Journal of Behavioral and Experimental Finance 51 (2026) 101232

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Finance

journal homepage: www.elsevier.com/locate/jbef

Full length article

Retail investors' disposition effect and order choices☆

Rudy De Winne [a], Nhung Luong [a], Stefan Palan [b],*

[a] UCLouvain, LIDAM, Louvain Finance (LFIN) - 151, chaussée de Binche, 7000 Mons, Belgium
[b] University of Graz, Department of Finance, Universitaetsstrasse 15/F2, 8010 Graz, Austria

ARTICLE INFO

JEL classification:
G11
G40

Keywords:
Disposition effect
Order choice
Limit orders
Retail investors

ABSTRACT

The disposition effect (DE)—the tendency to sell winning investments and hold on to losing investments—is well-documented in financial market transactions. Yet, there is little research into the types and pricing of the orders that lead to these transactions. Using a controlled laboratory experiment, we show that investors' empirical DE measures, though potentially biased by limit order mechanics, still serve as informative proxies for investors' respective DE levels. Combining our experimental results with data from retail brokerage accounts from a Belgian online broker spanning 2003–2021, we find that high-DE investors display a stronger dependence on the purchase price: they submit relatively more sell orders when positions are at a gain than at a loss; in the loss domain, they are more likely to choose sell limit prices at or above the purchase price, set these limit prices farther above prevailing market prices, and rely more on good-till-canceled instructions. Overall, our findings show that the DE is reflected not only in whether investors sell but also in how they sell, highlighting the feasibility of studying the DE from order, rather than solely from transaction, data.

1. Introduction

Although the original purchase price constitutes sunk costs and should be irrelevant for making sell-or-hold decisions in equity markets, there is robust evidence that individuals frequently use it as the reference point when they make such decisions. Investors tend to frame a prospective sale as a gain (a loss) when the asset's current market price is higher (lower) than the purchase price. Several empirical and experimental studies show that individuals exhibit the so-called "disposition effect" (DE) – the propensity to sell winners and hold on to losers (Shefrin and Statman, 1985; Odean, 1998; Weber and Camerer, 1998; Shapira and Venezia, 2001; Grinblatt and Keloharju, 2001; Barber et al., 2009). Furthermore, Frydman and Rangel (2014) provide clear evidence that greater salience of the purchase price strengthens the DE.

While the existence of the DE is thus well-documented, the question of how the DE should be measured has itself been the subject of considerable research, from the seminal contributions of Weber and Camerer (1998) and Odean (1998) to more recent approaches based on hazard models as in, e.g., Feng and Seasholes (2005). Regardless of the specific method employed, the measurement generally relies on transactions recorded by investors or groups of investors over a given period. In practice, this involves comparing current market prices with historical purchase prices in order to determine whether portfolio positions are at a gain or at a loss. Such measurement is often challenging, since it requires reconstructing the entire history of a portfolio and periodically valuing each position at the historically prevailing market price.

Yet, for any transaction to take place, two traders first need to submit matching buy and sell orders to implement their trading intentions. It is these orders that we focus on instead of transactions in this article. When retail investors submit orders to implement their trading intentions, they mainly resort to market and limit orders (Linnainmaa, 2010; Benamar, 2018). While a limit order explicitly includes the price conditions for the transaction to occur (i.e., it specifies the maximum price to be paid or the minimum price to be accepted), a market order does not include such conditions and will be filled against the best opposite-side order in the limit order book. These order types have their specific advantages and drawbacks. The price-contingency of limit orders generates execution uncertainty, whereas market orders, albeit virtually ensuring execution, generate price uncertainty. Order choice is therefore relevant and will tend to affect portfolio performance.

In this article, we study whether retail investors' propensity towards exhibiting the DE is related to their order choices. Prior studies show that investors are reluctant to sell at a loss, but they leave unanswered questions such as whether investors simply avoid submitting sell orders in the loss domain, or whether they submit limit sell orders that

☆ This work was ethics approved by the University of Graz IRB under ref. 39/123/63 ex 2022/23 and supported by the Fonds de la Recherche Scientifique - FNRS under Grant n° 40013829.

* Corresponding author.
E-mail addresses: rudy.dewinne@uclouvain.be (R. De Winne), nhung.luong@uclouvain.be (N. Luong), stefan.palan@uni-graz.at (S. Palan).

https://doi.org/10.1016/j.jbef.2026.101232
Received 19 December 2024; Received in revised form 8 April 2026; Accepted 29 July 2026
Available online 7 August 2026

are unlikely to be executed. This article fills this gap by focusing on the DE's microstructural correlates, i.e., on how decision makers translate their intentions into market actions. Specifically, we explore how investors' propensity towards the DE relates to their order choices. While doing so, note that we do not take a stance with regard to different possible explanations for why investors exhibit the DE — be they rational (e.g., diversification motives, or expectations of mean reversion), driven by individual taste (e.g., loss aversion, or realization utility) or due to biases (e.g., cognitive dissonance). Instead, we take an investor's preferences over selling winners and (not) selling losers as given and study how the investor implements these preferences.

There are at least three reasons why investigating this research question is worthwhile. First, the one seminal, prior contribution that links the DE and investors' order submissions, Linnainmaa (2010), argues that investors' order choices may bias these investors' empirically measured DE levels. Specifically, even when investors have no greater preference for selling winners rather than losers, the limit orders they submit may affect their DE measures mechanically, creating the appearance of the investors being prone to the DE. This is because a market sell order allows investors to rid themselves of a security with immediacy and certainty, whereas a (non-marketable) limit sell order is executed only if the market price moves up to the limit price. Hence, a limit sell order is more likely to be executed in an upward-trending market, increasing the probability of a stock being sold at a gain. In a downward-trending market, the order is less likely to be executed, such that the stock remains in the portfolio and is often considered to constitute a paper loss. In a sample drawn from the Finnish equity market, Linnainmaa (2010) finds that approximately half of the measured disposition effect disappears when one excludes sales originating from limit orders. Yet, investors' preferences (i.e., their DE levels) could themselves affect their order choices, implying endogeneity that would itself bias Linnainmaa's results. In the present study, we employ a controlled experiment to revisit Linnainmaa's conjectured mechanical effect of limit order use on measured DE levels, thereby avoiding potential endogeneity issues. This methodological innovation allows us to study the extent to which empirically measured DE levels can serve as unbiased proxies of investors' true, underlying trading intentions.

Second, whereas a link between investors' respective DE levels and their order submission choices may be intuitive, finance research should not have to rely on intuition when trying to understand important aspects of such a widespread and robustly documented phenomenon as the disposition effect. Our study documents, using both experimental and empirical trading data, whether, to which extent, and how investors' DE levels and their order choices correlate.

Third, there are potential gains for research and practice from being able to study the DE using orders instead of using transactions data. As argued above, measuring an investor's DE level currently requires extensive data regarding the investor's historical purchases. While we are unable to pin down a causal link in this paper, we hope to lay groundwork that may allow future research to measure the DE based on investors' order choices. Investigating the DE using orders would make it possible to study already the antecedents of transactions that would later come to be identified as constituting DE-like behavior. Studying these antecedents could in turn make it easier to distinguish between different motivations for investors to treat winners and losers asymmetrically.

Since it is impossible to determine the motivation behind each individual limit order, just as it is impossible to disentangle the mechanical effects (i.e., the fact that limit orders, by their price-contingent nature, can create a spurious appearance of DE because they are more likely to be executed during upwards price trends) from behavioral drivers, we cannot straightforwardly determine a trader's propensity towards exhibiting the DE by observing said trader's behavior in the market. Thus, determining an unbiased estimate of who is a 'high-DE' and who is a 'low-DE' investor based on empirical (field) data is not possible.

To overcome this shortcoming of an empirical approach, we commence our study with 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, they can submit both market and limit orders. Since the market-orders-only round is free of any mechanical effects stemming from limit order use, this round allows us to compute a DE measure that reflects traders' true propensities 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. Our main goal is to investigate how the high-DE and low-DE groups differ in their limit order submissions in the *main* round, in which traders are allowed to submit both market and limit orders. We furthermore record detailed data about the state of the market at the time of order submission (e.g., best bids and best asks), allowing us to control for the impact of market conditions on investors' order submission behavior.

Our experimental results reveal the extent to which the use of limit orders may bias empirically estimated DE levels for some investors. We find that any mechanical effects are not strong enough to invalidate the classification of investors into low-DE and high-DE groups based on field data; most of the low-DE (high-DE) participants in our 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 investors' true, underlying DE level. We furthermore note that, while our results are not incompatible with Linnainmaa's (2010), they suggest that the mechanical effect he describes may be less problematic than previously thought.

In the next step, we combine our experimental data with a comprehensive data set provided by a large Belgian brokerage house to test our hypotheses. Our second main contribution then is both experimental and empirical evidence on commonalities in retail investors' DE levels and their order choices. We show that high-DE investors strongly condition their order choices on the purchase price: their sell order submission behavior varies depending on whether their position is at a gain or at a loss. High-DE investors exhibit a greater propensity to submit sell orders in the gain domain than in the loss domain. They care more about breaking even on the purchase price compared to low-DE investors and thus more frequently set the limit sell price no lower than the purchase price when they find themselves in the loss domain, despite the higher non-execution risk this choice entails. Consequently, they set the limit price of sell orders for positions at a loss farther above the prevailing market price than that of sell orders for positions at a gain. Finally, high-DE investors more frequently use good-till-canceled orders instead of day orders for selling positions that are at a loss, trading off a more timely order execution against more favorable execution terms at a later date.

To summarize, this article shows that DE measures that are potentially biased by investors' order choices can nevertheless serve as useful proxies for demonstrably unbiased DE measures obtained for these same investors. We furthermore find and describe significant and robust associations between investors' DE levels and their order submission choices, both in controlled lab experiments and in a large dataset of retail investor brokerage data. As a result, our findings may help future researchers study DE in orders instead of in transactions, exploring the existence of a causal link between DE and order submission choices. Finally, we hope that our research can make investors more aware of their own behavioral patterns and the potential consequences thereof.

Overall, this paper extends previous research by demonstrating that investors' propensity towards exhibiting the DE is correlated not only with whether investors sell, but with how they sell. What is beyond the scope of this paper is determining what drives this correlation.

The remainder of the paper is organized as follows. We present our experimental study in Section 2 and our empirical study in Section 3.

Section 4 concludes. The Internet appendix contains additional details about our experimental design and instructions, analysis of mechanical effects from limit order use on measured DE levels, and various robustness checks.

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' portfolios are reset at the beginning of the second round, such that participants' performance in one round does not directly affect that in the other. 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 what we will call the *classification round*, participants can submit only market orders, while in what we will call the *main round*, they can submit both market and limit orders.

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. 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. The participant can manually pause to submit orders or to consider – at their leisure – their trading decisions. While trading is continuous throughout the 15 min 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 s each. We emulate the stock market treatment of Weber and 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 the beginning of Day 1. Participants can use the information from the three preceding days (from the end of Day -3 until the end of Day 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 section). Fig. 1 contains a screenshot of the trading interface that includes examples of the stock price chart participants see while trading.

At the beginning of the first day, each participant receives 1700 experimental currency units, which we will refer to as experimental dollars (e$) hereafter. They receive no initial endowment of shares.[1] Over the following 30 trading days, i.e., from Day 1 through 30, inclusive, they can submit orders to buy new shares (subject to their budget constraint) or to sell shares they hold. The trading round ends at the end of Day 30.

Trading mechanism: Trading takes place on a continuous basis. The market uses the price-time precedence hierarchy to arrange trades. Market orders are filled immediately at the counterpart limit order's price.[2] Participants are allowed to submit both marketable and non-marketable limit orders. A marketable limit order is a limit order with a limit price set at, or better than, the opposite-side best quote (bid price for sell orders and ask price for buy 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 and remains 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 can submit any number of buy and sell orders as long as these conditions are met, but all outstanding participant orders are checked for legality following each transaction. 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 the end of Day -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 60%,[3] 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 50%, a fourth one of 45%, and the last has one of 40%.[4] Which stock carries which probability of an FV increase changes randomly from the first to the second round of trading, but not between periods ("days") within a round.

We drew a total of two distinct sets of computer-generated FV paths following the procedure just outlined. We then follow Kirchler (2009) and invert these paths (we replace every upward change by a downward change, and vice versa) to arrive at a final set of four distinct sets of FV paths, which form the input for the second step of our simulation process.[5]

In the second step, we simulate (for each FV path) 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. This flow of orders submitted by the computer mechanically pushes the price of the stock towards its fundamental value of the "day". 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.[6]

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 limit price is randomly drawn from a normal distribution with a mean of $0.99{\cdot}\mathrm{FV}$ ($1.01{\cdot}\mathrm{FV}$) and a standard deviation of $0.045{\cdot}\mathrm{FV}$.

[1] In Weber and 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.

[2] A market order is not accepted if there is no counterpart limit order in the order book ("fill or kill"). This affects 3.62% and 1.34% of all orders in the classification and main rounds, respectively.

[3] Due to an error in the instructions, participants were told that this probability was 65%, not 60%. While regrettable, note that this error does not change participants' profit-maximizing strategy of fully investing in the stock with the highest price.

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

[5] Since our participants take part in two rounds of trading, this process yields eight different sequences of price paths.

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

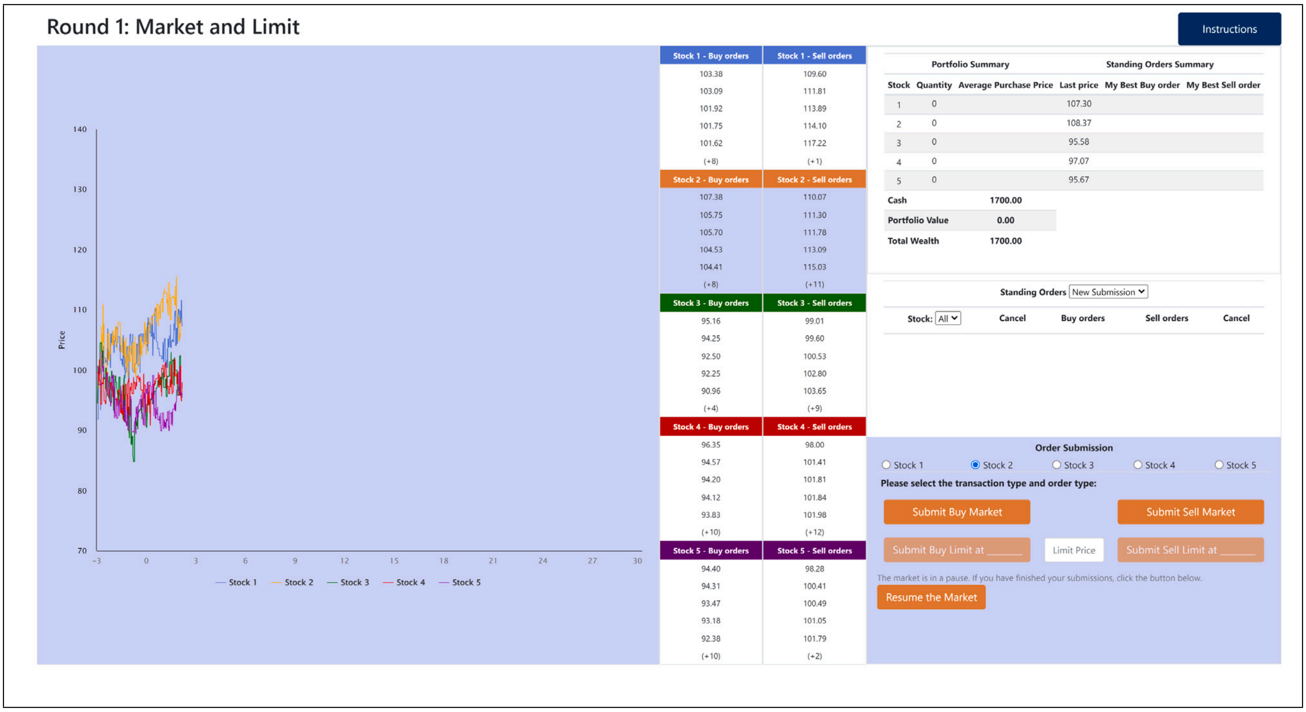

Fig. 1. Trading screen interface.

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 fundamental 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 $\epsilon \sim LogN(0, 1)$, measured in seconds.

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 pauses automatically when a participant starts 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 interface to ensure that participants are familiar with the software.

All participants start with the market-and-limit-orders 'main' round to avoid a bias towards using only market orders that might result from starting with the market-orders-only 'classification' 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 Section A of the Internet Appendix.

We programmed our experiment using oTree v3.3 (Chen et al., 2016) and conducted it online. The experiment involved a total of 217 undergraduate and graduate students .[7] Note that the experiment was not pre-registered. When the experiment was conducted in 2021, pre-registration was not yet the norm that it has become today.

We excluded 4 participants from 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 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 23.9. About 44% were male and nearly 56% were female. The experiment lasted approximately 1.5 to 2 h. 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.

[7] Druckman and Kam (2011) study the use of student participant pools and provide several strong arguments in favor of using student participants. Furthermore, the finance literature too reports few material differences in investment behavior between experiments with student and general retail participant pools. To cite just two recent studies, Baule and Muenchhalfen (2022) find that the differences between a group of subscribers of a stock exchange newsletter and a group of (undergraduate and graduate) students with a major in finance are small and insignificant. Siemroth and Hornuf (2023) likewise report that "job type (e.g., student, self-employed)" does not significantly affect the investments into green projects that their paper studies. In light of this evidence and given that our empirical analysis of brokerage trading data replicates our findings from the experiment with students, we believe that using student participants is justified and that our findings are externally valid and likely to be robust.

2.1.2. Measuring the DE

We primarily follow Dhar & Zhu's (2006) methodology to estimate the DE, yet to ensure the robustness of our results, we also use survival analysis as pioneered by Feng and Seasholes (2005) to calculate the DE level in a robustness check (see Section B.4 of the Internet Appendix).

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 respective portfolios. As a result, the DE, historically measured 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. Following Dhar and Zhu (2006), we calculate the DE as the ratio of PGR to PLR to cancel out the effect of portfolio size in the denominators of the two proportions. 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 a 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 s each, we also determine and count the paper gains and paper losses every 30 s.[8] 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.[9]

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) as the *biased* DE level.

[8] 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 s and 15 s in Sections B.1 and B.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 B.3 for details.

[9] In case of multiple sales in a given period, 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.

2.1.3. Main hypotheses

Genesove et al. (2001) show that, in the real estate market, owners of depreciated properties tend to set asking prices above market levels. Our hypotheses for the stock market are broadly consistent with such a pattern. In the stock market, the purchase price may also be linked to investors' sell order submission behavior because this price may determine whether investors consider their holdings to be winners or losers. If investors intend to sell winners, they may be inclined to submit market orders or to submit aggressively-priced limit orders to ensure execution. On the other hand, if they intend to avoid selling at a loss, they may (1) keep observing the market and wait for a rebound before submitting a market order or an aggressively-priced limit order, or they may (2) submit limit orders in which they set the limit price no lower than the purchase price despite the high associated non-execution risk.

The purchase price may thus be linked to *sell order* submissions in two respects: (1) a greater extent to which traders submit sell orders in the gain domain than in the loss domain, and (2) traders submitting limit orders with limit prices set no lower than purchase prices despite the high non-execution risk, leading to a greater distance between sell limit prices and prevailing market prices in the loss domain than in the gain domain. Accordingly, we formulate the following three hypotheses:

Hypothesis 1. Compared to low-DE investors, high-DE investors display a greater propensity to submit sell orders in the gain domain than in the loss domain.

Hypothesis 2. Compared to low-DE investors, high-DE investors are more likely to set the sell limit price no lower than the purchase price in the loss domain.

Hypothesis 3. Compared to low-DE investors, high-DE investors set the sell limit price in the loss domain farther above the market price than they do in the gain domain.

2.2. Experimental results

We first report general characteristics of participants' activity in Section 2.2.1. We then report on the relationship between unbiased and biased DE measures, and analyze the mechanical effect suggested by Linnainmaa. We finally provide an analysis of participants' order choices based on whether their position is at a gain or at a loss, and compare the results across DE terciles.

2.2.1. DE and trading activity

We obtain valid observations from 213 participants. Trading activity in both rounds of the experiment is comparable. In the classification round, our participants submit a total of 10,898 orders, 57.81% of which are buy orders. In the main round, they submit 12,803 orders, 56.47% of which are buy orders. Limit orders account for 36.09% of the total orders submitted in the main round, with limit orders being used more frequently for sell orders than for buy orders. Limit orders account for 43.53% of all sell orders submitted, yet for only 30.35% of the buy orders (Pearson Chi-square test, $p = 0.0000$). In both rounds, most traders trade shares of all stocks (i.e., they on average trade shares in 4.72 and 4.75 of the 5 different stocks in the classification and main rounds, respectively).

Of the 213 qualified participants, we can compute the DE level in the classification round for 172 participants. We are unable to calculate the DE for the remaining 41 because their PGR is undefined (1 case) and/or their PLR is zero (all 41 cases). To investigate how high-DE and low-DE individuals differ in their order submission behavior, we divide this 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 medium-DE group encompasses the middle tercile.

Table 1
DE and trading activity by group in the experiment (DE=PGR/PLR) PG and PL counted every 'trading day' of 30 s.

Group	All	Low	Medium	High	Medium-Low	High-Medium	High-Low
Panel A: DE levels							
(1) No. of investors	151	52	52	47	104	99	99
(2) Unbiased DE	2.97	0.29	3.15	9.75	2.86***	6.60***	9.46***
(3) Biased DE	2.40	0.67	2.59	5.08	1.92***	2.49***	4.41***
(4) Biased DE — Unbiased DE	0.00	0.16***	0.22	−5.34**	0.06	−5.56***	−5.50***
Panel B: Order submissions in the main round							
(1) No. of investors	172	57	58	57	115	115	114
(2) No. of orders	54.00	43.00	58.00	54.00	15.00*	−4.00	11.00
(3) No. of buy orders	31.00	29.00	35.50	30.00	6.50	−5.50	1.00
(4) No. of sell orders	25.00	18.00	26.50	27.00	8.50*	0.50	9.00*
(5) No. of limit orders	16.00	10.00	22.00	22.00	12.00**	0.00	12.00**
(6) Limit buy/Buy orders (in %)	22.79	22.22	22.18	31.82	−0.04	9.64	9.60
(7) Limit sell/Sell orders (in %)	40.00	15.85	47.97	63.46	32.12**	15.49	47.61***
(8) Sell in gain domain/Sell orders (in %)	44.44	29.41	48.05	47.83	18.64**	−0.22	18.42***
(9) Execution rate of limit orders (in %)							
(9a) buy	71.43	75.96	71.43	66.20	−4.53	−5.23	−9.76
(9b) sell in gain domain	77.53	83.33	79.80	76.92	−3.53	−2.88	−6.41
(9c) sell in loss domain	66.67	73.61	66.67	63.89	−6.94	−2.78	−9.72
Panel C: Performance							
(1) No of investors	172	57	58	57	115	115	114
(2) Wealth after classification round	1717.25	1673.91	1721.26	1734.23	47.35	12.97	60.32*
(3) Wealth after main round	1720.47	1674.34	1726.96	1723.31	52.62	−3.65	48.97
(4) Wealth Difference (main round - classification round)	−15.74	−28.69	−40.71	15.65	−12.02	56.36	44.34

This table presents summary statistics concerning the DE and trading activity at the participant level 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 estimate the DE using Equations (1) through (3), counting paper gains and paper 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 medium-DE group those in the middle tercile. Panel A reports median unbiased and biased DE levels across traders. The fourth row in Panel A reports the difference between the biased and unbiased DE levels for each participant. Panel B reports the median values of different trading activity measures in the main round. $Buy\ limit/Buy\ orders$ ($Sell\ limit/Sell\ orders$) is the proportion of buy (sell) orders that is limit orders. $Sell\ in\ gain\ domain/Sell\ orders$ is the proportion of sell orders that is submitted in the gain domain. $Execution\ rate\ of\ limit\ orders$ is the proportion of limit orders that is executed. Panel C reports median ending wealth levels in the two rounds of the experiment. We compute the difference between the main round and the classification round for each participant and report the median difference in the fourth row in Panel C. We perform paired Wilcoxon signed rank tests when comparing medians within groups and two-sample Wilcoxon tests when comparing medians between groups. Panels B and C report on the 172 participants for whom we can measure the DE level in the classification round. Panel A reports on the subset of 151 participants for whom we can measure the DE level in both rounds. The three rightmost columns report differences between participant groups and indicate significance levels from independent samples t-tests.
*, ** and *** indicate statistical significance at the 5%, 1% and 0.1% levels, respectively.

Panel A of Table 1 presents unbiased and biased DE levels by group. We compute the difference between the biased and unbiased DE levels for each participant and report the median difference in the fourth row in Panel A.[10] Note that Panel A reports only on the 151 participants for whom we can measure the DE level in both rounds. Panel B reports descriptive statistics concerning the median trading activity of the three groups in the main round. Panel C summarizes the median performance (in terms of final wealth, i.e., the sum of cash and portfolio value at the end of each round) of the three groups in both rounds.

Rows (2) and (3) in Panel A of Table 1 show that, in the low-DE group, the (median) biased DE measure is approximately twice as large as the unbiased measure, while in the high-DE group, the biased DE measure is approximately half as large as the unbiased measure. We attribute this roughly symmetric[11] finding to regression to the mean. Given that we cannot measure either DE measure free from noise, regression to the mean implies that some extreme realizations in the classification round tend to 'shrink' towards the mean in the main round.

As a final observation regarding Table 1, note that there is a significant difference between the earnings of Low- and High-DE participants in the classification round. We conjectured that low-DE investors may be more financially literate and may therefore be more aware of the risk-reducing effect of diversification than high-DE investors. This conjectured difference could have led low-DE investors to diversify more in the experiment. Indeed, we find that low-DE investors hold significantly more different stock positions at the end of a period (3.26) than medium- (2.97) and high-DE investors (2.61). In our specific experimental design, this may explain the difference in earnings. Since these analyses do not contribute to the main research questions of the article, however, we provide the details of this analysis in Section B.6 of the Internet Appendix.

2.2.2. Bias in DE measurement due to limit order use

Seru et al. (2010) provide evidence that individuals' DE level is time-invariant, suggesting that the participants should exhibit a constant inherent propensity towards the DE in both rounds of our experiment. Our experimental data allows us to test this conjecture. Since we focus our analysis on how high-DE and low-DE investors differ in their order submission behaviors, we study the extent to which limit order

[10] If a participant did not realize any losses in the main round, they have a PLR of 0 and their biased DE score is thus undefined. We exclude the participants with undefined biased DE scores from the calculation of the difference between the biased and unbiased DE scores. However, the undefined DE score may be considered equivalent to a very high DE score. (All 21 investors whose biased DE score is undefined while their unbiased DE score is defined did have paper losses in the main round. Their biased DE score is undefined because they chose not to sell at a loss, not because they did not face any losses.) Consequently, excluding the participants with undefined biased DE score means excluding those with a very large difference between the biased and unbiased DE scores. In other words, the differences between the biased and unbiased DE scores reported in the fourth row of Panel A may be biased downwards. Hence, a difference of 0 (or negative) should not be interpreted as evidence that there are no mechanical effects of limit order use on measured DE levels.

[11] Since our DE measure is a ratio and both differences roughly correspond to a factor of two, the effect can be interpreted as being symmetric.

Table 2
Group classification by DE level in the two rounds (DE=PGR/PLR) PG and PL counted every 'trading day' of 30 s.

Ranked by unbiased DE level	Ranked by biased DE level		
	Low-DE ($n = 50$)	Medium-DE ($n = 51$)	High-DE ($n = 50$)
Low-DE ($n = 50$)	66.00	30.00	4.00
Medium-DE ($n = 51$)	27.45	39.22	33.33
High-DE ($n = 50$)	6.00	32.00	62.00

This table presents the round-on-round migration of DE classifications for the participants for whom we can calculate both the unbiased and the biased DE. The numbers represent cross-tabulated percentage proportions belonging to each classification combination, calculated based on the numbers in each category of unbiased DE level.

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, and 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 = 0.0000).[12] The biased DE measure correctly classifies 66% of the low-DE participants and 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 2). Fig. 2 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.[13]

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. While our experiment was not designed to measure or replicate Linnainmaa's (2010) finding of a mechanical effect of limit order use, we cannot help noticing that the significant, negative difference between the biased and unbiased DE measures in the high-DE group (Row (4) of Table 1) seems to be at odds with such a mechanical effect.

We thus look more closely into Linnainmaa's (2010) mechanical effect by estimating the following simple Model using our experimental data:

$$Bias_i = \beta_0 + \beta_1 \cdot LimitRatio_i + \gamma \cdot X + \epsilon_i \tag{4}$$

where (i) $Bias_i$ is the difference between the biased and the unbiased DE levels of investor i, (ii) $LimitRatio_i$ is the ratio of the total number of limit sell orders to the total number of sell orders in the main round, and (iii) X is a vector of dummy variables that control for price path fixed effects. Note that $Bias_i$ captures the effects of several possible drivers of differences between biased and unbiased DE measures. The one we focus on here is the mechanical effect of limit order use. According to Linnainmaa (2010), traders who use more limit orders (i.e., those with greater $LimitRatio_i$) should exhibit greater bias. Linnainmaa's (2010) results thus predict a positive β_1 coefficient.

Table 3 shows that our results are not inconsistent with Linnainmaa's (2010) prediction of a mechanical effect of limit order use. The coefficient of $LimitRatio$ is positive and statistically significant

Table 3
Mechanical effects from limit order use.

	Dependent variable:			
	Bias All	Low-DE Group	Medium-DE	High-DE
$LimitRatio$	4.138*	0.983	2.794	9.441
	(1.759)	(0.832)	(2.263)	(4.985)
Constant	−3.087	−0.458	1.817	−10.094*
	(1.875)	(0.864)	(2.421)	(4.616)
Observations	151	52	52	47
R^2	0.093	0.093	0.167	0.273
Adjusted R^2	0.042	−0.076	0.012	0.120

This table presents results for the regression in Eq. (4). The dependent variable is $Bias_i$, the difference between a participant i's biased DE measure and this participant's unbiased DE measure. $LimitRatio_i$ is the ratio of the total number of limit sell orders to the total number of sell orders in the main round, and X is a vector of dummy variables that control for price path fixed effects. Clustering the standard errors at the DE-group level in Model 1 (Column "All") does not change the significance levels.
*, ** and *** indicate statistical significance at the 5%, 1% and 0.1% levels, respectively.

at the 5% level for the pooled data (β_1 = 4.138, p = 0.0200) and positive, though not significant, for each sub-group.[14] Nevertheless, and as documented in Table 1, the large, negative coefficient of the constant in the high-DE group still causes the biased DE measure to be smaller on average than the unbiased measure in this group. The intensive strategic use of limit orders by high-DE traders to implement their preferences thus outweighs any mechanical effects on these traders' measured DE levels.

The main reason for the relatively small mechanical effect we observe may be that even conceptually, the mechanical effect occurs only in relatively selected circumstances. Linnainmaa (2010) argues that "If an investor places a sell limit order and the order executes, then the stock price must have gone up. This run-up makes it more likely that the stock that is sold is a winner. If the order does not execute, then the stock price must have either stayed the same or declined, increasing the probability that the unsold stock is a loser."

This argument, while true, holds only if the current stock price is close to the original purchase price. Take the situation where the stock price has *decreased* since the original purchase of the stock. If the investor now submits a limit sell order at or around the new stock price, the non-execution of this limit sell order would indeed generate the impression of a reluctance to realize losses. However, if this limit sell order does execute, this would generate the impression of a willingness to realize losses. Conversely, in a situation where the stock price has *increased* since the original purchase of the stock, a limit sell order at or around the stock price would generate the impression of a willingness to realize gains if executed, yet would generate the impression of a reluctance to realize gains if not executed. Only if the purchase price lies between the current highest bid and the investor's limit ask price can the use of limit (as opposed to market) sell orders 'mechanically' create a pattern that is observationally equivalent to the disposition effect irrespective of the direction of the stock price's movement subsequent to the investor's sell limit order submission. If the purchase price does not lie between the current highest bid and the investor's limit ask price, the order's execution reflects the investor's revealed, true preferences, not a mechanical effect of limit order use.[15]

To provide further insights into the strength of the mechanical effect from limit order use that Linnainmaa (2010) describes, we briefly leave our experimental results behind and skip ahead to study this issue in the subset of our empirical data for which we have information on best

12 The Pearson correlation coefficient is 0.42, $p = 0.0000$.

13 Participants classified as medium-DE in the main round, however, are more likely to be misclassified than to be classified correctly. Consequently, we will continue to focus on the difference between the low- and high-DE groups in our analyses, while still reporting all group differences.

14 The coefficient of 9.441 in the high-DE group is significant at the 10% level.

15 This argument benefited from a discussion one of the authors had with Terry Odean, whose contribution is hereby acknowledged.

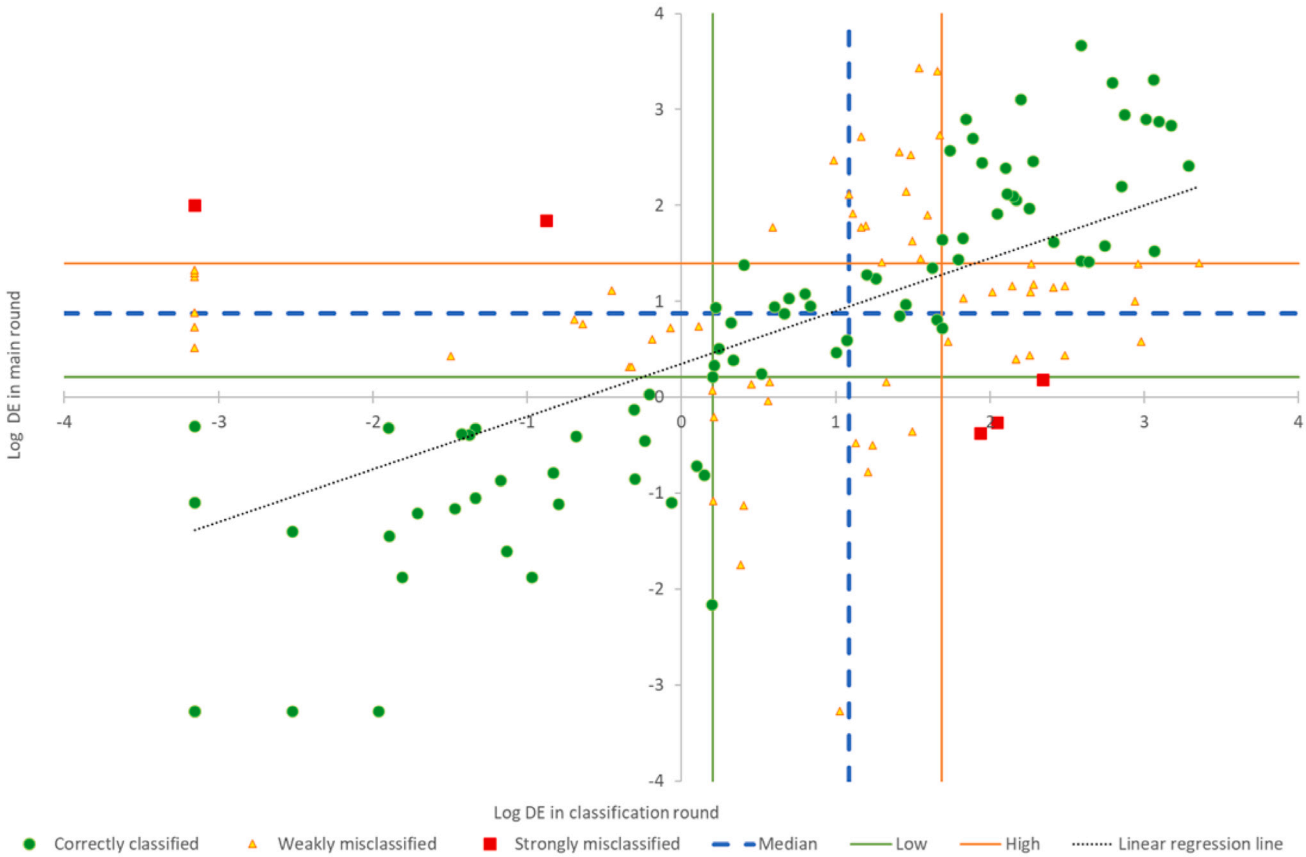

Fig. 2. DE levels in the two trading rounds (DE=PGR/PLR) PG and PL counted every 'trading day' of 30 s.
This figure plots the natural logarithm of DE levels in both trading rounds of the experiment. Note that a DE measure of 1 (or a log DE of 0) corresponds to a participant who exhibits neither the DE nor a reverse disposition effect. 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 medium-DE in the classification (main) round. The vertical (horizontal) orange line represents the border between investors classified as medium-DE and those classified as high-DE in the classification (main) round. The black dotted line represents the linear regression line of regressing the biased DE level on the unbiased DE level.

bids and asks (February 1, 2006 to April 30, 2006; see Section 3.1 for details). We find that this particular situation, i.e., that the investor submits a limit sell order such that the purchase price lies between the current highest bid and the investor's limit ask price, obtains in 6.32% (466 out of 7368 orders) of all limit sell order submissions. This leaves us with the impression that—in contrast with Linnainmaa's (2010) findings—the scope for a mechanical effect of limit order use on measured DE levels is not overly large.

To summarize, the results from both our experiment and our empirical data suggest that, although limit order use may impose certain mechanical effects on individuals' DE measures, such effects are not necessarily strong enough to invalidate inferences regarding individuals' propensity towards exhibiting the DE, particularly when we focus on traders' DE rankings.

2.2.3. The link between DE and order submissions

Our paper focuses on the link between investors' DE and their sell order submissions. Order choices can be an indicator of investors' willingness to trade. While the submission of a market sell order reflects their intention to sell immediately at any price, the submission of a limit sell order implies that investors are ready to sell in principle, but only if some price conditions are fulfilled. Furthermore, an aggressively-priced limit sell order demonstrates a greater willingness to sell than a sell order with a limit price that is set farther above the prevailing market price. Since DE investors have demonstrated a greater willingness to sell winners than to sell losers, we expect their sell order submission behavior in the gain domain to differ from that in the loss domain.

To explore this first intuition, we prepared a set of graphs (see Fig. 3) displaying the distance between the limit prices of sell orders and the purchase price, depending on whether a given position is at a gain or at a loss, and plotting separate graphs for each group based on the DE. For the market orders, we consider the best bid price prevailing at the time of submission instead of the limit price. This is the reason why a market order submitted in the gain (loss) domain is always characterized by a positive (negative) distance. Fig. 3 shows that investors in the medium- and high-DE groups display a clear pattern in their order choices. First, they are more likely to submit market orders in the gain domain than in the loss domain. Second, for their limit orders, the limit price is more often above the purchase price than is the case for the investors of the low-DE group. This is a first indication that investors' order choices are systematically related to their respective DE levels.

Consider the possible strategies available to a high-DE investor (i.e., an investor who is reluctant to sell at a loss) who wishes to (eventually) liquidate a position that is currently at a loss. As noted in Section 2.2.3, such an investor may choose between, on the one hand,

Table 4
Order submissions in the loss domain (DE=PGR/PLR) PG and PL counted every 'trading day' of 30 s.

	Low-DE	Medium-DE	High-DE
Panel A:			
(1) No. of investors	57	58	57
Panel B: (all values are % of total number of sell orders)			
(2) Sell orders in loss domain (Main Round)	68.98	54.30	47.90
(2a) Market sell orders	50.64	23.38	16.76
(2b) Limit sell orders	18.34	30.92	31.14
(2b1) with limit price ≥ purchase price	6.81	19.99	25.84
(3) Sell orders in loss domain (Classification Round)	68.96	42.90	24.51
(4) = (2) - (3) (in % points)	0.02	11.40***	23.29***

This table presents the number of investors and their sell order submissions in the loss domain in the two rounds of the experiment. All values in Panel B are expressed as a percentage of the total number of sell orders submitted by all investors in a given group in a given round. Rows (2) and (3) present the proportions of sell orders submitted in the loss domain in the main and classification rounds, respectively. Rows (2a) and (2b) present the proportions of market sell orders and limit sell orders in the loss domain, respectively. Row (2b1) presents the proportion of limit sell orders submitted in the loss domain with the limit price no lower than the purchase price. We perform Pearson chi-square tests to test the differences in the proportions of sell orders submitted in the loss domain between the two rounds (Row (4)).
*, ** and *** indicate statistical significance at the 5%, 1% and 0.1% levels, respectively.

Table 5
Link between the DE and the propensity to submit sell orders in the experiment (DE=PGR/PLR) PG and PL counted every 'trading day' of 30 s.

DE Group	All	Low	Medium	High	Medium-Low	High-Medium	High-Low
Panel A: Propensity to submit sell orders in the gain and loss domains (Median)							
PGS (in %)	40.74	18.98	43.17	59.65	24.19***	16.48**	40.67***
PLS (in %)	27.66	32.14	27.95	25.00	−4.19	−2.95	−7.14
PGS/PLS	1.49	0.56	1.55	2.32	0.99***	0.77**	1.76***
Panel B: Propensity to submit sell orders in the gain and loss domains (Mean)							
PGS (in %)	42.35	26.11	43.39	57.25	17.28***	13.86**	31.14***
PLS (in %)	30.02	34.26	29.12	26.79	−5.14	−2.33	−7.47*
PGS/PLS	1.92	0.96	1.88	2.87	0.92**	0.99*	1.91***

This table reports the propensity to submit sell orders in the gain domain (PGS), the propensity to submit orders in the loss domain (PLS), and the ratio of PGS to PLS at the participant level for the median investors (Panel A) and the average investors (Panel B) across the three groups.
*, ** and *** indicate statistical significance at the 5%, 1% and 0.1% levels, respectively.

observing the market and waiting for a rebound before submitting a market sell order, or, on the other hand, submitting a limit sell order with a limit price set no lower than the purchase price. Although the two alternatives involve different order submission decisions, both lead to one outcome: the investor avoids selling at a loss. If such investors were barred from using limit orders, we would expect them to simply wait. Given that the market setting in both rounds of our experiment only differs in the availability of limit orders, it allows us to examine the extent to which investors use limit orders in the loss domain as a means of preserving their hope of breaking even.

While both alternatives mentioned above are available in the main round of our experiment, limit orders are not available in the classification round. We thus calculate the ratio of the number of sell orders that are submitted in the loss domain to the total number of sell orders and compare this ratio across rounds (main round, classification round) to study differences between low-, medium- and high-DE investors (see Table 4).

To study our above conjecture, Row (4) in Table 4 shows the differences in the proportions of sell orders submitted for positions that are at a loss between the main and classification rounds.[16] This difference is positive and highly significant for the medium-DE and high-DE groups, while it is small and not significant for the low-DE group. More interestingly, 25.84% of the sell orders submitted for positions at a loss by the high-DE group in the main round are limit orders with the limit price set no lower than the purchase price. The comparison of investors' sell order submissions in the two rounds provides additional evidence that the DE and order submissions are related.

We move on to formally testing our three hypotheses concerning how the DE correlates with sell order submissions. We argue that the DE correlates with investors' order submissions such that sell order submissions of high-DE investors differ from those of low-DE investors. One such difference would be that high-DE investors are likely inclined to keep observing the market and wait for a rebound before submitting a sell order in the loss domain while they are willing to submit sell orders right away in the gain domain. Our Hypothesis 1 thus posits that high-DE investors' propensity to submit sell orders is smaller for positions at a loss than it is for positions at a gain. We refer to our measure for the propensity for order submissions in the gain domain as the proportion of gains submitted (PGS) and calculate it as the ratio of the number of positions at a gain which investors submit sell orders for, relative to the number of positions with paper gains. In a similar fashion, we refer to the propensity for sell order submissions in the loss domain as the proportion of losses submitted (PLS) and calculate it as the ratio of the number of positions at a loss which investors submit sell orders for, relative to the number of positions with paper losses. More concretely, we calculate PGS and PLS as follows:

$$PGS = \frac{Submitted\ Gains}{Submitted\ Gains\ +\ Paper\ Gains} \quad (5)$$

[16] Note that traders submit more sell orders in the loss than in the gain domain in the experiment. This is likely due to the experimental design, which incentivizes traders to disinvest from stocks whose price has declined, because these stocks are the most likely to have low probabilities of future fundamental value increases (see the description of the experimental design in Section 2.1).

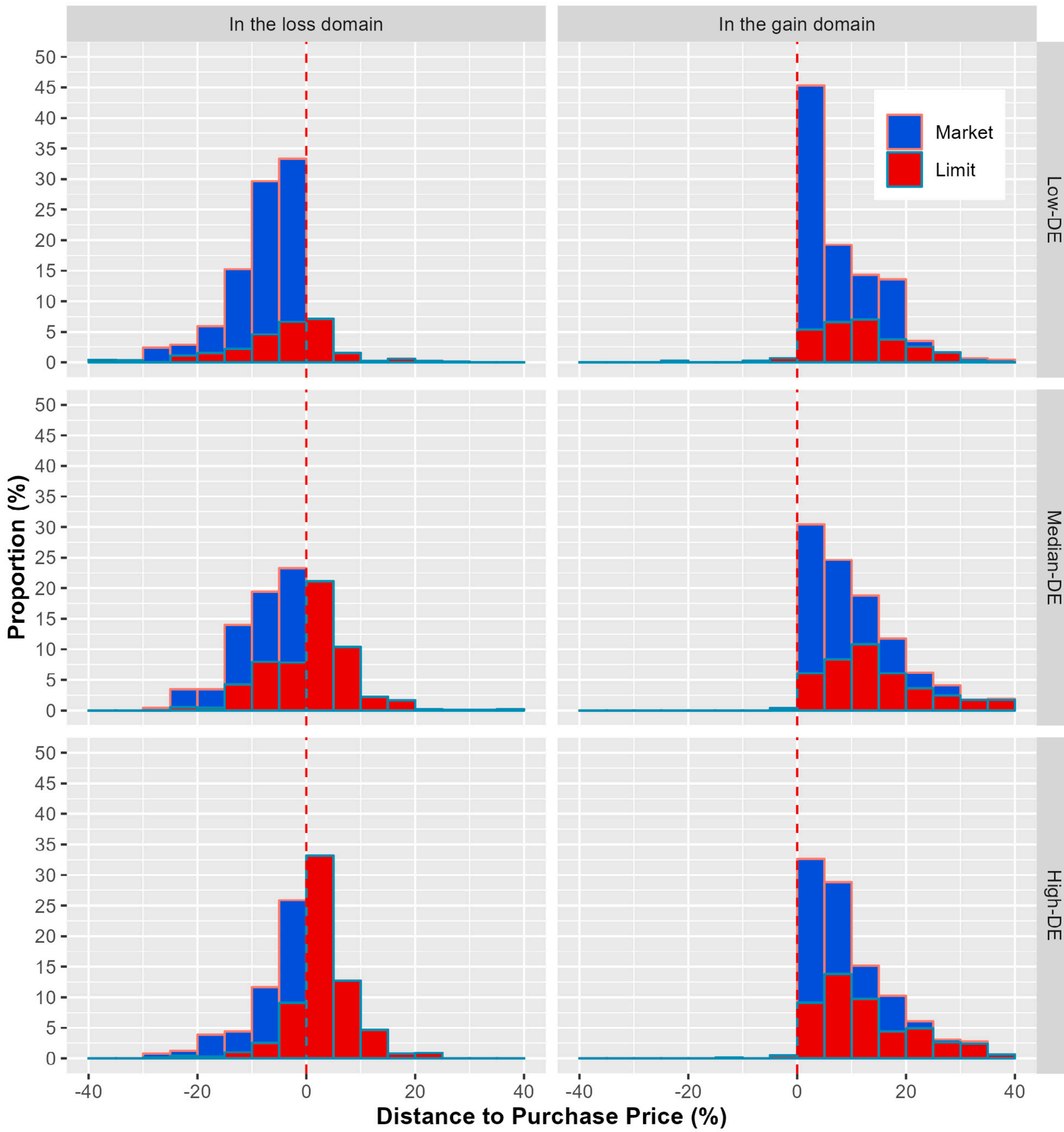

Fig. 3. Distance between sell order limit price and purchase price by gain/loss domain and DE-level group (main round)
This figure plots the distribution of the distance between the sell order limit price and the purchase price across groups in the gain and loss domains. For the market orders (in blue), we use the best bid price at the time of submission in lieu of the limit price.

$$PLS = \frac{Submitted\ Losses}{Submitted\ Losses\ +\ Paper\ Losses} \tag{6}$$

where $Submitted\ Gains$ ($Submitted\ Losses$) is the number of positions for which an investor submits a sell order in the gain (loss) domain, and $Paper\ Gains$ ($Paper\ Losses$) is the number of positions with paper gains (losses), all counted per 'trading day' of 30 s.

We compute PGS, PLS, and the ratio of PGS to PLS at the participant level. Panels A and B of Table 5 report the median and mean results for each of the three investor groups. The ratio of PGS to PLS for the median high-DE participant is 2.32, whereas it is 0.56 for the median low-DE participant. The difference between the two groups in the ratio of PGS to PLS is statistically significant. Compared to the low-DE group, the high-DE group thus has a greater propensity of submitting orders in the gain domain than in the loss domain. Our first hypothesis is supported.

Result Hypothesis 1. *Compared to low-DE investors, high-DE investors in the experiment display a greater propensity to submit sell orders in the gain domain than in the loss domain.*

Hypotheses 2 and 3 concern the link between investors' DE level and how they set their limit prices. Due to their reluctance to exit losing investments, we conjecture that high-DE individuals will set their limit prices 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 orders to get executed. Constructed based on this intuition, Hypothesis 2 directly tests how different investor groups set the limit price relative to the purchase price when they submit limit sell orders to exit a position that is currently at a loss. To test Hypothesis 2, we use logit Model (7), which studies the subset of limit sell orders submitted in the loss domain:

$$OS^{exp}_{i,t} = \beta_0 + \beta_1 \cdot MediumDE_i + \beta_2 \cdot HighDE_i + \beta_3 \cdot Spread_t + \gamma \cdot X + \epsilon_{i,t} \quad (7)$$

The binary dependent variable $OS^{exp}_{i,t}$ takes the value of 1 if the limit price is no lower than the purchase price and 0 otherwise.[17] The independent variables include (i) $MediumDE_i$, a dummy variable that takes the value of 1 if the order is submitted by an investor who is in the medium-DE group and 0 otherwise, (ii) $HighDE_i$, a dummy variable that takes the value of 1 if the order is submitted by an investor who is in the high-DE group and 0 otherwise, (iii) $Spread_t$, a continuous variable that measures the relative bid–ask spread (i.e., bid–ask spread/mid-point) when the order is submitted, and (iv) X, a vector of dummy variables to control for price path fixed effects.

Column [1] in Table 6 presents the coefficient estimates of this model. Our results show that the DE is related to the probability that individuals set the limit price no lower than the purchase price for a position at a loss. The greater the 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 a loss. The odds for the medium-DE group are 4.5 times as large as the odds for the low-DE group; the difference between the high-DE and low-DE groups is much larger yet at 8.38 times. We thus find support for Hypothesis 2.

Result Hypothesis 2. *Compared to low-DE investors, high-DE investors in the experiment are more likely to set the sell limit price no lower than the purchase price in the loss domain.*

Our results regarding Hypothesis 2 support our conjecture that the high-DE group anchors to the *purchase price* when choosing limit prices for their sell orders in the loss domain. A consequence of such an anchoring effect would be that the high-DE individuals set limit prices for positions at a loss farther above the *prevailing market price*, reducing the probability that their limit sell orders get executed. Hypothesis 3 predicts that compared to low-DE investors, high-DE investors set the limit price for sell orders in the loss domain farther above the market price than they do for sell orders in the gain domain. We call the relative distance of the limit price to the prevailing best bid at the time of order submission *Limit Price Position* (LPP). Since submitting a market order implies that investors accept to trade at the prevailing best quote, we set LPP of market orders to 0. Concretely, we calculate LPP for the order submitted by investor i at time t in our experimental data — denoted as $LPP^{exp}_{i,t}$ – as follows:

$$LPP^{exp}_{i,t} = \begin{cases} \frac{Limit\ Price_{i,t} - Bid\ Price_t}{Bid\ Price_t} & \text{for } limit\ sell \text{ orders} \\ \frac{Ask\ Price_t - Limit\ Price_{i,t}}{Ask\ Price_t} & \text{for } limit\ buy \text{ orders} \\ 0 & \text{for } market \text{ orders} \end{cases} \quad (8)$$

where $LimitPrice_{i,t}$ is the limit price of the corresponding order and $BidPrice_t$ ($AskPrice_t$) is the prevailing best bid (ask) at the time the order is submitted. We perform the following ordinary least squares regression to estimate how LPP for sell orders in the gain domain differs from that in the loss domain and from that for buy orders[18]:

$$\begin{aligned} LPP^{exp}_{i,t} = {} & \beta_0 + \beta_1 \cdot MediumDE_i + \beta_2 \cdot HighDE_i \\ & + \beta_3 \cdot SellLoss_{i,t} + \beta_4 \cdot Buy_{i,t} + \\ & \beta_5 \cdot MediumDE_i \cdot SellLoss_{i,t} + \beta_6 \cdot HighDE_i \cdot SellLoss_{i,t} + \\ & \beta_7 \cdot MediumDE_i \cdot Buy_{i,t} + \beta_8 \cdot HighDE_i \cdot Buy_{i,t} \\ & + \beta_9 \cdot Spread_t + \gamma \cdot X + \epsilon_{i,t} \end{aligned} \quad (9)$$

In addition to the independent variables included in Eq. (6), this model incorporates (i) $SellLoss_{i,t}$, a dummy variable that takes the value of 1 if the order is a sell order submitted by an investor when the position is at a loss and 0 otherwise, and (ii) $Buy_{i,t}$, a dummy variable equal to 1 if the order is a buy order, as well as several interaction terms.

Column [2] in Table 6 reports the results of Model (9). We are mainly interested in the interaction terms that capture how domain

Table 6
Link between the DE and limit price choice in the experiment (DE=PGR/PLR) PG and PL counted every 'trading day' of 30 s.

Dependent Variables:	OS^{exp} Eq. (7) [1]	LPP^{exp} Eq. (9) [2]
$MediumDE$	1.498***	0.0118
	(0.4214)	(0.0063)
$HighDE$	2.126***	0.0126*
	(0.4096)	(0.0059)
$SellLoss$		−0.0035
		(0.0033)
Buy		−0.0109*
		(0.0048)
$MediumDE \times SellLoss$		0.0300***
		(0.0074)
$HighDE \times SellLoss$		0.0455***
		(0.0084)
$MediumDE \times Buy$		−0.0008
		(0.0070)
$HighDE \times Buy$		0.0028
		(0.0064)
$Spread$	6.734	0.1167
	(3.815)	(0.0958)
Price path Fixed Effects	Yes	Yes
Fit statistics		
Observations	1181	10,773
Pseudo R^2	0.11506	−0.02230

This table reports the regression coefficients and corresponding standard errors (in parentheses) for the two models represented in Eqs. (7) and (9). Standard errors are clustered at the participant level. In Eq. (7), the dependent variable is OS^{exp}, which takes the value of 1 if the limit price is set no lower than the purchase price and 0 otherwise. In Eq. (9), the dependent variable is LPP^{exp}, a continuous variable calculated as in Eq. (8), which measures the distance between the limit price and the prevailing best opposite quote at the time of order submission. The independent variables include (i) $MediumDE$, a dummy variable that takes the value of 1 if the order is submitted by an investor who is in the medium-DE group and 0 otherwise, (ii) $HighDE$, a dummy variable that takes the value of 1 if the order is submitted by an investor who is in the high-DE group and 0 otherwise, (iii) $SellLoss$, a dummy variable that takes the value of 1 if the order is a sell order that is submitted by an investor when the position is at a loss and 0 otherwise, (iv) Buy, a dummy variable that takes the value of 1 if the order is a buy order, and (v) $Spread$, a continuous variable that measures the relative bid–ask spread (i.e., bid–ask spread/mid-point) when the order is submitted. Price path fixed effects are included in the model.
*, ** and *** indicate statistical significance at the 5%, 1% and 0.1% levels, respectively.

[17] The exp in $OS^{exp}_{i,t}$ stands for 'experiment'. We will later use the related variable $OS^{emp}_{i,w,t}$ when analyzing our empirical data.

[18] We exclude two orders with abnormally high LPP from this analysis. Their LPP is more than 9 times higher than the best bid. Casual inspection suggests that these high limit prices were likely driven by the participants in the experiment typing no or the wrong decimal separator when entering the limit price.

effects differ between groups. The base case in our model is the LPP that the low-DE investors choose for their sell orders in the gain domain. We find that, relative to the current best bid, the high-DE and medium-DE groups set limit prices for positions at a loss statistically and economically higher than for positions at a gain (Wald test of $\beta_2 + \beta_6 = 0$ for high-DE: $\chi^2 = 28.557$, $p = 0.0000$; Wald test of $\beta_1 + \beta_5 = 0$ for medium-DE: $\chi^2 = 15.164$, $p = 0.0000$). For an average investor in the high-DE group, the LPP of sell orders for a position at a loss is 4.2 percentage points greater than that for a position at a gain (see Column [2], sum of the coefficients for $SellLoss$ and for $HighDE \times SellLoss$). LPP does not differ significantly between the high-DE investors' sell orders in the gain domain and their buy orders. The results support our Hypothesis 3.

Result Hypothesis 3. *Compared to low-DE investors, high-DE investors in the experiment set the sell limit price in the loss domain farther above the market price than they do in the gain domain.*

3. Empirical study

To ascertain the external validity of our experimental results, we test our three hypotheses about the impact of the DE on order submissions also using a set of trading data provided by a large brokerage house in Belgium. The empirical dataset further allows us to test a fourth hypothesis related to traders' choices regarding order time in force. The brokerage allows orders to be valid either until the market closes (day orders) or until they are canceled (good-till-canceled orders, GTC). We present our data and sample in Section 3.1 and our empirical analysis in Section 3.4.

3.1. Data and sample

We use two different data sets for our different empirical analyses. The first is a comprehensive order data set provided by a Belgian online brokerage house. It contains detailed information about the order submissions of 26,637 retail investors over more than 21 years, from March 2000 to August 2021. For the present study, we focus on investors' order 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, execution price and total fees paid by the investor. Because there are few orders submitted before January 2003,[19] we consider a subset of orders submitted from January 1, 2003 until August 31, 2021.

The second data set consists of historical daily stock price data from Refinitiv Eikon. For a given stock, this provides information such as the opening and closing prices or highest/lowest prices of each trading day. This allows, for example, comparisons with the average purchase price to define whether a portfolio position is in the gain domain or in the loss domain.

Table 7 presents summary statistics for our trading data.

Note that Tables 1 and 7 reveal marked differences in the proportion of orders that are limit orders, which is considerably lower in the experimental than in the empirical data (22.79% vs. 82.73% and 40.00% vs. 81.45% for buy and sell orders, respectively). This difference is not surprising, however. While participants in the experiment are monitoring the market continuously throughout the 15 min of a trading period,[20] such continuous monitoring is neither feasible nor cost-effective for investors outside of the experiment. Many retail traders are at work during stock market trading hours and only log in to their brokerage accounts infrequently.[21] The latter must anticipate potential market fluctuations and incorporate constraints for the execution of their orders. Take as an example an investor whose reservation purchase price lies below the current market price. Unable to monitor the market continuously, only a limit order with a purchase price lower than the current market price ensures that such an investor can purchase in case that, and at the time when, the market price dips below the reservation price. It is therefore unsurprising to observe more intense use of limit orders in the empirical than in the experimental data.

Table 7 also shows that our investors' average DE score is 3.8 (median: 2.25). Similar to what we did for our experimental data, we also test the robustness of our empirical results using a hazard model to estimate the DE and find qualitatively unchanged results, albeit with lower power (see Section C of the Internet Appendix).

3.2. Methodology

Similar to the biased DE measure in the experiment, the DE measure computed using the trading data — 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, our experimental study shows that the biased DE measure can still be used as a proxy. We rely on this evidence (and on decades of empirical DE research that does the same) to justify using the *field* DE measure as a proxy for classifying investors in the trading data into high-, medium- and low-DE groups.

Analogous to what we did in the experimental study, where we distinguished between the classification and main rounds, in the empirical study we divide the sample period into 3-year non-overlapping windows.[22] We then use one window to classify investors based on their DE levels, and the subsequent window for the analysis of their order submissions. By analogy to the experimental study, we will refer to the first window as the 'classification window' and to the second window as the 'main window'. In the classification window, we measure investors' DE levels and classify them 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).[23] The first window spans the interval from 01 Jan 2003 to 31 Dec 2005, the second window the interval from 01 Jan 2006 to 31 Dec 2008, and so on. Following Seru et al. (2010), we then retain window-investor observations if they satisfy two conditions: the investor must (1) perform at least 7 sales in the classification window, and (2) submit at least 7 sell orders in the subsequent window. After applying these filters, the final sample for this analysis consists of 15,780 window-investor observations.

For each investor and each classification window, we calculate Dhar & Zhu's (2006) DE measure, using Eqs. (1)–(3). However, we make two changes to the DE measurement approach compared to the approach we used in the experimental section. First, we count paper gains and losses every day on which the investors completed a sale, in line with Odean (1998). Second, we use closing prices as the proxy for the

[19] The trading platform was established in 2000 and it took some time for it to reach a decent level of activity.

[20] Under these conditions, using limit orders might still offer some advantages in dealing with market volatility or illiquidity, but the ability to define the pricing conditions of a future transaction loses much of its appeal.

[21] Dierick et al. (2019) report that clients of a Belgian discount broker log in on an average of 36% (median of 31%) of all days in their sample.

[22] As a robustness check we also reproduce the analysis using 1-year and 5-year windows and report the results in Appendices C.3 and C.4.

[23] 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 commonalities between the DE and order submissions that we detect using empirical data will be biased downwards. 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 traders into low-DE and high-DE groups.

Table 7
Summary statistics — trading data.

	Entire data set (All investors) [1]	Final sample (Investors with defined DE scores) [2]
No. of investors	26,637	17,209
No. of orders	5,514,501	5,206,656
No. of trades	3,581,470	3,362,978
No. of buy orders/No. of all orders (in %)	57.73	56.98
No. of sell orders/No. of all orders (in %)	42.27	43.02
No. of limit orders/No. of all orders (in %)	82.18	82.58
No. of limit buy orders/No. of all buy orders (in %)	82.73	83.15
No. of limit sell orders/No. of all sell orders (in %)	81.45	81.84
Median order value (in €)	3426	3,515
Median trade value (in €)	3256	3,360
Average investor age in 2021	56.31	58.15
% female	8.45	7.36
Average DE (PGR/PLR)		3.80

This table presents summary statistics for the trading data at the aggregate level. Column [1] reports statistics for all investors in our data set. Column [2] reports statistics for our final sample, which includes only investors who make at least 7 round-trip stock trades during the sample period and for whom we can estimate the DE.

Table 8
DE, trading activity and portfolio characteristics by group in the trading data (DE=PGR/PLR)

Group	All	Low	Medium	High	Medium-Low	High-Medium	High-Low
Panel A: DE levels							
Field DE	2.15	0.86	1.98	5.75	1.11***	3.77***	4.88***
Panel B: Order Submissions							
(1) No. of orders	76.00	73.00	76.00	79.00	3.00	3.00	6.00
(2) No. of buy orders	41.00	41.00	41.00	42.00	0.00	1.00	1.00
(3) No. of sell orders	34.00	33.00	33.00	35.00	0.00	2.00	2.00*
(4) No. of limit orders	54.00	46.00	56.00	61.00	10.00***	5.00***	15.00***
(5) Limit buy/Buy orders (in %)	95.83	90.00	96.18	98.15	6.18***	1.97***	8.15***
(6) Limit sell/Sell orders (in %)	90.91	83.33	91.67	95.31	8.33***	3.65***	11.98***
(7) Sell in gain domain/Sell Orders (in %)	55.07	50.79	54.55	59.09	3.75***	4.55***	8.30***
(8) Execution rate of orders (in %)							
(8a) buy	80.00	83.33	80.00	78.14	−3.33***	−1.86**	−5.20***
(8b) sell in the gain domain	78.79	83.33	78.57	75.00	−4.76***	−3.57***	−8.33***
(8c) sell in the loss domain	79.23	85.71	77.78	74.00	−7.94***	−3.78***	−11.71***
Panel C: Portfolio Characteristics							
(1) Average monthly portfolio value (in k€)	45.78	38.76	42.49	54.90	3.73*	12.41***	16.14***
(2) Average no. of stocks in EOM portfolio	11.11	8.83	10.17	13.92	1.33***	3.75***	5.08***
(3) Average monthly gross return (in %)	3.15	3.15	2.99	3.26	−0.17	0.28	0.11
(4) Average monthly net return (in %)	1.84	1.61	1.48	2.28	−0.13	0.80**	0.67*
(5) Average monthly portfolio turnover (in %)	13.62	17.53	15.03	10.51	−2.50***	−4.52***	−7.02***

This table presents summary statistics at the investor level for each of the three groups 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 investor completes at least one sale. Investors are grouped into terciles by their DE level during 3-year windows: the low-DE and high-DE groups encompass the investors in the bottom and top terciles, respectively; the medium-DE group refers to the middle tercile. The statistics are computed during the next window. Panel A reports the median DE levels. Panel B reports trading activity. We calculate all measures for each investor and report the medians across investors. $Buy\ limit/Buy\ orders$ ($Sell\ limit/Sell\ orders$) is the proportion of buy (sell) orders that is limit orders. $Sell\ in\ gain\ domain/Sell\ Orders$ is the proportion of sell orders that is submitted in the gain domain. $Execution\ rate\ of\ limit\ orders$ is the proportion of limit orders that gets executed. Panel C reports stock portfolio characteristics, excluding all assets other than stocks. For each investor, we calculate each portfolio metric on a monthly basis and then take the averages. We report the medians of these monthly averages across investors. $Monthly\ gross\ return$, $Monthly\ net\ return$, and $Monthly\ portfolio\ turnover$ for a given month are calculated using Equations (15), (16), and (17), respectively. We winsorize the monthly gross returns, net returns and turnovers at the 99th percentile.
*, ** and *** indicate statistical significance at the 5%, 1% and 0.1% levels, respectively.

bid/ask price at the time of order submission, since the empirical data set does not include the prevailing bid and ask prices. Based on this measure in a given window, we classify investors into low-, medium- and high-DE groups.

We then test the three hypotheses presented in Section 2.1.3. We test Hypothesis 1 as in the experimental study, using Eqs. (5) and (6). For Hypothesis 2, we build a binary variable ($OS^{emp}_{i,w,t}$) that reflects the decision to set the limit price equal to or higher than the purchase price when the position to be sold is at a loss. In this case, the binary variable takes the value of one, and zero otherwise. We need to adapt the logit Model (7) since the market quotes at the time of order submission are not available in our empirical data set, so we cannot control for relative spreads. We thus estimate the following model (using window fixed effects α_w) with the subset of sell limit orders in the loss domain:

$$OS^{emp}_{i,w,t} = \alpha_w + \beta_1 \cdot MediumDE_{i,w-1} + \beta_2 \cdot HighDE_{i,w-1} + \epsilon_{i,w,t} \tag{10}$$

For Hypothesis 3, we estimate the following model with all orders submitted in the windows that satisfy the criteria outlined before:

$$\begin{aligned} LPP^{emp}_{i,w,t} = {} & \alpha_w + \beta_1 \cdot MediumDE_{i,w-1} + \beta_2 \cdot HighDE_{i,w-1} \\ & + \beta_3 \cdot SellLoss_{i,w,t} + \beta_4 \cdot Buy_{i,w,t} \\ & + \beta_5 \cdot MediumDE_{i,w-1} \cdot SellLoss_{i,w,t} \\ & + \beta_6 \cdot HighDE_{i,w-1} \cdot SellLoss_{i,w,t} \\ & + \beta_7 \cdot MediumDE_{i,w-1} \cdot Buy_{i,w,t} \end{aligned}$$

$$+ \beta_8 \cdot HighDE_{i,w-1} \cdot Buy_{i,w,t} + \epsilon_{i,w,t} \quad (11)$$

where $LPP^{emp}_{i,w,t}$ is calculated as follows:

$$LPP^{emp}_{i,w,t} = \begin{cases} \frac{Limit\ Price_{i,w,t} - Closing\ Price_{i,w,t}}{Closing\ Price_{i,w,t}} & \text{for } limit\ sell \text{ orders} \\ \frac{Closing\ Price_{i,w,t} - Limit\ Price_{i,w,t}}{Closing\ Price_{i,w,t}} & \text{for } limit\ buy \text{ orders} \\ 0 & \text{for } market \text{ orders} \end{cases} \quad (12)$$

Note that the $Closing\ Price_{i,w,t}$ is the closing price on the day corresponding to order submission time t and thus is constant within a given trading day.

3.3. Additional hypothesis

Investors outside of the experimental laboratory cannot monitor their investments continuously. To reflect this circumstance, they have the option to choose between different maturity instructions for their limit orders. The brokerage we obtain our empirical data from allows investors to choose between day orders (orders are valid until the end of the day on which they were submitted) and good-till-canceled orders (orders are valid until canceled by the investor). To the three hypotheses from the experimental study, we can thus add another hypothesis concerning the time expiration instruction attached to limit orders. We conjecture that high-DE investors, instead of using day orders, are more willing to give the market more time to settle their orders by using good-till-canceled sell limit orders.[24] We thus postulate the following hypothesis:

Hypothesis 4. Compared to low-DE investors, high-DE investors are more likely to submit GTC orders for their sell limit orders in the loss domain.

To test this hypothesis, we estimate the following logit model with the subset of sell limit orders:

$$\begin{aligned} GTC_{i,w,t} = {} & \alpha_w + \beta_1 \cdot MediumDE_{i,w-1} + \beta_2 \cdot HighDE_{i,w-1} \\ & + \beta_3 \cdot Loss_{i,w,t} + \\ & \beta_4 \cdot MediumDE_{i,w-1} \cdot Loss_{i,w,t} \\ & + \beta_5 \cdot HighDE_{i,w-1} \cdot SellLoss_{i,w,t} + \epsilon_{i,w,t} \quad (13) \end{aligned}$$

where

$$GTC_{i,w,t} = \begin{cases} 1 & \text{for good-till-canceled orders} \\ 0 & \text{for day orders} \end{cases} \quad (14)$$

3.4. Empirical results

The results presented in this subsection are based on 3-year windows. Table 8 provides a statistical description of DE measures (Panel A), order submissions and trading activity (Panel B), and portfolio characteristics (Panel C) in the main window, using the out of sample group classification performed based on the classification window preceding the main window.

To compute the gross and net monthly portfolio returns for each investor, we use an adapted version of the Modified Dietz Method, which yields an approximation of the money-weighted rate of return (Shestopaloff and Shestopaloff, 2007). Assuming that all purchases within a given month occur on the first day and all sales on the last day, we get:

$$R^{gross}_t = \frac{EMV_t - EMV_{t-1} - P_t + S_t}{EMV_{t-1} + P_t} \quad (15)$$

$$R^{net}_t = \frac{EMV_t - EMV_{t-1} - P_t + S_t - Cost_t}{EMV_{t-1} + P_t} \quad (16)$$

where R^{gross}_t (R^{net}_t) is the gross (net) portfolio return in month t and $Cost_t$ are the total transaction costs in month t.[25]

Following Hoffmann et al. (2013), we calculate the monthly portfolio turnover as:

$$Turnover_t = \frac{P_t + S_t}{\frac{BMV_t + EMV_t}{2}} \quad (17)$$

where $Turnover_t$ is the portfolio turnover of month t, P_t (S_t) is the value of the aggregate purchases (sales) in month t and BMV_t (EMV_t) is the portfolio market value at the beginning (end) of month t.[26]

We replicate the analyses in Section 2.2.3 with some modifications necessitated by the limited set of variables available in the trading data. As mentioned in Section 3.2, we use the closing price as a proxy for the bid/ask price at the time of order submission.[27]

Tables 9 and 10 report the results of the tests for the four hypotheses using the trading data. Just as in our analysis for Hypothesis 1 in the experimental data, we measure the propensity to submit orders in the gain and loss domains for each investor, with paper gains and losses of each stock counted every day the stock is held in the investor's portfolio. We find that, the greater the DE that investors display during a given three-year window, the larger the ratio of PGS to PLS during the subsequent window (see Table 9).

Result Hypothesis 1. *Compared to low-DE investors, high-DE investors in the empirical data display a greater propensity to submit sell orders in the gain domain than in the loss domain.*

When we move on to Hypothesis 2, the high-DE group is also most likely to set the limit price no lower than the purchase price for positions at a loss; their odds of doing so are 1.85 times greater than the odds for the low-DE group (Column [1] in Table 10).

Result Hypothesis 2. *Compared to low-DE investors, high-DE investors in the empirical data are more likely to set the sell limit price no lower than the purchase price in the loss domain.*

Regarding Hypothesis 3, we find that medium- and high-DE groups' LPP for positions at a loss are significantly greater than those for positions at a gain (see Column [2] in Table 10; Wald test of $\beta_1 + \beta_5 = 0$ for medium-DE: $\chi^2 = 56.3$, $p = 0.0000$; Wald test of $\beta_2 + \beta_6 = 0$ for high-DE: $\chi^2 = 124.3$, $p = 0.0000$). For buy orders, LPP is smaller than for sell orders submitted for positions at a gain, but we detect no relevant difference across DE groups (see the last two coefficients in column [2] of Table 10).

Result Hypothesis 3. *Compared to low-DE investors, high-DE investors in the empirical data set the sell limit price in the loss domain farther above the market price than they do in the gain domain.*

Finally, and also in Table 10, the results reported in Column [3] confirm that high-DE investors are more likely than other investors to submit GTC sell limit orders in the loss domain (Hypothesis 4).

---

[24] We thank an anonymous reviewer of a previous submission for suggesting this analysis and hypothesis.

[25] When the total value of intra-month sales is large relative to the sum of all intra-month purchases and the portfolio value at the beginning of the month, both Eqs. (15) and (16) take on extreme values which then bias mean returns. We thus winsorize at the 99th percentile.

[26] When the value of the aggregate purchases and sales is large relative to the average of the beginning-of-month and end-of-month portfolio values, the turnover calculated by Eq. (17) takes on extreme values which bias the mean turnovers. We thus winsorize at the 99th percentile to mitigate the impact of extreme turnover values that have little economic meaning.

[27] We do have access to intraday, tick-by-tick data from Euronext for the period from February 1, 2006, through April 30, 2006. Using this data, we similarly find that the high-DE group's sell order LPP for positions at a loss is significantly higher than that for positions at a gain.

Table 9
Link between the DE and the propensity to submit sell orders in the trading data (DE=PGR/PLR).

DE Group	All	Low	Medium	High	Medium-Low	High-Medium	High-Low
Panel A: Propensity to submit orders in the gain and loss domains (Median)							
PGS (in %)	20.25	17.65	20.83	22.08	3.19***	1.24*	4.43***
PLS (in %)	9.09	14.63	9.72	5.56	−4.91***	−4.17***	−9.08***
PGS/PLS	2.02	1.12	2.01	3.65	0.89***	1.64***	2.53***
Panel B: Propensity to submit orders in the gain and loss domains (Mean)							
PGS (in %)	27.89	25.90	28.56	29.04	2.65***	0.48	3.14***
PLS (in %)	15.44	22.20	15.59	9.58	−6.60***	−6.01***	−12.62***
PGS/PLS	3.89	1.75	3.03	6.42	1.28***	3.38***	4.67***

This table reports the propensity to submit sell orders in the gain domain (PGS), the propensity to submit sell orders in the loss domain (PLS), and the ratio of PGS to PLS at the investor level for the median investors (Panel A) and the average investors (Panel B) across the three groups. The DE-groups are defined in Window w while PGS and PLS are measured in Window $w+1$.
*, ** and *** indicate statistical significance at the 5%, 1% and 0.1% levels, respectively.

Table 10
Link between the DE and limit price choice in the trading data (DE=PGR/PLR)

Dependent Variables:	OS^{emp} Eq. (10) [1]	LPP^{emp} Eq. (11) [2]	GTC Eq. (13) [3]
$MediumDE$	0.3405***	0.0064***	0.1128
	(0.0894)	(0.0013)	(0.0770)
$HighDE$	0.6148***	0.0071***	0.2655***
	(0.0898)	(0.0009)	(0.0774)
Buy		−0.0017**	
		(0.0006)	
$SellLoss$		0.0110***	−0.0159
		(0.0010)	0.0349)
$MediumDE \times Buy$		−0.0018	
		(0.0011)	
$HighDE \times Buy$		−0.0011	
		(0.0009)	
$MediumDE \times SellLoss$		0.0115***	−0.0063
		(0.0018)	(0.0458)
$HighDE \times SellLoss$		0.0215***	0.1986***
		(0.0021)	(0.0567)
$Window$ Fixed Effects	Yes	Yes	Yes
Observations	238,712	2,032,998	633,019
Pseudo R^2	0.00925	−0.01027	0.07318

This table reports the regression coefficients and corresponding standard errors (in parentheses) for the three models represented in Eqs. (10), (11) and (13). Standard errors are clustered at the participant level. In Eq. (11), the dependent variable is LPP, a continuous variable calculated using Equation (12). It measures the distance between the limit price and the closing price on the day of order submission. In Eq. (10), the dependent variable is OS^{emp}, 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) $MediumDE$, a dummy variable that takes the value of 1 if the order is submitted by an investor who is in the medium-DE group and 0 otherwise, (ii) $HighDE$, a dummy variable that takes the value of 1 if the order is submitted by an investor who is in the high-DE group and 0 otherwise, (iii) $SellLoss$, a dummy variable that takes the value of 1 if the order is a sell order that is submitted by an investor when the position is at a loss and 0 otherwise, (iv) Buy, a dummy variable that takes the value of 1 if the order is a buy order, and (v) $Loss$, a dummy variable that takes the value of 1 if the sell order is submitted when the position is at a loss. The $MediumDE$ and $HighDE$ variables are defined during window w while the other variables are computed during window $w+1$.
*, ** and *** indicate statistical significance at the 5%, 1% and 0.1% levels, respectively.

Result Hypothesis 4. *Compared to low-DE investors, high-DE investors in the empirical data are more likely to submit GTC orders for their sell limit orders in the loss domain.*

The empirical results reported in Tables 9 and 10 provide evidence that high-DE investors condition more strongly on the purchase price when they submit sell orders. This aligns with and supports the initial findings from our laboratory experiment. Observing the same patterns once under the controlled conditions of the experimental lab and then again in two decades of trading data strengthens our conviction that the documented phenomena are indeed an integral dimension of the well-studied phenomenon that is the disposition effect.

4. Discussion and conclusion

This paper studies how the disposition effect relates to individuals' sell order submissions. We argue that high-DE investors condition more strongly on the purchase price when making sales decisions, causing their sell order submissions to differ from those of low-DE investors.

We resort to a 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 may mechanically inflate the DE measure (Linnainmaa, 2010). As a result, we cannot unambiguously distinguish high-DE and low-DE individuals based on empirical data. An experiment with two trading rounds and a within-participants design allows us to overcome this problem. We use one round in which investors can only trade using market orders to reliably classify investors into high-DE and low-DE individuals. We use another round in which they can trade using both market and limit orders to investigate investors' order submission behavior.

While we do find evidence that limit order use can bias measured DE, this bias is rarely large enough to overturn the relative ranking of investors by their DE: most individuals classified as high- (low-)DE based on unbiased, market-order data also appear as high- (low-)DE when their DE is computed from trading that includes limit orders. We conclude that DE measures derived from empirical trading records, though imperfect, can still be used as informative proxies for investors' underlying DE propensities, alleviating some of the skepticism about field-based DE estimates raised by Linnainmaa's (2010) results.

Our experiment furthermore shows that high-DE investors condition more strongly on the purchase price; they adjust their order submission behavior depending on whether their position is at a gain or at a loss. Compared to low-DE investors, high-DE investors display a greater propensity to submit sell orders in the gain domain than in the loss domain. They more frequently set the limit price no lower than the purchase price when facing losses, regardless of the increased non-execution risk this behavior entails. Consequently, they set the limit price of their sell orders for positions at a loss farther above the prevailing market price than that of sell orders for positions at a gain. High-DE investors furthermore prefer good-till-canceled orders for selling positions at a loss, allowing more time for such orders to potentially reach the desired selling price.

This study bridges the gap between the existing, largely transactions-based literature on the DE, and investors' order submission choices. Our results can help brokers and trading platform operators identify investors who are prone to the DE before these investors execute transactions that implement their intentions. Our results also open avenues for researchers to develop proxies for the DE based on order placement strategies, enabling a more efficient assessment of an investor's DE level without the need to collect daily prices for each portfolio position, a process that can be time-consuming and is often impeded by data availability constraints.

As a final note, the aim of our paper is neither to identify the actual causes of the DE nor to take a stance on its rationality (for example, as a strategic response to an expectation of mean reversion in the price process), even though most of the potential explanations discussed in the literature are consistent with our findings.[28] What motivates our paper is rather the established fact that large parts of the (retail) investor population exhibit an asymmetric tendency to sell winners quickly and to hold on to losers for longer. We thus base our study on investors' revealed preference for selling investments that are at a gain and for not selling investments that are at a loss. Taking this intent as given, our study sheds light on how investors implement these preferences.

In summary, we combine experimental data and extensive empirical trading data to demonstrate that the DE relates not only to the decision whether to sell but also to the specific order types and prices investors use for selling.

CRediT authorship contribution statement

Rudy De Winne: Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Nhung Luong:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Stefan Palan:** Writing – review & editing, Writing – original draft, Resources, Methodology, Conceptualization.

Declaration of the use of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used GPT-4o, GPT-5.1, Otio AI and Phi4 to improve the language of selected sections of the work as well as to assist with the literature review. After using these tools, the authors reviewed and edited the content as needed. They take full responsibility for the content of the article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jbef.2026.101232.

References

Barber, B.M., Lee, Y.T., Liu, Y.-J., Odean, T., 2009. Just how much do individual investors lose by trading? Rfs 22 (2), 609–632.
Baule, R., Muenchhalfen, P., 2022. What is your desire? Retail investor preferences in structured products. Rev. Behav. Financ. 14 (2), 197–222.
Benamar, H., 2018. To See Is to Know: Simultaneous Display of Market Data for Retail Investors*. Rev. Financ. 23 (2), 397–437.
Chen, D.L., Schonger, M., Wickens, C., 2016. Otree: An open-source platform for laboratory, online, and field experiments. J. Behav. Exp. Financ. 9, 88–97.
Dhar, R., Zhu, N., 2006. Up close and personal: Investor sophistication and the disposition effect. Manag. Sci. 52 (5), 726–740.
Dierick, N., Heyman, D., Inghelbrecht, K., Stieperaere, H., 2019. Financial attention and the disposition effect. J. Econ. Behav. Organ. 163, 190–217.
Druckman, J.N., Kam, C.D., 2011. Students as experimental participants: A defense of the "narrow data base". In: Druckman, J.N., Greene, D.P., Kuklinski, J.H., Lupia, A. (Eds.), Cambridge Handbook of Experimental Political Science. Cambridge University Press, pp. 41–57.
Feng, L., Seasholes, M.S., 2005. Do investor sophistication and trading experience eliminate behavioral biases in financial markets? Rev. Financ. 9 (3), 305–351.
Frydman, C., Rangel, A., 2014. Debiasing the disposition effect by reducing the saliency of information about a stock's purchase price. J. Econ. Behav. Organ. 107, 541–552.
Grinblatt, M., Keloharju, M., 2001. What makes investors trade? Jof 56 (2), 589–616.
Gutiérrez-Nieto, B., Ortiz, C., Vicente, L., 2023. A bibliometric analysis of the disposition effect: Origins and future research avenues. J. Behav. Exp. Financ. 37, 100774.
Hoffmann, A.O., Post, T., Pennings, J.M., 2013. Individual investor perceptions and behavior during the financial crisis. J. Bank. Financ. 37 (1), 60–74.
Joshipura, M., Joshipura, N., Sharma, A., 2023. Demystifying disposition effect: past, present and future. Qual. Res. Financ. Mark. 16 (1), 32–59.
Kirchler, M., 2009. Underreaction to fundamental information and asymmetry in mispricing between bullish and bearish markets. An experimental study. J. Econom. Dynam. Control 33, 491–506.
Linnainmaa, J.T., 2010. Do limit orders alter inferences about investor performance and behavior? Jof 65 (4), 1473–1506.
Odean, T., 1998. Are investors reluctant to realize their losses? Jof 53, 1775–1798.
Plessner, M., 2017. The disposition effect: a survey. Manag. Rev. Q. 67, 1–30.
Seru, A., Shumway, T., Stoffman, N., 2010. Learning by trading. Rev. Financ. Stud. 23 (2), 705–739.
Shapira, Z., Venezia, I., 2001. Patterns of behavior of professionally managed and independent investors. Jbf 25 (8), 1573–1587.
Shefrin, H., Statman, M., 1985. The disposition effect to sell winners too early and ride losers too long: Theory and evidence. Jof 40, 777–790.
Shestopaloff, Y., Shestopaloff, A., 2007. A hierarchy of methods for calculating rates of return. J. Perform. Meas. 12, 39–52.
Siemroth, C., Hornuf, L., 2023. Why do retail investors pick green investments? A lab-in-the-field experiment with crowdfunders. J. Econ. Behav. Organ. 209, 74–90.
Weber, M., Camerer, C.F., 1998. The disposition effect in securities trading: An experimental analysis. J. Econ. Behav. Organ. 33, 167–184.
Weber, M., Welfens, F., 2007. An individual level analysis of the disposition effect: Empirical and experimental evidence. 7, pp. 1–53, Sonderforschungsbereich 504 Working Paper Series.

[28] The interested reader is referred to Plessner (2017), Gutiérrez-Nieto et al. (2023) and Joshipura et al. (2023) for more general surveys of the literature's findings regarding the DE.