the 10% level only in some specifications and the size of the coefficient is quite small (one additional competitive choice associated with a 1.5% drop in profits). Females achieve

the whole stream of dividends and then passing this information to this friend. Moreover, asset prices are almost always above the fundamental value of the asset yielding constantly the highest dividend.

profits lower by approx. 15% (not controlling for other variables), but other demographic variables are statistically insignificant in all the specifications. Controlling for the traits, the difference in achieved profits between males and females is only slightly lower.

Examining the relationships between traits and trading activity, and between traits and profits, naturally leads to the idea of investigating the relationship between trading activity and profits. A simple ordinary least square regression approach yields a negative, but not quantitatively large, relationship between trading activity and achieved profits. This relationship is statistically significant at the 5% level. We employ more statistical specifications in which we control for various demographic variables and session fixed effects. The resulting size of coefficients translates to a drop in profit associated with one additional trade to be in range from 0.34 to 0.45 percentage points. However, one needs to be careful when interpreting this result in a causal way. One immediate idea would be to use the traits (either the full set or only the SET score) as instruments for trading activity and to investigate the causal relationship between trading activity (driven by the traits) and achieved profits. Even though a trading activity is not exogenous[27], the IV estimation cannot be used to obtain consistent estimates. This approach would need traits to satisfy standard IV assumptions. Statistical tests used in various specifications lead to a rejection of this approach due to the direct effect of traits on profits,[28] and the potential weakness of the instruments.[29] Both problems may lead to considerable bias in the estimates. Another approach to investigate the relationship between trading activity and the achieved profits would be an exogenous manipulation of trading activity. However, this would be difficult to implement without changing the essence of trading. Therefore, we leave the causal identification of this relationship for further research.

Conclusion

We investigate the relationship between the most common personal traits in experimental literature and trading activity in experimental asset markets. Using our approach, we can filter out or control for many confounding effects present in real financial markets.

[27] Either by using the Hausman test or Wooldridge (1995) robust score.

[28] For more details of the testing procedure see, for example, Wooldridge (2015).

[29] F-statistics in the first stage regression ranging from 2.36 to 10.47, depending on the specification and whether we use the full set of instruments or only the SET score. See, for example, Pflueger and Wang (2015) for a calculation of the potential bias.

It appears that the most important predictor for trading activity is the willingness to speculate measured by the SET score approach of Janssen et al. (2018). One additional speculative decision to buy in this "finding-a-greater-fool" task is, on average, associated with an increase in trading activity by approximately 8.5%. We find that other measured (and more traditional) personal traits that are linked with aggregate market outcomes in previous literature (risk, overconfidence, competitiveness, or cognitive skills) are not individually important as predictors for trading activity. However, we cannot exclude their joint effect. One interesting result is a much higher trading activity (roughly by 25%) by subjects who are inconsistent in their decisions when eliciting personal traits. These subjects also achieve lower profits (3.4 percentage point difference relative to the consistent subjects).

As for the achieved profits, we confirm the findings of previous studies that higher cognitive skills are associated with the higher profits (Breaban and Noussair, 2015, Shestakova et al., 2019). Moreover, the SET-score is again a significant predictor of the achieved profits, but the relationship is negative. One additional speculative decision to buy is, on average, associated with a drop in profits by approx. 3 percentage points. Of all other personal traits, only willingness to compete is statistically significant predictor for the subsample of consistent subjects (at the 10% level). However, again the joint significance of other traits cannot be excluded.

Comparing all the potential traits in one unified framework, we conclude that Speculative Elicitation Task Score is the most prominent predictor of decision making and outcomes in experimental asset markets. Surprisingly, willingness to compete, overconfidence measures and, to a large extent, risk attitude, are all non-significant in terms of predicting asset market outcomes at the individual level. While it is practically easier to measure these traits, they are not so helpful for identifying subjects who suffer serious financial loses by trading in asset markets.

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Appendix 1 - Quiz questions

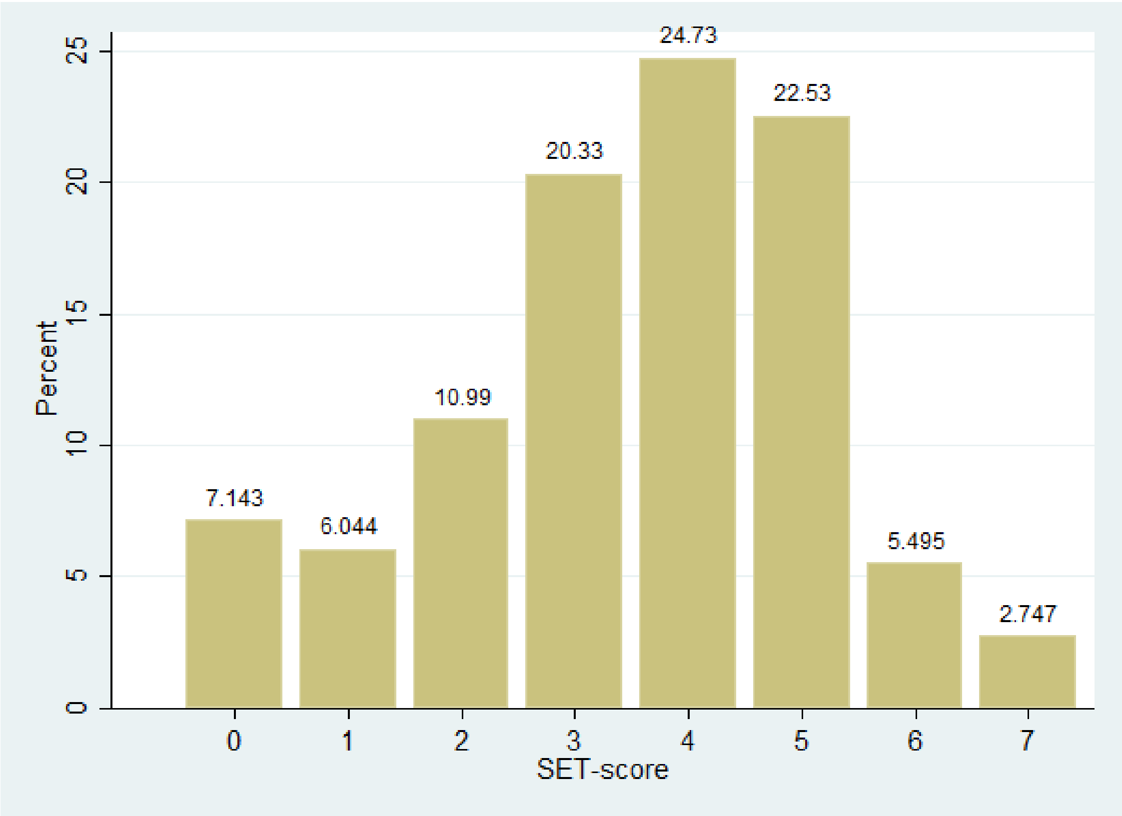
1. We have a pan and three pieces of bread that we want to fry in it. It takes 2 minutes to fry one side of a piece of bread. There is space for two pieces of bread at once. What is the shortest time of frying when we want to fry all three pieces of bread on both sides?
   6 minutes
2. This year a father of a family turned 45. If his three sons are 7, 11 and 15, in how many years will the father's age be equal to the sum of his sons' ages?
   6 years
3. A lake gets slowly covered with reed. Every day the surface covered by reed doubles (1st day 1m2,2nd day 2m2, 3rd day 4m2,4th day 8m2). If the reed covered the full lake in 48 days, how many days did it take to cover half of the lake?
   47 days
4. Margaret is 31, is rather quiet, single and very smart. She majored in philosophy and during her studies she was interested in topics connected to discrimination and social inequality and she was arrested several times for participating in demonstrations for human rights. Which of the following statements is more probable? ________
   a. Margaret works in a bank
   b. Margaret works in a bank and is an active member of Greenpeace
5. A drum and a drumstick cost 110 CZK in total. If the drum costs 100 CZK more than the drumstick, how much is the drum?
   105 CZK
6. Ian goes for a walk to visit Mary who lives in a village 12 km away with a constant speed of 4km/h. His dog can't wait to see Mary so it keeps running back and forth to Mary's house and back to Ian. The dog has a speed of 16km/h. How many kilometers does the dog run until Ian enters Mary's door? **48 km**
7. Fill in a fitting number:
   5+6=1 8+9=3 3+1=0 4+6=2 7+2=0 8+8=4 7+4=_______ **1**
8. Imagine you participate in a TV show where you can win a car, which is behind one of three closed doors (the other two doors hide no prize). You can pick one door and get what is behind it. After you select your door but before you open it, the host opens one of the remaining two doors to show the car is not there. Now you can either switch from the originally picked door and change your choice to the remaining door. Is it better for you to switch to the remaining door? **YES**
9. If 5 workers need 5 minutes to create 5 widgets, how long will 100 workers need for 100 widgets? **5 minutes**
10. Two cities A and B are 90 km apart. A train starts from A to B with a constant speed of 60 km/h. At the same time another train starts from B to A with a same constant speed. At the same moment a fly leaves a train from A to B with a speed of 100 km/h and it heads toward the other train. At the moment it reaches the other train it turns around heading towards the the first one. It goes on back and forths till the moment both trains collide and crush it in between them. How many km has the fly flown until it got crushed? **75**
11. A hotel contains 100 guest rooms. A sign-maker is called to number the guest rooms from 1 to 100. He has to order numerals to do the job. Can you figure out in your head how many 1's he will need?
    a) 10
    b) 11

c) 20
d) 21

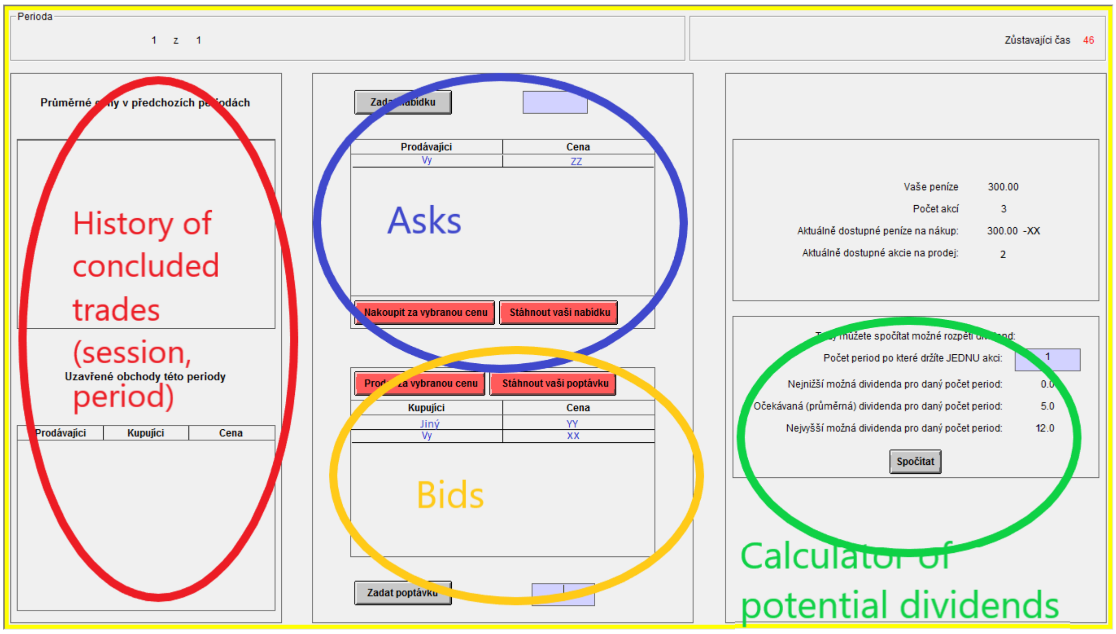
12. Twenty-four red socks and 24 blue socks are lying in a drawer in a dark room. What is the minimum number of socks one must take out of the drawer which will guarantee that one has at least two socks of the same color? **3**
13. Do you happen to know if the Catholic Church allows a man to marry his widow's sister?
    a) Yes
    b) No
14. A man was looking at a portrait. Someone asked him, "Whose picture are you looking at?" He replied: "Brothers and sisters have I none, but this man's father is my father's son." ("This man's father" means, of course, the father of the man in the picture.) Whose picture was the man looking at?
    a) His son
    b) He
    c) His father
15. A man was looking at a portrait. Someone asked him, "Whose picture are you looking at?" He replied: "Brothers and sisters have I none, but this man's son is my father's son." Now whose picture is the man looking at?
    a) His son
    b) He
    c) His father

Appendix 2 - SET-score distribution

Figure 2: SET scores

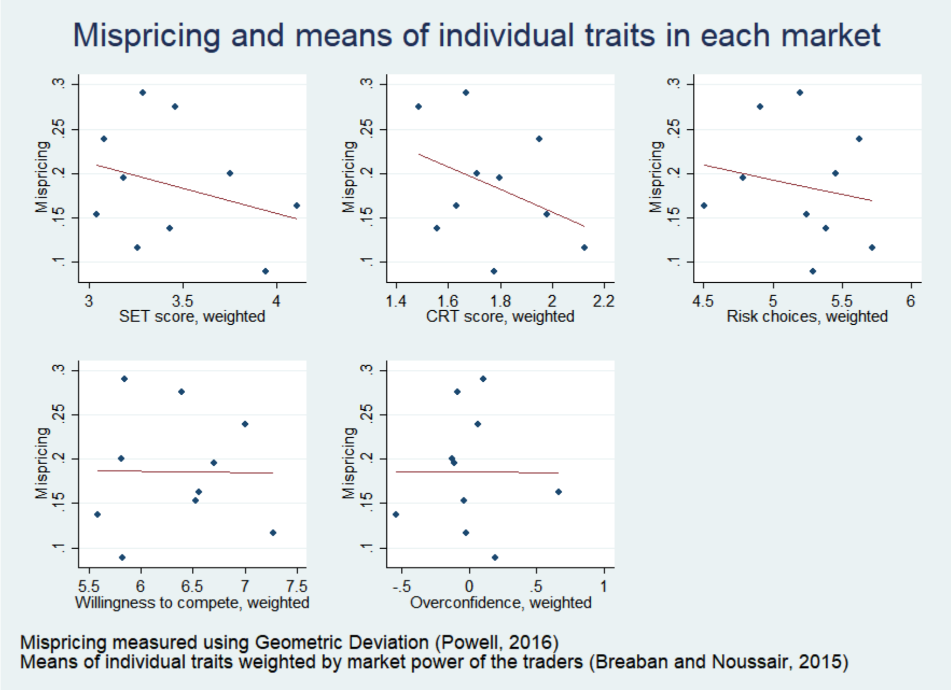


Appendix 3 - Trading screen



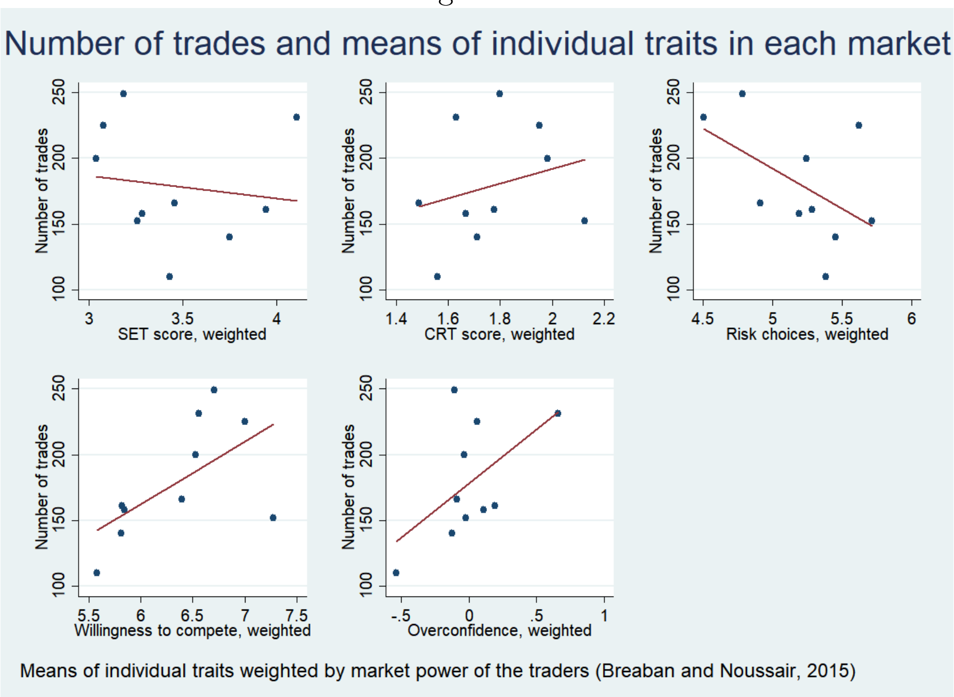
Appendix 4 - Mispricing and personal traits

Figure 3:



Appendix 5 - Number of trades and personal traits

Figure 4:



Abstrakt

Studujeme vztah mezi osobními charakteristiky a výsledky obchodování na finančních trzích s dvojitou aukcí. Existují smíšené teoretické předpovědi o tomto vztahu a také podobně smíšená empirická evidence. Zkoumáme korelaci kognitivních dovedností, ochotu spekulovat, postoj k riziku, ochotu soutěžit a nadměrnou sebedůvěru na velmi jednoduchém experimentálním trhu s jedním aktivem a bez nejistoty ohledně fundamentální hodnoty. Stavíme na tržním prostředí velmi blízkém prostředí ve stěžejním článku Smitha, Suchánka a Williamse (1988) s konstantní fundamentální hodnotou. Přicházíme k závěru, že ochota spekulovat je hlavní hnací silou obchodování. Ochota spekulovat a kognitivní dovednosti jsou jedinými významnými prediktory dosaženého zisku z obchodování. Naše experimentální výsledky poskytují výchozí základní měřítko pro obchodování ve složitějších prostředích reálného trhu s aktivy.

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