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RESEARCH PAPER

Beware of Performance Indicators

How Visual Cues Increase the Disposition Effect

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Abstract Online trading interfaces are important instruments for retail investors. For sound reasons, regulators obligate online brokers to inform customers about certain trade related risks. Research has shown that different behavioral biases can decrease traders' performance and hence lead to pecuniary losses. The disposition to hold losing stocks too long and sell winning stocks too early ('disposition effect') is such a deviation from rational behavior. The disposition effect is analyzed for the prediction market 'Kurspiloten' which predicts selected stock prices and counts nearly 2000 active traders and more than 200,000 orders. We show that the disposition effect can be aggravated by visual feedback on a trader's performance via colored trend direction arrows and percentages. However, we find no evidence that such an interface modification leads to higher activity. Furthermore, we can not confirm that creating awareness of the disposition effect with textual information is suited to decreasing its strength.

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1 Introduction

In 2002, 28 % of U.S. retail trades were executed via retail brokerage companies; one year later, U.S. online retail brokerage companies already managed more than 31 million accounts (Bakos et al. 2005). In contrast to direct-access brokerage where traders virtually have direct and thus low-latency access to stock exchanges, online retail brokerage describes, often web-based, trading interfaces offered to retail customers by banks and similar vendors. In a more recent analysis, Camargo (2013) estimate the U.S. self-directed online brokerage market to have reached over 40 million customers in 2012. Furthermore, they report that growth rates have slowed down since 2010 which can be an indication of saturation. From a customer's perspective, important distinguishing features of online retail brokerage companies are fees, trading capabilities, and the functionality of their trading interfaces. As designing trading interfaces gives brokerage companies an additional opportunity to distinguish themselves from competitors, a great deal of effort is put into designing 'attractive' trading interfaces for customers. Although it is common knowledge that a decision makers performance in general depends inter alia on the user interface used (Speier and Morris 2003), even a carefully designed interface that is easy to use may not prevent traders from being susceptible to behavioral biases.

The *disposition effect* is such a behavioral bias, which often leads to individual losses and missed gains. Although the disposition effect is well known in several research communities, it is not considered common knowledge. Therefore, providers of online trading platforms might have a particular interest to inform their customers about that bias – and if possible provide tools to avoid it. On the one hand, the strength of the bias is influenced by the individuals' internal decision making processes, their awareness, and their knowledge about the specific bias. On the other hand, the individuals' environment (e.g., information presentation) might impact the effect strength.

In this work, we conduct an experiment on an online prediction market wherein we can control and implement certain user interface modifications. Prediction markets are virtual stock markets used to forecast the outcome of future events. The chosen market 'Kurspiloten' forecasts prices of selected stocks – thus in a way resembling futures markets – and has an interface similar to online retail brokers, yet simplified 1. With nearly 2000 active traders and substantial financial incentives our field experiment closely resembles trading in financial markets. In contrast to most research on financial markets we are able to run a 2 by 2 between subject research design. We identify performance indicators as a driver of the disposition effect and show that their disuse can decrease the disposition effect and therefore its negative implications. However, the question persists how individuals can be sensitized for this bias. For instance, Bhandari et al. (2008) use decision support systems to debias traders.[1]

In a follow-up study, Bhandari and Hassanein (2010) propose debiasing strategies for major investment-related biases. Especially, they propose to apply a quantitative reasoning agent to debias affective biases such as the disposition effect. Nevertheless, more simplistic approaches might already decrease the disposition effect. For instance, there is evidence that textual information can – even under difficult circumstances – be effective in the area of health warnings on tobacco. Hammond (2011) is able to show that persons who noticed a textual warning sign in some cases started to think about changing their behavior. But he also emphasizes that the information must "capture [...] attention and educate" in order to be effective. Another study in the health domain examining effects of pictures and textual information found that only using textual arguments led to minor changes in intended behavior (Boer et al. 2006). To summarize, it has been shown that textual information can have an effect, although it does not seem to be a strong one. We address the following research questions in this paper: (1) Is the knowledge about the existence of the disposition effect suited to lower an individual's disposition effect? (2) Does a trend indicator arrow (like the ones often used in online trading screens) positively affect the disposition effect? Before addressing these questions we must first verify that the disposition effect is indeed prevalent in this market, and that whether it affects participants' trading performance.

The remainder of this paper is structured as follows: In the next section, we present related research concerning the disposition effect and prediction markets before we describe the conducted experiment. In the third section, we develop our hypotheses from the research questions posed above. Thereafter, we give a short description of our dataset and outline the methodology used, before we represent our findings in the results section. In the last two sections, we discuss results and their implications and make concluding remarks.

2 Related Research

In this section, we present related research on the disposition effect before we turn to prediction markets.

2.1 Disposition Effect

Across a wide range of markets, traders tend to hold on to paper losses for too long and realize gains too early. This tendency is a deviation from rational behavior, where the trader makes his decision based on relative gains and losses instead of the absolute valuation of his investment. Based on Kahneman and Tversky's (1979) prospect theory, the work of Machina (1982), and others, Shefrin and Statman (1985) examine this particular pattern and coined the term disposition effect (DE) for it. They develop a descriptive theory that enables a broader insight into this particular effect in real markets. But their explanatory approach goes beyond prospect theory and includes aspects of mental accounting (Thaler 1985), of the asymmetry of pride and regret (Kahneman and Tversky 1979; Thaler 1985), and of self-control (Thaler and Shefrin 1981). The existence of the disposition effect has been shown in stock markets (e.g., Lakonishok and Smidt 1986), for a U.S. discount brokerage house (Odean 1998), for the Taiwan Stock Exchange (Barber et al. 2007), as well in experimental settings (e.g., Andreassen 1988; Weber and Camerer 1998) or even in prediction markets (e.g., Teschner et al. 2012). Although the disposition effect can be shown in a wide range of markets, its strength seems to depend on individual factors such as professionalism, sophistication, and trading experience. Shapira and Venezia (2001) examine a dataset from an Israeli brokerage house and find out that independent investors tend to have a higher disposition effect than professional investors. Seru et al. (2010) show that the

[1] In an experiment based on (Lim and Benbasat 1996), they explore the effectiveness of decision support systems in the financial context to lower cognitive biases. Therefore, they use interactive feedback as well as selected different graphical representations in investment scenarios.

disposition effect declines with trading experience. But even a lower disposition effect for professional traders does not mean that the disposition effect's degrading implications on trading performance vanish with growing experience. Both studies imply that the strength of the disposition effect for an individual varies and can be influenced actively. Garvey and Murphy (2004) analyze a successful team of proprietary traders and find that even when the traders are experienced and perform very well, their performance could have been better, if they would have avoided the trading pattern of disposition effect. Feng and Seasholes (2005) show that a combination of sophistication and trading experience can even eliminate an investor's reluctance to realize losses, but it can only diminish the propensity of an investor to realize gains. Summing up, the disposition effect has shown to hinder individuals trading performance. Although it can be diminished by traders' experience and sophistication, it cannot be totally avoided.

2.2 Prediction Markets

"Prediction markets are remarkably accurate information aggregation mechanisms" (Gjerstad 2005). They are virtual markets, where stock prices represent the prediction of an upcoming event. Wolfers and Eric (2004) describe three possible contract types. First, a *Winner-takes-all* contract that models events with a binary outcome, such as the chance that a certain candidate will be elected in a majority election. Second, an *Index* contract that is suited to predict a mean value of a future outcome. Examples are the vote share of a certain party in a proportional representation or the number of unemployed persons at a given time (cf. Teschner et al. 2011). Third, a *Spread* contract that can be used to predict the median value of a future event.

Prediction markets may make use of a market maker mechanism (e.g., Hanson 2002) or simple continuous double auctions, but are not tied to a specific mechanism. They can operate with real money, like most sports betting platforms do, or use play money without losing their predictive power (e.g., Servan-Schreiber et al. 2004; Christiansen 2007; Slamka et al. 2008). The market design makes sure that participants have a proper incentive to reveal their true beliefs. On the one hand, participants buy a certain stock if the current market price is lower than their individual estimation of the future outcome (i.e., their expected payout). On the other hand, they sell if the price exceeds their belief. Since every single trade can influence the market price instantaneously, prediction markets provide immediate feedback as well as continuous predictions of future events. Prediction markets can be used in nearly every domain and have successfully been applied to predict events for topics like elections (e.g., Forsythe et al. 1992), sport events (e.g., Hartzmark and Solomon 2012), macroeconomic indicators (e.g., Teschner et al. 2011), sales forecasts (e.g., Chen and Plott 2002), supply chain management (e.g., Hedtrich et al. 2011), or even innovation assessment (e.g., Stathel et al. 2010).

2.3 Disposition Effect in Prediction Markets

Teschner et al. (2012) analyze the disposition effect in a prediction market for macroeconomic indicators as described in Teschner et al. (2011) with a sample size of 96 active traders. They conduct their analysis largely based on the work of Odean (1998), who found the disposition effect on an individual (DE = .021) and aggregated (DE = .050) level.[2] In line with previous research, they find a disposition effect on the individual level (DE = .1582) as well as on the aggregated level (DE = .2248). Furthermore, they find a significant asymmetry in the disposition effect towards the percentage of gains realized. Interestingly, there is neither a significant impact of the disposition effect on absolute forecast error nor a correlation between prediction accuracy and disposition effect. Hartzmark and Solomon (2012) examine a dataset of a NFL betting market from Tradesports.com and find that prices follow an S-shaped curve instead of linearly matching the underlying probabilities. They find this particular mispricing to be consistent with the disposition effect. In another study, Borghesi (2013) find strong evidence that the disposition effect in Tradesports' market for NBA totals contracts leads to significant differences between prices and underlying values, also consistent with the disposition effect. Summing up, there is evidence that the disposition effect exists in prediction markets.

3 Research Questions and Hypotheses

With this work we try to answer the two research questions:

(1) *Is the knowledge about the existence of the disposition effect suited to lower an individuals' disposition effect?*
(2) *Does a trend indicator arrow positively affect the disposition effect?*

[2] As the disposition effect's definition by Shefrin and Statman (1985) describes rather a behavioral pattern than a precise way of quantification, literature has adopted different approaches to verify the disposition effect's existence and measure its extent. As the methodology used in the work at hand (cf. Sect. 5) is largely based on Odean (1998), for comparison reasons we report the extent of the DE for studies that use a similar approach as the difference of PGR-PLR.

As stated earlier, the disposition effect (DE) is not part of general education and can therefore not be expected to be known to the vast majority of participants of an online prediction market. As research has shown, multiple factors can decrease the DE. Inter alia, active training (e.g., Fenton-O'Creevy et al. 2012) and trading experience (e.g., Dhar and Zhu 2006). Hence, literature suggests "[...] that brokerage firms should try to educate their clients of the disposition effect, thereby improving their clients' after tax portfolio performance [...]" (Dhar and Zhu 2006). We want to shed some light on the question whether it is expedient to inform about the DE with a short information text directly on an online trade screen or if a 'deeper understanding' of the DE is needed. This could be an interactive learning unit or active training on how to avoid the disposition effect. We expect that reading an information text leads to a lower disposition effect, simply by creating awareness of this particular deviation from rationality and thus increasing self-control. Therefore, we define an interface change 'DE Info Text' consisting of an information text about the disposition effect on the trading screen. In line with current research, we expect this information text to reduce the disposition effect:

Hypothesis 1 Mean disposition effect is lower if 'DE Info Text' is offered. (INFO $<$ CTRL)

Moreover, self-control might be decreased by confronting a trader with the portfolio state in a transparent fashion. The disposition effect is driven by the trader's perception of his portfolio development; e.g., if a trader cannot remember the purchase price of his stocks, he is obviously unable to tell if he is riding a gain or a loss. In a more complex market environment, traders repeatedly buy and sell different amounts of shares for different prices making it hard (or even impossible) to calculate the average purchase price in an intuitive way. That purchase price has to be compared to the current stock market price in order to determine the performance of one's own holdings. The easier it is for a trader to assess his portfolio value – and thus, whether he is riding a gain or a loss – the more he might be tempted to yield to the disposition effect.

Furthermore, it is well known that traders can fall victim to mental accounting. Showing traders a transparent state of their portfolio on a per-stock basis might intensify this biased perception. In order to support traders by means of an objective and comparable method to reflect the portfolio performance, we define an interface change 'Trend Indicator' that consists of a relative performance indicator of a trader's portfolio price development and a visual cue representing its direction. We therefore expect the 'Trend Indicator' to increase the disposition effect:

Hypothesis 2 Mean disposition effect is higher if 'Trend Indicator' is present. (TREND $>$ CTRL)

From a theoretical point of view, we neither see a reason for a mutual reinforcement nor a mutual weakening between an information text about the disposition effect and a trend indicator for the own portfolio's price development. In other words, we expect those interface changes to take effect independently of each other. Hence, the following hypotheses are inferred:

Hypothesis 3 (a) 'Trend Indicator' increases the mean disposition effect, even if 'DE Info Text' is present. (TREND_INFO $>$ INFO)

Hypothesis 3 (b) 'DE Info Text' is suited to reduce the mean disposition effect, even if 'Trend Indicator' is present. (TREND_INFO $<$ TREND)

We expect the trend indicator to induce a higher order activity, since it reflects the state of a portfolio in a more transparent way and thus might make trading opportunities more obvious. Therefore, we expect the trend indicator to affect traders' activity positively as expressed in the fourth hypothesis:

Hypothesis 4 'Trend Indicator' leads to an increase in the traders' activity.

4 Experimental Design

We conducted a field experiment on a prediction market called 'Kurspiloten'. This is a web-based prediction market designed to forecast the stock exchange value of selected stock indices and commodities on a weekly basis. Participants registered free of charge and traded with play money.[3] Therefore, they could not lose any real money. Prizes worth over 70,000€ (around 90,000$) are drawn among well-performing participants to incentivize them to reveal their true beliefs. Further details are presented in the next subsection. The experiment, consisting of treatment-specific user interface changes is described in the second subsection. The treatments actually used are explained in the last subsection.

4.1 Prediction Market Kurspiloten

As in financial markets, the Kurspiloten market is set up as a continuous double auction with one stock representing the final (real-world) price of one of the twelve

[3] Due to legal restrictions the market had to rely on play money; nonetheless '€' was used as currency name. To avoid confusion in this article 'P€' is used as currency sign for play money and '€' for real money.

Table 1 Tradable stocks

Stock	ISIN	Underlying (currency, unit)
DAX	DE0008469008	30 major German companies (€, Index)
MDAX	DE0008467416	50 major German companies[a] (€, Index)
TecDAX	DE0007203275	30 largest German technology companies (€, Index)
EuroStoxx 50	EU0009658145	50 Eurozone companies (€, Index)
Dow Jones industrial average	US2605661048	30 major U.S. companies ($, Index)
Nikkei 225	XC0009692440	Tokyo Stock Exchange (¥, Index)
EUR/USD	EU0009652759	EUR-USD exchange rate ($, €)
Euro-bund future	DE0009652644	Future contract on German national loan (€, €)
Gold	XC0009655157	Gold (€, Ounce)
Silber	XC0009653103	Silver ($, Ounce)
Brent crude oil	XC0009677409	Brent-Oil ($, Barrel)
Rogers international Commodity index	NL0000424505	38 commodities from 13 international exchanges (€, Index)

In *Kurspiloten* market all stocks are traded in P€, regardless of the currency of their underlying. (e.g., Nikkei 225 at 13,045¥ will have a payout value of 13,045P€)

[a] Excluding DAX and TecDAX

predicted stocks at a given time. For instance, the stock ‘DAX 07 October 2011’ represents the real-world value of DAX on 07 October 2011 at 5:35 pm. This particular stock is tradable on the Kurspiloten market, starting 30 September 2011 until 07 October 2011 5:30 pm. Participants buy if they think that current Kurspiloten prices underestimate the final value of the underlying stock market index or commodity and sell if they think prices overestimate the final value. By trading their price expectations of twelve selected stock indices and commodities on a weekly basis, participants are able to share their private information with others. Although the Kurspiloten market uses play money, participants are provided with the incentive to behave similarly to a real-money market. We offer prizes worth more than 70,000€ for well performing traders in order to provide incentives to truly reveal information. As the amount of play money was not extensible by some analogy of a deposit, participants had an incentive to economize their play-money budget. Hence, participants were supposed to buy undervalued stocks and sell overvalued stocks. Furthermore, they should realize gains as well as losses in order to increase their buying power. As performance measure, we use the traders’ total assets (i.e., total amount of money and stocks a trader owns at market prices). The wealthiest trader at the end of each week is awarded a material prize worth around 1,500€. The main prize worth over 40,000€ is given to the most successful trader at the end of the game according to his overall assets, i.e., – since all stocks are paid out – the total amount of money he owns. Four additional prizes worth over 15,000€ in total are awarded to the four next best traders at the end of the game. Six stock indices, three commodities, a commodity index, a future contract and one exchange rate can be traded (see Table 1). The tradable contracts represent their underlying stock one-on-one.

Upon registration each participant receives an initial endowment of 100,000P€ and 1000 stocks of each tradable asset. The trading period for all stocks is seven days. Each Friday at 5:30 pm, the market is closed for trading. Afterwards all 12 products (see Table 1) are paid out according to the stock exchange prices at 5:35 pm. To attenuate endgame effects we close the market for trading 5 min prior to the payout. All participants receive their new endowment consisting of 1000 stocks each for the next seven-day trading period.[4] Finally the market is reopened for trading. As we run the experiment for twelve weeks, we execute 144 payouts in total. Any order submitted for a paid out product can ex post be rated as ‘informed’ or ‘uninformed’ in relation to the payout price. For example, take the stock ‘DAX 07.10.2011’, which was tradable from 30 Septembar 2011 until 07 October 2011 at 5:30 pm and represents the (real-world) price of DAX on 07 October 2011 at 5:35 pm (GMT+1), which is 5673.08. Imagine (a) a buy order for this stock with a limit price of 5715 and (b) a buy order for this stock with a limit price of 5660. Order ‘a’ is an uninformed order, since its limit price is higher than the payout price (i.e., the final value of the

[4] Due to a bad money/stocks-ratio we introduced a second account for each user called “Geldspeicher” (engl. ’Money Bin’). Starting on 23 October 2011 all money exceeding 10,000,000P€ is booked to the Money Bin in the weekly payout procedure and can not be used for trading anymore. Nevertheless, the money contained in the Money Bin is considered for the ranking.

underlying) and will therefore most likely result in a loss. In contrast, order ‘b’ can be regarded as an informed order, since its limit price is below the payout price and its execution will result in a gain of 13.08P€ per stock when it comes to the payout. Registration for Kurspiloten was free of charge and open for anyone. In the registration process participants only had to enter a valid email address and a username. Participants could register any time from three days before market opening. As a trader receives repeated endowments of stocks for following trading periods after each payout, participants who registered after market opening would be disadvantaged. In order to give those traders a chance to catch up with the competitors, we adjusted their initial endowment to the account balance a hypothetical user who registered on the first day would have. This is achieved by creating a dummy user account on the first day of the market which receives the same initial endowment as each user and is paid out in the same way a normal user is. If a user registers after market opening, he receives the initial portfolio for the current week as well as the amount of money the dummy user account currently owns (i.e., all past endowments multiplied with their corresponding payout values).

We set proper incentives by using a public ranking list containing the usernames based on the traders’ absolute assets. This ranking’s primary use is to award the prizes worth more than 70,000€. The ranking is accessible to all traders throughout the market runtime. Therefore, the second incentive is a social comparison according to trading-performance. In order to inform participants about the market rules, we provide general instructions explaining the basic market rules and conditions of participation. Note that the instructions are neither individualized in any way nor adapted to the specific treatment a participant is part of. Besides individual decisions, the disposition effect also depends on market price developments. For example, traders on a bearish market have simply less chances to realize paper gains but more to make paper losses; the opposite applies to bullish markets. Since traders might concentrate their trading on different stocks, this dependency could be problematic for the analysis. In extreme situations traders may experience different or even opposed market effects due to their different portfolios. Nevertheless, for two reasons we expect the impact that market price developments have on the disposition effect to be rather small on this market. First, the tradable stocks (see Table 1) can roughly be grouped into stock indices and commodities. Within those groups, the single commodities/indices are somehow interdependent (e.g., DAX and MDAX, Gold and Silver.) and thus are unlikely to develop in opposed directions for a longer period of time. Second, traders on the Kurspiloten market start with an identical portfolio and receive an identical endowment each week which tempts traders to trade all kinds of stocks tradable. As all traders participate in the very same market, we assume that price market trends do not influence the disposition effect between individual traders significantly. Finally, traders’ profits are used as a control variable in the following regression models, which further smoothens the potential negative impact of market price developments on the comparability of the individual disposition effect.

4.2 User Interface Modifications

The experiment is setup as a 2×2 full factorial between subjects design. Both treatment conditions are visual changes to the trade screen (see Fig. 1 and “Appendix 2 of ESM)”. The first change (“DE Info Text”) consists of a linked text “Do you know about the Disposition Effect?” (authors translation) just above the price chart (see label (a) in Fig. 1). When a user clicks on this text, a paragraph explaining the disposition effect fades in. Appendix 1 of ESM contains the complete text. As the experiment takes place in the field compromises must be made in some areas. For that reason traders are not forced to read the DE Info Text prior to trading on the market, nor is it controlled whether they understand the text or not. Instead the text is offered to traders under the assumption that as they actively need to click on the link in order to expand the text, the ones who do so are actually interested and will read it. As the DE Info Text is rather short and aims to express the disposition effect as comprehensively as possible, we assume that the majority of participants is able to understand this text and its implications. The current time and user id is recorded with every click on the link to DE Info Text for further analyses. The second treatment condition (“Trend Indicator”) extends the box “Your Performance” (authors’ translation) on the lower right of the trade screen by one column (see label (b) in Fig. 1). The basic interface only contains the information “Average Purchase Price” (authors’ translation, left column in the box “Your Performance”), whilst the second treatment condition extends that box by a column named “Performance”, containing the relative performance of stocks held. First, the percentage difference between the current market price and the average purchase price for the corresponding stocks is shown. Second, a tiny trend direction arrow indicates whether this difference is negative, zero, or positive. The arrow is colored red, grey, or green, respectively. It is similar to stock trend indicators used in many online trading interfaces.

4.3 Treatments

All Participants registered on the Kurspiloten market are assigned to one of the three treatment groups or to the

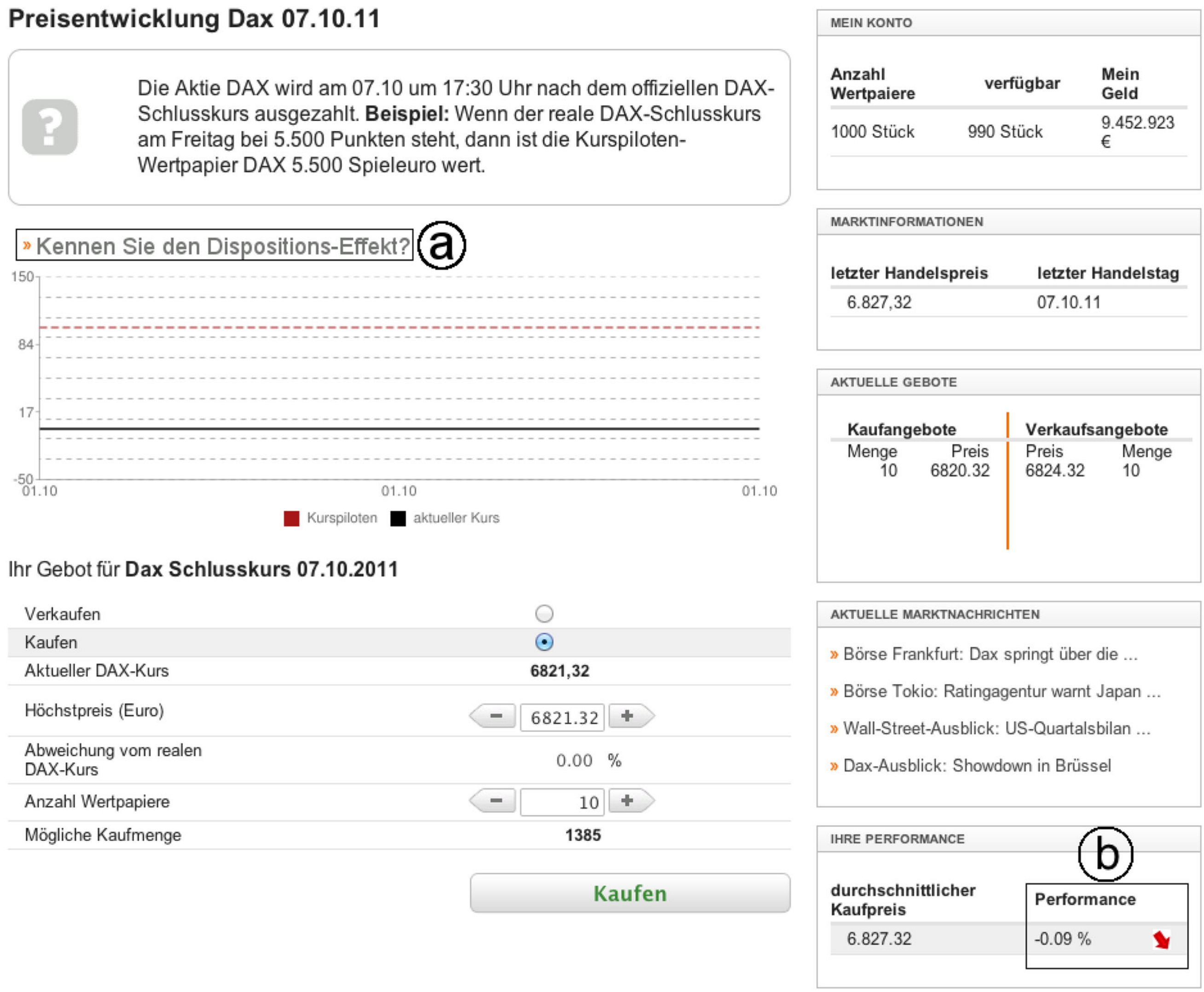

Fig. 1 Trade screen for treatment *Trend_Info*. (Containing both user interface modifications made: a and b. A click on the linked text (a) fades in an info text about the disposition effect. The whole text is depicted in "Appendix 1 of ESM". Modification (b) shows the 'Trend Indicator' element. *Screenshots* of the three remaining treatments can be found in Appendix 2 of ESM.) Heading: "Price development of Dax 07 October 2011"; In box (a): "Do you know about the Disposition Effect" (only available in treatments *Info* and *Trend_Info*); *Chart* price chart for *Kurspiloten* prices (*red dotted line*) and real-world prices (*black line*); *middle left* "Your Order for stock ...2011", radio buttons for buy and sell, information about the current real-world price of selected stock (*bold*), input field for limit price, information about deviation of limit price from real-world price, input field for quantity, information about buying power (*bold*), 'execute' button; *Right column* 1st box: "My Portfolio", own holdings, own holdings available, and money (P€); 2nd box: "Market Information", least recent price and closing date of current product; 3rd box: "Orderbook"; 4th box: "Current News", news stream from a major German financial newspaper; 5th box: "Your Performance", average purchase price of selected stock and relative performance (i.e., relative price difference of average purchase price and least recent market price) (only available in treatments *Trend* and *Trend_Info*)

Table 2 Treatments and research design

	DE info text	w/o DE info text
Trend indicator	Trend_Info	Trend
w/o Trend indicator	Info	Control

control group as shown in Table 2. Participants who registered in the pre-market phase are randomly assigned prior to the start of the market. Participants who joined after start of the market are assigned randomly at registration. Each trader remains a member of the assigned treatment group for the whole duration of the market. The first group is confronted with both conditions described above (treatment *Trend_Info*) and depicted in Fig. 1. One group sees the trend info (treatment *Trend*), another one the info text (treatment *Info*). No changes are made for the control group (*Control*), i.e., the control group sees neither the info text nor the trend info.

5 Dataset and Methodology

The Kurspiloten market was operational from 09 February to 25 November 2011. In these 84 days 1912 active users submitted a total of 215,432 orders. Those led to 131,561 transactions. A total of 144 payouts was executed (12 per product). Hence, we calculate the disposition effect only for traders who submitted at least 12 orders. Additionally, we filter out traders that had no chance to realize a gain or a loss and traders that did not realize at least one gain or one loss. Due to these circumstances we can determine the disposition effect for 514 traders. Descriptive statistics can be found in the Appendix of ESM 3 (Tables 9 and 10 of ESM). The sizes of the three treatment groups and the control group are nearly balanced out: $N_{Trend\_Info} = 123$, $N_{Trend} = 126$, $N_{Info} = 123$, and $N_{Control} = 142$. About one quarter of the traders, who could click on the info text link, actually made use of this possibility: $N^{clicked}_{Trend\_Info} = 30$, $N^{clicked}_{Info} = 30$. The average account age lies between 69.10 days (*Trend*) and 67.26 days (*Trend_Info*) with an overall mean of 68.05. Traders' performance – measured by their total trading profit – differs significantly (t-stat = 2.34, two-sample t test, p = 2.04 %) between treatments *Info* and *Trend*. Hence, variable *Profit* is used as a control variable in the regression analysis. Besides, variable *Trades per Day* is used to control for different trading activity. Although the number of trades per day does not significantly differ between treatments, it does for traders that clicked on the info link in comparison to those who did not (t-stat = 2.51, two-sample t test, $p = 1.24$ %).

We measure the disposition effect mainly based on Odean (1998). The only exception is the length of the time slices used. Since the trading period per product was rather short (seven days), we used the users' sessions instead of trading days to differentiate between paper gains and losses; e.g., if a trader's average purchase price was below the highest and lowest market price in the regarded session, it is counted as a paper gain.[5]

The disposition effect (DE) is calculated as DE = PGR - PLR where PLR denotes the Proportion of Losses Realized, and PGR the Proportion of Gains Realized. PGR and PLR are calculated as follows:

$$PLR = \frac{\#\ \text{realized losses}}{\#\ \text{realized losses} + \#\ \text{paper losses}} \quad (1)$$

$$PGR = \frac{\#\ \text{realized gains}}{\#\ \text{realized gains} + \#\ \text{paper gains}} \quad (2)$$

6 Results

In this section we present our empirical findings, starting with the overall and individual existence of the disposition effect, before we take a detailed look at the disposition effect with regard to the four treatments introduced earlier. Finally, we shed some light on the traders' order-based activity per treatment.

6.1 Disposition Effect on Prediction Markets

In line with current research, we found an aggregated disposition effect (DE) for the Kurspiloten market (DE = .154, PLR = .041, PGR = .196) which is slightly smaller than in a similar study of (Teschner et al. 2012) (DE = .225, PLR = .018, PGR = .242) and higher than in studies using data of online brokers (e.g., for an U.S. discount broker (Odean 1998) measured DE = .05, for a German online broker (Weber and Frank 2007) measured DE = .09). On the individual level the disposition effect is .148 and thus comparable to a similar study on a play-money prediction market conducted by (Teschner et al. 2012) (DE = .158). Further details are displayed in Table 3. As we can see PLR, PGR and DE are significantly greater than zero (using a two-sample t test, cf. second column in Table 3). Additionally, the disposition effect is asymmetric, since the absolute correlation between DE and PLR is slightly smaller than between DE and PGR.

Result 1 The disposition effect is prevalent in the observed market on an aggregated as well as on an individual level.

6.2 Disposition Effect's Influence on Trading Performance

As the disposition effect is prevalent in our market, the question arises of how the disposition effect influences the market. Since our research is focused on the trader, we have a

Table 3 Individual disposition effect

	Value	t-stat ($x > 0$)	Correlation (DE, x)
PLR	.094	11.67	−.69
PGR	.242	21.84	.85
DE	.148	9.89	–

N = 514 (complete groups), both correlations are significant at a 1 %-level

[5] As Odean (1998) had no information on when the users in his dataset could possibly sell a certain stock, he chooses to count paper gains/losses only on days when a user sells at least two stocks of his portfolio. The idea behind this approach is to derive the points in time (here: days) a user was logged into his account by analyzing the trading history. The assumption is that users have seen their portfolio on such days and – if they decided not to sell certain stocks – preferred a paper gain/loss (or neither). Since we have available the users' session data, we do not need to derive that information from trade data and thus 'directly' count stocks that are not sold within a session as paper loss/gain (or neither).

particular interest in the disposition effect's influence on traders' performance. Therefore, we take a look at the correlations between the traders' profits and the disposition effect, as well as their relative rank and the disposition effect. (Relative rank here indicates the rank within the 514 observed traders instead of the overall rank among all registered traders.) We neither found a significant correlation between profits and the disposition effect (Correlation: .011, Pearson's product-moment correlation, t value = .24), nor between the disposition effect and the traders' rank (Correlation: −.028, Pearson's product-moment correlation, t value = −.62).

6.3 Disposition Effect per Treatment

Table 4 (Fig. 2) shows the mean disposition effect in each treatment group and the control group. The differences between *Trend_Info* and *Trend* ($\delta = .019$), *Info* and *Control* ($\delta = .052$), *Trend_Info* and *Info* ($\delta = .036$), and *Trend* and *Info* ($\delta = .017$) are not significant. Solely, the disposition effect for *Trend_Info* as well as for *Trend* is significantly higher than for *Control* (both on a 5 %-level (two-sample t test); *Trend_Info:* $\delta = .088$, t-stat = 2.15, *p* value = .016 and *Trend*: $\delta = .069$, t-stat = 1.78, *p* value = .038). At first glimpse, this result seems to support Hypothesis 2. But as we

Table 4 Mean disposition effect per treatment

	DE info text	w/o DE info text
Trend indicator	*.185*	*.166*
w/o Trend indicator	.149	.097

N = 514 (complete groups)

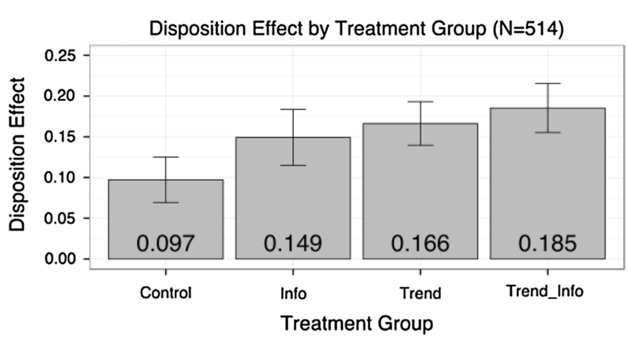

Fig. 2 Mean disposition effect per treatment (complete groups)

Table 5 Mean disposition effect per treatment (subsample)

	DE info text	w/o DE info text
Trend indicator	.128	*.166*
w/o Trend indicator	.128	.097

N = 310 (subsample: all traders who have not clicked on the 'DE info text' link mentioned in subsection 'User Interface Modifications' are filtered out)

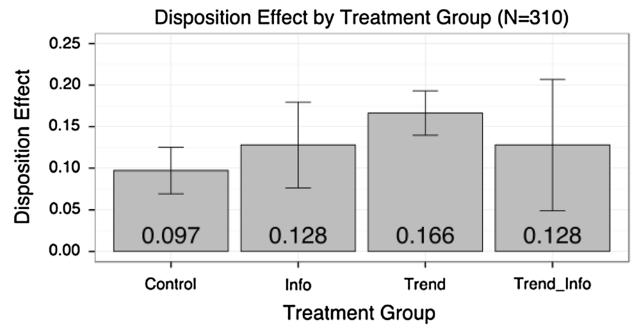

Fig. 3 Mean disposition effect per treatment (subsample)

mentioned earlier, even if all traders in treatments *Info* and *Trend_Info* can read the disposition effect info text, we have not controlled for whether they actually *do* so.

Therefore we repeated the former analysis with a slight adaptation: Table 5 (and Fig. 3) shows the mean disposition effect for a subsample, in which we only take traders from the *Info* and *Trend_Info* treatment group into account that clicked on the info text link. Furthermore, the disposition effect for those traders is calculated on the basis of trades they executed *after* they first clicked on the info text link. Hence, N is slightly smaller.

As we can see, there is hardly difference between the treatments *Trend_Info* and *Info* ($\delta = .001$, not sign.). Also, the differences between *Trend_Info* and *Trend* ($\delta = .038$), *Info* and *Trend* ($\delta = .038$), *Trend_Info* and *Control* ($\delta = .031$), as well as *Info* and *Control* ($\delta = .031$) are not significant. Solely, the disposition effect for *Trend* is significantly higher than for *Control* on a 5 %-level ($\delta = .069$, t-stat = 1.78, two-sample t test, *p* value = .038). Again, this finding supports Hypothesis 2. However, these results cannot confirm Hypothesis 1.

Result 2 Textual information about the disposition effect has no significant influence on its strength (invalidating Hypothesis 1).

Result 3 Treatment Trend shows a significantly higher disposition effect than the control group (confirming Hypothesis 2).

When we look at the tiny difference between *Trend_Info* and *Trend* ($\delta = .001$) in Table 5 in contrast to the rather large difference of .069 between *Trend* and *Control*, one might assume that the treatment condition 'DE Info Text' has an influence on the treatment condition 'Trend Indicator'. It seems reasonable to examine whether the info text hinders the trend indicator's increasing influence on the disposition effect. To control for such an interaction effect, we use the regression model shown in Table 6, model 2 and 4. (Please note that we adjusted the dummy-coding for 'DE Info Text' appropriately.) Additionally we applied an

Table 6 Measuring interaction effects (subsample)

	(1) Direct effects	(2) Interaction	(3) (1) + Controls	(4) (2) + Controls
Trend indicator	.060·	.069·	.061·	.070·
(visible = 1, hidden = 0)	(1.66)	(1.78)	(1.70)	(1.81)
DE info text	−.005	.031	−.014	.020
(visible = 1, hidden = 0)	(−.09)	(.41)	(−.27)	(.27)
Trend indicator		−.069		−.067
×		(−.65)		(−.63)
DE info text				
Trades per day			.003· (1.89)	.003· (1.87)
Profit			.000	.000
			(−.35)	(−.36)
(Intercept)	.102***	.097***	.088***	.084**
	(3.96)	(3.66)	(3.33)	(3.07)
Adj. R^2	.25 %	.06 %	.76 %	.56 %
N	310	310	310	310

OLS regression estimates on subsample; dependent variable: disposition effect; t-statistics in parenthesis

· $p<.1$, * $p<.05$, ** $p<.01$, *** $p<.001$

Table 7 Measuring interaction effects (complete groups)

	(1) Direct effects	(2) Interaction	(3) (1) + Controls	(4) (2) + Controls
Trend indicator	.054·	.062·	.055·	.062·
(visible = 1, hidden = 0)	(1.83)	(1.94)	(1.83)	(1.95)
DE info text	−.017	.014	−.025	.005
(visible =1, hidden=0)	(−.37)	(.21)	(−.54)	(.08)
Trend indicator		−.062		−.061
×		(−.67)		(−.66)
DE info text				
Trades			.002	.002
per day			(1.57)	(1.56)
Profit			.000	.000
			(−.29)	(−.31)
Intercept	.123***	.120***	.114***	.111***
	(5.75)	(5.43)	(5.16)	(4.87)
Adj. R^2	.28 %	.17 %	.37 %	.26 %
N	514	514	514	514

OLS regression estimates on complete groups; dependent variable: disposition effect; t-statistics in parenthesis

· $p<.1$, * $p<.05$, ** $p<.01$, *** $p<.001$

ANOVA. Neither method shows an interaction between the treatment conditions ‘DE Info Text’ and ‘Trend Indicator’. That means that neither of the treatment conditions have a stronger or weaker effect under the premise that the other treatment condition is present or absent. Furthermore, we control for potential differences in treatment groups with models 3 and 4. Nevertheless, all models in Table 6 show a positive influence of the trend indicator on the individual disposition effect.

For the sake of completeness, Table 7 contains the result for the complete treatment groups. The result of the OLS regression and the ANOVA are qualitatively similar to what we have seen for the subsample (Table 6), including the trend indicator’s influence on the disposition effect.

Result 4 We found no interaction effects between the disposition effect and showing visual cues (confirming Hypothesis 3a, invalidating Hypothesis 3b).

We have reason to believe that the trend indicator itself increases the individual disposition effect strength. Therefore, we compare the average disposition effect of all traders who can see the trend indicator (mean DE = .176), with those who cannot (mean DE = .121). In other words, we compare the joined treatment *Trend* and *Trend_Info* with the treatment *Info* and the *Control* group. This analysis results in a significantly higher value for traders who see the trend indicator on a 5 %-level ($\delta = .054$, t-stat = 1.82, two-sample t test, p value = .034, N = 514). Again, the repetition of this analysis for the subsample from above leads to analogous results ($\delta = .060$, t-stat = 1.66, two-sample t test, p value = .049, N = 310).

Result 5 Displaying visual cues (specifically trend arrows) increases the individual disposition effect (confirming Hypothesis 2).

6.4 Activity per Treatment

As mentioned in the section Hypotheses, we suspect traders with the treatment *Trend* to have submitted a higher number of orders (H4). Therefore we compare the number of (a) orders submitted and (b) logarithmized number of orders submitted between all treatment groups. The logarithmization is used, since it diminishes the effect of extreme values. We found one significant difference between *Info* and *Control* ($\delta = 382.24$, t-stat = 1.71, two-sample t test, p value = .045) for the comparison 'a' and four differences for case 'b': logarithmized trading activity in treatment *Info* is slightly higher than in *Control* group on a 0.1 %-level ($\delta = 1.126$, t-stat = 3.91, two-sample t test, p value $< .001$). Additionally, the logarithmized trading activities for treatment *Trend_Info* and *Info* are significantly higher than for treatment *Trend* (*Trend*: $\delta = 1.059$, t-stat = 3.55, two-sample t test, p value $< .001$, *Trend_Info*: $\delta = .819$, t-stat = 2.81, two-sample t test, p value = .003). Finally, the logarithmized trading activity for treatment *Trend_Info* is significantly higher than for *Control* ($\delta = .885$, t-stat = 3.15, two-sample t test, p value $< .001$).

Since this analysis uses the afore-stated subsample (only traders who clicked on the 'DE Info Text' link), the result may also be interpreted in a different way: the more orders a trader submits, the more often she sees the 'DE Info Text' link. Therefore one may argue that it is more likely for her to click on this link, which will result in such a pattern. To clarify that question, we analyzed the complete group, but found no significant differences (see Table 8). Hence, we reject Hypothesis 4.

Table 8 Activity per treatment

	DE info text	w/o DE info text
Trend indicator	5.479	4.922
w/o Trend indicator	5.502	4.855

N = 514 (complete groups); mean logarithmized number of orders submitted per Treatment

Result 6 The trend indicator does not lead to a higher trading activity (invalidating Hypothesis 4).

7 Discussion and Implications

As our results show, the disposition effect can be aggravated by a minute modification of the user interface. The modification consists of a simple percentage value and a trend direction arrow showing the trader's portfolio value, as used by online trading sites throughout the web as trend indicator for stock prices or for similar applications. Surprisingly, even such a small change significantly increases the strength of the disposition effect. As mentioned earlier, this interface change provides traders with a transparent overview of their portfolio positions. One explanation might be that for unexperienced traders this enhanced transparency could lead to an initial recognition of the state of their portfolio and thus only made them susceptible to the disposition effect in the first place. As no information on trading experience is available, we can only speculate on the causality of the observed correlation while the true reason remains yet to be discovered in further research. Nevertheless, we expected that those interface changes would not only have a downside. On the upside, we assumed that traders seeing the interface elements described above would submit more trades, since it showed the current state of the traders' portfolio in a fast and easily recognizable manner. But interestingly we were unable to verify this assumption in our setting. As private investors are regularly confronted with trading interfaces containing such elements, these results are especially interesting for providers of market interfaces. For market interface providers such as retail brokers, these results imply to not use trend indicators. Nevertheless, currently most online brokers make excessive use of such interface elements, at least for the reason of easier recognition of relative (price) changes. As retail brokers have incentives to increase trading frequency, another reason for the application of these interface elements might be their impact on the average trading frequency and/or volume. In order to help retail investors to avoid the disposition effect – which has previously been shown to reduce investor prosperity – online brokers should consider redesigning their interfaces.

These results also have an implication for regulators. They should carefully think about obligating online brokers to elucidate customers about behavioral biases which are known to degrade their performance. As our results suggest, textual advice does not seem to be the best possible solution in this case. (Besides, our results put a question mark over the effectiveness of textual information and advice already given to traders.) However, as we only controlled for offering a text and thus could merely assume that traders offered that piece of information actually read and understood it, we cannot conclude that textual information about the disposition effect has no effect on trading behavior. Perhaps, a more striking 'warning message' on the disposition effect would be more apt to decrease the disposition effect. Regulators might furthermore think about banning certain types of visual cues that are known to lead to a great share of 'wrong' decisions and a substantial degradation of performance. Further research is needed to show if the visual cue examined in this paper satisfies the requirements to belong to this category. Nevertheless, retail brokers should be interested in good user experience and hence motivated to deliver a 'good' user interface which is supporting instead of misleading. Innovative retail brokers might even use results like these to create a unique sales proposition, thus playing a pioneer role in providing user interfaces that reduce the disposition effect.

8 Conclusion

The disposition effect is a well-explored deviation from rational behavior. As many studies show, the disposition effect can have a negative impact on the decision performance in trading environments. This paper analyzed the disposition effect on aggregated and individual level in an online prediction market with nearly 2000 active traders and more than 200,000 orders. In line with research, we found a disposition effect at both levels. Furthermore, we conducted a field study with over 500 traders for which we could measure the individual disposition effect. Although we could not verify that creating awareness for the disposition effect by means of textual information could decreases its strength, we could show that even tiny visual cues can significantly increase the strength of the disposition effect. Nevertheless, our study leaves room for further research. On the one hand, the trend indicator was solely used to represent the average purchase price of the traders' portfolios in contrast to the current market price. A future study could examine whether the disposition effect is also affected if trend indicators are used to represent price changes of tradable stocks. On the other hand, we have seen that only about one quarter of traders clicked on the link to the offered info text. Furthermore, even if a trader clicked on the link, we have no possibility to validate if the trader has either (a) understood the text and its implications, or (b) read the text at all. A lab experiment could be set up to control for these factors; an additional questionnaire may provide certainty whether a participant has read and understood the concept of the disposition effect and its implications for her trading performance. In a follow-up field study, a repositioning of the offered link which shows the information text about the disposition effect in a more conspicuous location in the interface is worth considering.

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