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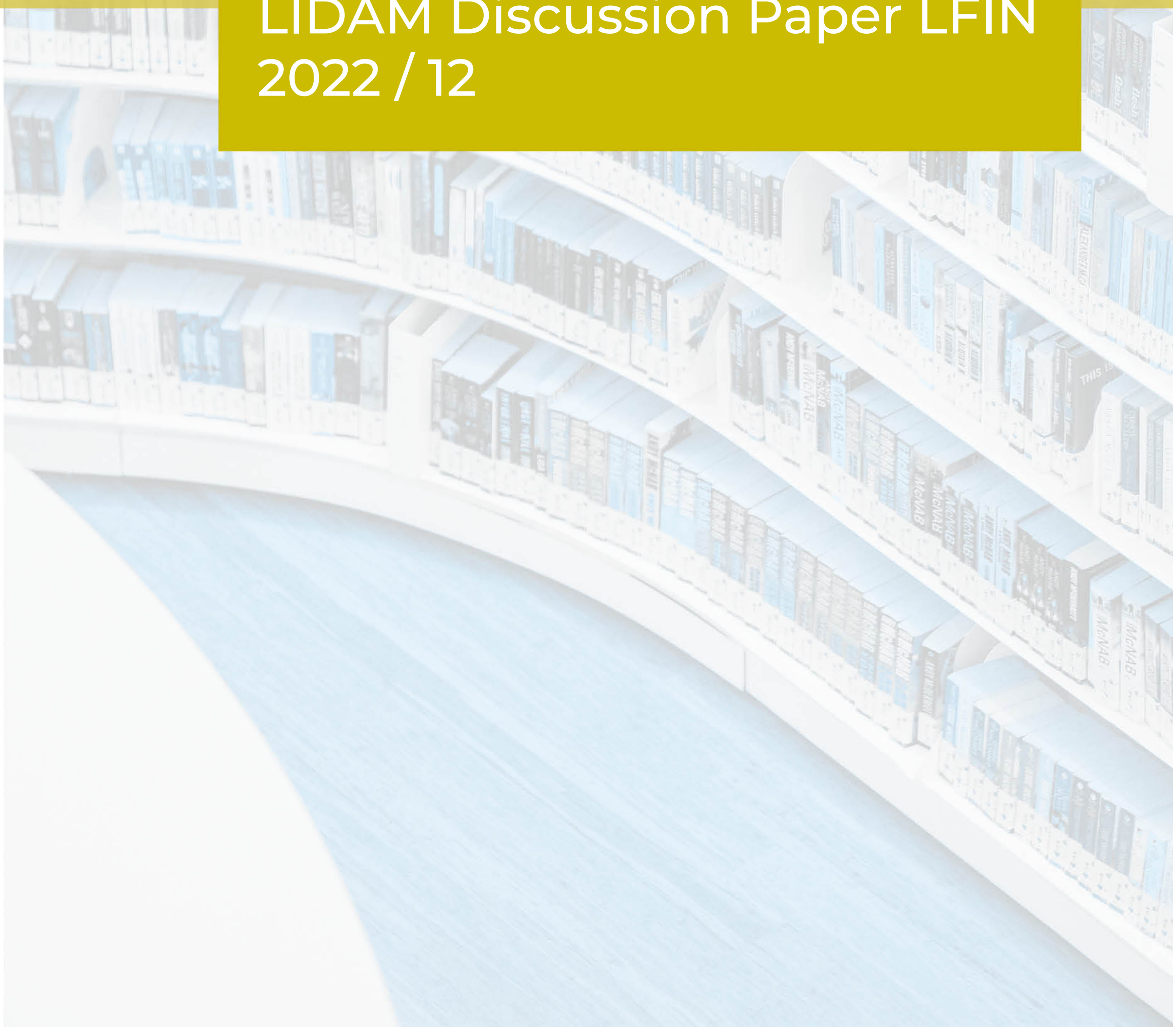

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Retail Investors' Disposition Effect and Order Choices*

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Abstract

Retail investors are prone to the disposition effect and submit many more limit orders than market orders. Mechanical effects stemming from the price-contingency conditions for order executions can lead these limit orders to inflate an investor's measured disposition effect (Linnainmaa 2010). Our paper is the first to demonstrate that the relationship between the disposition effect and order choices is bi-directional. Using a controlled experiment on the one hand and empirical trading data of thousands of investors on the other hand, we show that investors who are prone to the disposition effect differ from others in their use of limit orders and in their choice of limit prices.

Keywords: *disposition effect, order choice, limit orders, retail investors*
JEL classification: *G11; G40*

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1 Introduction

Retail investors use limit orders extensively and there are several possible explanations for why they prefer limit orders over market orders. Market conditions such as high volatility or a wide bid-ask spread, combined with infrequent market monitoring, may encourage investors to submit limit orders to avoid unfavorable prices. Alternatively, they may choose limit orders for non-economic reasons, at random, or simply because it is the default order type on their respective trading platforms.[1] While the reasons for individuals' preference for limit orders over market orders remain unclear, their order choices for sell orders may be affected by the original purchase price.

Although the original purchase price should be irrelevant for making sell or hold decisions, there is robust evidence that individuals use the purchase price as the reference point when they make sales decisions. Investors tend to frame a prospective sale as a gain (a loss) when the current market price is higher (lower) than the purchase price. Several empirical and experimental studies show that individuals exhibit the disposition effect (DE) – the propensity to sell winners and hold on to losers (see, e.g., Shefrin & Statman (1985), Odean (1998)). Frydman & Rangel (2014) provide clear evidence that greater salience of the purchase price strengthens the DE.

We combine an experiment and the analysis of empirical market data to study how the DE affects individuals' sell order submissions. If investors are eager to sell winners (i.e., stocks whose price has increased since the investors purchased them), they may be inclined to use market orders or to set the limit price aggressively to ensure execution. If they are reluctant to sell losers (i.e., stocks whose price has decreased since the investors purchased them), they may (1) keep observing the market and wait for a rebound before submitting a market order, or (2) they may be tempted to set the limit price no lower than the purchase price despite high non-execution risk. The DE may thus affect sell order submissions in two respects: by (1) investors submitting more limit orders in the loss domain than in the gain domain, and by (2) investors setting the limit price for sell orders in the loss domain farther away from the prevailing market price than that for sell orders in the gain domain. To be clear, when we refer to "order submissions in the gain (loss) domain" in this study, we mean orders submitted for positions which are at a gain (loss) at the time of order submission.

Linnainmaa (2010) argues that the use of limit orders inflates the DE measure because of the price-contingent execution of limit orders. A sell limit order is more likely to be executed in an upward-trending market, increasing the probability that the stock will be sold at a gain. A sell limit order is less likely to be executed in a downward-trending market, increasing the probability that the stock will remain in the investor's portfolio and be counted as a paper loss. In other words, the DE measure from field data may not correctly reflect an investor's true tendency to sell winners and hold on to losers. Investors who are indifferent to selling winners or losers may have a positive DE measure which results mechanically from their limit order

[1] Many brokers in Europe set limit orders as the default option(Linnainmaa 2010).

use.

Since it is impossible to determine the motivation behind each individual limit order, just as it is impossible to disentangle the mechanical effects of limit order use on the DE measure from behavioral drivers, we cannot straightforwardly classify high-DE and low-DE investors using empirical (field) data. To overcome this shortcoming of the available empirical data, we perform a within-participants experiment – an investment game that consists of two *independent* trading rounds. In one round, participants can submit market orders only. In the other round, they can submit both market and limit orders. Since the market-orders-only round is free of any mechanical effects of limit orders, this round allows us to compute a DE measure that reflects the traders' true propensity towards the DE. We can then reliably distinguish individuals with a high DE level from those with a low DE level. We will hereafter refer to the market-orders-only round as the *classification* round and call the DE measure computed from this round the *unbiased* DE measure in the sense that it is not affected by any effects stemming from limit order use.

Seru et al. (2010) provide evidence that individuals' disposition effect level is persistent over time so we assume that the participants in our experiment exhibit the same inherent propensity towards the DE in both rounds of the experiment. Our main goal is to investigate how the high-DE and low-DE groups differ in their limit order submissions in the *main* round – the round in which they are allowed to submit both market and limit orders. We design our experiment to provide us with detailed data about the state of the market (i.e., best bids and best asks) at the time of order submission, allowing us to control for the impact of market conditions on investors' order submission behavior.

Following up on the experimental part of our paper, we confirm the external validity of our experimentally-derived results using an empirical approach. We use a comprehensive data set provided by a large Belgian brokerage house to test our hypotheses. According to Linnainmaa (2010), the DE measure calculated from the trading data ("*field* DE measure", hereafter) may be magnified due to the mechanical effects of limit order use. As a result, the trading data does not allow us to unambiguously classify investors into low and high-DE individuals. However, our experimental results show that the mechanical effects of limit order use add noise, but are not strong enough to invalidate the classification of high-DE and low-DE investors based field data; most of the low-DE (high-DE) participants in the classification round also have relatively low (high) DE measures in the main round. We take this as evidence that we can use the *field* DE measure as a proxy for classifying the investors in our empirical data set into low-DE and high-DE groups.

Given that the *field* low-DE group may also include some traders who should in truth be classified as high-DE, and vice versa, the effect sizes of the impact of DE on order submissions that we detect using empirical data will be biased downward. Any effects we uncover using our empirical trading data can thus be considered lower bounds on the true effect sizes that one would observe if one could unambiguously classify the low-DE and high-DE groups.

Our main contribution is to offer a behavioral explanation for investors' order choices. We find both experimental and empirical evidence of how the DE affects investors' order choices. High-DE investors condition their trading behavior more strongly on the purchase price; their order submission behavior differs depending on whether their position is at a gain or at a loss. They are more inclined to use limit orders in the loss domain than in the gain domain. They set the limit price farther away from the prevailing market price in the loss domain than in the gain domain. They frequently set the limit price no lower than the purchase price when facing losses, despite the higher non-execution risk this choice entails.

Another contribution is that we provide evidence regarding how the use of limit orders may mislead the meaning of DE measures. Linnainmaa (2010) voices concerns that the DE measure in several empirical studies may be magnified by the use of limit orders. The impossibility to control for mechanical effects on the DE measure in empirical studies casts doubt on the reliability of DE measures computed from field data. Our experiment shows that, although the use of limit orders inflates the DE measure, the effect is not strong enough to invalidate all inferences regarding investors' preferences for selling winners over losers.

The remainder of the paper is organized as follows. We present our experimental study in Section 2 and our empirical study in Section 3. We report robustness checks in Section 4. Section 5 concludes. Finally, we provide additional details about our experimental design and software in the Appendix.

2 Experimental Study

2.1 Experimental Design

2.1.1 Basic Design

Each participant plays an investment game that consists of two *independent* trading rounds. Participants' performance in one round thus does not directly affect that in the other. Their portfolio is reset at the beginning of the second round. At the end of the experiment, one of the two trading rounds is randomly chosen for actual payment.

The market setting for both rounds is the same, with the single exception that in the classification round, participants can submit only market orders, while they can submit both market and limit orders in the main round.

In both trading rounds, participants trade five risky stocks, labeled 'Stock 1' through 'Stock 5', in an order-driven market. Participants do not interact; instead, every participant trades against computer-generated limit and market orders in both rounds. The sequences of computer orders for the five stocks are predetermined by a process that we describe in more detail later. This means that the arrival of computer orders does not depend on participants' own actions in the market. Nevertheless, participants' orders interact with the pre-generated orders, triggering transactions and affecting prices.

In each round, a participant can trade the five stocks in continuous double auction markets that the participant can manually pause to submit orders or to consider – at their leisure – their trading decisions. While trading is continuous throughout the 15 minutes of a round (except for the time the participant decides to manually pause the market), the round is nominally divided into 30 "days" of 30 seconds each. We emulate the stock market treatment of Weber & Welfens (2007) in that, at the beginning of the round, participants are provided with the five stocks' price developments over the three days preceding the beginning of their trading round. The time index of each round thus runs from -3 through 30, measured in days, with participants entering the market at time 0. Participants can use the information from the three initial days (time -3 through 0) to form priors concerning which of the stocks they believe to be more or less likely to outperform the others over the trading period (we will provide details about the determinants of stock prices later in this chapter). Appendix 6.1 contains a screenshot of the trading interface that includes the stock price charts participants see while trading. At the beginning of the first day (time 0), each participant receives 1700 experimental currency units, which we will refer to as experimental dollars (e$) hereafter. They receive no initial endowment of shares.[2] Over the following 30 trading days, i.e., from time index 0 through 30, they can submit orders to buy new shares (subject to their budget constraint) or to sell shares they hold. The trading round ends at time 30.

Trading mechanism: Trading takes place on a continuous basis. The market uses the price-time precedence hierarchy to arrange trades. A market order is not accepted if there is no counterpart limit order in the order book ("Fill or Kill"). If there is, then the market order is filled immediately at the counterpart limit order's price. Participants are allowed to submit both marketable and non-marketable limit orders. A marketable limit order is executed immediately at the counterpart limit order's price. A non-marketable limit order is entered into the order book and sorted according to its price-time precedence rank; the non-marketable limit order stands in the order book until executed, expired or canceled. Each computer limit order is valid until its pre-determined expiry time, while each participant limit order is valid until the participant actively cancels it. Each order submitted is for a volume of one share, but participants may submit as many orders as they wish and can afford.

Short selling and leverage are not allowed. Thus, a market (limit) buy order can be submitted only when participants have enough money to buy at the best ask (at the limit price), while a sell order can be submitted only when participants hold at least one share of the asset. Participants do not earn interest on money held in the form of cash.

Computer order-generating process: We simulate the 33 days of market activity in the five stocks' shares in a two-step process. First, we simulate the stocks' fundamental values (FVs). Each stock's FV starts out at e$ 100 at time -3. Each day thereafter, FV changes by either +6% or -5%. These changes are independent across stocks and i.i.d. within each stock. The probability of an upward change differs across stocks. There is exactly one stock that has a probability of an upward FV change of 65%, and this probability remains constant for all 33 FV changes within a round. A second stock has a probability of 55%, a third has a probability of

[2]In Weber & Welfens (2007), the initial endowment is 2000 currency units to trade six stocks. Since our participants trade only five stocks, they receive a pro rata endowment of e$ 1700.

50%, a fourth one of 45%, and the last has one of 40%.[3] Which stock carries which probability of an FV increase changes from the first to the second round of trading.

In the second step of our simulation process, we simulate the orders of the computerized market participants. We generate random sequences of orders using a set of parameters including the arrival rate of orders, order direction (buy or sell orders), order type (market or limit order), limit price and expiry time (applicable only to limit orders). On average, three computer orders arrive every second. The probability that a randomly generated order is a buy order is 50%. The probability that a buy (sell) order is a market order is 3% (4%), respectively. Limit orders are marketable 32% of the time.[4]

For a limit order, we set two additional parameters – the limit price and the expiry time. The limit price is determined based on FV at the time the order is generated. If it is a buy (sell) order, the bid (ask) price is randomly drawn from a normal distribution with a mean of $-0.01 \cdot \text{FV}$ ($0.01 \cdot \text{FV}$) and a standard deviation of $0.045 \cdot \text{FV}$.

Participants are informed that bid and ask prices offered by computer orders are randomly distributed around stocks' FVs (but the parameters of the distributions remain unknown to them) and that a pronounced upward (downward) trend in one asset's market price is likely to result from an increase (decrease) in the asset's underlying value. They know the set of probabilities of value increases, yet are not informed about which stock carries which probability of an FV increase. However, they can update their priors based on the prices they observe in the markets the five stocks' shares are traded in.

Each computer limit order's randomly generated expiry time is calculated as follows:

$$Expiry\ time = Creation\ time + 0.5 \cdot \epsilon,$$

where $\epsilon \sim LogN(0, 1)$.

Since trades take place in a continuous environment, participants can submit orders at any time. Participants can make decisions without time pressure because market activity in all five stocks automatically pauses when they start the process of submitting an order (i.e., time in the experiment stops, no new orders arrive in the order book and no trades occur).

The trading screen presents the price charts and the order books of all five stocks. To reflect how retail investors experience markets outside of the lab, we display at most the five best quotes on each side of the order book, and display asset prices with a delay. To prevent participants from discovering real-time asset prices, the user interface also informs them of the implementation of their orders with a delay, even though their orders are implemented immediately after submission. In addition to market information, the trading screen displays participants' portfolios and their standing limit orders. Participants are allowed to cancel their standing limit orders at any time.

The instructions carefully describe the stochastic value-generating process, as well as all other details of the experiment. In addition, a short video illustrates how to use the market

[3] Thus, $ln\,(\text{FV})$ is binomially distributed.

[4] These odds of being market, marketable limit or non-marketable limit orders mirror the proportions of these order types in the subset of our empirical order data for which we have information about the best bids and best asks at the time of order submission, i.e., from February 1 through April 30, 2006.

interface to ensure that participants are familiar with the software.

All participants start with the market-and-limit-orders round to avoid a bias towards using only market orders that might result from starting with the market-orders-only round. Before the trading rounds commence, written instructions ensure that all participants know how market and limit orders can be submitted and how they interact with the market in the experiment. Participants also have to correctly answer a set of control questions about market and limit orders and another question concerning how asset prices are generated. The full instructions and the set of control questions are included in Appendix 6.2.

We programmed our experiment using oTree (Chen et al. (2016)) and conducted it online. The experiment involved a total of 217 undergraduate and graduate students at the University of Graz, Austria. We excluded 4 participants from the our analyses because they reloaded the browser page at least once during one of the trading rounds, which meant that, after reloading, they would start the round anew while already knowing the price paths they would face up to the point where they reloaded.

The participants were aged between 18 and 44 years, with an average of 24. About 44% were male and nearly 56% were female. The experiment lasted approximately 1.5 hours to 2 hours. The earnings ranged from 12.83 € to 24.79 €. The average earnings were 18.90 € (median 18.52 €) with a standard deviation of 1.94 €.

2.1.2 Measuring the DE

We primarily follow Odean's (1998) methodology to estimate the DE, yet to ensure the robustness of our results, we also use survival analysis as pioneered by Feng & Seasholes (2005) to calculate the DE level in a robustness check (see Appendix 4.1.4).

Odean (1998) shows that the proportion of gains realized (PGR) and the proportion of losses realized (PLR) tend to get smaller when investors hold more securities in their portfolio. As a result, the DE defined as the difference between PGR and PLR is mechanically correlated with investors' trading activity. Since our primary interest is to classify the participants into high-DE and low-DE groups, it is particularly important to avoid such an impact of trading activity on the DE measure. To cancel out the effect of portfolio size in the denominators of the two proportions, we thus calculate the DE as the ratio of PGR to PLR. More specifically, we estimate the DE using the following equations:

$$PGR = \frac{Realized\ Gains}{Realized\ Gains + Paper\ Gains} \tag{1}$$

$$PLR = \frac{Realized\ Losses}{Realized\ Losses + Paper\ Losses} \tag{2}$$

$$DE = PGR/PLR \tag{3}$$

where *Realized Gains (RG)* is the total number of positions realized at a gain and *Paper Gains (PG)* is the total number of positions at gain that could have been sold, but were not. A corresponding interpretation applies to *Realized Losses (RL)* and *Paper Losses (PL)*. A value of $DE > 1$ indicates a greater tendency to realize winners than to realize losers.

Since we divide each 15-minute trading round into 30 'days' of 30 seconds each, we also determine and count the paper gains and paper losses every 30 seconds.[5] For every 30-second period, we count each stock in the participant's portfolio that the participant did not sell as a paper gain if the average purchase price for this stock is lower than the lowest best bid offered during this period. We count each stock as a paper loss if the average purchase price is higher than the highest best bid offered during this period. If a stock's purchase price lies between the lowest and the highest best bids, we count it as neither a paper gain nor a paper loss. We count stocks of which participants sell any holdings as a realized gain (loss) if the execution price is higher (lower) than the average purchase price. (In case of multiple sales, we compare the weighted average execution price to the average purchase price to determine whether to count the sale as a realized gain or loss.)

Because of the potential mechanical effects of limit order use documented by Linnainmaa (2010), a participant may display two different DE levels in the two trading rounds of the experiment. Throughout this study, we will refer to the DE level computed from the classification round (i.e., the round in which participants can submit only market orders) as the *unbiased* DE level (i.e., the DE level that is not distorted by the use of limit orders) and to that from the main round (i.e., the round in which participants can submit both market and limit orders orders) as the *biased* DE level.

2.1.3 Main hypotheses

The purchase price may affect investors' sell order submission behavior because this price determines whether investors consider their holdings to be winners or losers. If investors are eager to sell winners to realize their gains, they may be inclined to submit marketable orders, i.e., to use market orders or set the limit price lower than the best bid (i.e., post marketable limit orders) to ensure execution. On the other hand, if they are reluctant to sell losers to avoid realizing their losses, they may (1) keep observing the market and wait for a rebound before submitting a marketable order, or they may (2) be tempted to set the limit price no lower than the purchase price despite high non-execution risk.

Since marketable limit orders (i.e., buy limit orders with a limit price higher than or equal to the prevailing best ask at the time of submission, or sell limit orders with a limit price lower than or equal to the prevailing best bid) are typically executed with immediacy, we consider them to serve a similar purpose as market orders. Throughout the remainder of the paper, we will therefore collectively refer to market orders and marketable limit orders as "marketable

[5] Using different frequencies at which the paper gains and paper losses are counted does not change our conclusions. We present results calculated at frequencies of 5 seconds and 15 seconds in Sections 4.1.1 and 4.1.2, respectively. Furthermore, since the participants in our experiment monitored the market continuously, one could argue that participants could make decisions whenever they wished. Hence, we also compute Odean's (1998) DE measure with the paper gains and paper losses counted every time participants paused the market (irrespective of whether they then submitted an order or just studied the market during the pause). Using this variant of the DE measure also does not change our main conclusions. See Section 4.1.3 for details.

orders".

The purchase price may thus affect *sell order* submission in two respects: (1) a greater extent to which traders use non-marketable limit orders in the loss domain than in the gain domain, and (2) traders setting limit prices in the loss domain farther away from prevailing market prices than they set limit prices in the gain domain.

We argue that high-DE investors are more strongly affected by the purchase price when making sales decisions than are low-DE investors. We thus conjecture that high-DE investors' sell order submissions differ from those of low-DE investors. Accordingly, we formulate the following three hypotheses:

Hypothesis 1: *High-DE investors submit non-marketable limit orders to a greater extent for sell orders in the loss domain than for sell orders in the gain domain.*

Hypothesis 2: *High-DE investors set the limit price for sell orders in the loss domain farther way from the market price than that for sell orders in the gain domain or for buy orders.*

Hypothesis 3: *High-DE investors are more likely to set the limit price no lower than the purchase price in the loss domain.*

2.2 Experimental Results

2.2.1 DE and Trading Activity

Trading activity of the participants in both rounds of the experiment is comparable. In the classification round, they submit a total of 12,601 orders, 58.29% of which are buy orders. In the main round, they submit 14,384 orders, 54.76% of which are buy orders. Limit orders account for 32.54% of the total orders. In both rounds, most traders trade shares of all stocks (i.e., they on average trade shares in 4.69 stocks).

Out of the 213 qualified participants, we can compute the DE level in the classification round for 172 participants (we are unable to calculate DE for the remaining 41 because their PGR or PLR is undefined or PLR is 0). To investigate how high-DE and low-DE individuals differ in their order submission behavior, we divide our remaining sample into terciles by unbiased DE levels: the low-DE and high-DE groups encompass the participants in the bottom and top terciles, respectively; the median-DE group refers to the middle tercile. Panel A of Table 1 presents unbiased and biased DE levels by group. Panel B reports descriptive statistics concerning trading activity of the three groups in the main round.

Table 1: DE and Trading activity by group in the experiment (DE=PGR/PLR)

This table presents summary statistics concerning DE and trading activity in the experiment. We measure the unbiased DE using trading activity in the classification round and the biased DE using trading activity in the main round. We use Equation (1) to Equation (3), determining paper gains and losses in 30 second intervals. We group participants by terciles of unbiased DE levels: the low-DE and high-DE groups encompass the participants in the bottom and top terciles, respectively; the median-DE group refers to the middle tercile. Panel A presents unbiased and biased DE levels by group. Panel B reports descriptive statistics concerning trading activity of the three groups in the main round. The fourth row in Panel A shows the difference between the biased and unbiased DE levels. We perform two-sample t-tests of the difference in mean DE values and Wilcoxon signed rank tests of the difference in medians, reporting the resulting p-values in parentheses.

	Mean			Median		
Group	Low	Median	High	Low	Median	High
Panel A: DE levels						
(1) No. of investors	57	58	57	57	58	57
(2) Unbiased DE (in %)	0.43	3.14	12.85	0.31	3.07	10.18
(3) Biased DE (in %)	1.22	4.94	9.88	0.67	2.59	5.08
(4) = (3) - (2)	0.78	1.79	-2.96	0.37	-0.48	-5.10
	(0.0007)	(0.0525)	(0.1112)	(0.0019)	(0.7358)	(0.0004)
Panel B: Order submissions in the main round						
(1) No. of orders	58.47	67.26	63.09	43.00	58.00	54.00
(2) No. of buy orders	33.68	37.64	34.04	29.00	35.50	30.00
(3) No. of sell orders	24.79	29.62	29.05	18.00	26.50	27.00
(4) No. of limit orders	11.61	24.53	28.02	6.00	17.00	20.00
(5) Buy limit/Total buy (in %)	17.87	27.37	31.02	11.11	15.69	19.51
(6) Sell limit/Total sell (in %)	22.45	42.49	50.95	8.13	35.50	59.09

2.2.2 The impact of the DE on order submission

As mentioned earlier, the purchase price may affect investors' sell order submissions because investors use the purchase price to distinguish their holdings between winners and losers. We argue that high-DE investors are more strongly affected by the purchase price and that their sell order submissions thus differ from those of low-DE individuals.

Our first hypothesis (Hypothesis 1) suggests that high-DE individuals' order choices (marketable versus non-marketable orders) depend on whether the sell order is submitted at a time where the position is at gain or at loss. To test Hypothesis 1, we run Logit model (4) on the subset of sell orders:

$$NMO_{i,t} = \beta_0 + \beta_1 \cdot MedianDE_i + \beta_2 \cdot HighDE_i + \beta_3 \cdot Loss_{i,t} + \beta_4 \cdot MedianDE_i * Loss_{i,t} + \beta_5 \cdot HighDE_i * Loss_{i,t} + \beta_6 \cdot Spread_t \quad (4)$$

The dependent variable $NMO_{i,t}$ takes the value of 1 if the sell order submitted at time t by investor i is a non-marketable limit order and 0 otherwise. The independent variables include (i) $HighDE_i$, a dummy variable that takes the value of 1 if the order is submitted by investor i who is in the High-DE group and 0 otherwise, (ii) $MedianDE_i$, a dummy variable that takes the value of 1 if the order is submitted by investor i who is in the Median-DE group and 0 otherwise, (iii) $Loss_{i,t}$, a dummy variable that takes the value of 1 if the sell order is submitted by investor i at time t when the position is at a loss and 0 otherwise, and (iv) $Spread_t$, a continuous variable that measures the relative bid-ask spread (i.e., bid-ask spread/mid-point) in experimental dollars at time t when the order is submitted.

Column [1] of Table 2 reports the coefficient estimates of this model. In this model, the two interaction terms are of key interest because they directly capture the difference in the impact of being in the loss domain on the extent of non-marketable order use for the median-DE and high-DE group compared to the low-DE group. We introduce the two dummy variables indicating the DE groups (i.e., $HighDE$ and $MedianDE$) in order to control for the general preference between marketable and non-marketable orders of each group. The *Spread* variable allows control for the market condition.

The omitted dummy variable for the group is the low-DE group. Then, the coefficient estimate of *Loss* (β_3) measures the impact of being in the loss domain on the choice of non-marketable order for the low-DE group. Our results suggest that the odds that the low-DE group chooses non-marketable orders over marketable orders do not depend on whether they are submitting a sell order for a position at gain or at loss (the coefficient estimate of *Loss* is insignificantly negative). However, the more the individuals exhibit the DE, the greater the difference in the odds of submitting a non-marketable order between the loss and the gain domains. The coefficient estimate of the interaction term between $HighDE$ and *Loss* (β_5) is positive and significant at the 1% level, supporting Hypothesis 1 that the high-DE group is more strongly affected by the purchase price when choosing non-marketable orders over marketable orders.

Table 2: Impact of the DE on sell order submissions in the experiment (DE=PGR/PLR)

This table reports the regression coefficients and corresponding standard errors (in parentheses) for the three models represented in Equations (4), (6) and (7). Standard errors are clustered at the individual level. In Equation (4), the dependent variable is NMO, which takes the value of 1 if the order is a non-marketable limit order and 0 otherwise. In Equation (6), the dependent variable is LPP – a continuous variable defined in Equation (5), which measures the distance between the limit price and the prevailing best bid at the time of order submission. In Equation (7), the dependent variable is $I(LP \geq PP)$, which takes the value of 1 if the limit price is set no lower than the purchase price and 0 otherwise. The independent variables include (i) $HighDE$, a dummy variable that takes the value of 1 if the sell order is submitted by an investor in the High-DE group and 0 otherwise, (ii) $MedianDE$, a dummy variable that takes the value of 1 if the order is submitted by an investor in the Median-DE group and 0 otherwise, (iii) *Loss*, a dummy variable that takes the value of 1 if the sell order is submitted when the position is in the loss domain and 0 otherwise, and (iv) *Spread*, a continuous variable that measures the relative bid-ask spread (i.e., bid-ask spread/mid-point) in experimental dollars at the time of order submission.
*, ** and *** indicate statistical significance at the 5%, 1% and 0.1% levels, respectively.

Dependent Variable	NMO	LPP	$I(LPP \geq PP)$
	Eq (4)	*Eq (6)*	*Eq (7)*
	[1]	[2]	[3]
$Intercept$	-1.1288***	0.0112	-0.4566
	(0.3096)	(0.0063)	(0.3197)
$MedianDE$	0.7885*	0.0272*	0.9610*
	(0.3963)	(0.0147)	(0.4038)
$HighDE$	0.9109*	0.0141*	1.7919***
	(0.3834)	(0.0058)	(0.4076)
Loss	-0.2355	-0.0037	
	(0.2150)	(0.0029)	
$MedianDE \times Loss$	0.4812	0.0212	
	(0.3187)	(0.0203)	
$HighDE \times Loss$	1.0781**	0.0512***	
	(0.3350)	(0.0095)	
Spread	1.7182	0.1436	3.2926
	(1.9607)	(0.1532)	(4.4874)
N	4739	4739	962
Likelihood Ratio			
(p-value)	<.0001		0.0002
F-value		10.94	
Adjusted R-square		0.01214	

Hypothesis 2 concerns the impact of DE on limit price setting. Due to their reluctance to get out of losers, high-DE individuals are more likely to set the limit price no lower than the purchase price when their position is in the loss domain. As a result, we expect their limit prices for sell orders in the loss domain to be set farther way from the prevailing best bid than those for sell orders in the gain domain. We call the distance between the limit price and the prevailing best bid at the order submission *Limit Price Position* (LPP). The results concerning Hypothesis 1 indicate that the choice between limit and market orders dependents on investors' DE levels. Thus, to make the LPP measure comparable between the groups, we also include marketable orders in this analysis. We set the LPP of marketable orders to 0, because submitting a marketable order implies that investors accept to sell at the best bid. Concretely, we calculate the LPP for the order submitted by investors i at time t – denoted as $LPP_{i,t}$ – as follows:

$$LPP_{i,t} = \begin{cases} \frac{LimitPrice_{i,t} - BidPrice_t}{BidPrice_t} & \text{for } \textit{non-marketable} \quad \textit{limit} \text{ orders} \\ 0 & \text{for } \textit{marketable} \text{ orders} \end{cases} \tag{5}$$

where $LimitPrice_{i,t}$ is the limit price of the corresponding order and $BidPrice_t$ is the prevailing best bid at time t when the order is submitted. We perform an ordinary least squares regression (Model (6)) to estimate how the LPP for sell orders in the gain domain differs from that in the loss domain. We regress $LPP_{i,t}$ on the same set of independent variables as in those in Model (4).

$$\begin{aligned} LPP_{i,t} = \beta_0 + \beta_1 \cdot MedianDE_i + \beta_2 \cdot HighDE_i + \beta_3 \cdot Loss_{i,t} \\ + \beta_4 \cdot MedianDE_i * Loss_{i,t} + \beta_5 \cdot HighDE_i * Loss_{i,t} + \beta_6 \cdot Spread_t \end{aligned} \tag{6}$$

Similar to Model (4), we are mainly interested in the interaction terms that capture how being in the loss domain affects limit price setting. Only the high-DE group shows a significantly higher LPP for sell orders submitted for positions at loss than for those at gain. For an average investor in the high-DE group, the LPP of sell orders for a position at loss is 5.12 percentage points larger than that for a position at gain (see Column [2]). This supports our Hypothesis 2.

Our explanation for the difference in the impact of being in the loss domain on the limit price setting between groups would be that the high-DE group anchors to the purchase price; when their positions are at loss, they still set the limit price no lower than the purchase price in the hope of breaking even regardless of the probability that the market will in fact bounce back, allowing their order to get executed. Constructed based on this intuition, Hypothesis 3 directly tests how they set the limit price relative to the purchase price when submitting non-marketable sell orders to exit a position that is currently at loss. To test Hypothesis 3, we run logit Model (7) on the subset of non-marketable sell orders submitted in the loss domain. The dependent variable ($I(LP \geq PP_{i,t})$) takes the value of 1 if the limit price is set no lower than the purchase price and 0 otherwise. Column [3] of Table 2 presents the coefficient estimates of this model.

$$I(LP \geq PP_{i,t}) = \beta_0 + \beta_1 \cdot HighDE_i + \beta_2 \cdot MedianDE_i + \beta_3 \cdot Spread_t \tag{7}$$

Our results show that the DE affects the probability that individuals set the limit price no lower than the purchase price for a position at loss. The greater extent to which individuals display the DE, the greater are the odds that they set the limit price no lower than the purchase price for positions at loss. The odds for the median-DE group are 161% higher than the odds for the low-DE group; the difference between the high-DE and low-DE groups is much larger, ranging up to 500%. Hypothesis 3 is thus supported, suggesting that order submissions reflect individuals' reluctance to realize losses.

2.3 To what extent does limit order use alter inferences about investors' DE?

Seru et al. (2010) provide evidence that individuals' DE level is persistent over time, leading us to assume that the participants in our experiment exhibit a constant inherent propensity towards the DE in both rounds of our experiment. Given that both trading rounds of the experiment are similar except for the availability of limit orders, we can interpret the difference in participants' measured DE levels between the two rounds as being attributable to their use of limit orders. We estimate Model (8) to see how the extent of limit order use explains the strength of the mechanical effect of limit order use on the DE measure.

$$\text{Mechanical effects}_i = \beta_0 + \beta_1 \text{Unbiased DE}_i + \beta_2 \text{LO Use}_i \tag{8}$$

where $MechanicalEffects_i$ is the difference between the biased DE level of investor i and her unbiased DE level, $UnbiasedDE_i$ is the unbiased DE level of investor i, and $LOUse_i$ is the ratio of sell limit orders to total sell orders.[6] In line with Linnainmaa (2010), we also find that the use of limit orders magnifies the DE measure. The coefficient of *LO Use* (β_2 = 5.9308, with a standard error of 1.6809) is significantly positive. On the other hand, the strength of mechanical effects inversely relates to the unbiased DE level; the coefficient of *Unbiased DE* (β_1 = -0.5020, with a standard error of 0.0954) is significantly negative.

Since we focus on how high-DE and low-DE investors differ in their order submission behaviors, it is more relevant, however, to study the extent to which the mechanical effect of limit order use can lead to strong misclassification of high-DE and low-DE individuals – i.e., how likely individuals classified as low-DE (first tercile) in the classification round are to be classified as high-DE (third tercile) in the main round, or vice versa. We restrict this analysis to the subset of 151 participants for whom we can calculate the DE measure for both trading rounds. The Spearman correlation coefficient between the DE levels of the two rounds is 0.65 ($p < .0001$).[7] The biased DE measure correctly classifies 66% of the low-DE participants and

[6]We also tested for an impact of our different price paths, but found no significant effect on our results.
[7]The Pearson correlation coefficient is 0.42, $p < .0001$.

strongly misclassifies only 6% as high-DE individuals. It furthermore correctly classifies 62% of the high-DE group and strongly misclassifies only 4% (see Table 3). Figure 1 shows that most of the participants with a DE level lower (higher) than the median in the main round also exhibit a DE level lower (higher) than the median DE level in the classification round. This suggests that the biased DE can be considered a less than perfect, but nevertheless useful proxy for distinguishing high-DE from low-DE individuals.

Our results have an important implication. Linnainmaa (2010) voices the concern that the DE measures in several empirical studies may be upwards biased because of the use of limit orders and the attendant mechanical effects. The infeasibility of controlling for mechanical effects on the DE measure in empirical studies thus casts doubt on the reliability of DE measures computed from field data. The results from our experiment suggest that, although limit order use imposes certain mechanical effects on individuals' DE measures, such effects may not be strong enough to invalidate inferences regarding individuals' propensity towards exhibiting behavior consistent with the DE.

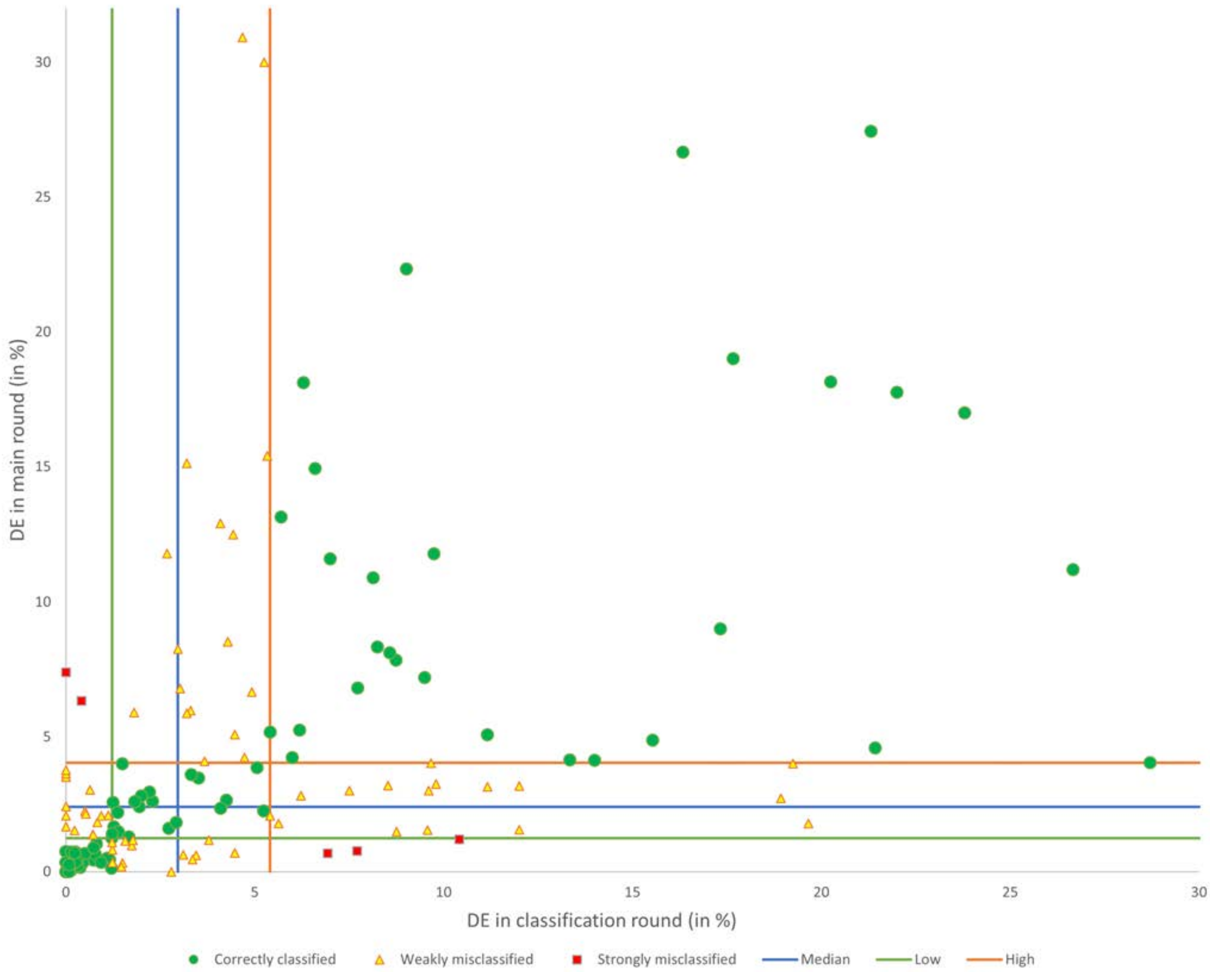
Table 3: Group Classification by DE level in the two rounds

This table presents the round-on-round migration of DE classifications. The numbers represent cross-tabulated percentage proportions belonging to each classification combination.

	Ranked by unbiased DE level		
Ranked by biased DE level	Low-DE	Median-DE	High-DE
Low-DE	66.00	28.00	6.00
Median-DE	29.41	39.22	31.37
High-DE	4.00	34.00	62.00

Figure 1: DE levels in the two trading rounds

This figure plots the DE levels in both trading rounds of the experiment; the unbiased DE level (from the classification round) is plotted on the horizontal axis and the biased DE level (from the main round) on the vertical axis. Green disks represent participants who are correctly classified by the biased DE level (i.e., who have the same ranking in both rounds). Yellow triangles represent participants who have been weakly misclassified, i.e., whose rankings in the two rounds are adjacent to each other. Red squares represent those who have been strongly misclassified, i.e., who have shifted from the bottom to the top tercile or vice versa. The vertical (horizontal) blue line represents the median DE level in the classification (main) round. The vertical (horizontal) green line represents the border between investors classified as low-DE and those classified as median-DE in the classification (main) round. The vertical (horizontal) orange line represents the border between investors classified as median-DE and those classified as high-DE in the classification (main) round.



3 Empirical Study

To provide the external validity for our experimental results, we also test our three hypotheses about the impact of the DE on order choices using the trading data provided by a large brokerage house in Belgium. We present our data and sample in Section 3.1 and our empirical analysis in Section 3.2.

3.1 Data and sample

We use three different data sets for our empirical analyses. The first is a comprehensive order data set provided by a large Belgian online brokerage house. It contains detailed information about the order submission decisions of 25,328 retail investors over more than 10 years, from January 2003 to March 2012. For the present study, we focus on investors' orders submissions for stocks only and do not include orders pertaining to other asset classes. The order data provide very detailed information about order submissions, including, for each order placed: type (market or limit), time-in-force (day order or Good-Till-Canceled order), direction (buy or sell), status (executed or non-executed), sending time, execution time, limit price, order size, executed quantity and execution price. However, the market information at the time of order submission (best bid for sell and best ask for buy orders) is available only for market orders. Because we do not know the prevailing market quotes at the time of submission of limit orders, we cannot distinguish between marketable and non-marketable limit orders with certainty. We therefore use the lag between the time at which an order is sent and its execution time as a proxy to identify marketable limit orders. If a limit order is executed within 6 seconds after its submission, we classify it as marketable.[8]

In addition to this comprehensive set of order data, we have public and private information directly provided by Euronext[9] for the three-month period from February 1, 2006 to April 30, 2006. Following De Winne & D'Hondt (2007), we combine these public and private Euronext data in order to rebuild the limit order book (LOB) second by second. These LOB data represent orders and trades for 82 common stocks belonging to the AEX, BEL20 or CAC40 indexes. The ID code variable allows us to identify all orders and trades originating from the brokerage house. Merging data from the LOB and data from the brokerage house allows us to determine the best quotes at the time of order submission for 14,227 orders in the order dataset. We thus restrict our empirical analysis concerning Hypothesis 2 to this subset of data because the precise bid price at the time of order submission is necessary to calculate the Limit Price Position (LPP) in Equation (5). The third data set includes historical daily price data

[8]As mentioned in the following paragraph, we can reliably determine the best bids and best asks at the time of submission for a subset of our orders using a data set provided by Euronext. We use this subset of our data to determine the length of lag between the submission time and the execution time that classifies marketable and non-marketable limit orders most reliably. For each lag between 1 to 20 seconds, we calculate the F1-score measure – the harmonic mean of the model's precision and recall. We choose the lag of 6 seconds because it gives the highest F-score of 0.9126.

[9]Each month, Euronext used to publicly publish very detailed data about orders, trades and best limits of the order book. In addition to publicly available information, for each order, we also use a private dataset provided by Euronext that includes the ID member code, the time when the order disappears from the system (due to cancellation or execution for example) and the date of the order modification, if any; for each trade, this private Euronext dataset provides us with both buyer and seller ID codes as well as the date when both orders triggering the trade were introduced (or last modified) and the sequence number of both orders in the file of Euronext order data. For more details on the public and private information provided by Euronext and the approach used to rebuild the limit order book (LOB), see De Winne & D'Hondt (2003).

collected from Eurofidai or, where this is not available, from Bloomberg.

Following Seru et al. (2010), we retain only investors who make at least 7 round-trip stock trades during the nine-year sample period (11,800 investors). We are unable to calculate our DE measure for 621 of these investors because they have undefined PGR (3), undefined PLR (15), or PLR of 0 (603). We end up with a final sample of 11,178 investors who submit a total of 2,166,428 orders, involving 5,220 different stocks. Our investors' average (median) DE score is 4.4 (2.16). Non-marketable orders account for 68.74% of all total orders.

We adapt the methodology presented in Section 2.1.2 to estimate the DE of investors in our sample; the only difference is that we count paper gains and losses every day where the investors make a trade (either a buy or a sell). Similar to what we did for our experimental data, we also test the robustness of our empirical results using survival analysis to estimate the DE (see Section 4.2).

3.2 Empirical Results

Similar to the biased DE measure in the experiment, the DE measure computed using the trading data – we will refer to it as the *field* DE measure – may be inflated by limit order use. As a result, we cannot unambiguously classify investors in the trading data into high-DE and low-DE groups. However, as shown by our experimental study, the biased DE measure can still be used as a proxy for distinguishing between high-DE and low-DE individuals. We rely on this evidence to similarly use the *field* DE measure as a proxy for classifying investors in the trading data into high-DE and low-DE groups. That is, we divide the investors in the trading data into three equally-sized groups by their *field* DE measure, and argue that the *field* high-DE group (i.e., the top tercile) disproportionately consists of high-DE individuals (and analogously for the low-DE or bottom tercile group). Table 4 summarizes the trading activity of the three groups.

Table 4: DE and Trading activity by group in the trading data (DE=PGR/PLR)

This table presents summary statistics concerning the DE and trading activity in the trading data. The DE is estimated using Equations (1) to (3) with the paper gains and paper losses counted every day on which an investors completes a trade (either a buy or a sell). Investors are grouped into terciles by their DE level: the low-DE and high-DE groups encompass the investors in the bottom and top terciles, respectively; the median-DE group refers to the middle tercile.

	Mean			Median		
Group	Low	Median	High	Low	Median	High
(1) No. of investors	3726	3727	3726	3726	3727	3726
(2) DE = PGR/PLR	0.88	2.25	10.19	0.91	2.16	6.37
(3) No. of orders	182.70	203.71	194.97	84.00	103.00	100.00
(4) No. of buy orders	104.13	112.98	108.19	48.00	55.00	57.00
(5) No. of sell orders	78.57	90.73	86.78	35.00	43.00	41.00
(6) No. of buy limit orders	59.31	77.95	81.10	24.00	34.00	39.00
(7) No. of sell limit orders	44.56	65.79	70.96	18.00	27.00	31.00
(8) Buy limit/Total buy (in %)	53.80	61.45	67.90	58.59	68.59	75.00
(9) Sell limit/Total sell (in %)	53.75	64.70	74.82	58.24	71.67	83.39

We replicate the analyses in Section 2.2.2 with some modifications depending on the information available in the trading data. As mentioned in Section 3.1, we do not have access to the prevailing quotes at the time of order submission for all limit orders. As a result, we cannot always compare the market price at the time of order submission with the purchase price to determine whether a given order is submitted when the position is at gain or at loss. Instead, we use the high and low prices of the day when the sell order is submitted in case the market quotes are not available. If the high price of the is lower than the original purchase price, we are certain that investors made their transaction as the position was in the loss domain; if the low price is higher than the purchase price, investors made their transaction in the gain domain; if the purchase price is between the low and the high prices, we cannot unambiguously determine the domain and consequently exclude these cases from our analysis.

Since it is necessary to have the best bids at the time of order submission to calculate the Limit Price Position (LPP) in Equation (5), we test Hypothesis 2 using the subset of sell limit orders for which the prevailing quotes at the time of order submission are available. On the other hand, we include all sell orders to test Hypothesis 1 (using Model (9)) and all sell limit orders submitted for positions at loss to test Hypothesis 3 (using Model (10)). Due to the unavailability of the market quotes at the time of order submission for some orders, we cannot control for relative spreads when testing Hypotheses 1 and 3.

$$NMO_{i,t} = \beta_0 + \beta_1 \cdot MedianDE_i + \beta_2 \cdot HighDE_i + \beta_3 \cdot Loss_{i,t} + \beta_4 \cdot MedianDE_i * Loss_{i,t} + \beta_5 \cdot HighDE_i * Loss_{i,t} \quad (9)$$

$$I(LP \geq PP_{i,t}) = \beta_0 + \beta_1 \cdot HighDE_i + \beta_2 \cdot MedianDE_i \quad (10)$$

Table 5 reports the results of the three models. In line with our experimental results, our empirical results support all of the three hypotheses, providing evidence that high-DE group investors are more strongly affected by the purchase price when they submit sell orders. Consistent with our first hypothesis, the odds that the high-DE group submits non-marketable orders for positions at a loss is 27% higher than the odds for the low-DE group. Interestingly, being in the loss domain increases the odds that the high-DE group chooses non-marketable orders, but significantly lowers the odds for the low-DE group (see Column [1]).

Regarding Hypothesis 2, while the low-DE and median-DE groups show no significant difference in LPP between sell orders submitted for positions at loss and those at gain, the high-DE group's sell order LPP for positions at loss is significantly (2.11 percentage points) higher than that for positions at gain (see Column [2]). The high-DE group also shows the highest odds of setting the limit price no lower than the purchase price for positions at loss, 165% higher than the odds for the low-DE group (see Column [3]).

Table 5: Impact of the DE on sell order submissions in the trading data (DE=PGR/PLR)

This table reports the regression coefficients and corresponding standard deviations (in parentheses) for the three models represented in Equations (9), (6) and (10). Standard errors are clustered at the individual level. In Equation (4), the dependent variable is NMO which takes the value of 1 if the order is a non-marketable limit order and 0 otherwise. In Equation (6), the dependent variable is LPP, a continuous variable and calculated as in Equation (5), which measures the distance between the limit price and the prevailing best bid at the time of order submission. In Equation (7), the dependent variable is $I(LP \geq PP)$, which takes the value of 1 if the limit price is set no lower than the purchase price and 0 otherwise. The independent variables include (i) $HighDE$, a dummy variable that takes the value of 1 if the order is submitted by an investor in the High-DE group and 0 otherwise, (ii) $MedianDE$, a dummy variable that takes the value of 1 if the order is submitted by an investor in the Median DE group and 0 otherwise, (iii) *Loss*, a dummy variable that takes the value of 1 if the sell order is submitted when the position is in the loss domain and 0 otherwise, and (iv) *Spread*, a continuous variable that measures the relative bid-ask spread (i.e., bid-ask spread/mid-point) in dollars at the time of order submission.
*, ** and *** indicate statistical significance at the 5%, 1% and 0.1% levels, respectively.

Dependent Variable	NMO	LPP	$I(LPP \geq PP)$
	Eq (9)	*Eq (6)*	*Eq (10)*
	[1]	[2]	[3]
$Intercept$	0.3151***	0.0053***	-1.4761***
	(0.0406)	(0.0012)	(0.0356)
$MedianDE$	0.6183***	0.0047**	0.3018***
	(0.0525)	(0.0017)	(0.0556)
$HighDE$	1.0575***	0.0067**	0.8619***
	(0.0574)	(0.0020)	(0.0538)
Loss	-0.1383***	-0.0013	
	(0.0233)	(0.0014)	
$MedianDE \times$ *Loss*	0.1106**	0.0037	
	(0.0325)	(0.0031)	
$HighDE \times Loss$	0.2905***	0.0235**	
	(0.0362)	(0.0067)	
Spread		0.1885	
		(0.7388)	
N	763,856	5,367	217,536
Likelihood Ratio			
(p-value)	<.0001		<.0001
F-value		10.39	
Adjusted R-square		0.01539	

4 Robustness checks

In this section, we produce several robustness tests for our experimental (Section 4.1) and empirical results (Section 4.2). For the experimental results, we first check the robustness of our results using three different frequencies at which the paper gains and paper losses are counted when computing Odean's (1998) DE measure. In addition, we test the robustness of both experimental and empirical results by using survival analysis to estimate the DE.

Our results are robust to all variants of methodology to estimate the DE. Most of our robustness checks lead to qualitatively unchanged conclusions as those in Section 2.2. The only potential exception is test of Hypothesis 2 on the experimental data. There, if we calculate DE using survival analysis, the results remain in line with Hypothesis 2 in that the high-DE group sets the limit price farther away from the prevailing market price compared to the low-DE group, yet the difference is no longer significant (see Column [2] of Table 13). We attribute this change in part to the substantially smaller sample size, since due to the data requirements for the survival analysis, we can only include the data from 126 instead of 172 participants in this test.

4.1 Robustness Checks for Experimental Results

4.1.1 Frequency of 5 seconds

In this section, we estimate the DE following Odean's (1998) method presented in Section 2.1.2, except that the paper gains and paper losses are counted every 5 seconds. We then replicate the analyses in Section 2.2. Table 6 reports DE levels and trading activity by group. Table 7 presents the results of Regressions (4), (6) and (7).

Table 6: DE and Trading activity by group in the Experiment (DE=PGR/PLR)
PG an PL are counted every 5 seconds

This table presents the summary statistics concerning the DE and trading activity in the experiment. Unbiased DE is measured using trading activity in the classification round. Biased DE is measured using trading activity in the main round. The DE is estimated using Equation (1) to Equation (3) with the paper gains and paper losses counted every 5 seconds. We group participants into terciles by their unbiased DE level: the low-DE and high-DE groups encompass the participants in the bottom and top terciles, respectively; the median-DE group refers to the middle tercile. Panel A presents the unbiased and biased DE levels by group. Panel B reports descriptive statistics concerning the trading activity of the three groups in the main round. The fourth row in Panel A shows the difference between the biased and unbiased DE levels. We perform two-sample t-tests of the difference in mean ratios and Wilcoxon signed rank tests of the difference in median ratios. We report the resulting p-values in parentheses.

	Mean			Median		
Group	Low	Median	High	Low	Median	High
Panel A: DE levels						
(1) No. of investors	58	59	58	58	59	58
(2) Unbiased DE (in %)	0.44	3.46	16.96	0.33	3.34	13.38
(3) Biased DE (in %)	1.45	7.53	13.47	0.69	2.80	7.40
(4) = (3) - (2)	1.01	4.06	-3.50	0.35	-0.54	-5.98
	(0.000)	(0.047)	(0.151)	(0.001)	(0.630)	(0.005)
Panel B: Order submissions in the main round						
(1) No. of orders	58.88	68.61	61.52	44.50	57.00	55.00
(2) No. of buy orders	33.84	38.29	33.19	29.00	36.00	30.00
(3) No. of sell orders	25.03	30.32	28.33	17.50	26.00	27.00
(4) No. of limit orders	12.02	24.56	28.78	7.50	21.00	20.00
(5) Buy limit/ Total buy (in %)	17.71	28.07	32.15	12.39	18.18	28.13
(6) Sell limit/ Total sell (in %)	21.63	42.43	52.98	7.14	35.29	59.55

Table 7: Impact of the DE on order submission in the experiment (DE=PGR/PLR)
PG an PL are counted every 5 seconds

This table reports the regression coefficients and corresponding standard errors (in parentheses) for the three models represented in Equations (4), (6) and (7). Standard errors are clustered at the individual level. In Equation (4), the dependent variable is NMO which takes the value of 1 if the sell order is a non-marketable limit order and 0 otherwise. In Equation (6), the dependent variable is LPP, a continuous variable and calculated as in Equation (5), which measures how far the limit price is set far away from the prevailing best bid at the time of order submission. In Equation (7), the dependent variable is $I(LP \geq PP)$, which takes the value of 1 if the limit price is set no lower than the purchase price and 0 otherwise. The independent variables include (i) $HighDE$, a dummy variable that takes the value of 1 if the sell order is submitted by an investor in the High-DE group and 0 otherwise, (ii) $MedianDE$, a dummy variable that takes the value of 1 if the order is submitted by an investor in the Median-DE group and 0 otherwise, (iii) *Loss*, a dummy variable that takes the value of 1 if the sell order is submitted when the position is in the loss domain and 0 otherwise, and (iv) *Spread*, a continuous variable that measures the relative bid-ask spread (i.e., bid-ask spread/mid-point) at the time of order submission in experimental dollars.
*, ** and *** indicate statistical significance at the 5%, 1% and 0.1% levels, respectively.

Dependent Variable	NMO	LPP	$I(LPP \geq PP)$
	Eq (4)	*Eq (6)*	*Eq (7)*
	[1]	[2]	[3]
$Intercept$	-1.1568***	0.0112	-0.5716
	(0.3183)	(0.0061)	(0.3014)
$MedianDE$	0.8456*	0.0277	1.2993**
	(0.4034)	(0.0143)	(0.3873)
$HighDE$	1.0410**	0.0163**	1.9539***
	(0.3819)	(0.0058)	(0.3885)
Loss	-0.1053	-0.0034	
	(0.2151)	(0.0029)	
$MedianDE \times Loss$	0.1714	0.0190	
	(0.3296)	(0.0199)	
$HighDE \times Loss$	1.0761**	0.0536***	
	(0.3318)	(0.0088)	
Spread	1.4369	0.1336	2.2220
	(1.9735)	(0.1513)	(4.5083)
N	4836	4836	993
Likelihood Ratio			
(p-value)	$< .0001$		$< .0001$
F-value		13.37	
Adjusted R-square		0.01307	

4.1.2 Frequency of 15 seconds

In this section, we estimate the DE following Odean's (1998) method presented in Section 2.1.2 except that we count paper gains and losses every 15 seconds. We then replicate the analyses in Section 2.2. Table 8 reports DE levels and trading activity by group. Table 9 presents the results of Regressions (4), (6) and (7).

Table 8: DE and Trading activity by group in the Experiment (DE=PGR/PLR)
PG and PL are counted every 15 seconds

This table presents summary statistics concerning the DE and trading activity in the experiment. Unbiased DE is measured using trading activity in the classification round. Biased DE is measured using trading activity in the main round. The DE is estimated using Equation (1) to Equation (3), with paper gains and paper losses counted every 15 seconds. We group participants into terciles by their unbiased DE level: the low-DE and high-DE groups encompass the participants in the bottom and top terciles, respectively; the median-DE group refers to the middle tercile. Panel A presents the unbiased and biased DE levels by group. Panel B reports descriptive statistics concerning trading activity of the three groups in the main round. The fourth row in Panel A shows the difference between the biased and unbiased DE levels. We perform two-sample t-tests of the difference in mean ratios and Wilcoxon signed rank tests of the difference in median ratios. We report the resulting p-values in parentheses.

	Mean			Median		
Group	Low	Median	High	Low	Median	High
Panel A: DE levels						
(1) No. of investors	58	58	58	58	58	58
(2) Unbiased DE (in %)	0.45	3.40	15.63	0.37	3.23	13.11
(3) Biased DE (in %)	1.44	6.14	12.42	0.76	2.76	7.99
(4) = (3) - (2)	0.99	2.74	-3.20	0.39	-0.46	-5.12
	(0.0004)	(0.0293)	(0.2034)	(0.0012)	(0.8508)	(0.0028)
Panel B: Order submissions in the main round						
(1) No. of orders	56.55	69.69	62.36	43.50	59.50	55.00
(2) No. of buy orders	32.69	38.86	33.69	29.00	36.00	30.00
(3) No. of sell orders	23.86	30.83	28.67	16.50	26.50	27.00
(4) No. of limit orders	12.26	22.57	29.86	7.50	14.50	21.00
(5) Buy limit/ Total buy (in %)	18.35	25.94	33.17	12.71	14.91	21.98
(6) Sell limit/ Total sell (in %)	24.23	37.86	54.35	7.69	29.15	60.43

Table 9: Impact of the DE on sell order submissions in the experiment (DE=PGR/PLR)
PG and PL are counted every 15 seconds

This table reports the regression coefficients and corresponding standard errors (in parentheses) for the three models represented in Equations (4), (6) and (7). Standard errors are clustered at the individual level. In Equation (4), the dependent variable is NMO which takes the value of 1 if the sell order is a non-marketable limit order and 0 otherwise. In Equation (6), the dependent variable is LPP, a continuous variable and calculated as in Equation (5), which measures the distance between the limit price and the prevailing best bid at the time of order submission. In Equation (7), the dependent variable is $I(LP \geq PP)$, which takes the value of 1 if the limit price is set no lower than the purchase price and 0 otherwise. The independent variables include (i) $HighDE$, a dummy variable that takes the value of 1 if the sell order is submitted by an investor in the High-DE group and 0 otherwise, (ii) $MedianDE$, a dummy variable that takes the value of 1 if the order is submitted by an investor in the Median-DE group and 0 otherwise, (iii) *Loss*, a dummy variable that takes the value of 1 if the sell order is submitted when the position is in the loss domain and 0 otherwise, and (iv) *Spread*, a continuous variable that measures the relative bid-ask spread (i.e., bid-ask spread/mid-point) at the time of order submission in experimental dollars.
*, ** and *** indicate statistical significance at the 5%, 1% and 0.1% levels respectively.

Dependent Variable	NMO	LPP	$I(LPP \geq PP)$
	Eq (4)	*Eq (6))*	*Eq (7)*
	[1]	[2]	[3]
$Intercept$	-0.9632**	0.0130*	-0.5237
	(0.3015)	(0.0061)	(0.2957)
$MedianDE$	0.4332	0.0220	1.2102**
	(0.3984)	(0.0144)	(0.3964)
$HighDE$	0.9127*	0.0160**	1.8245***
	(0.3700)	(0.0060)	(0.3815)
Loss	-0.2187	-0.0044	
	(0.2015)	(0.0030)	
$MedianDE$×*Loss*	0.3954	0.0201	
	(0.3277)	(0.0200)	
$HighDE$×*Loss*	1.0231**	0.0518***	
	(0.3126)	(0.0089)	
Spread	1.5240	0.1394	2.6141
	(1.9907)	(0.1502)	(4.4673)
N	4787	4787	973
Likelihood Ratio			
(p-value)	$< .0001$		$< .0001$
F-value		11.47	
Adjusted R-square		0.01151	

4.1.3 At pause

In this section, we compute Odean's (1998) DE measure (using Equation (1) to Equation (3)) with paper gains and paper losses counted every time the participants paused the market (irrespective of whether they then submitted an order or just studied the market during the pause). At each market pause, we count each stock that is in the participant' portfolio as a paper gain if the average purchase price for this stock is lower than the prevailing best bid, or as a paper loss if its average purchase price is higher than the prevailing best bid. We count it as neither a paper gain or a paper loss if its purchase price is equal to the prevailing best bid. For stocks, any holdings of which are sold, we count a realized gain or loss if the execution price is higher (lower) than the average purchase price. (In case of multiple sales, we compare the weighted average execution price with the average purchase price to determine whether the sale is a realized gain or loss.)

We then replicate the analyses in Section 2.2. Table 10 reports DE levels and trading activity by group. Table 11 presents the results of Regressions (4), (6) and (7).

Table 10: DE and Trading activity by group in the Experiment (DE=PGR/PLR)
PG and PL are counted at market pauses

This table presents summary statistics concerning DE and trading activity in the experiment. Unbiased DE is measured using trading activity in the classification round. Biased DE is measured using trading activity in the main round. The DE is estimated using Equation (1) to Equation (3), with paper gains and losses counted every time participants pause the market. We group participants into terciles by their unbiased DE level: the low-DE and high-DE groups encompass the participants in the bottom and top terciles, respectively; the median-DE group refers to the middle tercile. Panel A presents the unbiased and biased DE levels by group. Panel B reports descriptive statistics concerning trading activity of the three groups in the main round. The fourth row in Panel A shows the difference between the biased and unbiased DE levels. We perform two-sample t-tests of the difference in mean ratios and Wilcoxon signed rank tests of the difference in median ratios. We report the resulting p-values in parentheses.

	Mean			Median		
Group	Low	Median	High	Low	Median	High
Panel A: DE levels						
(1) No. of investors	58	58	58	58	58	58
(2) Unbiased DE (in %)	0.44	2.52	8.89	0.38	2.45	7.30
(3) Biased DE (in %)	1.09	5.32	7.27	0.76	3.49	5.22
(4) = (3) - (2)	0.65	2.80	-1.62	0.38	1.04	-2.08
	(0.000)	(0.003)	(0.173)	(0.000)	(0.062)	(0.004)
Panel B: Order submissions in the main round						
(1) No. of orders	59.33	67.64	62.93	44.50	58.00	56.00
(2) No. of buy orders	34.12	37.10	34.48	29.00	33.50	31.00
(3) No. of sell orders	25.21	30.53	28.45	17.50	26.50	27.00
(4) No. of limit orders	12.59	23.86	29.33	9.00	16.00	22.50
(5) Buy limit/ Total buy (in %)	18.55	24.04	35.83	12.39	12.86	34.06
(6) Sell limit/ Total sell (in %)	23.07	43.65	51.08	8.57	39.29	59.35

Table 11: Impact of the DE on sell order submissions in the experiment (DE=PGR/PLR) PG and PL counted at market pauses

This table reports the regression coefficients and corresponding standard errors (in parentheses) for the three models represented in Equations (4), (6) and (7). Standard errors are clustered at the individual level. In Equation (4), the dependent variable is NMO, which takes the value of 1 if the order is a limit order and 0 otherwise. In Equation (6), the dependent variable is LPP, a continuous variable and calculated as in Equation (5), which measures the distance between the limit price and the prevailing best bid at the time of order submission. In Equation (7), the dependent variable is $I(LP \geq PP)$, which takes the value of 1 if the limit price is set no lower than the purchase price and 0 otherwise.The independent variables include (i) $HighDE$, a dummy variable that takes the value of 1 if the sell order is submitted by an investor in the High-DE group and 0 otherwise, (ii) $MedianDE$, a dummy variable that takes the value of 1 if the order is submitted by an investor in the median-DE group and 0 otherwise, (iii) *Loss*, a dummy variable that takes the value of 1 if the sell order is submitted when the position is in the loss domain and 0 otherwise, and (iv) *Spread*, a continuous variable that measures the relative bid-ask spread (i.e., bid-ask spread/mid-point) at the time of order submission in experimental dollars.
*, ** and *** indicate statistical significance at the 5%, 1% and 0.1% levels respectively.

Dependent Variable	NMO	LPP	$I(LPP \geq PP)$
	Eq (4)	*Eq (6)*	*Eq (7)*
	[1]	[2]	[3]
$Intercept$	-1.0955***	0.0116	-0.6286*
	(0.2981)	(0.0061)	(0.2989)
$MedianDE$	0.8238*	0.0302*	1.4976**
	(0.3873)	(0.0144)	(0.3752)
$HighDE$	0.9469*	0.0143*	2.0160***
	(0.3733)	(0.0059)	(0.3932)
Loss	-0.0846	-0.0032	
	(0.2177)	(0.0029)	
$MedianDE \times Loss$	0.1814	0.0173	
	(0.3338)	(0.0200)	
$HighDE \times Loss$	0.8741*	0.0521***	
	(0.3440)	(0.0097)	
Spread	1.2926	0.1253	1.8553
	(1.9386)	(0.1530)	(4.5409)
N	4835	4835	993
Likelihood Ratio			
(p-value)	$< .0001$		$< .0001$
F-value		10.9	
Adjusted R-square		0.01266	

4.1.4 Hazard Ratio

De Winne (2021) shows that hazard models are a quite robust method to measure the DE because they are not sensitive to investors' trading activity. To test the robustness of our results, we thus use a Cox proportional hazards model to estimate the DE and report the results in this section. Specifically, we estimate the hazard ratio for each participant using the following model:

$$h(t|x(t)) = h_0(t)exp(\beta_1 \cdot TGI) \tag{11}$$

where the hazard ratio, $h(t)$ is the probability that a given participant sells a position conditional on not having sold the position until time t, and $h_0(t)$ is the participant's baseline hazard, which is unknown. *TGI* is the only time-varying covariate included in the model. *TGI* is an indicator of whether the position is in the gain or in the loss domain, which is determined every 30 seconds of the trading round. *TGI* gets the value of 1 if the purchase price is higher than the lowest best bid of the period and gets the value of 0 otherwise. The higher the β_1, the more the participant is prone to exhibiting the DE. The hazard ratio is given as e^{β_1}.

We can calculate the hazard ratio for 101 participants and rank and divide them into terciles based on this hazard ratio. The low-DE and high-DE groups include the participants in the bottom and top terciles, respectively. When the coefficient estimate is very high, the hazard ratio is too great to be interpretable. This happens to several investors in the high-DE groups. We therefore do not report average hazard ratios for each group; we use the hazard ratios only to classify high-DE and low-DE individuals.

We then replicate the analyses in Section 2.2. Table 12 reports DE levels and trading activity by group. Table 13 presents the results of Regressions (4), (6) and (7).

Table 12: Trading activity by group in the Experiment (DE=Hazard ratio)

This table presents summary statistics concerning trading activity in the experiment. The DE is estimated using Model (11), a Cox proportional hazards model. We group participants into terciles by their unbiased DE level (the DE measured in the classification round): the low-DE and high-DE groups encompass the participants in the bottom and top terciles, respectively; the median-DE group refers to the middle tercile.

	Mean			Median		
Group	Low	Median	High	Low	Median	High
Order submissions in the main round						
(1) No. of investors	42	43	42	42	43	42
(2) No. of orders	69.38	64.05	60.98	64.00	54.00	57.50
(3) No. of buy orders	37.71	35.49	33.95	33.00	30.00	31.00
(4) No. of sell orders	31.67	28.56	27.02	25.00	24.00	26.50
(5) No. of limit orders	14.26	28.84	21.95	9.00	18.00	15.00
(6) Buy Limit/Total Buy (in%)	18.79	32.63	25.79	11.12	18.18	19.93
(7) Sell Limit/Total Sell (in %)	23.24	42.50	45.92	7.69	35.29	44.44

Table 13: Impact of the DE on order submission in the experiment
(DE=Hazard Ratio)

This table reports the regression coefficients and corresponding standard errors (in parentheses) for the three models represented in Equations (4), (6) and (7). Standard errors are clustered at the individual level. In Equation (4), the dependent variable is NMO, which takes the value of 1 if the order is a limit order and 0 otherwise. In Equation (6), the dependent variable is LPP, a continuous variable and calculated as in Equation (5), which measures the distance between the limit price and the prevailing best bid at the time of order submission. In Equation (7), the dependent variable is $I(LP \geq PP)$, which takes the value of 1 if the limit price is set no lower than the purchase price and 0 otherwise. The independent variables include (i) $HighDE$, a dummy variable that takes the value of 1 if the sell order is submitted by an investor in the High-DE group and 0 otherwise, (ii) $MedianDE$, a dummy variable that takes the value of 1 if the order is submitted by an investor in the Median-DE group and 0 otherwise, (iii) $Loss$, a dummy variable that takes the value of 1 if the sell order is submitted when the position is in the loss domain and 0 otherwise, and (iv) $Spread$, a continuous variable that measures the relative bid-ask spread (i.e., bid-ask spread/mid-point) at the time of order submission in experimental dollars.
*, ** and *** indicate statistical significance at the 5%, 1% and 0.1% levels respectively.

Dependent Variable	NMO	LPP	$I(LPP \geq PP)$
	Eq (4)	*Eq (6)*	*Eq (7)*
	[1]	[2]	[3]
$Intercept$	-1.1753***	0.0154*	-0.4075
	(0.3394)	(0.0077)	(0.4064)
$MedianDE$	1.3062**	0.0400*	1.1681*
	(0.4399)	(0.0182)	(0.5427)
$HighDE$	0.6386	0.0086	1.0469*
	(0.4406)	(0.0071)	(0.4670)
$Loss$	0.0218	0.0034	
	(0.2007)	(0.0050)	
$MedianDE \times Loss$	-0.1762	0.0037	
	(0.3285)	(0.0276)	
$HighDE \times Loss$	0.8199*	0.0327**	
	(0.3469)	(0.0104)	
$Spread$	1.6262	0.0506	7.1466
	(2.2746)	(0.1883)	(4.7023)
N	3651	3651	734
Likelihood Ratio			
(p-value)	0.0009		0.0383
F-value		6.43	
Adjusted R-square		0.007568	

4.2 Robustness Checks for Empirical Results

In this section, we replicate the analyses in Section 3, but using Cox proportional hazards model from Equation (11) to estimate the DE for investors in our trading data. The estimation relies on daily observations during the sample period. Following Seru et al. (2010), we include only investors who make at least 7 round-trip trades during the sample period. There are a total of 11,579 investors who submit an aggregate of 2,191,921 orders. Table 14 presents a summary of the trading activity of the three groups. Table 15 reports the results of Regressions (9), (6) and (10).

Table 14: DE and Trading activity by group in the trading data (DE = Hazard Ratio)

This table presents summary statistics concerning DE and trading activity in the trading data. The DE is estimated using Model (11), a Cox proportional hazards model.
*The hazard ratio is reported as the exponential of the coefficient estimate. When the coefficient estimate is very high, the hazard ratio is too great to be interpretable. This happens to several investors in the high-DE groups. We therefore do not report average hazard ratios for each group; we use the hazard ratios only to classify high-DE and low-DE individuals.

	Mean			Median		
Group	Low	Median	High	Low	Median	High
(1) No. of investors	3859	3860	3860	3859	3860	3860
(2) Hazard Ratio*				1.32	4.19	25.96
(3) No. of orders	181.88	212.52	173.50	90.00	104.00	84.00
(4) No. of buy orders	105.50	118.04	94.70	52.00	58.00	47.00
(5) No. of sell orders	76.38	94.48	78.80	36.00	44.00	35.00
(6) No. of buy limit orders	61.51	80.70	71.65	27.00	36.00	32.00
(7) No. of sell limit orders	43.58	68.09	65.44	19.00	28.50	27.00
(8) buy limit/total buy (in %)	54.47	61.94	67.69	59.54	69.10	75.33
(9) sell limit/total sell (in %)	53.87	65.66	75.32	58.33	73.33	84.62

Table 15: Impact of the DE on sell order submissions in the trading data
(DE = Hazard Ratio)

This table reports the regression coefficients and corresponding standard errors (in parentheses) for the three models represented in Equations 9, (6) and (10). Standard errors are clustered at the individual level. In Equation (4), the dependent variable is NMO, which takes the value of 1 if the sell order is a non-marketable limit order and 0 otherwise. In Equation (6), the dependent variable is LPP, a continuous variable and calculated as in Equation (5), which measures the distance between the limit price and the prevailing best bid at the time of order submission. In Equation (7), the dependent variable is $I(LP \geq PP)$, which takes the value of 1 if the limit price is set no lower than the purchase price and 0 otherwise. The independent variables include (i) $HighDE$, a dummy variable that takes the value of 1 if the order is submitted by an investor in the High-DE group and 0 otherwise, (ii) $MedianDE$, a dummy variable that takes the value of 1 if the order is submitted by an investor in the MedianDE group and 0 otherwise, (iii) *Loss*, a dummy variable that takes the value of 1 if the sell order is submitted when the position is in the loss domain and 0 otherwise, and (iv) *Spread*, a continuous variable that measures the relative bid-ask spread (i.e., bid-ask spread/mid-point) at the time of order submission in experimental dollars.
*, ** and *** indicate statistical significance at 5%, 1% and 0.1% levels, respectively.

Dependent Variable	*LO*	*LPP*	*I(LPP≥PP)*
	Eq (9)	*Eq (6)*	*Eq (10)*
	[1]	[2]	[3]
$Intercept$	0.3734***	0.0056***	-1.6249***
	(0.0363)	(0.0012)	(0.0341)
MedianDE	0.5719***	0.0043**	0.5768***
	(0.0534)	(0.0016)	(0.0617)
HighDE	1.0600***	0.0076**	1.0422***
	(0.0577)	(0.0022)	(0.0481)
Loss	-0.1648***	-0.0008	
	(0.0192)	(0.0015)	
$MedianDE \times Loss$	0.0753	0.0027	
	(0.0395)	(0.0026)	
HighDE×Loss	0.4062***	0.0274**	
	(0.0394)	(0.0082)	
Spread		0.0612	
		(0.7231)	
N	772,971	5,449	217,668
Likelihood Ratio			
(p-value)	< .0001		< .0001
F-value		8.97	
Adjusted R-square		0.01838	

5 Conclusion

In this paper, we combine an experiment and the analysis of empirical trading data to study how the DE affects individuals' sell order submissions. We argue that high-DE investors are more strongly affected by the purchase price when making sales decisions, causing their sell order submissions to differ from those of low-DE investors.

We resort to an combination of an experiment and an analysis of empirical market data as the ideal means of addressing our research question. The use of limit orders mechanically inflates the DE measure (Linnainmaa (2010)). As a result, we cannot unambiguously distinguish high-DE and low-DE individuals based on empirical data. A within-participants design allows us to overcome this shortcoming. In particular, the experiment consists of two trading rounds. One round, in which only market orders are allowed, is used to reliably classify investors into high-DE and low-DE individuals. The other round, in which both market and limit orders are allowed, is used to investigate their order submission behavior.

Our experiment provides evidence that high-DE investors are more strongly affected by the purchase price; their order submission behavior depends on whether their position is at gain or at loss. They are more inclined to using non-marketable orders to sell positions at loss than those at gain. They set the limit price farther away from the prevailing market price when desiring to sell a position that is at loss than one that is at gain. They are tempted to set the limit price no lower than the purchase price when facing losses regardless of the increased non-execution risk.

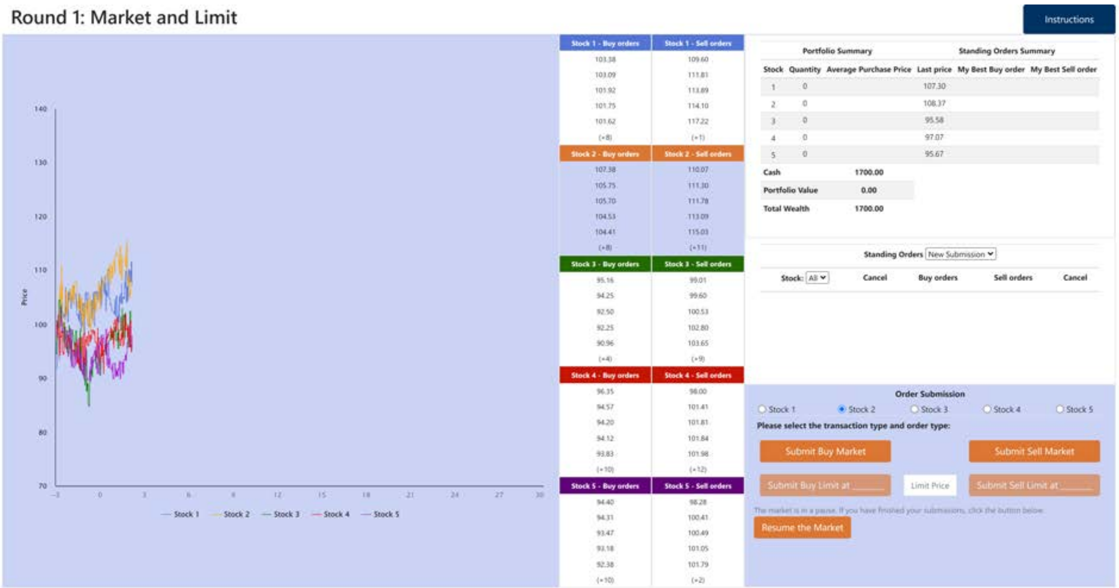
Our experimental data furthermore allows us to examine to what extent limit order use alters inferences about investor's DE levels. We show that the mechanical effects of limit order use add noise, but are not strong enough to completely invalidate the classification of high-DE and low-DE investors based field data. We take this as evidence that we can use the *field* DE measure as a proxy for classifying the investors in our empirical data set into low-DE and high-DE groups. We also find supporting empirical evidence that high-DE investors are more strongly affected by the purchase price when making sales decisions. The analysis of empirical data provides the external validity for our experimental results.

We offer a behavioral explanation for investors' order submissions. We show that the DE affects sell order submissions. Our findings have important implications for the study of the impact of order submissions on investor performance. Furthermore, we provide supporting evidence of the reliability of DE measures computed from empirical data.

6 Appendices

6.1 Trading screen

Figure 2: Interface of trading screen



6.2 Experimental instructions

6.2.1 Introduction

The Experiment

The experiment consists of two independent investment rounds of 15 minutes each. In each of the investment rounds, you will be buying and selling five stocks by trading with the computer (we will also refer to your investments as your "portfolio"). We will now first tell you how to buy and sell stocks before we go on to tell you more about the stocks themselves.

Do not worry if you are not familiar with the trading of stocks – we will now explain how it works. You trade by submitting orders to the market. An order can be a buy or a sell order, and it can be a limit or a market order: BUY orders allow you to obtain additional units of a stock, for which you have to pay money. SELL orders allow you to give units of a stock away in exchange for receiving money.

A BUY LIMIT order is an order in which you specify a MAXIMUM price for which you wish to BUY a stock. A SELL LIMIT order is an order in which you specify a MINIMUM price for which you wish to SELL a stock. The price you specify is called the "limit price". The stock market keeps a list of limit orders that have not yet been executed, i.e., matched with another order permitting a trade. This list is called the "order book". The following is an example of what such an order book may look like:

Buy orders	Sell orders
103.4	104.37
102.92	105.69
100.56	107.07
99.37	108.93
99.03	109.63
(+5)	(+7)

The numbers under the heading "Buy orders" are the limit prices at which someone wishes to buy, while those under the heading "Sell orders" are the limit prices at which someone wishes to sell. Each order in the order book is for one unit of stock. The last row displays the number of additional buy and sell orders which cannot be shown due to space constraints.

The market will show computer orders, which your own orders allow you to trade with. In other words, the computer will submit buy and sell orders to the market, just as you can. However, the computer will not change its orders in reaction to the actions you take in the market. The orders the computer will submit were randomly generated before the experiment began. If you submit a limit order and there is already a computer order in the order book that allows your order to be executed, this execution happens immediately. If, for example, you submit a buy limit order priced at 106.00 and there is a sell limit order in the order book with a price lower than or equal to the price of your order (in the example order book, there are such ask orders, priced at 104.37 and at 105.69), you immediately buy the stock at the (minimum) price of the sell limit order (in this case 104.37). If there is currently no order in the order book that would allow your order to be executed, your order gets added to the order book and rests there, waiting for a new computer order that permits a trade.

In contrast to a limit order, a buy or sell MARKET order is an order that is executed against the best available order in the order book. This means that a BUY market order trades with the SELL order with the LOWEST limit price in the order book. A SELL market order trades with the BUY order with the HIGHEST limit price in the order book. Thus, if you buy using a market order, you pay the lowest price available in the market. If you sell using a market order, you receive the highest price available in the market.

To summarize, limit orders allow you to specify a price limit, such that you know the possible price you will trade at, but do not know whether the trade will be executed right away or at all. Market orders are nearly certain to execute and lead to a trade, but you cannot be certain at which price.

We hope that our training did give you a good overview of the trading mechanism and that you're ready to start the experiment now!

Before giving you detailed instructions on the investment game, we kindly ask you to answer the following eight questions. (Participants have to answer correctly Question 1 to Question 8 in the set of control questions in 6.2.3 to go to the Instructions)

6.2.2 Instructions

Remember that you will participate in two rounds of trading. These two rounds are independent, so your performance in one round will not affect the other. Your portfolio will be reset before the second round starts.

In the first round, you can choose between a market and a limit order for each order you submit. In the second round, you can submit only market orders. ***The Stocks***

At the beginning of each round, you have no positions in your stock portfolio, but you have a starting balance of 1700 experimental dollars (e$). You can use this money to invest in five different stocks. Please note that you cannot buy if you do not have enough cash, and you cannot sell units of the stock if you do not have any (that is, "short selling" is not allowed). Money that you hold and that is not invested in any of the five stocks does not pay you any interest. There are no transaction costs.

In each round, we will simulate 33 days of trading. The simulation will start at today's day (Day 0), but you will also see the stock prices for the last three days (since the beginning of Day -3).

Underlying value and price of stocks

Each of the five stocks had a starting **underlying value** of 100 on Day -3 . From the beginning of the round on then, the underlying value of each stock either increases by 6% or decreases by 5% on each day. In other words, value increases are slightly greater than value decreases. Each of the five stocks has a different probability that the value increases. The five probabilities of value increases for the five stocks are 65%, 55%, 50%, 45%, and 40%. The value changes of each stock are independent of the value changes of any other stock. The probability that the value of a specific stock increases remains the same for all periods in a round. Nevertheless, the value changes are independent of the preceding period's: in each period the computer randomly decides (with the stock-specific probability), whether the value of the stock increases or decreases.

Which stock has which probability of a value increase – 65%, 55%, 50%, 45% or 40% – is something you can only figure out by observing these stocks' **price** developments. The **prices** the computer traders submit are randomly distributed around a stock's underlying **value**. In other words, when the price of a stock in the market exhibits a pronounced upward or downward trend, this is likely to be caused by an increase or a decrease, respectively, in the stock's value.

Note that the probabilities of value increases for the five stocks will be reset at the beginning of the second round. Also, your choices and actions in the experiment do not affect the value changes. (Participants have to answer Question 9 in the set of control questions in 6.2.3 correctly before going to the following part of the instructions)

Trading stocks

You have the possibility to trade stocks throughout the simulated time period spanning from today's date to 30 days from today's date. You can buy an additional unit of stock as long as the money in your account exceeds the price for one unit of this stock and you can sell units as long as you have at least one unit of that stock in your portfolio.

You will trade against computer-generated orders. The arrival of computer orders for the five stocks has been pre-determined by an algorithm and does not react to your own actions in the market. For each stock, you can observe the order book and a price chart with 10 seconds of delay.

On your trading screen, you can keep track of the status of your portfolio and your best buy and sell orders for each stock. You will also see the average purchase price and the last trading price for each stock. In case the average purchase price is equal to or lower than the last trading price, the row of the stock is printed in green. Otherwise it is printed in red.

You can submit orders any time you want. Once you click on a stock on the trading screen, activity in all markets will pause and you can make your decision without time pressure (that is, time in the experiment will stop, no new orders will arrive in the order book, and no trades will be made). All orders are for one unit of stock, but you can enter multiple similar orders at the same time. Please carefully check the orders before submitting them because once your new orders are sent to the market, you can no longer cancel your market orders, and only once 10 seconds have passed after you have resumed the market can you cancel those limit orders (of the new submissions) that did not get executed right away.

It is important to remember that the prices of the stocks and the state of the order book are displayed with 10 seconds of delay. This means that the state of the order book that you see at the time you submit your orders is likely to differ from the state of the order book when your orders actually get executed or added to the order book. Although your orders are processed immediately once you resume the market, you see the results of your submission only 10 seconds later.

You cannot trade with yourself. More specifically, your market orders will not be executed, but will instead be cancelled if the opposite side of the order book is empty or if the best order on the opposite side is your own limit order.

After a trade takes place (either because one of your orders traded against computer orders in the book, or because a computer order traded against one of your orders in the book), your cash and stock balances will be updated. After you have purchased a stock, all of your standing limit buy orders (for any stock) with a limit price higher than the amount of cash you have left will be removed from the order book.

We now ask you to watch a short video to learn how to operate the trading screen. Please return to this window when the video is over. Please click the following link to start the video. (https://youtu.be/sKlA5h_RVV4)

Payment: To determine your payout from the experiment, the computer will randomly choose one of the two rounds of trading. Your payout will depend on your final wealth, that is, the sum of your experimental cash and the value of your shares (number of shares times underlying value of a share) at the end of the round. You will receive 1 euro for every 94 experimental dollars you possess. This amount (rounded to the nearest euro cent) will be wired to your bank account two or three weeks after the experiment.

You will now start the first round of the experiment. In this round, you will be able to submit limit and market orders. In the second round, you will only be able to submit market orders.

At the beginning of each round, the market is paused. Please take as much time as you need to familiarize yourself with the trading interface. Once you are ready, please click the START button to start trading!

Click the Next button to start the first investment round.

6.2.3 List of Control questions

Question 1:

Buy orders	**Sell orders**
103.4	104.37
102.92	105.69
100.56	107.07
99.37	108.93
99.03	109.63
(+5)	(+7)

Imagine that you have submitted an order for one unit of Stock A. Suppose that when your order arrives in the market, the state of the order book is above.
If your order is a BUY MARKET order, at which price will you buy?

- At 103.50
- At 109.63
- At 99.03
- At 104.37
- My order will not be executed

Question 2:

Buy orders	**Sell orders**
103.4	104.37
102.92	105.69
100.56	107.07
99.37	108.93
99.03	109.63
(+5)	(+7)

Imagine that you have submitted an order for one unit of Stock A. Suppose that when your order arrives in the market, the state of the order book is above.
If your order is a SELL MARKET order, at which price will you sell?

- At 103.50
- At 109.63

- At 99.03
- At 104.37
- My order will not be executed

Question 3:

Buy orders	Sell orders
103.4	104.37
102.92	105.69
100.56	107.07
99.37	108.93
99.03	109.63
(+5)	(+7)

Imagine that you have submitted an order for one unit of Stock A. Suppose that when your order arrives in the market, the state of the order book is above.
If your order is a LIMIT BUY order with a limit price of 105.06, what will happen?

- The order will not be executed, but will enter into the order book as a SELL order
- The order will not be executed, but will enter into the order book as a BUY order
- I will buy at 103.50
- I will buy at 104.37

Question 4:

Buy orders	Sell orders
103.4	104.37
102.92	105.69
100.56	107.07
99.37	108.93
99.03	109.63
(+5)	(+7)

Imagine that you have submitted an order for one unit of Stock A. Suppose that when your order arrives in the market, the state of the order book is above.
If your order is a SELL LIMIT order with a limit price of 103.00, what will happen?

- The order will not be executed, but will enter into the order book as a SELL order
- The order will not be executed, but will enter into the order book as a BUY order
- I will sell at 103.50
- I will sell at 104.37

Question 5:

Buy orders	Sell orders
93.50	94.37
92.92	95.69
90.56	97.07
89.37	98.93
89.03	99.63
(+17)	(+14)

Imagine that you have a standing LIMIT BUY order for one share of Stock A in the order book. Your order is highlighted in blue.
What happens to your order if a computer SELL MARKET order arrives in the market?

- My order will be executed. I will BUY a unit of stock at 93.50
- My order will move to the second place on the buy order side
- Nothing will change regarding my order
- My order will be executed. I will BUY a unit of stock at 94.37
- My order will be executed. I will SELL a unit of stock at 93.50
- My order will be executed. I will SELL a unit of stock at 94.37

Question 6:

Buy orders	Sell orders
93.50	94.37
92.92	95.69
90.56	97.07
89.37	98.93
89.03	99.63
(+17)	(+14)

Imagine that you have a standing LIMIT BUY order for one share of Stock A in the order book. Your order is highlighted in blue.
What happens to your order if a computer BUY MARKET order arrives in the market?

- My order will be executed. I will BUY a unit of stock at 93.50
- My order will move to the second place on the buy order side
- Nothing will change regarding my order
- My order will be executed. I will BUY a unit of stock at 94.37
- My order will be executed. I will SELL a unit of stock at 93.50

- My order will be executed. I will SELL a unit of stock at 94.37

Question 7:

Buy orders	**Sell orders**
93.50	94.37
92.92	95.69
90.56	97.07
89.37	98.93
89.03	99.63
(+17)	(+14)

Imagine that you have a standing BUY LIMIT order for one share of Stock A in the order book. Your order is highlighted in blue.
What happens to your order if a computer BUY LIMIT order priced at 94.01 arrives in the market?

- My order will be executed. I will BUY a unit of stock at 93.50
- My order will move to the second place on the buy order side
- Nothing will change regarding my order
- My order will be executed. I will BUY a unit of stock at 94.37
- My order will be executed. I will SELL a unit of stock at 93.50
- My order will be executed. I will SELL a unit of stock at 94.37

Question 8:

Buy orders	**Sell orders**
93.50	94.37
92.92	95.69
90.56	97.07
89.37	98.93
89.03	99.63
(+17)	(+14)

Imagine that you have a standing BUY LIMIT order for one share of Stock A in the order book. Your order is highlighted in blue.
What happens to your order if a computer SELL LIMIT order priced at 93.00 arrives in the market?

- My order will be executed. I will BUY a unit of stock at 93.50
- My order will move to the second place on the buy order side
- Nothing will change regarding my order

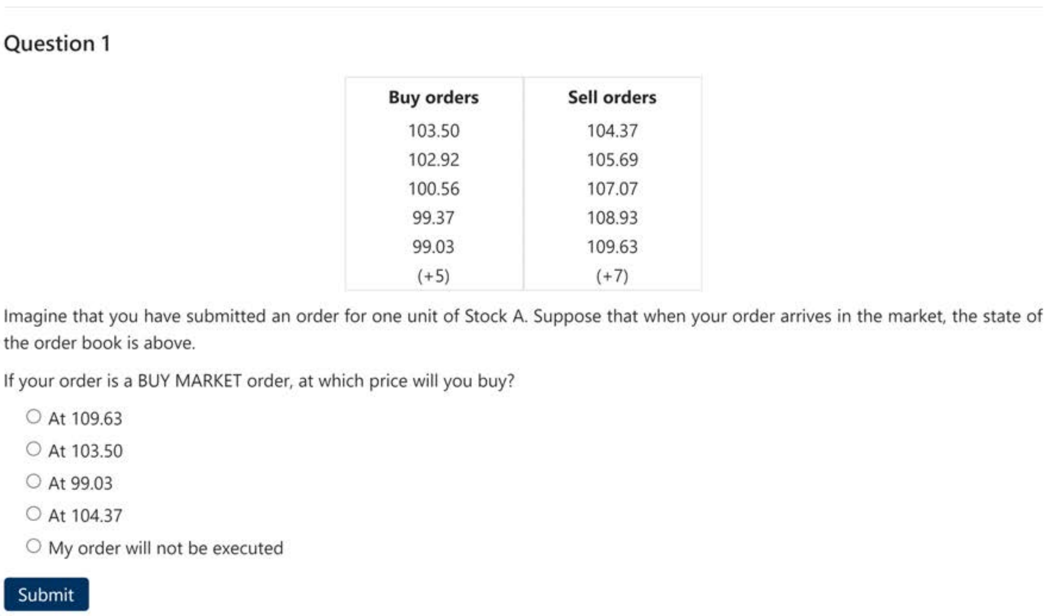
- My order will be executed. I will BUY a unit of stock at 94.37
- My order will be executed. I will SELL a unit of stock at 93.50
- My order will be executed. I will SELL a unit of stock at 94.37

Question 9: Which statement about the stocks is correct?

- There can be more than one stock with the same probability of a value increase
- A given stock's probability of a value increase remains unchanged over an entire investment round
- The prices you can observe in the market equal the underlying values of the stocks
- A stock's value can increase by 5% or decrease by 6%.
- None of the above.

6.2.4 Example of computer screenshot of questions

Figure 3: Example of screenshot of questions



Question 1

Buy orders	Sell orders
103.50	104.37
102.92	105.69
100.56	107.07
99.37	108.93
99.03	109.63
(+5)	(+7)

Imagine that you have submitted an order for one unit of Stock A. Suppose that when your order arrives in the market, the state of the order book is above.

If your order is a BUY MARKET order, at which price will you buy?

- At 109.63
- At 103.50
- At 99.03
- At 104.37
- My order will not be executed

Submit

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