User Heterogeneity in Trading Systems: Assessing Trader's Market Predisposition via Personality Questionnaires

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Abstract

One of the main objectives facing service designers is presenting users with information from which to base their decisions. While traditional service research often emphasizes understanding of end users from a technology acceptance perspective, it fails to consider the individual economic dimensions of interactions within a system as in electronic markets. We study market participants from an individual perspective who interact in a repeated decision-making environment that closely resembles decision-making in financial markets. In contrast to financial markets (i) the outcome of events in our market is finally known and (ii) we can ex-post measure the participants' trading performance. In our field study with nearly 2,000 active traders and over 215,000 single trading decisions we analyze the impact of emotion regulation, cognition and risk on trading behavior and performance. Our analysis indicates a significant user heterogeneity, which suggests individualizing future market experiences.

1. Introduction

In this work we link behavioral aspects of market participants with the quality of their trading decisions and behavior in the market. Creating a link between behavioral aspects of the participants and quality is important in that the quality of the predictive power is directly negatively affected if participants make systematically biased decisions. This is a relatively well known, but still not well understood or studied hypothesis of behavioral finance literature. In our market *decision quality* is obviously described by the participants' trading performance as well as their share of profitable trades. To our knowledge current research does not clearly answer the question which personal attributes support or hinder specific successful behavior in markets. We extend the current approach by taking *user heterogeneity aspects* such as personal attributes into account. Besides trading performance we focus on trader activity and if they provide or take liquidity to/from the market as qualitative measures for *trading behavior*. Specifically, we conduct a two-staged study to investigate the influence of *cognitive reflection* abilities, grade of *risk aversion*, and use of *emotion regulation strategies* on trading behavior and decision quality in a prediction market context.

The remainder of this paper is structured as follows: the second section gives a brief review of prediction markets and market behavior. The third section details our research questions. Section four explains the field study setting. The fifth section describes the dataset and the methodology used. Subsequently, we present our results from two perspectives: *trading behavior* and *decision quality*. Finally section seven concludes this paper.

2. Related work

In the following subsections we present related work in the domain of prediction markets and introduce related work in the area of trading behavior and service analytics.

2.1. Prediction markets

With the growth of the Internet, markets that trade predictions about future events have emerged as a promising alternative forecasting tool. In these markets, participants trade contracts whose payoff depends on the outcome of uncertain future events. For example, a market contract might reward one dollar if a particular presidential candidate is elected. In an extreme situation, where a candidate has no chance to win at all, his stock will be worthless. The higher a candidate's chances to win are the more his stock will be worth, converging to one dollar; a rational individual who thinks the candidate has a 65% chance to be elected is therefore willing to pay up to 65 cent for such a contract. Hence, the stock price reflects the probability of the event. Market participants form expectations about the outcome of an event. Comparable to financial markets, traders

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buy if they find that prices underestimate the probability of the event in question and sell stocks if they find that prices overestimate the probability of an event.

"Prediction markets are remarkably accurate information aggregation mechanisms" [13]. They are online markets, which predict upcoming events via stock prices that can be traded in real money or play money. Prediction markets neither rely on a specific market system (e.g. they may use an automated market maker based on a scoring rule [16], but can also use a continuous double auction to bring demand and supply together) nor are restricted to simple binary outcomes (cf. predicting economic indicators [29]). Due to their flexibility, they are not *the* ultimate out-of-the-box solution for forecasting challenges. For instance, *too few* participants –especially noise traders– (so-called 'thin markets'), poor incentives or poorly designed contracts may hurt a prediction market's accuracy. In a way, those circumstances are for prediction markets what behavioral biases are for (their) traders; they hinder markets from unveiling their full potential. Nevertheless, proper designed prediction markets have shown to be successful in a variety of applications in the last decades [9], [17], [28].

2.2. Personal attributes and trading behavior

Psychologists have demonstrated a variety of systematic departures from "rational" decision-making by individuals. These lead to substantial information processing biases or judgment biases and colored expectations [10]. Markets suffer from biases as well and there is an ongoing debate to which extent their efficiency is affected [2]. Objectively irrelevant [19] and selectively presented information [6] can and does influence individual trading behavior. A promising approach to describe and explain financial decision-making may be the explicit consideration of psychological factors. Lo et al. for example have shown the negative influence of extreme emotional states on trading performance [21]. Additionally, they conclude that "[t]he lack of correlation between personality traits and trading performance begs for additional data and a more refined analysis […]". Their approach of acquiring psychological factors via personality questionnaires seems promising. Frederick introduced a well-established questionnaire to measure cognitive ability, the *cognitive reflection test* (CRT) [11]. It builds upon the existence of two types of cognitive processes which Stanovich and West call "System 1" and "System 2" processes [25]. *"System 1 processes occur spontaneously and do not require or consume much attention. [...] System 2 processes [are] mental operations requiring effort, motivation, concentration, and the execution of learned rules."* [11] By offering participants three short tasks, which –at the first glimpse– seems to be solved best by "System 1" processes while actually being more complex tasks (i.e. "System 2"), it is possible to differentiate the more impulsive from the more cognitive reflective ones. The *ten paired lottery* (TPL) introduced by Holt and Laury is a widely used risk aversion test that offers *"[a] menu of paired lottery choices[,] structured so that the crossover point to the high-risk lottery can be used to infer the degree of risk aversion"* [18]. Participants can choose between 'A' (safe choices) and the more risky 'B'. By design, the risk neutral choice pattern is four 'A' choices followed by six 'B' choices. Gross and John introduced a questionnaire to determine emotion regulation strategies, the *emotion regulation questionnaire* [14]. It consists of ten statements –four concerning suppression and six concerning reappraisal– the participant agrees or disagrees with on a seven-point Likert scale. The concept of *reappraisal* takes place in the context of antecedent-focused emotion regulation and means a cognitive change in the interpretation of a situation. *Suppression* happens in the context of response-focused emotion regulation and aims to hide a specific emotion. All three questionnaires are rather short whilst reliable and can therefore be used altogether in one questionnaire without overly stretching a participant's attention.

2.3. Risk aversion and trading behavior

Several authors have identified risk aversion as a reason for certain market behavior [26]. It may cause participants to not make profitable but risky trades in a market. If participants suffer from this aversion, valuable information may not be impounded into prices and thereby reduce the predictive power of a market. Unfortunately, useful insights can only rarely be obtained from empirical data on security prices since risk aversion measures must be obtained independently of trading data. By merging household investment decisions with data from external risk questionnaires Wärneryd did not find a relationship between risk aversion and portfolio choice [30]. This is in line with findings from an empirical asset market in which participants' portfolio choice is unrelated to a risk aversion proxy [15]. In contrast to portfolio choice, individual market behavior seems to be influenced by risk aversion. Fellner and Maciejovsky find that the higher the degree of risk aversion, the lower the observed market activity [7].

Kirchler and Maciejovsky find the higher the degree of risk aversion the lower the total number of contracts traded [20]. In an early experimental study, Ang and Schwarz separated participants in two markets according to their degree of risk aversion [1]. They show that the market with lower risk aversion (speculators) exhibit greater volatility but it also tend to converge closer and faster to the expected equilibrium price than the risk averse (conservative) market. Finally, the interaction between risk attitude and overconfidence with respect to trading activity deserves further attention. Theoretical finance models predict higher market activity as a consequence of overconfidence[1] [3]. People tend to be overconfident about their capabilities and level of knowledge. This could also negatively impact the information content of prices.

2.4. Trading behavior in the market

We measure *trading behavior* in the market via two measures. First, we use the traders' activity; i.e. the number of submitted orders. Second, we take a look at their "roles" in the market. A common perspective to categorize *trading behavior* is to group traders depending on how they submit their orders. One possibility is to separate between a) *liquidity providers* or *market makers* and b) *liquidity takers* or *price takers*. *Market makers* usually buy and sell the same contract at the same time, trying to profit from the spread. Another feature is placing orders on top of the order queue instead of taking the opposite first offer. The *marginal trader hypothesis* by Forsythe et al. assumes that marginal and not average traders determine prices [9]. These traders "make the market" and appear to be more rational [24], plus they are more unlikely to produce trading violations [9]. Oliven and Rietz reported that *price takers* make errors on average 47% of the time whereas *market makers* had an average 8% error rate [24]. Consistently Forsythe et al. described an error rate for *price takers* as high as nearly 6 times the error rate for *market makers* [10]. As a result when traders act as market makers, they make fewer mistakes and hence appear more rational. Furthermore market makers serve as liquidity providers and allow continuous trading [22]. The usually small group of market makers has a disproportionately large effect on aggregated market behavior [27]. Previous work on trading behavior consistently suggests that *liquidity providers* perform better in market environments. In order to understand the motives behind the self-selection into these roles, Oliven and Rietz used demographic information. They find that *"[…] this choice is significantly affected by market-specific experience and general financial knowledge, education, sex, and religious affiliation […]"* but nevertheless *"remains largely unexplained"* [24].

2.5. Service analytics

Following [12], service analytics can be separated in *basic analytics* as a foundation (comprising data management and reporting) and *advanced analytics* using methods from statistics and operations research building on top of it. Especially the latter is predestined to unveil a service's full potential.

In an e-service system context (like a prediction market), the needed data to apply *advanced service analytics* can often easily be obtained, since the provider and customers are connected by design [12].

3. Research questions

In this paper, we apply *advanced service analytics* on an e-service system in order to gain comprehensive insights on customers' *market predisposition*. Based on this, we should be able to substantially improve a customer's service experience in a second step. This can be achieved by adapting the service to customers' preferences and abilities via personalized tweaks (interface adaptions, product choice and the like). In particular, we try to shed some light on the following questions:

(i) *Which personal attributes influence trading behavior in the market?* (following an aspect of [24])

(ii) *How do certain personal attributes influence decision quality in markets?*

Specifically, we are interested in the influence of *cognitive refection abilities*, *risk aversion*, and *emotion regulation strategies* on the aforementioned *trading behavior* and *decision quality*.

As a person's cognitive reflection is known to be positively correlated to her IQ as well as other measures for cognitive ability [11], we assume that a higher cognitive reflection leads to "better decisions" in general. For trading behavior, –in particular for activity– it is not quite clear, what "better" means, nevertheless we expect the more cognitive reflective traders to be less likely liquidity takers (i.e. price takers) [10]. In case of decision quality, we expect that a high CRT-value leads to a higher trading performance as well as a higher probability to make a profit. As stated in section 2, risk aversion has been shown to have an impact on trading behavior. Hence, we expect risk averse traders to be less active. Furthermore, we assume that risk attitude does

[1] The habit of overestimating ones ability to perform a task.

induce certain trading behavior. According to a study of Fenton-O'Creevy et al. [8], the emotion regulation strategy used by traders differs according to their experience and performance. Therefore, we expect to discover certain behavioral patterns depending on the emotion regulation strategy used. Among others, these behavioral patterns include how traders engage in a market, what their decision quality will be or how they self-select into the roles of *price takers* or *market makers*.

4. Study design

In order to answer the research questions presented earlier we conducted a two-staged field study. In the first part participants took part on an online prediction market. Afterwards, participants are invited to take part in an online questionnaire.

4.1. Market design

The study's first part took place in a repeated market environment called *Kurspiloten*. It is a prediction market designed to forecast the stock exchange prices of selected stock indices and commodities, a future contract, and an exchange rate as shown in Table 1. In contrast to the example in subsection 2.1, the outcome of the event is not binary, nor is the payout function. Here, the tradable contracts represent their underlying value one-to-one. Hence, the payout function *is* the stock exchange price of the specific asset at a given time. Therefore, the prediction market's stock price ("forecast") should converge to the stock index' or commodity's price at the time given. Like in financial markets, *Kurspiloten* is setup as a continuous double auction[2] with one stock to represent each new release of economic information. When products are underpriced in a participant's view (i.e., undervalue an event's outcome), she buys –otherwise she sells. For instance, a participant that expects the (real) EUR/USD exchange rate to be 1.25€ will be interested in a buy offer of such a stock below 1.25€ on *Kurspiloten*. (Note, that due to legal restrictions *all trading took place in play money* which we nevertheless called '€'.) By accepting such an offer, she shares her information on the prediction market. We improve participants' motivation and provide incentives to truly reveal information by offering prizes worth more than 70,000€ (real money). Weekly prizes worth roughly around 1,500€ are awarded according to the portfolio ranking at the end of each week. The main prize worth over 40,000€ is given to the most successful trader according to his overall performance. Additional prizes were given to the following top traders; also according to their overall performance.

Table 1. Tradable products on Kurspiloten

Stock	Underlying (currency, unit, ISIN)
DAX	30 major German companies (€, Index, DE0008469008)
MDAX	50 major German companies[1] (€, Index, DE0008467416)
TecDAX	30 largest German tech. companies (€, Index, DE0007203275)
EuroStoxx 50	50 Eurozone companies (€, Index, EU0009658145)
Dow Jones Industrial Average	30 major US companies ($, Index, US2605661048)
Nikkei 225	225 selected stocks from Tokyo Stock Exchange (¥, Index, XC0009692440)
EUR/USD	EUR-USD exchange rate ($, €, EU0009652759)
Euro-Bund Future	Future on German national loan (€, €, DE0009652644)
Gold	Gold (€, Ounce XC0009655157)
Silber	Silver ($, Ounce, XC0009653103)
Brent Crude Oil	Brent-Oil ($, Barrel, XC0009677409)
Rogers International Commodity Index	38 commodities from 13 exchanges (€, Index, NL0000424505)

Note: Stocks traded in play money; [1]excl. DAX and TecDax

In 84 trading days participants were able to trade their price expectations of twelve selected stock indices and commodities on a weekly basis. At the end of each week, stocks are paid out according to their fundamental value: each Friday at 5:30 pm the trading stops and all twelve products (see Table 1) are paid out according to their real world prices at 5:35 pm. (We implemented a delay of five minutes to attenuate end-game effects.) Afterwards, every participant received a new endowment of 1,000 stocks of each of the twelve products and the market is reopened. For example: if the exchange rate EUR/USD was 1.32€ (real world price) at payout time on 2011/10/07, the corresponding *Kurspiloten*-stock 'EUR/USD 07.10.2011' is paid out for 1.32€ (play money). Afterwards, new stocks 'EUR/USD 14.10.2011' are issued.

Since the *Kurspiloten* market was developed in close cooperation with *Handelsblatt* –a leading German economic newsletter– the intended target group is not comprised of professional traders. On the

[2] Participants can continuously submit buy and sell orders for a particular quantity of stocks and price (*limit*). Those orders are gathered in an order book. When the limit prices of two orders overlap, the minimum quantity of both orders is transferred.

contrary, *Handelsblatt* published several newspaper and online articles about *Kurspiloten* in order to reach a broad variety of people who are interested in economics as such. Our setup is well-suited to studying the behavioral aspects of decision making because, in contrast to financial markets (i) the value of shares in our market is ultimately known and (ii) we can measure the participants' trading performance ex post. Furthermore, upon registration we asked for contact data, which gives us the opportunity to invite participants to take part in a follow-up survey.

4.2. Assessment of personal attributes

For the study's second part we invited all market participants to take part in a four-section online survey, five days after the market's end. The first section concerns general feedback of the market platform and its game design. The main part combines the three questionnaires introduce in subsection 2.2. Namely, the *cognitive reflection test*, followed by the *emotion regulation questionnaire* and as last one the *ten-paired lottery*. The questionnaire closes with a "final evaluation question" which asks if participants answered truthfully throughout the questionnaire. The survey was active for 14 days and we incentivize participants by giving away ten Amazon vouchers worth 30€ each via a raffle.

5. Dataset and methodology

The dataset used is taken form the *Kurspiloten* market running from September the 2nd to November the 25th 2011. Most participants registered in the first few days and thus were able to participate for the majority of the markets' runtime (Figure 1). After the first week the registration quote per day stabilized around roughly 25 before it dropped to around five in the last two weeks. Nevertheless participants registered until the last day of the market. The number of orders peaked in the market's first week and stayed above 2,000 orders per day for about two-thirds of the runtime (Figure 2). In the last third of the market lifecycle, it slowly declines towards the minimum of around 800 orders per day. With more than 2,500 orders submitted on average per day (see Figure 2) our dataset contains 131,561 transactions. In total, we received 512 at least partly processed online questionnaires, 386 of them are completely filled. 320 of those contain a positive answer to the "final evaluation question". The median processing time of those 320 replies is 11 minutes 26 seconds (mean: 26m 43s) for the whole questionnaire and 9 minutes 21 seconds (mean: 24m 26s) for the main part containing CRT, ERQ, TPL. In order to statistically analyze our dataset the survey responses have to be filtered and –as well as the trade data– operationalized. Therefore, we filter replies based on the answer for the TPL. We filter the so-called "stay in bed" types (i.e., participants that report to be irrational risk averse). These respondents have chosen 'A' over 'B' in question nine and/or ten of the TPL, where the expected payoff is lower for 'A' than for 'B' (\$1.96 vs. \$3.47 and \$2 vs. \$3.85). Note, that we do not filter the so-called "ABBA" types of the TPL (i.e. respondents who switch multiple times forth and back between A and B). According to Holt and Laury [18] *"[e]ven for those who switched back and forth, there is typically a clear division point between clusters of A and B choices, with few 'errors' on each side. Therefore, the total number of 'safe' A choices will be used as an indicator of risk aversion."* In our survey, the mean difference in the number of 'A' answers with and without "ABBA" types is a mere 0.03 (4.86 to 4.89).

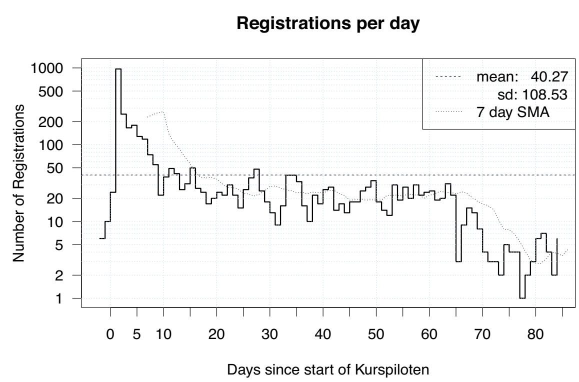

Figure 1. Registration per day including simple moving average (SMA)

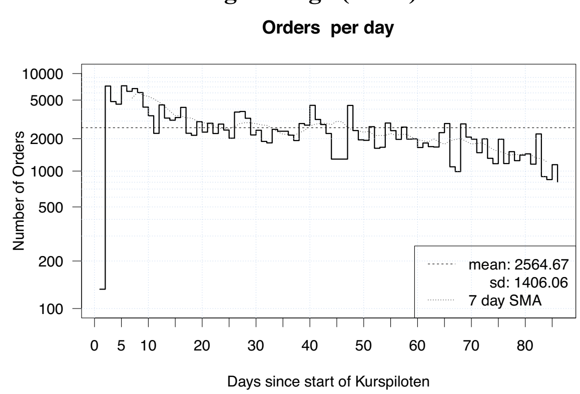

Figure 2. Orders per day including simple moving average (SMA)

This step leaves us with 246 questionnaires. Of those, 50 participants did not actively trade in the Kurspiloten market, i.e. they submitted no order at all. This leaves 196 usable questionnaires for evaluation. This corresponds to 10.25% of active participants (50.78% of completely filled questionnaires) or to an overall response rate of 20.19% (completely filled questionnaires in relation to active participants), which is a fairly normal response rate for online questionnaires [4].

The variables used in our analyses (see Table 2) are described in the following:

Table 2. Variables

Variable	Description	Value
CRT_{high}	Cognitive Reflection Test – Three correct answers = 1	1 or 0
$TPL_{risk\ averse}$	Ten Paired Lottery – Five or more 'safe choices' = 1	1 or 0
$ERQ_{suppress}$	Emotion Regulation Questionnaire – Suppression is used = 1	1 or 0
$ERQ_{reappraise}$	Emotion Regulation Questionnaire – Reappraisal is used = 1	1 or 0
buy_o	Order *o* is a buy = 1	1 or 0
$initialize_o$	Order *o* initialized a trade = 1	1 or 0
$quantity_o$	Size of order *o* in stocks	[1, inf]
$limit\ price_o$	Limit price of order *o*	[0.01, inf]
$profit_o$	Profit made with order *o*	[-inf, inf]
win_o	Order *o* was profitable = 1	1 or 0
$order\ count_p$	Number of orders executed by participant *p*	[1, inf]

The CRT consists of three questions that can be answered either correctly or incorrectly. To derive a dichotomous variable for the CRT, we assign participants with zero to two correct answers in the group CRT_{low} thereby only participants who answered all three questions correct are put in the group CRT_{high}. Since the responses of the ERQ are collected via a seven point Likert scale, we simply calculate the mean of the answers concerning the suppression and reappraisal strategy separately and normalize them to the interval [−1, 1]. Finally we assign a 1 to the dummies $ERQ_{suppress}$ or $ERQ_{reappraise}$ if the normalized averages of replies concerning the corresponding strategy are above or equal to zero; else they are set to 0. We estimate the reliability of the ERQ with Cronbach's α[5], which is 0.673 for the $ERQ_{suppress}$ questions and 0.819 for the $ERQ_{reappraise}$ questions. With an α of more than 0.8, the assessment of 'Reappraisal' can be considered good. Although, the α for $ERQ_{suppress}$ is slightly below 0.7, we consider the survey's results to be reliable since we measure the latent construct 'Suppression' –by design of the ERQ– with just four items. Responses of the TPL are also segregated into two groups: $TPL_{risk\ averse}$ is set to 1 for participants with five or more 'A' choices, while it is 0 for participants with four or less safe choices. The trading direction is identified by the variable *buy*, which is 1 for a buy and 0 for a sell order. The variable *initialize* is used to distinguish between liquidity taking and liquidity providing orders. An order that is not immediately executed provides liquidity to the market, whereas an order that initializes a trade directly after submission to the market "takes" liquidity from it. (For example, a buy order *a* of 125 Stocks for 120.00€ is submitted while a sell order *b* of 100 stocks for 120.00€ and another sell order *c* of 150 Stocks for 119.95€ are the highest sell orders in the order book. The initializing order is order *a*, since it initializes the trade, as it completely fulfills order *b* and partly (25 units) order *c*. Note, that under certain circumstances order *b* and *c* can also be initializing, due to a prior (partly) execution.) In the first case *initialize* is set to 0, since the order does not trigger a trade, else it is set to 1, i.e. if an order takes liquidity from the market. Furthermore, we use the limit price of an order in € (*limit price*) and the number of shares traded (*quantity*). The variable w*in* indicates if a specific transaction led to a (positive) *profit*. Last, the number of orders submitted per participant is encoded by *order count*.

6. Results

The results of our study are presented in the following subsections. We first analyze the trading behavior in the market then we take a look at the traders' decision quality.

6.1. Trading behavior

In the following we investigate the trading behavior in the market with two types of regression models. First, we connect the traders' personal attributes (namely, *cognitive reflection* abilities, *emotion regulation strategies*, and *risk aversion*) with their *activity* proxied by the *order count* on a per-user basis. Second, we investigate the personal attributes in terms of *trading strategy* on a per-order basis. We therefore classify orders as *liquidity providing* or *liquidity taking* via the variable *initialize*.

6.1.1 Activity. We build a linear regression model to analyze how the activity per user depends on the personal attributes. As we can see in both models in Table 3, the activity is significantly higher for participants with a high cognitive reflection (standardized coefficients: 0.16 in A1, 0.15 in A2). Also, risk aversion significantly increases the number of orders submitted to the market (Model A1, std. coef.: 0.15). Even though risk aversion is significant positive correlated with the number of submitted orders (cor=0.148, t-stat=2.08), risk aversions' influence declines and its significance fades to the 10%-level when we include the participants' emotion regulation strategies (Model A2, std. coef.: 0.13). Similarly, $ERQ_{suppress}$ is significantly negatively correlated with the number of submitted orders (cor=-0.146, t-stat=-2.07); both emotion regulation strategies have no significant effect in model A2 (using the logarithmized order count as dependent variable leads to similar results.).

In contrast to [7] and [20], we have *not* found a robust relation between risk aversion and activity.

Table 3. Activity

Model	A1 order count	A2 order count
CRT_{high}	165.95* (2.25)	160.50* (2.15)
$TPL_{risk\ averse}$	157.76* (2.17)	138.89• (1.89)
$ERQ_{suppress}$	–	-118.98 (-1.62)
$ERQ_{reappraise}$	–	45.03 (0.57)
(Intercept)	21.97 (0.35)	64.41 (0.68)
Adj. R^2	3.69%	4,05%
N	196	196

t-statistic in parenthesis
•p<0.1, *p<0.05, **p<0.01, ***p<0.001

6.1.2 Trading strategy. In order to investigate the participants' personal attributes on their *trading strategy* (i.e. their role in the market), we conduct a logistic regression on the variable *initialize*. The results in Table 4 show that high cognitive reflection favors the initialization of trades (Marginal Effects (mfx): 0.02 in I1 and I2, 0.01 in I3) whereas risk aversion hinders it (mfx: -0.02 in I1, -0.03 in I2 and I3). While the strengths of those effects are about equal in I1, they diverge more and more from I2 to I3. Like risk averse traders, ones using the suppression strategy also tend to initialize less often (mfx: -0.02 in I2, -0.03 in I3) whereas traders using the reappraisal strategy tend to initialize trades more often (mfx: 0.04 for I2, 0.04 for I3). Although the *limit price* of an order is highly significant, its impact on *initialize* is diminishable as those for the trading direction (*buy*) and trading *quantity*. Nevertheless, those control variables do support the validity of Model I2, specifically the influences of risk aversion and emotion regulation strategies.

Putting it all together, we show that on the one hand, high cognitive reflection leads to higher activity and –contrary to previous research– drives *liquidity taking*, as reappraisal does; on the other hand, risk aversion and suppression impels *liquidity providing*.

Table 4. Trading strategy

Model	I1 initialize	I2 initialize	I3 initialize
CRT_{high}	0.07*** (5.20)	0.09*** (6.23)	0.04** (2.81)
$TPL_{risk\ averse}$	-0.07*** (-4.09)	-0.11*** (-6.02)	-0.12*** (-6.86)
$ERQ_{suppress}$	–	-0.09*** (-5.95)	-0.07*** (-4.58)
$ERQ_{reappraise}$	–	0.16*** (10.57)	0.16*** (10.22)
Control for products	–	–	✔
buy	–	–	0.01 (0.61)
quantity	–	–	0.00 (-0.89)
limit price	–	–	0.00*** (3.34)
(Intercept)	0.08*** (5.27)	0.02 (1.19)	0.13*** (4.49)
AIC	48,001.96	47,885.59	47,399.02
Pseudo-R^2	6.42%	6.74%	8.11%
N	34,729	34,729	34,729

z-statistic in parenthesis, pseudo-R^2 [23]
•p<0.1, *p<0.05, **p<0.01, ***p<0.001

Result 1: Based on the analyzed personal attributes we can identify specific *trading behavior*.

6.2. Decision quality

In our dataset, the final value of all stocks is known. To answer the question *"What features does a trader need to be successful?"* we calculate the total *profit* of each trade based on the final value of the corresponding stock. Furthermore, we classify each trading decision according to its profitability (in other words: as "right" or "wrong"). From an ex-post perspective, we consider the profitability (*win*) as the *probability to make a profit*.

6.2.1 Trading performance. In order to analyze the influence of a trader's personal attributes on her performance, we conduct a linear regression on the *profit* in € (play money) on a per order basis (Table 5). In the model P1 we see a strong significance for cognitive reflection (standardized coefficients: 0.02 for P1 to P3) and risk aversion (std. coef.: -0.02 for P1 and P2, -0.01 for P3). Our dataset shows that cognitive reflection, risk aversion, and usage of the suppression strategy (std. coef.: 0.04 in P2, 0.05 in P3) have significant influence on traders' performance (Model P2). In model P3 even the reappraisal strategy has a significant influence (std. coef.: -0.02). Nevertheless, the trading direction has the strongest effect on the traders' performance and the highest contribution to the profit (std. coef.: 0.33).

Table 5. Trading performance

Model	P1 profit	P2 profit	P3 profit
CRT_{high}	116.35*** (3.90)	124.09*** (4.14)	116.92*** (4.06)
$TPL_{risk\ averse}$	-160.99*** (-4.43)	-110.40** (-2.95)	-91.64** (-2.60)
$ERQ_{suppress}$	–	232.23*** (6.90)	276.37*** (8.66)
$ERQ_{reappraise}$	–	8.30 (0.26)	-102.85*** (-3.35)
Control for products	–	–	✔
buy	–	–	1794.55*** (64.18)
initialize	–	–	134.43*** (4.92)
(Intercept)	330.02*** (9.75)	211.25*** (5.17)	-816.32*** (-13.91)
Adj. R^2	0,08%	0,23%	11,44%
N	34,729	34,729	34,729

t-statistic in parenthesis
•p<0.1, *p<0.05, **p<0.01, ***p<0.001

6.2.2 Probability to make a profit. When we compare the OLS regression results for *profit* (Table 5, P3) with the logistic regression for *win* (Table 6, W3), we see only minor changes in the estimators' significance and direction. Interestingly, the traders' cognitive reflection ability has a significant influence in model W3 *only* (Marginal Effect (mfx): 0.01). (Obviously, highly cognitive reflective traders do not robustly have a higher probability to make a profit, but *if* they gain, their average profits are higher.) The suppression strategy improves *decision quality* and slightly improves from W2 to W3 (mfx: 0.02 in W2 and W3). The usage of the reappraisal strategy had a higher significance level through the models –and additionally keeps its sign (mfx: -0.01 in W2, -0,02 in W3) as well. Contrary to that, risk aversion declines in significance and strength from model W1 to W2, but still beats a strong 5% significance level in model W3 (mfx: -0.02 in W1, -0.01 in W2 and W3). Interestingly *initialize* plays no role in a trader's *probability to gain a profit*. As we have seen before with *limit price* in Model I1 (Table 4), we see strong significances in combination with weak (marginal) effects for the control variables *quantity* and *limit price* in Model W3. Analogous to Model P3, *buy* has the strongest effect in Model W3 (mfx: 0.14).

Table 6. Probability to make a profit

Model	W1 win	W2 win	W3 win
CRT_{high}	-0.02 (-1.16)	-0.02 (-1.43)	0.04** (2.65)
$TPL_{risk\ averse}$	-0.07*** (-4.12)	-0.05** (-2.64)	-0.04* (-2.17)
$ERQ_{suppress}$	–	0.08*** (5.23)	0.09*** (5.48)
$ERQ_{reappraise}$	–	-0.06*** (-3.93)	-0.10*** (-6.51)
Control for products	–	–	✔
buy	–	–	0.58*** (40.01)
quantity	–	–	0.00*** (-7.31)
limit price	–	–	0.00*** (-3.54)
initialize	–	–	0.00 (-0.35)
(Intercept)	0.34*** (21.06)	0.34*** (17.44)	0.04 (1.13)
AIC	46493.89	46464.39	44060.04
Pseudo-R^2	6,31%	6,40%	12,73%
N	34,729	34,729	34,729

z-statistic in parenthesis, pseudo-R^2 [23]
•p<0.1, *p<0.05, **p<0.01, ***p<0.001

Summing up, high cognitive reflection leads to better trading performance, whilst it does not (robustly) increase the probability to make a profit. Risk averse trader's performance is slightly worse, as are their chances to make a profit. Suppressors decide 'better' and are more likely to make a profit, whereas reappraisal tends to impair good decisions as well as the probability to make profits.

Result 2: Personal attributes do significantly influence *trading performance* as well as the *probability to make a profit*.

7. Conclusions

In this work, we applied *advanced service analytics* in order to gain comprehensive insights on participants' *market predisposition*. Based on a relatively short questionnaire, the trading history and regression models, we were able to characterize participants' *trading behavior* and *decision quality* up to a certain degree. The applied methodology is hereby not tied to the context of play money prediction markets and can hence be used throughout similarly designed e-service systems like retail-trading systems. In particular, we investigated the influence of a subjects' cognitive reflection ability, grade of risk aversion and use of emotion regulation strategies on trading behavior and decision quality in a play money prediction market. Putting all results together we see that cognitive reflection abilities have a significant positive influence on all investigated variables. One may argue that traders with higher cognitive reflection abilities performing better and having a higher probability to make a profit than the average is not very surprising. But traders in the high CRT group also behave differently: they submit more orders and tend to be liquidity takers. Interestingly, risk aversion has a positive impact on the number of submitted orders and a negative influence on a trader's performance as well as on her probability to make a profit. Finally, risk averse traders tend to be liquidity providers. Although neither emotion regulation strategy has a significant influence on a traders' activity, it can be shown that emotion regulation influences the initialization of trades: traders who confirm using the suppression strategy tend to provide liquidity, while the use of the reappraisal strategy leads to liquidity-taking trading behavior. Looking at the traders' performance, there is also a clear distinction between the reappraisal and the suppression strategy; traders who confirm using the suppression strategy have a higher probability to make a profit, whereas traders who make use of the reappraisal strategy have a smaller chance to decide profitable. Even if it may look like in our findings that the emotion regulation strategies reappraisal and suppression are opposite effects a person has to decide between, they are not. Even though both strategies seem to compensate each other in our study, we have to keep in mind that they are two strategies of emotion regulation a person makes use of 'simultaneously' in a different shape. Risk aversion has shown to affect the trading strategy towards liquidity providing. It further slightly positively influences trading activity. In case of decision quality, risk aversion proved to be obstructive; both for profit and for the probability to make a profit.

Summing up, we found out that it is possible to categorize (potential) traders *ex ante* with *advanced service analytics*. The implications of our results are at least twofold. First, we can partly predict individual trading behavior and therefore are able to adapt the market accordingly. One possibility is to alter the user interface depending on the *market predisposition* of the particular user. A highly risk averse user with low cognitive reflection abilities who regulates his emotions mainly by using the suppression strategy for instance is less likely to need an order book since she tends to set limit orders instead of simply taking the quoted prices. Based on such knowledge, it is possible to create personalized and hence much clearer, user-centric trading interfaces. Second, we can predict a certain bonus/malus a trader is going to experience in a market setting. This enables traders to self-assess their market predisposition and behave accordingly; e.g. by not joining a market. But even from the market providers' point of view, these results can be useful, since they can *ex ante* identify potential traders that do not have the 'right' predispositions. Additional, they could identify potentially "aptly traders" and recommend them to trade specific products. By following those implications, we should be able to improve the participants' decision performance within our e-service system, which itself will lead to a better 'predictive power'.

8. References

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