Journal of Finance and Investment Analysis, Vol. 11, No. 2, 2022, 1-21
ISSN: 2241-0988 (print version), 2241-0996(online)
https://doi.org/10.47260/jfia/1121
Scientific Press International Limited

Incidental Negative Life Events and the Disposition Effect at the Individual Level

Gianluca Vagnani[1] and Francesco Mazzurco[2]

Abstract

In this study, we 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 COVID-19. We also manipulated and elicited the emergence of specific emotions from the exposure to COVID-19 and tested whether such emotions 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 is elicited in the individual decision-maker.

JEL classification numbers: G11, G41.
Keywords: Disposition effect, Negative life events, Experiment.

[1] Department of Management, Sapienza University of Rome, Rome, Italy.
[2] Ph.D. School in Social and Economic Sciences, Sapienza University of Rome, Rome, Italy.

Article Info: *Received:* June 21, 2022. *Revised*: July 11, 2022.
Published online: July 17, 2022.

1. 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 (Barberis and Thaler 2005). It relates to an investor's tendency to realize gains to a greater extent than realize a loss in trading risky assets (Ben-David and Hirshleifer, 2012; Brettschneider, et al. 2021; Dhar and Zhu, 2006; Odean, 1998; Pelster and Hofmann, 2018; Shefrin and Statman, 1985; Weber and Camerer, 1998). The DE has been observed across geographies, such as North America (Odean, 1998), Europe (Weber and Camerer, 1998), and Asia (Li, et al. 2021), and is also typical in commodities (Nofsinger, et al. 2018) and even real estate markets (Chang, et al. 2017). Moreover, the disposition effect is likely to have market-wide impacts (Kaustia, 2004) and will induce negative consequences for traders' investment returns (Odean, 1998), volume, volatility, and stock prices (Goetzmann and Massa, 2008).

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. Our study considers how incidental negative life events _ENREF_7_ENREF_8_ENREF_9_ENREF_15_ENREF_44 (Brettschneider at al. 2021) would influence the DE. A negative event has an incidental effect if it is neither directly nor normatively related to an individual decision to trade a risky asset in financial markets. In this regard, we differ from extant studies which tested the effects of negative life events on individuals' willingness to invest and risk-taking behaviors (Bucciol and Zarri, 2015; Callen, et al. 2014; Cameron and Shah, 2015; Eckel, et al. 2009; Seo and Barrett, 2007). We focused instead 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 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. Our study builds on the appraisal emotion theory (Loewenstein and Lerner 2003; Lerner and Keltner, 2000) to introduce candidate mechanisms. Thus, it considers 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. The disposition effect has been directly measured in actual transaction data using logs at large brokerage houses (e.g., Frydman and Wang, 2020; Odean, 1998). However, because of individual trader privacy, it is rather difficult to collect data on individual exposure to negative life events. Even more difficult is to appraise individuals' assigned valences and the significance of exposure to negative life events.

A quasi-experimental setting lets us overcome the privacy issue that characterizes actual transaction data and better control for potential confounding effects and heterogeneity 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 as an incidental negative event the exposure of an individual to the COVID-19 pandemic. Accordingly, in study 1, we compared the disposition effect in two samples of individuals' trading decisions collected before and during COVID-19. In study 2, we focus on data collected during the pandemic and compare the disposition effect across individuals exposed to a different extent to COVID-19. In study 3, we stimulated specific emotions in individuals exposed to the pandemic, specifically anger and fear, and tested whether such emotions can 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.

2. Theoretical background

2.1 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 $t = 0, \ldots, T$. The stock is flagged as a *realized gain* if sold when the stock price exceeds the purchase price and 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:

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

Similarly, the proportion of losses realized (PRL) is measured as follows:

$$PLR = \frac{number\ of\ realized\ losses}{number\ of\ realized\ losses + number\ of\ paper\ losses} \quad (2)$$

It follows that the disposition effect is present when PGR > PLR.
The theoretical framework can be built from Kahneman and Tversky's (Kahneman and Tversky 1979) prospect theory, whose primary assumption is an S-shaped utility function, concave for the gain's 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:

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

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

$$w(p)u(x) + w(1-p)u(y) \quad (4)$$

with $w(p)$ taking the following form (Kahneman and Tversky, 1979)

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

Considering that the number of traded stocks equals one, the investor aims to maximize 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:

$$\max u(k_t)\ subject\ to\ 1 \geq k_t \geq 0 \quad (6)$$

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

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

Assuming $k = [0{,}1]$ variable, hence the investor either has the stock ("1") or keeps cash ("0"), and that the investor already holds the stock, the individual would exit the long position if (adapted from Hens and Vlcek, 2011):

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

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.

2.2 Experimental trading environment

Our study analyzes decision patterns 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, et al. (2021), Frydman and Rangel (2014), Weber and Camerer (1998), 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. Stock price dynamics are randomly generated. Thus, individuals' trading decisions do not influence these dynamics. When the trading session begins, participants must buy the three shares at an initial price of €100, with a residual €50 in cash. The first nine trials only present price updates to the individual. In contrast, the software presents two interfaces for the rest of the experiment: a price update page and a trading decision page (see Figure 1).

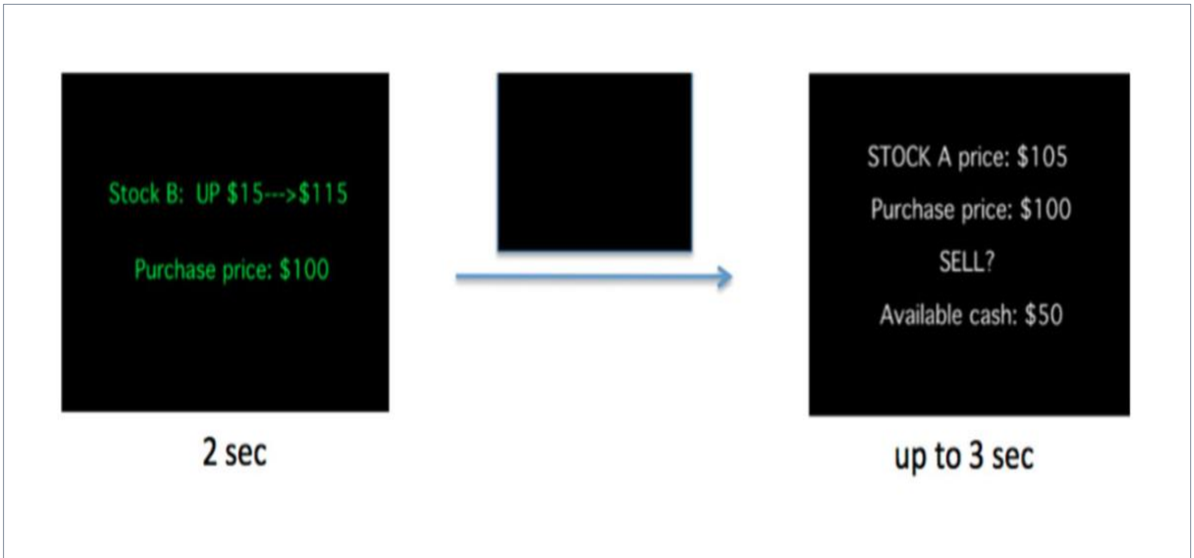

Figure 1: Sample screens

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 stocks A and B. The purchase price would not be displayed on the price update screen if a participant did not hold stock B. A participant has the opportunity to buy a stock if she does not own stock A on the trading screen. For trials 1 to 9, participants see only the price update screen and the blank screen; this allows them to accumulate information about price changes before making any decisions.

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. The participant is provided with the necessary information to decide on both screens. With the first 1 to 9 trials, participants familiarize themselves with the trading environment; in this stage, as mentioned, they cannot trade with any of the stocks, enabling the participants to process the price dynamics. Afterward, there are only two trading decisions: buy the asset or not hold it, sell it, or keep 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 stock's probability distribution is state-dependent and 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). Each stock's state will remain as in the previous period with a probability of 0.80. It changes with a chance of 0.20. As mentioned, the participants see 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. We stimulated careful trading decisions by offering a reward to each individual. The reward is 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 (Komai and Grossman, 2006; Wright, et al. 1993), and considering the participants pool composed entirely of university students currently enrolled in the course of business management (Voslinsky and Azar, 2021), 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 sample university students, giving extra-credit points to motivate applicants produces qualitatively comparable data on average as participants are rewarded with cash (Luccasen III and Thomas, 2014).

2.3 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:

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

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

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:

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

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

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

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

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

The utility function is defined in (3) (see Figure 2).

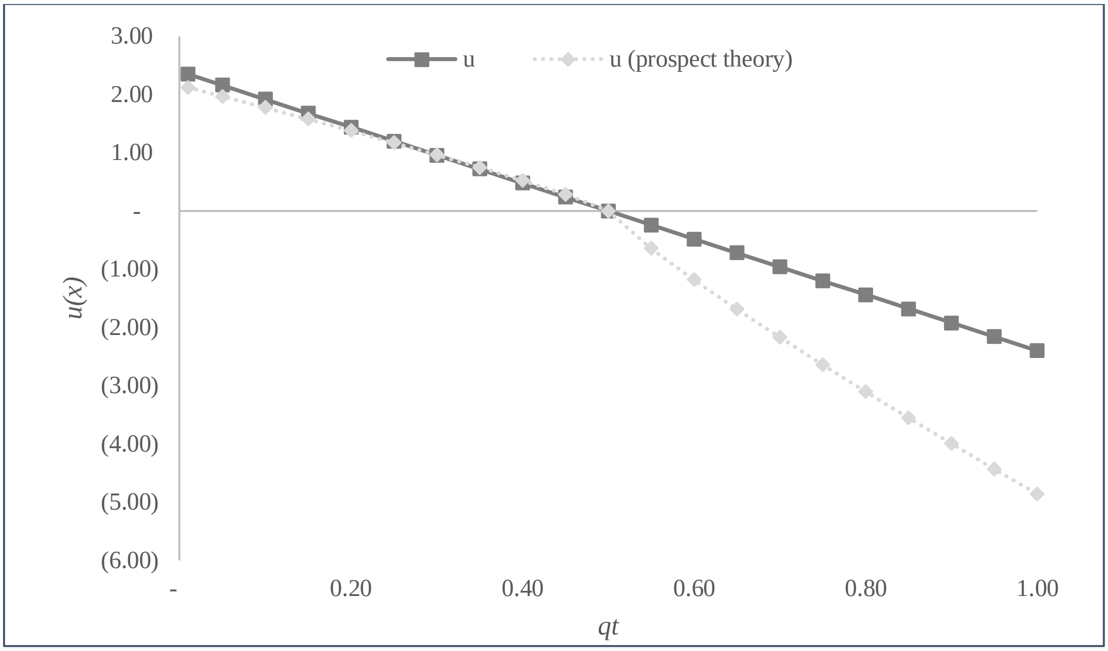

Figure 2: The prospect theory utility value function

The figure plots the utility value function adopting the rational investor and prospect theory views, considering the proposed parameters: α = 0.88 and β = 2.25. In the presented chart, the value function's quadrants are inverted compared to what is usually found in literature as we are representing on the x-axis the probability of the stock being 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→0, the higher the utility of selling the stock.

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 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 (Barberis and Xiong, 2009), simple prospect theoretic preferences (Kahneman and Tversky, 1979) or an irrational belief in the mean reversion of stock prices (Poterba and Summers, 1988), and trading stock 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, $\pi_{0;\,t} \leq \pi_{-;\,\Delta t}$.

3. 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, can reach outside the domain that elicits the situation. These events thus produce incidental effects on other decision domains, such as willingness to invest (Browne, et al. 2021), risk-taking behaviors (Eckel et al. 2009) intention to purchase an insurance (Innocenti, et al. 2019). In our study, we extend the 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. Individuals get a jolt of positive (negative) prospects when they realize a gain (loss). Negative life events induce a negative shock in the individual's utility. Individuals will try to realize more significant gains and lower losses to compensate for the negative shock induced by the negative events. Therefore, the disposition effect will increase after an individual exposure to a negative life event since her marginal utility of realizing a stock's gain and loss increases and decreases, respectively (Henriksson, 2020).

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 causes an individual post-traumatic stress disorder (Yehuda, 2002). Consequently, they could trade significantly less due to inattention, and the difference between their propensity to sell gains and losses may be insignificant. Thus, the disposition reduces because an individual stops actively investing (Henriksson, 2020).

Differently, using an experimental laboratory, Sacco et al. (2006) 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. The tendency toward risk-taking in the loss domain disappears, and the value function for losses no longer mirrors the value function for gain; instead, the two functions are similar. One potential explanation of these results can be traced back to individuals' cognitive efforts. Individuals exposed to negative life events tend to develop a strive 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 (Elsbach and Barr, 1999; Park and Banaji, 2000).

To test whether a negative life event will increase or decrease the disposition effect and the potential explanation of such impact, 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. We have 30 participants 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 among the most impacted because of the shocks induced to their business-as-usual lives. Before the experiment began, we gave participants precise instructions on the trading exercises. At the end of two trading sessions, we asked all participants to respond to some questions concerning their demographic characteristics: (i.e., age, gender, education, stock-market knowledge, and experience).

Moreover, to control for the presence of post-traumatic stress disorder, we ask participants to respond to the Post-traumatic stress disorder checklist (PCL-5) (Forte et al. 2020; Weathers et al. 2013). Participants in the before and during groups showed comparable demographic, knowledge, and experience on stock market characteristics. Nevertheless, participants during the COVID-19 pandemic scored higher in the PCL-5 than their counterparts in the pre-COVID-19 group.

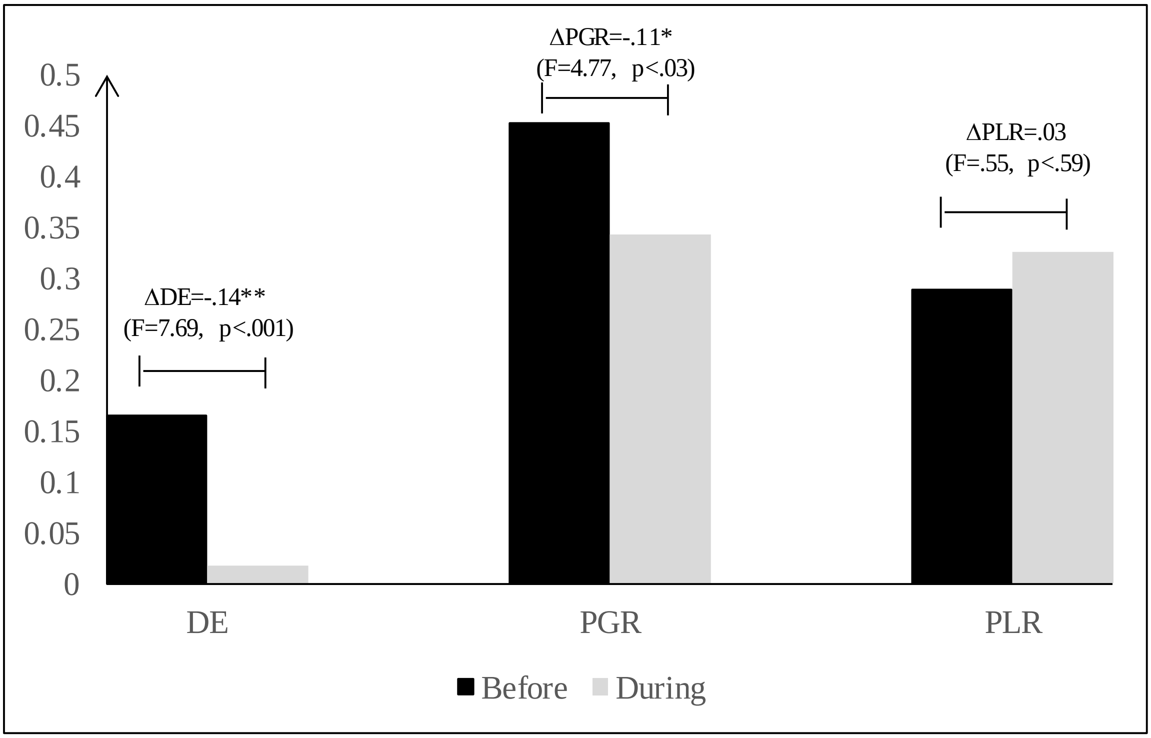

Figure 3: Mean comparisons of DE, PGR, and PLR before and during the COVID-19 pandemic

Figure 3 reports mean values for DE, *PGR*, and *PLR* levels before and during COVID-19 groups. Before COVID-19, participants showed a much higher DE than counterparts during the COVID-19 pandemic. DE reduction is linked to the *PGR* and, to a minimal extent, to the *PLR*.

4. Study 2

We triangulated the results of study 1, considering individuals' exposure to a negative life event like 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 a 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 a father, mother, grandfather, brother, sister, grandmother, girlfriend) become seriously ill with COVID-19 and needed hospitalization? (iii) Did a friend of yours get sick and then die from the COVID-19 pandemic? (iv) Have you witnessed in your life, or have they happened to you personally, negative events during this period of COVID-19? 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 the individual exposure to a negative life event associated with the COVID-19 pandemic. We collected data on 70 students, out of which 59 showed the exposure of zero, 25 exposure of .25, 13 exposure of .5, and one exposure of 1.

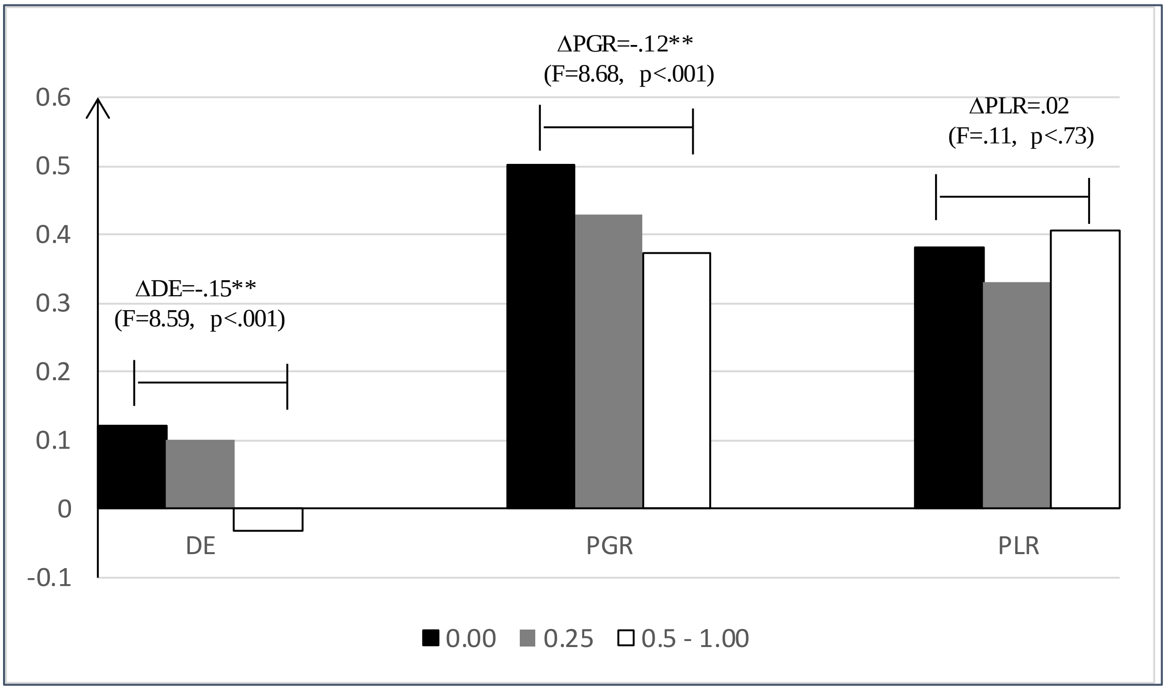

Figure 4: Mean comparisons of DE, PGR, and PLR over different levels of individual exposure to negative life events (i.e., COVID-19)

Study 2 confirms that negative life events, captured by the degree of individual exposure to the COVID-19 pandemic, reduce the DE, and the reduction of the PGR mainly drives such an effect.

Experimental data allows us to investigate whether the negative live events-DE linkage is channeled via a reduction of trading volume or better considering the expected 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 post hoc 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 (3) compute the estimated difference $\beta_{diff} = \beta_{CG} - \beta_{REV}$ at the subject level. The 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.

Figures 5 and 6 show 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 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 suggest that the reduction in the disposition effect tends to be correlated to the better use of information available (Elsbach and Barr, 1999; Park and Banaji, 2000).

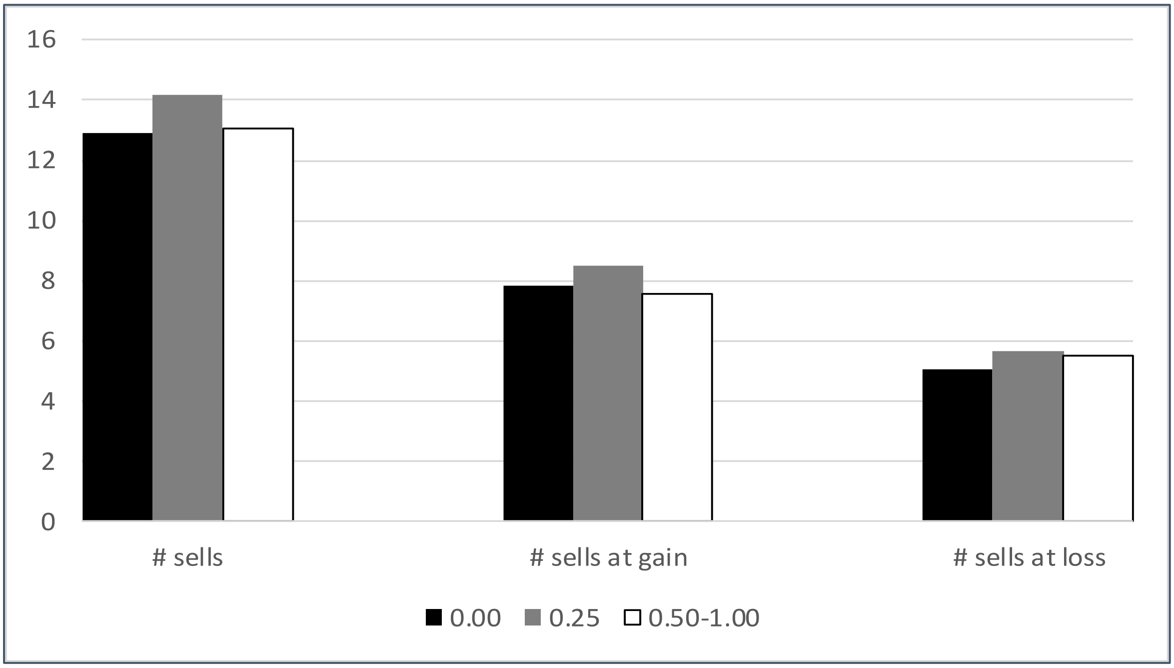

Figure 5: Mean comparisons of trade volumes aver different levels of individual exposure to negative life events (i.e., COVID-19)

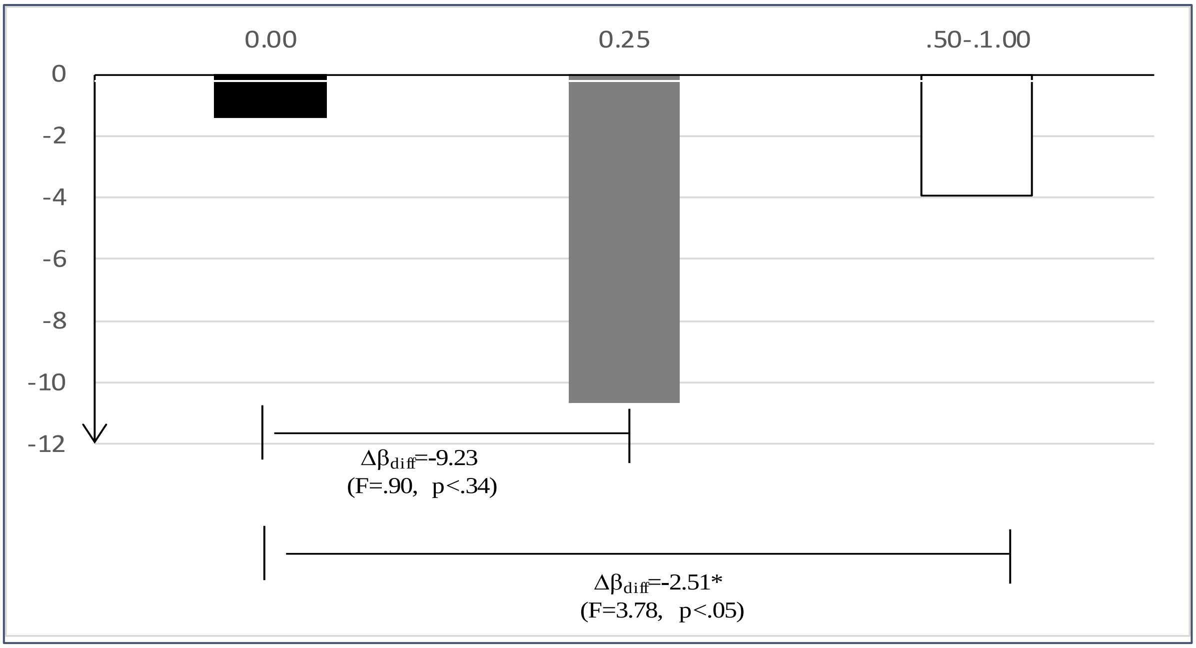

Figure 6: Mean comparisons of traders' focus on E[〖Δp〗_(t+1) ┤| q_t,p_t] and CG at different levels of individual exposure to negative life events (i.e., COVID-19)

5. 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 in purely experimental research leveraging the same framework of Study 1 and Study 2. We focused on the appraisal-tendency framework (Lerner JS, Keltner D., 2000). Accordingly, individual exposure to negative life events elicits emotions likely to influence their subsequent decisions far beyond the domain in which the negative events occurred (Loewenstein and Lerner 2003; Lerner and Keltner 2000).

Emotions are not identical (Jeon and Yim, Walker, 2011; Raghunathan and Pham, 1999). Instead of focusing on the valence of an emotion (e.g., positive vs. negative) elicited by an event, we consider specific reactions emerging from such occurrence, namely fear and anger. The effects of anger on decision-making can influence the personal perception of risks (Litvak et al. 2010): relative to fear, anger can be associated with a more optimistic attitude, sometimes reckless, towards the future (Lerner and Keltner 2001) combined with a more superficial depth of processing, i.e., being more prone to heuristic processing (Tiedens and Linton 2001). 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 (DeSteno et. al. 2000). Specifically, it has also been proposed (Lerner at al. 2009) 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 frantic 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, recruited by announcements in the course of business and economics, to one of three groups. After providing an overview of the trading environment, 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, we terminated the interview. In case of a negative response, we followed the procedure adopted to elicit negative emotions introduced by Lerner et al. (2003). Respondents were first to watch 1,30-minute images concerning the COVID-19 pandemic that may elicit fear (e.g., cemetery, ambulances near hospitals, people in intensive therapy) or anger (e.g., riots, broken shops, fire, violent protesters). Right after, we asked participants to read a text that evoked the same emotions. Finally, we asked them to provide their views on: "(i) what makes you most ANGRY (FEARFUL) about the COVID-19 pandemic. Please describe the one thing that makes you most ANGRY (FEARFUL) about the COVID-19 pandemic." We also added: "write a detailed description of this and, if you can, write your description so that someone reading it might get ANGRY (FEARFUL) from learning about the situation." Once the interview finished, participants started the trading sessions. At the end of these, participants indicated how they felt while watching pictures and reporting their emotions. We employed the same scale used by Lerner et al. (2003), 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 COVID-19 is likely to elicit, we also checked the cross-emotion emergence by comparing the emotions of people in the angry group with those in the fear group. From the data, we observed the general effectiveness of the treatment and minimal cross-emotional 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.

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 (1.40)	.03 (1.31)		.05** (2.79)	.05** (2.64)
Fear		.01 (.01)	.01 (.01)		-.05* (-2.20)	-.05* (-2.07)
Age	.04 (1.12)	.04 (1.19)	.04 (1.12)	.02 (.60)	.04 (1.30)	.04 (1.22)
Gender	-.15* (-2.20)	-.13† (-1.73)	-.13 (1.63)	-.18** (-3.03)	-.22** (-3.51)	-.22** (-3.30)
Knowledge	.04 (.31)	.05 (.45)	.05 (.43)	.12 (1.12)	.12 (1.13)	.12 (1.06)
Experience	.10 (1.32)	.09 (1.26)	.09 (1.19)	-.09 (-1.32)	-.11 (-1.68)	-.11 (-1.58)
Constant	-.42 (-.53)	-.57 (-.72)	-.57 (-.68)	.01 (.70)	-.36 (-.54)	-.36 (-.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 zero if female and one if male. *t*-statistics in parentheses.
†$p < 0.1$; *$p < 0.05$; **$p < 0.01$

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 prone 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 offers evidence that, while specific negative emotions are to influence the DE, such effects tend to be different according to the specific reaction elicited by an individual exposure to a negative life event and the target component of the DE, specifically the *PLR*.

6. Discussion and conclusions

Our study explores 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 events 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*. Our study thus offers good hope: even a negative event may thus bring some positive things for individuals.

The results are of great interest, considering how they can be framed in the broader context of decision-making monitoring and analysis. In particular, the evidence suggests that a change in behavioral propensities can be driven by the surrounding social environment, even if subjects have had limited exposure to the impacts of such events. In our study, we have presented how direct or indirect exposure to the COVID-19 pandemic has enhanced the thought process propensity in the sample group, reducing the decisional bias compared to pre-COVID results. Future studies can investigate the time-persistency of our effects. At the same time, we call for studies to investigate the boundary conditions for these effects to remain and hold.

Finally, the results of this paper are extracted from a population of business management university students. However, we believe they can be representative of a broader behavioral propensity where decision-making is influenced by negative events, even if those do not directly impact the individual, and stimulate a more thoughtful and less biased decision-making process.

References

[1] Barberis, N. and Thaler, R. (2005). Chapter1. A Survey of Behavioral Finance. In: Richard HT, editor. Advances in Behavioral Finance, Volume II: Princeton University Press; 2005. p. 1-76.

[2] Shefrin, H. and Statman, M. (1985). The disposition to sell winners too early and ride losers too long: Theory and evidence. The Journal of finance. 1985;40(3):777-90.

[3] Weber, M. and Camerer, C.F. (1998). The disposition effect in securities trading: An experimental analysis. Journal of Economic Behavior & Organization. 1998;33(2):167-84.

[4] Odean, T. (1998). Are investors reluctant to realize their losses? The Journal of finance. 1998;53(5):1775-98.

[5] Dhar, R. and Zhu, N. (2006). Up close and personal: Investor sophistication and the disposition effect. Management Science. 2006;52(5):726-40.

[6] Ben-David, I. and Hirshleifer, D. (2012). Are investors really reluctant to realize their losses? Trading responses to past returns and the disposition effect. The Review of Financial Studies. 2012;25(8):2485-532.

[7] Pelster, M. and Hofmann, A. (2018). About the fear of reputational loss: Social trading and the disposition effect. Journal of Banking & Finance. 2018;94:75-88.

[8] Brettschneider, J., Burro, G. and Henderson, V. (2021). Wide framing disposition effect: An empirical study. Journal of Economic Behavior & Organization. 2021;185:330-47.

[9] Li, J.J, Massa, M., Zhang, H. and Zhang, J. (2021). Air pollution, behavioral bias, and the disposition effect in China. Journal of Financial Economics. 2021;142(2):641-73.

[10] Nofsinger, J.R., Chatjuthamard, P. and Dai, X. (2018). Behavioral aspects of commodity markets. In: H. Kent Baker GF, Jeffrey H. Harris, editor. Commodities: Markets, Performance, and Strategies. New York: Oxford University Press; 2018. p. 56-71.

[11] Chang, C.C., Chao, C.H. and Yeh, J.H, (2017). Comprehensive Disposition Effect in Real Estate Market. The 29th Asian Finance Association Annual Meeting, 30th Australasian Finance and Banking Conference; 2017.

[12] Kaustia, M. (2004). Market-wide impact of the disposition effect: evidence from IPO trading volume. Journal of Financial Markets. 2004;7(2):207-35.

[13] Goetzmann, W.N. and Massa. M. (2008). Disposition matters: Volume, volatility, and price impact of a behavioral bias. The Journal of Portfolio Management. 2008;34(2):103-25.

[14] Cameron, L. and Shah, M. (2015). Risk-taking behavior in the wake of natural disasters. Journal of Human Resources. 2015;50(2):484-515.

[15] Callen, M., Isaqzadeh, M., Long, J.D. and Sprenger, C. (2014). Violence and risk preference: Experimental evidence from Afghanistan. American Economic Review. 2014;104(1):123-48.

[16] Bucciol, A. and Zarri, L. (2015). The shadow of the past: Financial risk-taking and negative life events. Journal of Economic Psychology. 2015;48:1-16.
[17] Seo, M.G. and Barrett, L.F. (2007). Being emotional during decision-making—good or bad? An empirical investigation. Academy of Management Journal. 2007;50(4):923-40.
[18] Eckel, C.C., El-Gamal, M.A. and Wilson, R.K. (2009). Risk loving after the storm: A Bayesian-Network study of Hurricane Katrina evacuees. Journal of Economic Behavior & Organization. 2009;69(2):110-24.
[19] Loewenstein, G. and Lerner, J.S. (2003). The role of affect in decision making. In: Davidson, R.J., Scherer, K.R., Goldsmith, H.H. Handbook of affective sciences. New York, NY, US: Oxford University Press; 2003. p. 619-42.
[20] Lerner, J.S. and Keltner, D. (2000). Beyond valence: Toward a model of emotion-specific influences on judgment and choice. Cognition & emotion. 2000;14(4):473-93.
[21] Frydman, C. and Wang, B. (2020). The impact of salience on investor behavior: Evidence from a natural experiment. The Journal of finance. 2020;75(1):229-76.
[22] Kahneman, D. and Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica. 1979;47(2):263-91.
[23] Hens, T. and Vlcek, M. (2011). Does prospect theory explain the disposition effect? Journal of Behavioral Finance. 2011;12(3):141-57.
[24] Cecchini, M., Bagozzi, R. and Vagnani, G. (2021). Promotion and prevention focus orientation in mitigating the disposition effect. Journal of Neuroscience, Psychology, and Economics. 2021;14(2):81.
[25] Frydman, C. and Rangel, A. (2014). Debiasing the disposition effect by reducing the saliency of information about a stock's purchase price. Journal of Economic Behavior & Organization. 2014;107(11):541-52.
[26] Komai, M. and Grossman, P. (2006). Incentivizing experiments: Monetary rewards versus extra credits. Economics Faculty Working Papers 9, 2006.
[27] Wright, P.M., George, J.M., Farnsworth, S.R. and McMahan, G.C. (1993). Productivity and extra-role behavior: The effects of goals and incentives on spontaneous helping. Journal of Applied Psychology. 1993;78(3):374-81.
[28] Voslinsky, A. and Azar, O.H. (2021). Incentives in experimental economics. Journal of Behavioral and Experimental Economics. 2021;93:101706.
[29] Luccasen, III, R.A. and Thomas, M.K. (2014). Monetary incentives versus class credit: Evidence from a large classroom trust experiment. Economics Letters. 2014;123(2):232-5.
[30] Barberis, N. and Xiong, W. (2009). What drives the disposition effect? An analysis of a long-standing preference-based explanation. The Journal of finance. 2009;64(2):751-84.
[31] Poterba, J.M. and Summers, L.H. (1988). Mean reversion in stock prices: Evidence and implications. Journal of Financial Economics. 1988;22(1):27-59.
[32] Browne, M.J., Jäger, V., Richter, A. and Steinorth, P. (2021). Family changes and the willingness to take risks. Journal of Risk and Insurance. 2021.

[33] Innocenti, S., Clark, G.L, McGill, S. and Cuñado, J. (2019). The effect of past health events on intentions to purchase insurance: Evidence from 11 countries. Journal of Economic Psychology. 2019;74:102204.
[34] Henriksson, M. (2020). Essays on the disposition effect. Graduate Theses and Dissertations 2020.
[35] Yehuda, R. (2002). Post-traumatic stress disorder. New England journal of medicine. 2002; 346(2):108-14.
[36] Sacco, K., Galletto, V. and Blanzieri, E. (2003). How has the 9/11 terrorist attack influenced decision making? Applied Cognitive Psychology: The Official Journal of the Society for Applied Research in Memory and Cognition. 2003;17(9):1113-27.
[37] Park, J. and Banaji, M.R. (2000). Mood and heuristics: the influence of happy and sad states on sensitivity and bias in stereotyping. Journal of personality and social psychology. 2000;78(6):1005.
[38] Elsbach, K.D. and Barr, P.S. (1999). The effects of mood on individuals' use of structured decision protocols. Organization Science. 1999;10(2):181-98.
[39] Forte, G., Favieri, F., Tambelli, R. and Casagrande, M. (2020). COVID-19 pandemic in the Italian population: validation of a post-traumatic stress disorder questionnaire and prevalence of PTSD symptomatology. International Journal of Environmental Research and Public Health. 2020;17(11):4151.
[40] Weathers, F.W., Litz, B.T., Keane, T.M., Palmieri, P.A., Marx, B.P. and Schnurr, P.P. (2013). The PTSD checklist for DSM-5 (PCL-5). Scale available from the National Center for PTSD at: www.ptsd.va.gov 2013.
[41] Jeon, M., Yim, J.B. and Walker, B.N. (2011). An angry driver is not the same as a fearful driver: effects of specific negative emotions on risk perception, driving performance, and workload. Proceedings of the 3rd international conference on automotive user interfaces and interactive vehicular applications; 2011.
[42] Raghunathan, R. and Pham, M.T. (1999). All negative moods are not equal: Motivational influences of anxiety and sadness on decision making. Organizational behavior and human decision processes. 1999;79(1):56-77.
[43] Litvak, P.M., Lerner, J.S., Tiedens, L.Z. and Shonk, K. (2010). Fuel in the fire: How anger impacts judgment and decision-making. International handbook of anger: Springer; 2010. p. 287-310.
[44] Lerner, J.S. and Keltner. D. (2001). Fear, anger, and risk. Journal of personality and social psychology. 2001;81(1):146.
[45] Tiedens, L.Z. and Linton, S. (2001). Judgment under emotional certainty and uncertainty: the effects of specific emotions on information processing. Journal of personality and social psychology. 2001;81(6):973.
[46] DeSteno, D., Petty, R.E., Wegener, D.T. and Rucker, D.D. (2000). Beyond valence in the perception of likelihood: the role of emotion specificity. Journal of personality and social psychology. 2000;78(3):397.

[47] Lerner, J.S. and Tiedens, L.Z. (2006). Portrait of the angry decision maker: How appraisal tendencies shape anger's influence on cognition. Journal of behavioral decision making. 2006;19(2):115-37.
[48] Young, M.J, Tiedens, L., Jung, H. and Ming-Hong, T. (2009). Mad enough to see the other side: Anger and the confirmation bias. 22nd Annual IACM Conference Paper; 2009.
[49] Lerner, J.S., Gonzalez, R.M., Small, D.A. and Fischhoff, B. (2003). Effects of fear and anger on perceived risks of terrorism: A national field experiment. Psychological science. 2003;14(2):144-50.