Incidental negative life events and the disposition effect at the individual level

So, so you think you can tell, Heaven from hell, Blue skies from pain (Pink Floyd, Wish You Were Here, 1975)

ABSTRACT

In this study, we attempt to explore the role of individual exposure to negative life events on the disposition effect (*DE*) – i.e., the tendency of traders in financial markets to sell assets at gain faster than those at a loss. We hypothesize that individual exposure to negative life events may influence the disposition effect through different behavioral mechanisms, namely trading volume reduction, better information processing, and emotions. In three studies, we combine a quasi-natural experiment by considering the disposition effect, as measured with individual financial data from a trading exercise, both before and during the COVID-19 pandemic and across individuals exposed to a different extent to the COVID-19. We also manipulated and elicited the emergence of specific emotions from a separate exposure to COVID-19 and tested whether such emotions are to influence the DE. Our results show that individual exposure to negative life events will reduce the disposition effect, mainly via better information processing emotion. Negative life events further reduce the DE when anger emotion is elicited in the individual decision-maker.

Keywords:

Disposition effect, Negative life events, experiment

INTRODUCTION

An extensive stream of literature in behavioral finance and economics has theoretically discussed and empirically analyzed the disposition effect (DE). DE is a bias on trading behavior [1] which relates to an investor's tendency to realize gains to a greater extent than realize a loss in trading risky assets [2-8]. Concerning financial markets, the DE is evident in different contexts, such as North America [4], Europe [3], and Asia [9]. DE is also typical in commodities [10] and even real estate markets [11]. Moreover, the disposition effect is likely to have market-wide impacts [12] and will induce negative consequences for traders' investment returns [4], volume, volatility, and stock prices [13].

While extant studies have widely investigated the disposition effect's presence and consequences, some critical question remains: is the disposition effect stable over the life course at the individual level? Is any change in disposition effect deterministic or simply a random occurrence? A study that answers these questions matters since it may offer policymakers and firms' decision-makers key information on how to mitigate the disposition effect and thus render such a bias confined to a desirable level.

Borrowing from the broad literature on the effects of negative life events on individual decision making [14-18], we considered how incidental negative life events - neither directly nor normatively related with an individual decision to trade a risky asset in financial markets - will influence the DE. In this vein, different from extant studies which tested the effects of negative life events on individuals' willingness to invest and risk-taking behaviors, we focused on the choices within securities and, specifically, on the disposition effect emerging from such choices. Within such a focus, we attempt to understand whether the disposition effect will change in correlation with such incidental negative life events and whether such correlation depends on the degree of personal exposure to these events. Moreover, we try to unfold additional mechanisms that channel the effects of incidental negative life events on the disposition effects. Building on the appraisal emotion theory [19, 20], as candidate mechanisms, we consider not only the valence but also the appraisals that arise from an individual exposure to a negative life event (i.e., specifically fear and anger).

In studying the incidental negative life events-emotion-disposition associations, we employed a quasi-experimental design as the method of choice. Disposition effect has been directly measured in actual transaction data using logs at large brokerage houses [e.g., 4, 21]. Because of individual trader privacy it is rather difficult to collect data on an individual exposure to negative life events. Enve more difficult is to appraise individuals assigned valences and significance to exposure to negative life events. A quasi-experimental setting lets us overcome the privacy issue that characterizes real transaction data and better control for potential confounding effects and heterogeneity with all common to all non-experimental designs.

Given our method of choice, we designed three laboratory experiments with study 1, N = 60; study 2, N = 70; and study 3, N = 61. We consider an incidental negative event the exposure of an individual to the pandemic COVID-19. Accordingly, in study 1, we compared the disposition effect in two samples of individuals' trading decisions collected before and during the pandemic COVID-19. In study 2, we focus on data collected during the pandemic COVID-19 and compare the disposition effect across individuals that were exposed to a different extent to the pandemic COVID-19. In study 3, we stimulated individuals exposed to the pandemic COVID-19 specific emotions, specifically anger and fear, and tested whether such emergent emotions will explain changes in the disposition effect.

The paper tends to offer different contributions to extant research. On the one hand, it focuses on whether the disposition effect is to vary because of individual exposure, to a different extent, to incidental negative events. On the other hand, our paper offers some first theoretical pillars and empirical evidence on the mechanisms that will channel the effects of negative life events on the disposition effect. Finally, our method of choice allows us to better control for problems of heterogeneity and spurious correlations, which are common in non-experimental conditions.

THEORETICAL BACKGROUND

Disposition effect

As stated earlier, the disposition effect can be described as the higher propensity to sell shares of a stock whose price has increased since the original purchase compared to one whose price has fallen. The stock is bucketed in one of four different states for each time *t*, with $t = 0, \dots, T$. The stock is flagged as a *realized gain* if sold when the stock price exceeds the purchase price, as a *realized loss* if sold below the original purchase value. If the investor does not sell the stock in time *t*, it is counted as either a *paper gain* if the stock's value has increased or a *paper loss* if the stock's value has decreased. From this, the proportion of gains realized (PGR) is calculated as:

$$PGR = \frac{number\ of\ realized\ gains}{number\ of\ realized\ gains + number\ of\ paper\ gains} \tag{1}$$

And similarly, the proportion of losses realized (PRL) is calculated as follows:

$$PLR = \frac{number\ of\ realized\ losses}{number\ of\ realized\ losses + number\ of\ paper\ losses} \tag{2}$$

It follows that the disposition effect is present when PGR > PLR.

The theoretical framework can be built from Kahneman and Tversky's [22] prospect theory, whose primary assumption is an S-shaped utility function, concave for the gains quadrant and convex for losses. We define *u(x)* as the utility function linked to a stock whose price can increase by x, with probability p, or decrease by y with probability $1 - p$. W, is the initial wealth of the investor, or initial cash endowment.

The utility function is defined as:

$$u(x) = \begin{cases} x^{\alpha} & if\ x \geq 0 \\ -\beta(-x)^{\alpha} & if\ x < 0 \end{cases}\ and\ 0 < \alpha < 1 \text{ and } \beta > 1 \tag{3}$$

The loss aversion is parametrized with the coefficient β. The overall value of the prospected gain is, therefore

$$w(p)u(x) + w(1-p)u(y) \tag{4}$$

with $w(p)$ taking the following form [22]

$$w(p) = \frac{p^{\theta}}{(p^{\theta} + (1-p)^{\theta})^{\frac{1}{\theta}}}\ and\ 0 \leq \theta \leq 1 \tag{5}$$

Considering the number of traded stocks is equal to one, the investor aims at maximizing his utility by choosing the optimal timing for selling and buying the stock. The portion of his endowment allocated in the stock at time t, is k_t. The optimization function is

$$\max u(\,k_t)\ subject\ to\ 1 \geq k_t \geq 0 \tag{6}$$

where under the assumption of a risk-free rate between periods equal to 1:

$$u(k_t) = w(p)\ [u\big(W_t\big(k_t x + (1-k_t)\big) - W_{t-1}\big) + w(1-p)[u(W_t(k_t y + (1-k_t) - W_0) \tag{7}$$

Assuming $k = [0{,}1]$ variable, hence the investor either has the stock or keeps cash, and that the investor already holds the stock, the individual would exit the long position if [adapted from 23]:

$$u(k_t = 0) > u(k_t = 1) \rightarrow w(p)(x-1)^{\alpha} - w(1-p)\beta(1-y)^{\alpha} > 0 \tag{8}$$

under the assumption of a risk-free rate deemed not material, and *x* and *y*, in this case, considered in the context of the expected rate of return or loss on the initial investment. In the case of (8) < 0, the investor has a higher utility in holding the stock.

Experimental trading environment

The decision patterns are analyzed in a simulated market environment where the individual can sell, buy, or hold a given number of stocks. In particular, in our set-up, which is consistent with Cecchini, Vagnani e Bagozzi [24], Frydman and Rangel [25], and Weber and Camerer [3], participants were allowed to trade with €350 in experimental currency, three stocks are available for trading (labeled A, B, and C) across a period of 108 trials. Stocks price dynamic are randomly generated and thus they not impacted by individuals' trading decisions. When the trading session begins, participants must buy each of the three shares at an initial price of €100, with a residual €50 in cash. The first nine trials are only presenting price updates to the individual, while for the rest of the experiment, the software presents two interfaces: a price update page and a trading decision page (both are presented in Figure 2)

Insert Figure 1 about here

A stock is randomly shown to the participant on the price update page alongside its price change. Similarly, in the trading decision screen, a stock is randomly chosen, but in this interface, the participant is asked if they want to trade with that stock or not. The stock's price only changes after a price update page; therefore, each individual sees the entire path for the stock. On both screens, the participant is provided with the necessary information to decide. With the first 1 to 9 trials, the subject familiarizes him/herself with the trading environment; in this stage, as mentioned, they cannot trade with any of the stocks, but this allows the participants to process the price dynamics. There are only two trading decisions: buy the asset or not hold it, sell it, or hold it; short selling is not allowed. Note that in our experimental setting, while the earned capital gain is immediately and readily available to our participants on the trading screen, the expected value from selling the stock must be inferred by our traders from the information on the update page.

The price dynamic of each stock follows a two-state Markov chain, where the asset can be either in a good or a bad state. The stocks probability distribution is state dependent and it is randomly defined at the beginning of each session. If the stock is in a good state, in trial t, the same stock has a probability of a price increase of 0.70 and a decrease of 0.30. If the asset is in a bad state, the likelihood of a price increase is 0.30 and 0.70 for a decrease. The price change, either up or down, is randomly chosen between (€5, €10, and €15). The state of each stock will remain the same as in the previous period with a probability of 0.80 and will change with a probability of 0.20. As mentioned earlier, the participants are shown the entire price evolution of every stock; therefore, if the price update in $t > 1$ is not about the same stock shown in time t, then the state will not change. Understandably, given the price dynamic, it is very likely that a price increase is associated with a stock in a good state.

Participants were instructed on the probability distribution in both states. In order to enhance a careful thought process, a reward is offered to each individual as a function of the average total wealth, in cash and stocks, held at the end of two experimental sessions.

Consistently with the psychological literature on the prediction of experiments based on non-monetary rewards [26, 27], and considering the participants pool composed entirely of university students currently enrolled in the course of business management [28], two out of the five exam questions are linked to the reward of the trading session, in line with the average wealth of 35% that a family holds in financial assets. The exam points gained by each student are maintained constant for one academic year; for example, for an average total gain of €600 in the two trading sessions, given the initial endowment of €350 = 6 exam points, the reward is calculated as (6 * 600) / 350 = 10.28. In samples of university students, giving extra-credit points to motivate applicants produces qualitatively comparable data on average as participants are rewarded with cash [29].

Disposition effect and individual choices in our experimental trading environment

Given our experimental environment, continuing from (8), we adapt the model to the experimental design described and price dynamics linked to the stock's good or bad state. As a first step, following Frydman and Rangel (2014), we calculate the ex-post probability of the stock to be in a good state, given q_t the ex-post probability of the stock *s* to be in a good state in period *t*, and z_t equal to 1 if the price has increased in *t*, zero otherwise. Note that trading participants in our experiment can form such an expectation by considering stock price dynamics as in the price update screens. Thus, we have

$$q_t = \Pr(s_t = good \mid q_{t-1}; z_t) = \frac{\Pr(x \mid s_t = good) \Pr(s_t = good \mid q_{t-1}; z_t)}{\Pr(x)} \tag{9}$$

$$= \frac{\Pr(\Delta p > 0 \mid s_t = good) \Pr(s_t = good \mid q_{t-1}; z_t)}{\Pr(\Delta p > 0 \mid s_t = good) \Pr(s_t = good \mid q_{t-1}; z_t) + \Pr(\Delta p < 0 \mid s_t = bad) \Pr(s_t = bad \mid q_{t-1}; z_t)}$$

The probabilities of price up or down in each of the state are known upfront, hence (9) becomes

$$= \frac{(0.5 + 0.2z_t)(0.8q_{t-1} + 0.2(1 - q_{t-1})}{(0.5 + 0.2z_t)(0.8q_{t-1} + 0.2(1 - q_{t-1})) + (0.5 - 0.2z_t)(0.2q_{t-1} + 0.8(1 - q_{t-1}))} \tag{10}$$

It follows from (8), always assuming that the investor already holds the stock, that

$$u(k_t = 0) \rightarrow \; u(E[\Delta p_{t+1}|q_t]) \rightarrow \; (E[\Delta p_{t+1}|q_t]) = \tag{11}$$

$$= \Pr(s_{t+1} = good \mid q_t) E(\Delta p_{t+1} \mid s_{t+1} = good) + \Pr(s_{t+1} = bad \mid q_t) E(\Delta p_{t+1} \mid s_{t+1} = bad)$$

$$= [(0.6q_t + 0.2)[0.7(x) + 0.3(y)] + (0.8 - 0.6q_t)[0.7(y) + 0.3(x)]$$

where, as stated earlier, $x > 0$ and $y < 0$; therefore

$$if\ u(E[\Delta p_{t+1}|q_t]) > 0 \rightarrow sell, otherwise\ hold$$

with the utility function as defined in (3) (see Figure 2).

Insert Figure 2 about here

We can generalize the model to the experimental design by including the capital gain (*CG*), whose information is available to participants in our experiment directly on trading screens, excluded so far given the assumptions made. *CG* is defined as the difference between the previous purchase price of the stock and the current price; hence (11) becomes

$$u(k_t = 0) \rightarrow \; u(CG_t + E[\Delta p_{t+1}|q_t, p_t] + \; \varepsilon_t) > 0 \tag{12}$$

Where ε_t are i.i.d. draws from a normal distribution. In equation (12), we consider that traders focus on two aspects of their decisions: trading stocks according to the capital gain, which can be the outcome of realization utility preferences [30], simple prospect theoretic preferences [22] or an irrational belief in the mean reversion of stock prices [31]; trading stock in order to achieve the maximum wealth at the end of the trading session by focusing on the $E[\Delta p_{t+1}|q_t, p_t]$ component. Given these two motives, we say that there is a disposition effect if the relative propensity to sell shares is greater after a gain than vice-versa; considering

$$\pi = \frac{allocation\ in\ stocks\ A, B, and\ C}{allocation\ in\ stocks\ A, B, and\ C + cash} \tag{13}$$

we have from (1) and (2)

$$\begin{cases} PGR > PLR & if \pi_{+;\,\Delta t} < \pi_{0;\,t} \leq \pi_{-;\,\Delta t}\ and\ \Delta t = 1 \\ PGR < PLR & if \pi_{-;\,\Delta t} \leq \pi_{0;\,t} < \pi_{+;\,\Delta t}\ and\ \Delta t = 1 \\ & PGR = PLR\ otherwise \end{cases} \tag{14}$$

Describing (14), we have a disposition effect if the investor tends to focus more on the CG component and sell stock according to its realized gain, i.e., reduces the stock allocation π going from *t* to *t+1* as described with $\pi_{+;\,\Delta t} < \pi_{0;\,t}$, and increases or hold his position after a loss, $\pi_{0;\,t} \leq \pi_{-;\,\Delta t}$.

STUDY 1

Although neither directly nor normatively linked with an individual decision problem, extant literature has offered theoretical arguments and empirical evidence that negative life events, like hurricanes, tornados, earthquakes, and pandemic spread of diseases, diffuse outside the domain that elicits the situation and produce incidental effects on other decision domains, such as willingness to invest [32], risk-taking behaviors [18], intention to purchase an insurance [33]. In our study, we extend the considered influence of negative life events on the decision domain of trading choices with asset stocks and, specifically, on the disposition effect observed in such choices. Such a specific extension has been already considered by some few available contributions, yet with mixing conclusions.

On the one hand, some researchers propose negative life events will increase the disposition effect of individual traders. Considering that an individual gets a jolt of positive (negative) prospects when she or he realizes a gain (loss), given that negative life events induce a negative shock in the utility of the individual, it is expected that the same individual will try to realize a more significant number of gains and lower number of losses in order to compensate for the negative shock induced by the negative events. Therefore, it has been hypothesized that the disposition effect will increase after an individual exposure to a negative life event because the marginal utility of realizing a stock gain increases and of realizing a loss decreases [34].

On the other hand, some scholars suggest negative life events will reduce the disposition effect of individual traders. One theoretical argument that supports this proposition builds on the cognitive limitations induced by a negative life event, notably when the exposure to these events induces in an individual a posttraumatic stress disorder [35]. Consequently, she or he could trade significantly less due to inattention, and the difference between their propensity to sell gains and losses may be insignificant. Thus, their disposition effect could be reduced if they stop actively investing [34].

Differently, using an experimental laboratory, Sacco et al. [36] observed that for people exposed to the 9/11 terrorist attack, in choosing among risky prospects, the overestimation of low probabilities of gain is absent, and the tendency toward risk-taking in the loss domain disappears and the value function for losses seemed to no longer mirror the value function for gain; instead, the two functions are similar. One potential explanation of these results can be again traced back to individuals' cognitive efforts. Individuals exposed to negative life events tend to develop a negative state that reacts to them by striving to fix and improve their lives. Therefore, they will search for more relevant information in different domains and use a more structured decision-making process. They make better use of available information and make better, more informed decisions [37, 38].

In order to test whether a negative life event will increase or decrease the disposition effect and the potential explanation of such effect, we designed a laboratory experiment based on university students enrolled in the Faculty of Economics at Sapienza, University of Rome. Such students have a background in economics and understand concepts like selling and buying assets, realizing the capital gain, defining the expected value of a sale, and having a goal of increasing wealth.

Specifically, we recruited 60 students through announcements during class lectures in business and economics, of which 30 in 2018 and 30 in 2021 (before and during the COVID-19 pandemic). Note that Italy was one of the most affected countries by the COVID-19 pandemic, and students were most impacted because of the shocks induced to their business as usual lives. Before the experiment began, participants were given precise instructions on the trading exercises. At the end of two trading sessions, all participants were asked to respond to some questions concerning their demographic characteristics: (i.e., age, gender, education, stock-market knowledge, and experience). In addition, to control for the presence of posttraumatic stress disorder, we ask participants to respond to the Posttraumatic stress disorder checklist (PCL-5) [39, 40]. Participants in the before and during groups show comparable demographic and knowledge and experience on stock market characteristics. Concerning the score on PCL-5, participants during the COVID-19 pandemic scored higher than their counterparts in the pre-COVID-19 group.

Insert Figure 3 about here

Figure 3 reports the mean values for the *DE*, the *PGR*, and the *PLR* levels for our before and during groups. It may be observed that participants before show a much higher DE than counterparts during the COVID-19 pandemic. It is also interesting to show that much of the DE reduction is linked to the *PGR* and, to a minimal extent, to the *PLR*.

STUDY 2

To triangulate the results of study 1 and to consider that different exposure to a negative life event like the COVID-19, we designed a second experiment in which participants were first instructed on the trading session and were then asked to fill a questionnaire asking the following four questions: (i) Did you have a person close and dear to you (such as father, mother, brother, sister, grandfather, grandmother, girlfriend) who died from the COVID-19 pandemic? ; (ii) Has a person close and dear to you (such as father, mother, grandfather, brother, sister, grandmother, girlfriend) become seriously ill with COVID-19 with hospitalization? (iii) Did a friend of yours get sick and then die from the COVID-19 pandemic?; (iv) In addition to the events listed above, in your life, they have happened to you personally, or you have been a spectator of particularly negative events or facts during this period of the COVID-19 pandemic. Participants have to answer yes or no. We assigned 1 to yes and zero to no, summed all ones, and took the average score to measure individual exposure to a negative life event associated with the COVID-19 pandemic. We collected data on 70 students, out of which 59 showed exposure of zero, 25 exposure of .25, 13 exposure of .5, and 1 exposure of 1.

Insert Figure 4 about here

Study 2 confirms that negative life event, here captured by the degree of individual exposure to the COVID-19 pandemic, reduces the DE, and such an effect is mainly driven via the reduction of the *PGR*.

Experimental data allows us to further investigate whether the negative live events-DE linkage is channeled via a reduction of trading volume or better considering the expecting value of a trading episode, focusing on trading decisions more on the $E[\Delta p_{t+1}|q_t, p_t]$ than on the *CG*. Concerning the latter two components, as in Frydman and Rangel (2014), we run the following logistic regression separately for every subject and only on trials in which the subject has an opportunity to sell a stock,

$$\Pr(Sell_t) = \alpha + \beta_{REV} \cdot E[\Delta p_{t+1}|q_t, p_t]_t + \beta_{CG} \cdot CG_t + \varepsilon_t$$

Where the first component is the expected wealth by trading an asset (here also REV), and the second one is the magnitude of capital gain that can occur on any stock that is sold for a price higher than the purchase price that was paid for it, and ε is the error term. To better control for heterogeneity in estimates, we built a posthoc computation of the comparative consequence of the CG and the $E[\Delta p_{t+1}|q_t, p_t]$ variables. This quantity is calculated in three steps: (1) z-score the considered variables, (2) re-estimate the logistic model at the subject level, and compute the estimated difference $\beta_{diff} = \beta_{CG} - \beta_{REV}$ at the subject level. The estimated coefficient β_{diff} captures the degree to which subjects are more influenced in their selling decisions by the readily and immediately available CG variable in the trading screens compared to the more cognitively challenging REV variable to be estimated according to the information available in the update screens.

Insert Figure 5 about here

Insert Figure 6 about here

From Figures 5 and 6, we observed that while trading volume is relatively constant across different levels of individual exposure to negative life events, the relative sensitivity to the expected value of a sell versus the capital gain changes. Specifically, our experimental data suggest that individuals that were significantly exposed to a negative life event tend to rely more on the more cognitive demanding $E[\Delta p_{t+1}|q_t, p_t]$ than on the easily available capital gain. Thus, our data suggests that the reduction in the disposition effect tends to be correlated to the better use of information available [37, 38].

STUDY 3

In the previous studies, we provided empirical evidence on how an individual exposure to a negative life event is to reduce the disposition effect, mainly via the reduction of the *PGR* but not the *PLR*. In the current study, we explored the associations between individual exposure to negative life events and PLR. We focused on the appraisal-tendency framework [20].

Accordingly, individual exposure to negative life events elicits emotions that are likely to influence her or his subsequent decisions, far well beyond the domain in which the negative events occurred [19, 20].

Among the emotions that may stem from an individual exposure to negative life events, given that emotions are not all the same [41, 42], instead of just focusing on the valence of an emotion (e.g., positive vs. negative) elicited by an event, we consider specific affective emerging from such event, namely fear and anger. The effects of anger on decision making can influence the personal perception of risks [43]: relative to fear, anger can be associated with a more optimistic attitude, sometimes reckless, towards the future [44] combined with a more superficial depth of processing, i.e., being more prone to heuristic processing [45]. In literature, anger has also been characterized by an increased perception of the likelihood of angering events, for example, intentionally being sold a lemon from a used car dealership [46]. Elaborating on this, it has also been proposed [47, 48] that anger can enhance the individual's thought process. It can also be associated with the desire to oppose and confront; this can drive a more vigilant behavior. In the context of the disposition effect, it is crucial to understand whether the prevailing attitudes from anger are skewing more towards negative outcomes such as heuristic processing, over-confidence, and irrationality, or this emotion can drive a positive outcome through a fueled push towards action, avoidance of over-analysis and enhanced focus on the final goal, thus reducing the disposition effect compared to those operating under fear. Regarding this, it is also equally interesting whether, in a trading experiment, fear would enhance the participants' conscientiousness or instead paralyze or slow down their thought process and drive a more frenetic and irrational behavior.

In this study, we composed three groups of university students, control, fear, and anger, with the latter two defined as treatment groups. We developed a simple computer algorithm to randomly assign participants to one of three groups. Respondents were recruited by announcements in the course of business and economics. Accordingly, we explained the trading sessions then we asked them to answer questions about their mood. We also asked participants whether they were under psychological treatment for ethical reasons. In case of a positive answer, the interview was terminated. In case of a negative answer, we followed the procedure adopted to elicit negative emotions introduced by Lerner et al. [49]. Respondents were first to watch 1,30 minute images concerning the COVID-19 pandemics that may elicit fear (e.g., cemetery, ambulances near hospitals, people in intensive therapy) and anger (e.g., riots, broken shops, fire, violent protesters) emotions. Right after, we asked participants to read a text that evoked emotions. Finally, we asked two questions: (i) what makes you most ANGRY (FEAR) about the COVID-19 pandemic. Please describe the one thing that makes you most ANGRY (FEAR) about the COVID-19 pandemic. We also added: write as detailed a description of that thing as possible. If you can, write your description so that someone reading it might get ANGRY from learning about the situation. Once the interview finished, participants started the trading sessions. At the end of the trading sessions, participants indicated how they felt while watching pictures and reporting their emotions. We employed the same scale used by Lerner et al. [49] which comprises five-item scales for each focal emotion (fear: ± = .92, anger: ± = .93). Answer scales extended from 0 (do not feel the emotion the slightest bit) to 8 (feel the emotion even more strongly than ever). We averaged responses on each scale for subsequent analyses. We also collected demographic information and knowledge and experience with trading decisions.

We first checked the effectiveness of the treatment by comparing the specific emotions evoked in the treatment groups with those in the control group. Because of the multiple emotions that the COVID-19 pandemic is likely to elicit, we also checked the cross-emotion emergence by comparing the emotions of people included in the angry group with those included in the fear group. From the data, we observed the general effectiveness of the treatment and minimal crossemotional effects. Accordingly, we run two regressions, with the dependent variables defined as the *PGR* and the *PLR* and independent variables fear and anger, controlling for other covariates like age, gender, knowledge, and experience. Note that we employed a Tobit regression since our dependent variables are bounded. As robustness, we also employed a simple OLS regression and observed consistent results.

Insert Table 1 about here

From Table 1, we noted that anger and fear would not influence the *PGR* but the *PLR*, with different signs and magnitudes. Specifically, while more significant levels of anger induced by an individual exposure to a negative life event increase the *PLR*, making the trader more prose to sell assets at a loss, more extended levels of fear will produce the opposite effect, making the individual less ready to realize losses. Our laboratory experimental data offer evidence while specific negative emotions are to influence the DE, such effects tend to be different according to the emotion elicited by an individual exposure to a negative life event and the target component of the DE, specifically the *PLR*.

DISCUSSION AND CONCLUSIONS

Our study attempts to explore the effects of individual exposure to negative life events on the disposition effect, a behavioral bias that characterizes trading choices. We use quasi-experimental design as a method of choice. Such a method allows us to compare, in a well-controlled research setting, the disposition effect in trading activities of individuals exposed or not to a given negative event (here specifically the COVID-19 pandemic) as well as the degree of exposure to such a negative event, with the associated potential emotions that may stem from such exposure. From our results, we observed consistent evidence that individual exposure to negative life even will reduce the disposition effect via the reduction in the *PGR*. Individuals exposed to negative life events are more likely to hold gains to a greater extent than individuals with no o more limited exposure to such events. At the same time, we explored whether an individual exposure to negative life events may trigger changes also in the *PLR*. In our last experiment, we elicited specific emotions, specifically anger and fear, and noted that greater levels of anger are to reduce the *PLR*.

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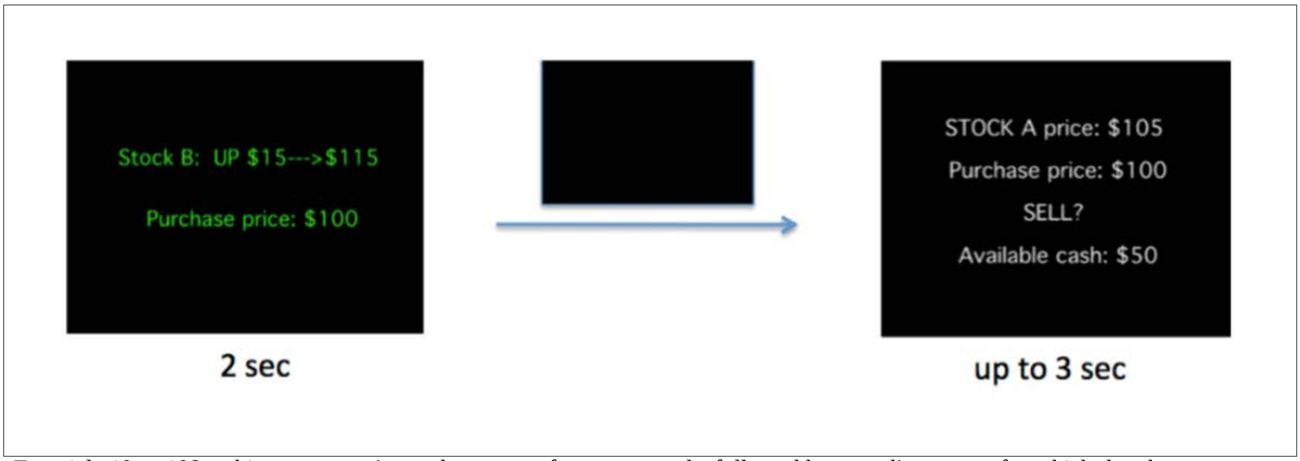
FIGURES

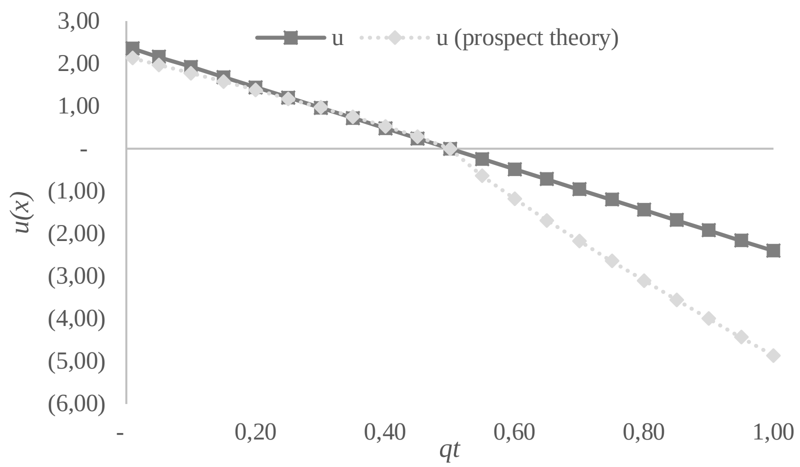
Figure 1 Sample screens



For trials 10 to 108, subjects see a *price update* screen for two seconds, followed by a *trading* screen for which they have up to three seconds to enter a decision. The screens below are for a trial in which the subject owns both stocks A and B. If the subject did not own stock B at the price update screen, the purchase price would not be displayed. If the subject did not own stock A on the trading screen, he would be given the opportunity to buy it. For trials 1 to 9, subjects see only the price update screen and the blank screen; this allows them to accumulate information about price changes before having to make any decisions.

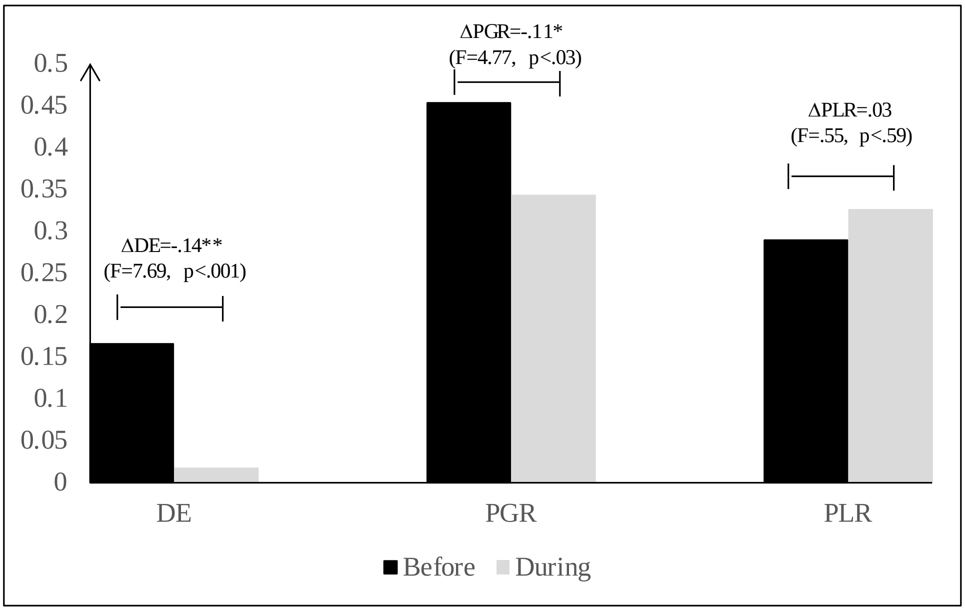
*

Figure 2. The prospect theory utility value function.



The figure plots the utility value function from the rational investor and from Kahneman and Tversky's (1979) prospect theory, considering the proposed parameters: $\alpha = 0.88$ and $\beta = 2.25$; in the presented chart, the value function's quadrants are inverted compared to what usually found in literature as we are representing on the x-axis the probability of the stock to be in a good state in time t. The lower the expected value, due to the high probability of not being in the good state, $q_t \rightarrow 0$, the higher the utility of selling the stock.

Figure 3 Mean comparisons of DE, PGR, and PLR before and during the COVID-19 pandemic.



*

Figure 4 Mean comparisons of DE, PGR, and PLR over different levels of individual exposure to negative life events (i.e., COVID-19)

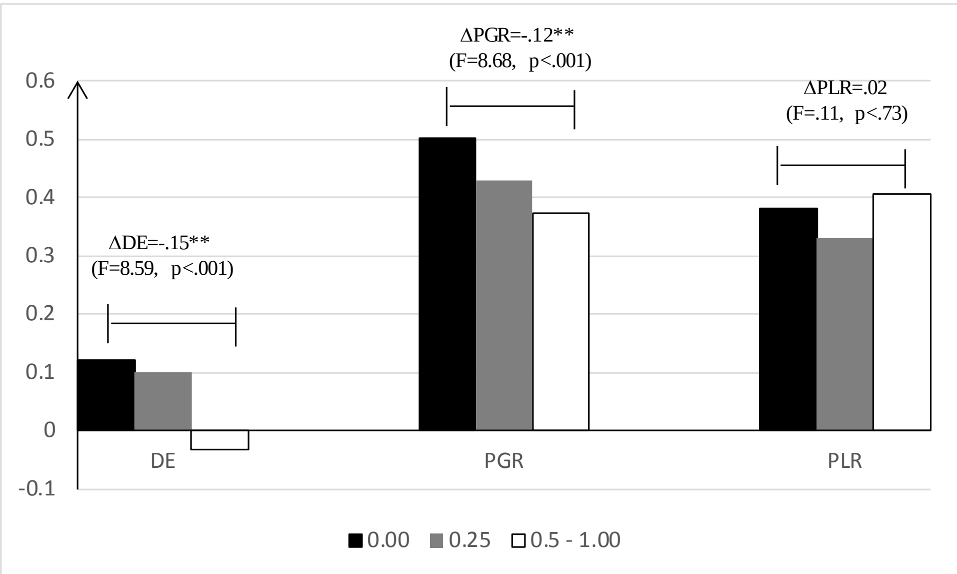


Figure 5 Mean comparisons of trade volumes aver different levels of individual exposure to negative life events (i.e., COVID-19)

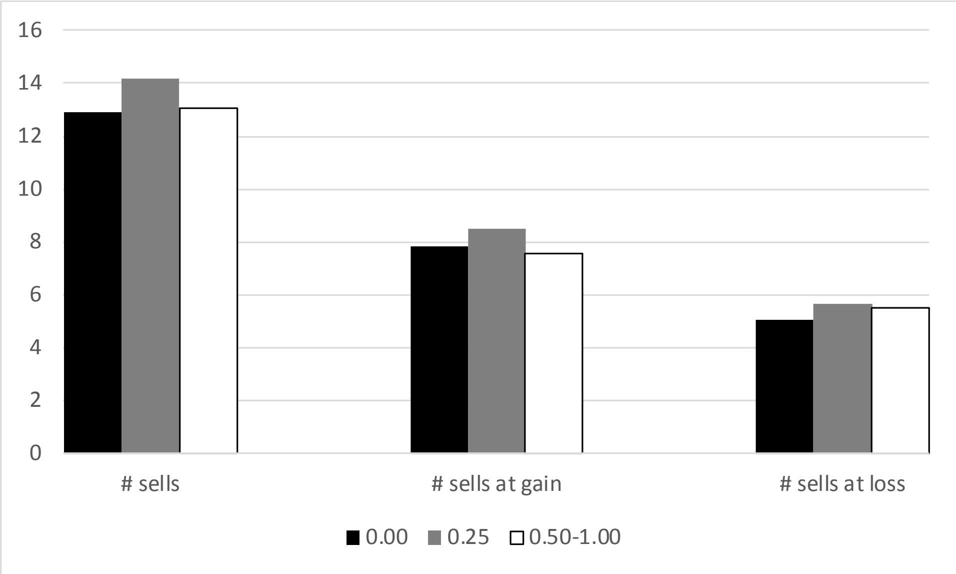
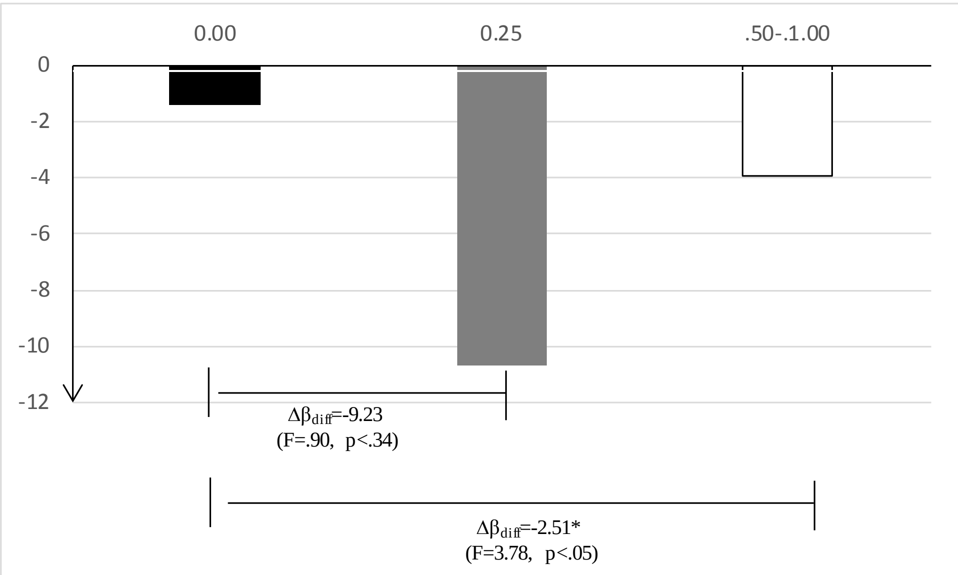


Figure 6 Mean comparisons of traders' focus on $E[\Delta p_{t+1}|q_t, p_t]$ and CG aver different levels of individual exposure to negative life events (i.e., COVID-19)



TABLES

Table 1 Fear, Anger, and their effect on PGR and PLR

	Model (1) PGR	Model (2) PGR	Model (3) PGR	Model (4) PLR	Model (5) PLR	Model (6) PLR
Anger		.03	.03		.05**	.05**
		(1.40)	(1.31)		(2.79)	(2.64)
Fear		.01	.01		-.05*	-.05*
		(.01)	(.01)		(-2.20)	(-2.07)
Age	.04	.04	.04	.02	.04	.04
	(1.12)	(1.19)	(1.12)	(.60)	(1.30)	(1.22)
Gender	-.15*	-.13†	-.13	-.18**	-.22**	-.22**
	(-2.20)	(-1.73)	(1.63)	(-3.03)	(-3.51)	(-3.30)
Knowledge	.04	.05	.05	.12	.12	.12
	(.31)	(.45)	(.43)	(1.12)	(1.13)	(1.06)
Experience	.10	.09	.09	-.09	-.11	-.11
	(1.32)	(1.26)	(1.19)	(-1.32)	(-1.68)	(-1.58)
Constant	-.42	-.57	-.57	.01	-.36	-.36
	(-.53)	(-.72)	(-.68)	(.70)	(-.54)	(-.51)
LR [*F-test*]	5.91	8.85	[1.41]	[11.92]	19.80	[3.45]
df	(4)	(6)	(6,54)	(4)	(6)	(6,54)
Pseudo R^2 [R^2]	.62	.93	[.13]	-83.17	-138.10	[.28]

This table contains a set of all Tobit regressions but Models 3 and 6 in which an OLS estimator is employed. In models 3 and 6, the *VIF* as a measure of collinearity is well below 3. Note that the dummy gender takes the value of 0 if female, 1 if male.

t-statistics in parentheses

†$p < 0.1$

*$p < 0.05$

**$p < 0.01$