Evaluating Hidden Market Design

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Abstract. Electronic markets are increasingly gaining importance in the coordination of complex allocation problems. One reason for market failure is the inherent complexity excluding non-sophisticated users. Recently researchers proposed the idea of hidden market design which merges the fields of market design with user interface design in order to make complex markets accessible to a broader audience. One way to accomplish that is to simplify the market interface. Thus far it remains empirically unclear how using such interfaces affects market efficiency and individual trading performance. In a prediction market for economic variables, traders can choose between a standard trading interface, and one that hides most market complexities. We find that market participants using a simplified trading -*hidden market*- interface are more likely to submit profitable orders.

Key words: Hidden market design, Prediction markets, Trading interfaces, Marco-economic variables

1 Introduction

The Internet has increased the number of complex (e.g. Energy, P2P resource sharing) markets dramatically. As more and more non-sophisticated users have to interact with complex markets, the question arises how to provide interfaces for such users to participate. Promoting the idea of *Hidden Market Design*, researchers have recently identified the need to merge interface and market design [17]. The main idea is to hide or reduce market complexities while maintaining economic efficiency. One way to accomplish that is to simplify the market interface. However it remains empirically unclear how simplified trading interfaces effect market efficiency and individual trading decisions.

We study a prediction market called Economic Indicator Exchange[1] (EIX) forecasting economic indicators such as GDP, inflation, investments, export and unemployment figures in Germany. The basic idea of prediction markets is to trade contracts whose payoff depend on the outcome of future events. Market participants form expectations about the outcome of an event (e.g. the economic growth in the next quarter). Comparable to financial instruments, they buy if they find that prices underestimate the event in question and they sell if they find that prices overestimate the probability of an event.

The advantages of this research setting are twofold. First, from an individual perspective market participants interact in a repeated decision-making environment closely reassembling decision-making in financial markets. Secondly, as the outcome of events in prediction markets is finally

[1] www.eix-market.de and eix.handelsblatt.de

known, we can ex-post measure the participants' trading performance. In a field experiment with more than 600 participants and over 40,000 trading decisions, participants can individually choose between two trading interface types. One interface type is a standard trading interface, whereas the other hides most market complexities. Recording through which interface an order is submitted allows us to link trading performance and interface type. Evaluating the hidden market design paradigm from an individual perspective, we find that alternative trading interfaces change participants' behavior. Furthermore, and against naive intuition, we find that orders submitted through a simplified interface are more likely to be profitable compared to orders which are submitted through the default trading interface.

The remainder of this paper is structured as follows: the second section presents a review of related work in the hidden market domain. Additionally a short introduction to prediction markets is given. The third section details the field experiment setting and the framing of the participants' trading process. The subsequent section first presents some descriptive data and then introduces the evaluation methodology. Specifically, we use market measures to separately analyze trading performance and trading behavior. In section five we link the interface types to trading outcome and interpret the results. Finally section six concludes this paper.

2 Related Work

In the following section we will first present related work in the hidden market domain and then introduce related work in the prediction market area.

Hidden Market Design

Challenged by the rise of complex markets (e.g. Energy, P2P resource sharing) in which non-sophisticated users find it hard to interact, Seuken et al. proposed the idea of Hidden Market Design. *'The Hidden Market Design challenge is to find new techniques and approaches towards designing and building hidden markets for non-sophisticated users. The primary goal [..] is to find the right trade-off between hiding or reducing some of the market complexities while maximizing economic efficiency attained in equilibrium.'* [17]. Hence the goal is to lower the entrance barriers (e.g. market complexities) for non-sophisticated users to participate in markets. The simplification can be achieved by either changing the user interface or adapting the market rules. Following the idea they design a market-based P2P backup application [18]. In the paper they address both aspects; the user interface eliciting participants' preferences and the market rules, standardizing the market interaction. However it remains unclear how the simplified trading interface effects market efficiency and individual trading decisions.

Decision processes in trading environments

To our knowledge there exist no empirical work on decision processes in trading environments with focus on the trading interface. Kauffman and Diamond [13] highlight the importance of research on behavioral decision making and information presentation effects. They examine how behavioral effects may become operative in screen-based securities and foreign exchange trading activities, where users can choose among information presentation formats which support trader decision making. They present a model to identify where and how information, heuristics and biases might effect decision making in the trading environment. There exists -to our knowledge- no empirical work linking the decision making in continuous markets to the trading interface. In the domains of decision support systems and online shopping environments the influence of the interface on decision behavior has been repeatedly demonstrated. To summarize previous work the amount and control of information, as well as the information representation [22, 23] does influence user behavior. On the one hand information control improves performance by improving the fit between actions and outcomes. On the other hand in terms of cost (disadvantages), information control requires the user to invest processing resources in managing the information amount and flow. As a conclusion information control has both positive and negative effects on performance [1]. The two tasks of processing and managing information are related and codependent. Turning to the optimal pool of available information in decision support systems, empirical work has shown that users can handle only a certain amount of data. Malhotra [15] concludes that individuals cannot optimally handle more than ten information items or attributes simultaneously. Testing decision accuracy Streufert et al. [20] show that as information load increases, decision making first increases, reaches an optimum (information load ten) and then decreases.

Prediction markets for economic derivatives

Prediction markets have a long track of successful application in a wide area ranging from political to sport events sometimes outperforming established forecast methods [3, 14, 9]. The roots of their predictive power are twofold; the market provides the incentives for traders to truthfully disclose their information and an algorithm to weight opinions [2]. They facilitate and support decision making through aggregating expectations about events [11, 4, 12]. The most basic trading mechanism for prediction markets is based on a continuous double auction for one stock which represents the outcome of an event. The stock will pay 1 if an event has the predicted outcome and else the stock will be worthless. Market participants form expectations about the outcome of an event. Comparable to financial markets, they buy if they find that prices underestimate the event in question and they sell a stock if they find that prices overestimate the probability of an event.

In an attempt to set up a market to predict economic variables in 2002 Goldman Sachs and Deutsche Bank created the so called 'Economic Derivatives' market. It tries to predict macro-economic outcomes such as ISM Manufacturing, change in Non-Farm Payrolls, Initial Jobless Claims and consumer price index [7]. The traded contracts are securities where payoffs are based on macroeconomic data releases. The instruments are traded as a series (between 10-20) of binary options. For example a single data release of the retail sales in April 2005 was traded as 18 stocks. In order to maximize liquidity the market operators use a series of occasional dutch auctions just before the data releases instead of the more common continuous trading on most financial markets. Thus the market provide hedging opportunities against event risks and a short horizon market forecast of certain economic variables. By analyzing the forecast efficiency Gurkaynak and Wolfers [10] find that market generated forecasts are very similar but more accurate than survey based forecasts [2]. In an attempt to forecast inflation changes in Germany, Berlemann and Nelson [6] set up a series of markets. The markets feature continuous trading of binary contracts. In a similar field experiment Berlemann et al. [5] use a similar system in order to aggregate information about inflation expectations in Bulgaria. All in all, the reported forecasts results in both experiments are mixed but promising.

[2] One must note that the Bloomberg survey forecasts are published on Fridays before the data release, whereas the auction was run -and the forecast was generated- on the data release day.

An economic indicator exchange

In October 2009 a play money prediction market was launched specifically designed to forecast economic indicators such as GDP, inflation, investments, export and unemployment figures in Germany. The goal is to forecast the indicators over longer time periods in advance and continuously aggregate economic information. The market called Economic Indicator Exchange (EIX)[3] was launched in cooperation with the leading German economic newspaper 'Handelsblatt'. The cooperation aims at reaching a wide and well informed audience interested in financial markets and economic development. We thus expect no problems understanding the indicators and the concept of trading. The market is publicly available over the Internet and readers where invited to join. The registration is free and requires besides a valid email address just minimal personal information.

Market & contract design

The market design features a continuous double auction without designated market maker. Participants are allowed to submit marketable limit orders with 0.01 increments through the web-based interface. After registration participants are endowed with 1,000 stocks of each contract and 100,000 play money units. We propose to represent continuous outcomes with one stock and define a linear payout function. Contracts for each economic indicator are paid out according to equation 1.

$$p = 100 + \alpha \times (\frac{I_{t0} - I_{t-1}}{I_{t-1}}) \ with \ \alpha = 10 \tag{1}$$

A contract is worth: 100 +/- α times the percentage change for an indicator in play money (e.g. a change of 2.1 % results in a price of 121). We set α to 10. Therefore the representable outcome events range from -10% to infinity. To represent the whole outcome range from -100%, α could be set to one. Previous work indicates that market participants find it difficult to estimate minor changes in the underlying event [19]. Hence we propose to scale the minor changes to a certain level. Looking at historical data there were no events where German GDP dropped 10% per quarter. The rationale for setting α to 10 was the deliberation that participants find it more intuitive to enter integers in order to to express reasonable accuracy. Additionally German statistical data releases rarely come with more than one decimal.

Table 1 summarizes the economic variables tradable on the market. Due to the payout function and the selection of the corresponding units; all stock prices are expected to roughly range between 50 and 150. Therefore participants could similarly gain by investing in specific indicators. The indicators are a mix of leading -forecasting the economy- (e.g. Investments) and lagging -describing the state of the economy-(e.g. Unemployment numbers) economic indicators. To facilitate longer forecast horizons every indicator is represented by three independent stocks each representing the next three data releases (t_1, t_2, t_3). As a consequence the initial forecast periods vary between 1 month for monthly released indicators up to 3 quarters for quarterly released variables. One day before the release date the trading in the concerned stock is stopped. Finally the stocks are liquidated according to the payout function defined in equation 1. As soon as the trading in one stock stops a new stock of the same indicator (e.g. t_4) is introduced into the market. This means that participants received 1000 new stocks of the respective indicator. All in all participants are able to continuously trade 18 stocks at all times.

[3] www.eix-market.de

Indicator	Unit	Data release cycle	Number of Payouts	Payout function
Exports	$rel. - Changes_{t-1}$	monthly	12	$100 + \alpha \times (\frac{I_{t0} - I_{t-1}}{I_{t-1}})$
GDP	$rel. - Changes_{t-1}$	quarterly	4	$100 + \alpha \times (\frac{I_{t0} - I_{t-1}}{I_{t-1}})$
IFO Index	$abs. - Changes_{t-1}$	monthly	3	$100 + \alpha \times (I_{t0} - I_{t-1})$
Inflation	$rel. - Changes_{t-12}$	monthly	11	$100 + \alpha \times (\frac{I_{t0} - I_{t-12}}{I_{t-12}})$
Investments	$rel. - Changes_{t-1}$	quarterly	5	$100 + \alpha \times (\frac{I_{t0} - I_{t-1}}{I_{t-1}})$
Unemployment	Million (abs.)	monthly	12	$100 + \frac{ABS(Number)}{100.000}$

Table 1. Economic variables

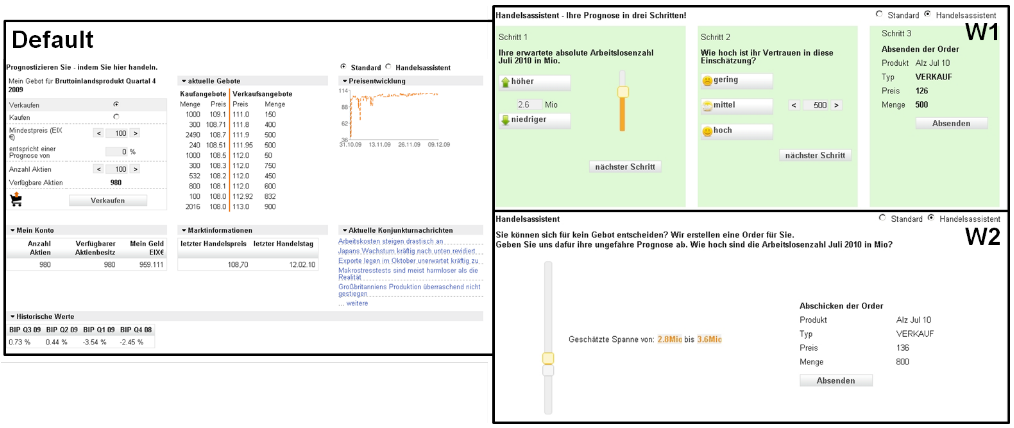

Fig. 1. Three trading interfaces

Incentives

As mentioned the market is a free to join play money market. In order to motivate participants intrinsically we provided two interface features; traders could follow their performance on a leader board and they could form groups with others to spur competition with friends. Previous research in the field of prediction markets has shown that play-money perform as well as real-money markets predicting future events [24, 16]. Due to the legal restrictions on gambling the EIX prediction market has to rely on play money. To increase participants' motivation and to provide incentives to truly reveal information we hand out prizes worth 36,000 Euro. As we try to forecast longer periods the incentive scheme has to address this problem. So the incentives are divided in two parts (a) monthly prizes and (b) yearly prizes. The 8 yearly prizes (total value 10,000 Euro) are handed out according to the portfolio ranking at the end of the market. The monthly prizes are shuffled among participants who fulfilled two requirements for the respected month: (i) they increased their portfolio value and (ii) they actively participated by submitting at least five orders. Both incentives are clearly communicated through the interface. For the yearly prizes the leader board indicates the current status of all participants. the monthly winning status is displayed individually just after each login.

Trading interfaces

The three trading interfaces are displayed in figure 1. In the default trading screen (left side), participants have convenient access to the order book with 10 levels of visible order book depth, the price chart, the account information and market information such as the last trading day. As additional information the Handelsblatt provides access to an up-to-date economic news-stream and finally the indicator's last years performance is displayed. Participants are able to customize their default trading interface individually. By clicking the small arrows the six information panels open and close. In the default setting, only the trading mask and the six headlines are visible. After each submitted order the chosen interface is saved per user. On user return the system opens the previously used interface elements on default. Moreover, a short description of the market comprising the respective payoff function is shown as part of the trading screen.

Additionally to the default trading interface, participants have the choice to switch to a trading wizard guiding their trading decisions. In order to test for the interface influence on trading performance we designed two different wizards displayed on the right hand side, marked with W_1 and W_2. Participants are randomly assigned in one of two groups with access to one of the two different trading wizards. Interface W_1 is designed as a three step trading wizard, with three (green) boxes appearing in order. In the first step participants indicate if they believe the prediction to be higher or lower than the current market forecast. In the second step they are asked about their confidence in their prediction. The third box just displays the generated order. Interface W_2 simply asks the participant to indicate a prediction interval with two handles. On the right hand side an order is automatically generated depending on the current orderbook and the distance between lowest and highest indicated prediction value. The interface is similar to and was inspired by the Yoopick interface [8]. It is noteworthy that both wizards provide far less information than the default interface. In terms of Seuken et al. interface type W_1 can be considered as a weakly hidden market interface, whereas type W_2 hides the market completely [17].

3 Research Model

As more trading decisions are facilitated through (web-based) trading support systems one of the most urging questions is how to design such interfaces. In order to answer this higher research question we have to deeply understand if and how different interfaces influences trading behavior and performance.

To give indications for these research questions we start by analyzing the participants' trading behavior and how the resulting trading performance is influenced by different trading interfaces (Figure 2). We expect users who are familiar with market environments to use the default interface with more information. Users with no market experience might feel confused by too much data and hence reduce the interface to the simple basics. In the first step (H1) we present how the self-chosen interface influences the participants' trading behavior. As all traders have the same start portfolio the size of a trade is a proxy for the trader's confidence perception. Assuming that participants using the wizards are less confident about how to trade, it seems reasonable that the resulting order size is on average lower.

Another individual market behavior is how participants submit their orders. We distinguish between market orders and limit orders. Market orders trade instantaneously against a standing limit order. Therefore the trader submitting a market order pays the effective spread in order to

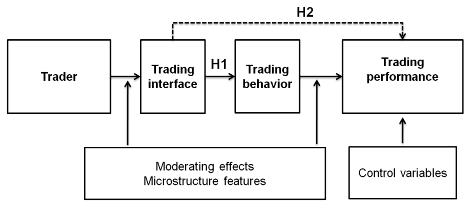

Fig. 2. Research Model

execute directly knowing that the order will be executed. A less confident trader wants to keep the effective spread and posts limit orders. As the wizards do not display the current orderbook, it is reasonable to assume that wizard users are more likely to submit market orders. As a consequence the hypothesis for participants trading behavior (H1) are:

H1a) *Orders which are submitted through a trading wizard are smaller in size on average.*

H1b) *Using the trading wizard increases the chance that participants submit market orders.*

Finally and most importantly, we analyze how the self-chosen interface influences the participants' trading performance (H2). As more information is displayed in the default trading interface an intuitive assumption is to expect a better trading performance through the default interface. However an alternative perspective from decision theory is, that the more information, the worse the performance [15]. Thus the hypothesis for the interface influence on trading performance (H2) are:

H2a) *Using a trading wizard improves the participants' trading performance.*

H2aa) *Using a trading wizard impairs the participants' trading performance.*

In combination the two steps provide a first empirical analysis of the hidden market design paradigm. Moreover they provide insight how a market's interface effect individual trading behavior and subsequently trading performance.

4 Data and Methodology

The following section first presents some descriptive market statistics and then details the tools to systematically analyze the effect of different trading interfaces on trading behavior.

4.1 Descriptive Statistics

The following data includes the timespan from 30th October 2009 till 31st of October 2010. In total 1006 participants registered at the EIX market, of those 680 submitted at least one order. We discard all stocks with less than 50 transactions. Altogether participants submitted 45,808 orders resulting in 22,574 executed transactions. In the respected time frame 47 stocks were paid out. Previous work showed that the market-generated forecasts performed well in comparison to the 'Bloomberg'-survey forecasts, the industry standard. [21]. Out of the 45,808 orders, 821 were submitted through one on the trading wizards. For every order the interface used for order submission is recorded. In the following an interface variable is 1 when the element is used otherwise it is 0, e.g. variable W_1 is 1 if the alternative trading screen W1 is used (see Figure 1). In our field experiment we asked participants to self-assess their market-knowledge and their knowledge of the German economy. These two self-assessment scales combined give us a confidence proxy ($Conf. = 1$).

4.2 Measuring trading behavior and performance

In our continuous market we observe the outcome, i.e. the fundamental value of each stock. Therefore we can ex-post measure the information content of each order. If an order moved the price in the right direction with respect to the final outcome of the stock, it is informed; whereas an order moving the price in the opposite direction with respect to the final outcome price, it is considered uninformed. Thus we present the following score (equation 2) to capture this process. The price of an order o for the stock i is represented as $price_{o,i}$. The fundamental final outcome value of a stock is represented by fv_i. In other words the score rates an order as profitable or not.

$$score_{o_i} = \begin{cases} 1\, if\ \ price_{o,i} \leq fv_i \,\&\, o_{type} = BUY \\ 1\, if\ price_{o,i} \geq fv_i \,\&\, o_{type} = SELL \\ 0\, if\ \ price_{o,i} \geq fv_i \,\&\, o_{type} = BUY \\ 0\, if\ price_{o,i} \leq fv_i \,\&\, o_{type} = SELL \end{cases} \tag{2}$$

As described in the last section to measure the participant's trading confidence we use two proxies. In order to capture how different interfaces impact the submitted quantity we use the following OLS regression.

$$Quantity_o = \alpha + \beta Wiz. + \gamma Init. + \delta Conf. + \sum_{i=1}^{5} \phi_i M_i \tag{3}$$

$$Quantity_o = \alpha + \beta_1 W_1 + \beta_2 W_2 + \gamma Init. + \delta Conf. + \sum_{i=1}^{5} \phi_i M_i \tag{4}$$

We first compare the differences of the submitted order quantity between the wizards and the regular trading interface. We then relate the quantity to the specific interface used by replacing $Wiz.$ dummy by two dummies W_1 and W_2 one for each trading wizard. As the different indicators exhibit different historic variances, e.g. exports are much more volatile than inflation, we control by adding the market dummy variables $M_1 - M_5$. Similarly, to control for the self-assessed confidence we add a $Conf.$ dummy. The control variables are included in all presented regressions.

For the second proxy we look at how users submit their offers. For an executed trade there are only two possibilities; either an order is a limit order or it is market order. The market order is initializing a trade against a standing limit order. As this is a binary outcome we use a binomial logistic regression. If a trade is initializing, which means it is market making, the dependent variable is 1 otherwise it is 0. We code liquidity taking (initializing) orders with $Init. = 1$.

Equation (5) measures the influence of the interfaces on the probability whether a trade is initializing or passive.

$$\log \frac{\pi_{Init}}{\pi_{Trade}} = \beta Wiz. + \gamma Init. + \delta Conf. + \sum_{i=1}^{5} \phi_i M_i \tag{5}$$

Finally for the profitability measures we adapt equations (5) the following way; we exchange the dependent variable $\log \frac{\pi_{Init}}{\pi_{Trade}}$ by $\log \frac{\pi_{Score}}{\pi_{Trade}}$.

$$\log \frac{\pi_{Score}}{\pi_{Trade}} = \beta Wiz. + \gamma Init. + \delta Conf. + \sum_{i=1}^{5} \phi_i M_i \tag{6}$$

The dependent variable is the score defined in equation 2 which is 1 for a profit and 0 for a loss. As before we control for different risks in the market categories by adding dummy variables $M_1 - M_5$.

5 Results

In this section we will evaluate how two alternative interfaces support non-sophisticated traders participating in a (complex) prediction market. We show how individual behavior differs depending on the interface used. Controlling for different trading behavior we find that market participants using a trading wizard are more likely to submit profitable orders. Following the presented research model we start by analyzing how trader behavior differs if participants use different interfaces. A common proxy for confidence in a trading environment is the submitted quantity. We assumed that participants using the wizards are less confident about trading, and hence the resulting order size is lower on average. In Table 2 the results for regression 3 (Model A) and 4 (Model B) are depicted. Participants using one of the wizards submit orders with a lower quantity of -858 per order on average. Thus we can accept hypothesis H1a. Separating the effect for certain wizard types (Model

	Wizard	W_1	W_2	Init.	Conf.
Model A	-858^c	-	-	-53	92
(t-Value)	(-2.2)	(-)	(-)	(0.97)	(1.57)
Model B	-	-742	-911^c	-53	93
(t-Value)	(-)	(-1.07)	(-1.94)	(-0.97)	(1.58)

Table 2. Influence of trading wizards on submitted quantity. Model A gives the values for the regression (3). The estimates show that if a trading wizard is used, the submitted quantity per order is reduced by 858. The effect is significant for the wizard type W2 (Model B). The market dummies $M_1 - M_5$ are omitted. The superscript 'a' denotes significance at the 0.1%, 'b' at the 1% level and 'c' at the 5% level.

B), we see that the result holds -in direction- for both alternative trading interface but only for type W_2 significantly. We assumed that participants using the wizard do not see the orderbook and hence submit more market orders. As the estimates in in Table 3, Model C; show this is the case. Accordingly we accept H1b. Additionally we find that confident traders are more likely to submit limit orders possibly in order to keep the realized spread.

Again looking at the particular influence of each interface we find that the results are due to different behavior supported by the wizard type W_2.

	Wizard	W_1	W_2	Conf.
Model C	1.38^a	-	-	-0.37^a
(χ^2)	(28.33)	(-)	(-)	(124.61)
Model D	-	0.55	1.83^a	-0.37^a
(χ^2)	(-)	(1.9)	(27.51)	(125.84)

Table 3. Influence of trading wizards on order type. The estimates represent the change in the log odds of the outcome if the predictor variable is one. (The chance that an order is a market order is increased if the order is submitted through the trading wizards.) The market dummies $M_1 - M_5$ are omitted. The superscript 'a' denotes significance at the 0.1%.

We suggested two alternative hypotheses regarding the interface influence on trading performance. One might intuitively suspect that more information on the default trading interface leads to better trading decisions. Turning to Table 4, Model E; reveals that the chance of submitting a profitable order is higher using one of the wizards. We thus reject hypothesis H2aa and accept H2a. A possible explanation for this result might be that certain information provided by the system may not actually help but impair the trading decision process. Interestingly, looking at how trading behavior relates to successful orders, we see that initializing orders are less likely to be profitable. However without controlling for different market behavior (Table 4; Model E_1) we find that the order submitted through the wizards are still more likely to be profitable. As before it seems that the results are stronger for interface W_2 the strongly hidden market interface.

	Wizard	W_1	W_2	Init.	Conf.
Model E	0.93^a	-	-	-0.17^a	0.18^a
(χ^2)	(13.3)	(-)	(-)	(28.21)	(29.71)
Model E_1	0.87^a	-	-	-	0.19^a
(χ^2)	(11.9)	(-)	(-)	(-)	(35.1)
Model F	-	0.13	1.42^a	-0.16^a	0.18^a
(χ^2)	(-)	(0.11)	(16.05)	(28.6)	(28.86)
Model F_1	-	0.11	1.33^a	-	0.19^a
(χ^2)	(-)	(0.77)	(14.59)	(-)	(34.21)

Table 4. Influence of trading wizards on order profitability. The estimates represent the change in the log odds of of the outcome if the predictor variable is one. (The chance that an order is profitable is increased if the order is submitted through one of the trading wizards.) The market dummies $M_1 - M_5$ are omitted. The superscript 'a' denotes significance at the 0.1%.

6 Conclusion

In future, various allocation problems call for market based solutions. However market complexities impose high entry barriers for non-sophisticated users. One reason is that in markets preferences are usually communicated through bids and offers which requires participants to adapt to a different mental model. Recently researchers proposed the idea of hidden market design which merges the fields of market design with user interface design in order to make complex markets accessible to a broader audience. As more trading decisions are facilitated through (web-based) 'trading support systems' one of the most urging questions is how to design such interfaces. Moreover it is important to design such interfaces without reducing market efficiency and individual trading performance. In our field experiment participants trade in a complex prediction market which closely reassembles trading in financial markets. As the outcome of events in prediction markets is finally known, we can ex-post measure the participants' trading performance. Evaluating the hidden market paradigm from an individual perspective, we find that alternative trading interfaces change participants' behavior. Using the trading wizards, traders are more likely to submit market orders and submit orders with smaller sizes. Against naive intuition, we find that orders submitted through the strongly hidden market interface are more likely to be profitable compared to orders submitted trough the default trading interface. A reason for that may be found in cognitive theory. Market complexity increases the participants' cognitive load and hence may reduce trading performance and confidence. As a result this work provides insight into the interplay between market design, interface, and trading behavior. Specifically in the domain of financial markets it is the first work to show the influence of the trading interface on trading behavior and performance.

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