A leopard never changes its spots: Persistency in retail investors' behavior

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Jan Hanousek, Jr.
University of Memphis,
and Mendel University in Brno
Email: jan.hanousek12@gmail.com

Jan Hanousek
CERGE-EI, Charles University and the Academy of Sciences, Prague,
Mendel University in Brno, and CEPR London
Email: jan.hanousek@cerge-ei.cz

Abstract

We analyze investor response after suffering shock to their portfolio value and the persistence of such a response. The results suggest that following the shock, investors tend to change diversification levels and the asset distribution across the asset types, but those effects are of a short-term nature. The investors will revert to their pre-shock levels after sufficient time passes or when the opposite shock washes out the initial shock. It suggests that each investor has a default investment strategy set by their personality, and the personality persistence is greater than the shock effect.

Keywords: Behavior finance, portfolio shocks: medium- and long-run effects, retail investors, stock market simulators, trading, and risk persistence

JEL Classification: C58, G11, G41

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Abstract

We analyze investor response after suffering shock to their portfolio value and the persistence of such a response. The results suggest that following the shock, investors tend to change diversification levels and the asset distribution across the asset types, but those effects are of a short-term nature. The investors will revert to their pre-shock levels after sufficient time passes or when the opposite shock washes out the initial shock. It suggests that each investor has a default investment strategy set by their personality, and the personality persistence is greater than the shock effect.

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1. Introduction:

Despite extensive research, behavioral finance still cannot adequately explain why individual investors react the way they do. While the literature classifies various patterns and traits associated with investor behavior (e.g., Barberis and Huang ,2001; Frydman et al, 2017; Kahneman and Tversky, 1979), there is only very limited research devoted to their interactions with external shocks such as sizeable profits and losses. In particular, the long-term effects of significant gains or losses on investor behavior have not yet been studied.

One of the main reasons for this lack of research is data limitations. Apart from the dataset used by Barber and Odean (2000), which is, however, outdated and not representative of the market today. To our best knowledge, there is no other dataset of individual investor transactions available in the US. In the present paper, we aim to fill the gap by using a unique paper-trading dataset that allows us to study individual investors' medium and long-term behavior. We use data on two different paper-trading competitions from Investopedia[1], representing large data set with more than 33 thousand personal accounts.

Our main hypotheses are related to persistency in individuals' behavior: Do investors have a personal default investment behavior that they retain? Is there an equilibrium-type mix of individual strategy, weights of the primary type of assets in the portfolio, attitudes towards risk, and diversification? If there is a considerable shock, where they lose or win a large percentage of their portfolio/capital, does this shock result in a change in their strategy? We hypothesize that their personality determines each investor's strategy and risk-seeking, and as a result, any changes

[1] The Investopedia competition uses real capital-market data to allow users the opportunity to learn how the stock market works, without the danger of losing real money. In the simulated environment, which fully mimics the real stock market, each player receives a starting capital of 100,000$ and their investment decisions are recoded. Open internet data contains user id, date of transaction, ticker of the stock (option), identification of long/short, use of margin account, etc. For a detailed data description, see the data section and the Internet appendix with the variable definitions.

are only temporary and will revert either after sufficient time has passed, or the losses/gains are sufficiently reduced.

These hypotheses are consistent with several established theories. First, they are consistent with the mental accounting theory, where the investors track the losses and gains. However, we would argue that the shocks and reaction to them, as observed in the literature (e.g., Barberis and Huang, 2001; Frydman et al., 2017), would be of a short-term nature. We expect that in the medium- and long-run investors will revert to their default behavior and make similarly risky investments and investment choices to those conducted before the shock. Second, these hypotheses are also in line with prospect theory in which, after a loss, investors reinvest in riskier assets to get back to "zero."

The datasets used in this study allow a deeper analysis of whether the riskier behavior persists in the medium and long run. Previous studies either use different data sources which mimic investor choices in stocks (e.g., mutual fund choices analyzed by Bailey et al., 2011) or employ laboratory experiments (e.g., Kahneman and Tversky, 1979). However, using any experimental data design makes it difficult to answer research questions regarding behavioral patterns and long-term effects (e.g., Mental accounting, Disposition effect, etc.). The difficulties arise because of a short time horizon and the end-of-the-game problem. While similar to experimental studies, Investopedia simulators do not suffer from the end-of-the-game problem since they do not have a specified end date, and participants can even enter at a later date. Furthermore, while the games do not offer any direct monetary reward, performing well should translate to success in the stock market, providing an indirect monetary reward. An important paper for analysis is a study by Sui and Wang (2022), which shows that investors behave similarly across simulated and real-life accounts. Moreover, it demonstrates that real accounts exhibit stronger biases and perform worse in their higher stakes.

Our results show that while there is an immediate reaction after the user suffers a shock, the shock is absorbed after sufficient time passes. This is consistent with our hypothesis and with the behavioral consistency theory. We observe this hypothesis holds across various measures of portfolio activity, such as risk, portfolio composition, and diversification. Furthermore, our results support the findings of Sui and Wang (2022) and suggest that simulated trading data can be used to proxy for individual trading activity.

This paper contributes to the literature in the following ways. Firstly, it contributes to the literature studying the effect of shocks on account value. Prior literature focuses on the immediate effects of shocks (see, e.g., Frydman et al., 2017; Kahneman and Tversky, 1979), and to the best of our knowledge, this paper is the first to analyze the long-term effects of shocks contrasted with the persistence of behavior. Secondly, the paper contributes to the literature on winning and losing streaks (see, e.g., Xu & Harvey, 2014; Clotfelter & Cook, 1993; Smith et al., 2009) by analyzing the effects of streaks and sizes of shocks. Lastly, it contributes to the literature studying the psychological profile of the investor (see, e.g., Rzeszutek et al., 2015; Baddeley et al., 2010) by analyzing the persistence of behavior (see, e.g., Epstein, 1979, 1980; Funder and Colvin, 1991) and the long-term effects of shocks to the portfolio value.

The paper is organized as follows: Section 2 summarizes previous research on the effects of shocks on the portfolio value and the behavior of individual investors and outlines the hypotheses of this paper. Section 3 describes the rules of trading competitions and data availability. Section 4 describes the methodology used and specifies the testable versions of the hypotheses. Section 5 describes the sample creation process and reports summary statistics. Section 6 reports the results and robustness tests. Finally, Section 7 concludes.

2. Literature review and hypothesis development

Despite extensive research, the retail investor is not yet fully understood. Much of the past literature suggests that retail investors are generally uninformed and make systematic mistakes (e.g., Barber and Odean, 2000, 2008). However, current literature suggests that retail investors could be skilled (e.g., Boehmer et al., 2021; Bradley et al., 2022). While the skill level is debated, some evidence shows that behavior and personality influence the investing choices of retail investors.[2]

Baddeley et al. (2010) reveal that empathic individuals have a greater tendency to follow the behavior of other investors (i.e., present herd behavior). On the other hand, Rzeszutek et al. (2015) show that extroverted, adventurous, and open to new experiences, individuals tend to make more rational financial decisions that are less affected by biases. Nevertheless, research does suggest that retail investors are more affected by personal biases and decision biases, such as disposition effects. (Odean, 1998; Frazzini, 2006)

While personality is difficult to categorize, the most well-established overall framework identifies the Big Five personality traits (Soldz and Vaillant, 1999; Costa and McCrae, 1994), which has already been used in financial research (e.g., Colbert et al., 2014; Peterson et al., 2003). Psychological research does suggest that these traits and, therefore, the personality as a whole is reasonably stable over a lifetime, and some traits are even considered heritable (Costa & McCrae,

[2] The effect of personality is not only tied to retail investors with questionable skills. An existing stream of research suggests that even CEOs and CFOs are affected by their personality biases, such as narcissism, overconfidence, or extraversion in their corporate decisions (e.g., Malmendier and Tate, 2008; Ham et al. 2017).

1988; Digman, 1989). Furthermore, a large number of well-cited studies in psychology research verify the idea of "behavioral consistency" (i.e., that individuals are more likely to adhere to the same principles throughout life, and their past behavior can be used to predict future behavior)[3]. As a result, even if the effects of behavior and personality on investing and risk-seeking are not fully understood, the personality traits are stable. Therefore, it suggests that the risk sought in investments and other investment decisions should be stable over time. This allows us to specify the first hypothesis.

Hypothesis H1: The average risk of an investment sought by the investor is stable over time.

However, many potential external factors can affect investment behavior in the short term. For example, it has been shown that large losses or gains impact investment behavior, a finding consistent with the theory of a rolling mental account described by Frydman et al. (2017). They argue that investors have rolling mental accounts, meaning that if they buy an asset shortly after selling another, they roll over the mental stock (losses or gains) from the previous stock to the new one. In a clinical setting, they also observed that when an investor sells an asset with a loss, they are more likely to reinvest in a riskier asset to get back to "zero." This phenomenon is also observed in poker by Smith et al. (2009), who show that poker players are likelier to be less cautious after a significant loss. This allows us to specify the second hypothesis:

Hypothesis H2: Large losses or gains cause short-term deviations in the investment strategy and risk being sought.

[3] See, e.g., Allport (1937, 1966), Epstein (1979, 1980); Funder and Colvin (1991).

Our central research hypothesis is that personality sets investors' risk-seeking and investment choices. While past research shows that past losses or gains affect risk-seeking (e.g., Kahneman and Tversky, 1979), it is again important to note that these observations were made either in a laboratory setting or in poker games that evidently suffer from end-game problems. Therefore, it is unclear how this will affect stock market investors long-term and whether these effects will persist. We argue that these deviations are only temporary and that the average riskiness of investment will revert to the value predetermined by the investor's personality and individual characteristics. An important result that supports our hypothesis is from Hoffman et al. (2013), who analyze the brokerage records and questionnaire data for investors during the 2008 crisis. They observe a decrease in investors' return expectations and risk tolerance during the worst months of the crisis, which later recovers towards the crisis end. Most importantly, individual investors continue to trade and do not de-risk their investment portfolios during the crisis, suggesting a certain persistence of risk-seeking behavior contrary to popular belief. This allows us to specify our central hypothesis.

Hypothesis H3: Investors revert to their default position after every shock after recouping their losses or after sufficient time has passed.

Another important note is that the shock size may not be the deciding factor. Kahneman and Tversky (1979) point out that even relatively small losses that follow a string of losses can cause substantial shock, while a loss following a win is "cushioned" by the previous gains. Cognitive psychology extensively researched the effects of losing and winning streaks using betting data (See, e.g., Xu & Harvey, 2014). There are two major associated theories. First, it is the hot hand fallacy (Gilovich et al., 1985), which is the tendency to bet more after winning because the bettor overestimates their chance of success. The second is the gambler's fallacy (Clotfelter & Cook, 1993), which is the opposite tendency to bet less since the bettor perceives a lower chance of successive wins. While the effect is not yet apparent, we argue that the size of the shock is only relevant up to a certain threshold to classify it as a considerable shock. After this threshold is reached, we hypothesize that the size of the shock will be dominated by the sequence, consistent with the winning and losing streak literature (e.g., Smith et al., 2009). This leads us to specify the following corollary:

Corollary 1: The sequence of shocks dominates the size of the shocks.

Additionally, the immediate response to the shock is also not understood. The gambling research suggests that individuals increase risk-seeking following losses and decrease it after large wins, as Smith et al. (2009) documented when studying poker players' reactions. This is in line with prospect theory, where individuals want to get back to "zero" following significant losses. However, the question remains whether this increase in risk-seeking is only caused by the fact that gambling games have the end game problem and that poker players are only subject to shocks to the individual and not wide shocks like those in the stock market. Furthermore, this increase in risk-seeking behavior is not consistent with the results of Hoffmann et al. (2013), who observe a decrease in risk tolerance following a large shock. Therefore, it is unclear which of these effects will persist in the long term.

The stock market does not face the end-of-the-game problem. Consequently, we hypothesize that stock investors tend to decrease their risk following negative shocks rather than increase it. The aim could be to maximize their longevity in investing and thereby increase their chances of winning and recouping their losses. This allows us to specify our following hypothesis:

Hypothesis H4: Following a NEGATIVE shock, investors are more likely to decrease the risk and or leverage sought until reverting to the default level of risk.

Lastly, personality and behavioral consistency play a prominent role even for CEOs, as documented by several studies (e.g., Cronqvist et al.,2012; Malmendier and Tate, 2008; Ham et al., 2017). Cronqvist et al. (2012) show that the CEO's personal leverage is a predictor of the leverage of a firm they manage. They refer to behavioral consistency theory, and their result supports the idea that individuals exhibit consistent behaviors across different situations and, when given the opportunity, impose their preferences. Following their hypothesis, we theorize that for traders in our sample, the initial trade is primarily driven by their personality because there is no incentive to use a different strategy since there were not yet any losses or gains, and there are no monetary rewards. As a result, the initial investment should be the same as the mean investment sought over time. This allows us to specify the last hypothesis:

Hypothesis H5: The first trade is the default and equal to the average risk being sought or the average investment.

3. Available information from trading competitions

3.1 Rules of the game

We use unique paper trading competition data collected from Investopedia to test the stock-market-related hypotheses. Despite the popularity of paper trading, its data is rarely used in research, even though it is very similar to laboratory-experiment data. To enroll in any of the games, a user must have a valid email address to sign up to Investopedia, but then can register into any number of games, both official and unofficial, or even start their own game. After enrolling, the user can then trade as if he was on a real stock market, with the market prices delayed by 20 minutes. Execution of trades is also delayed to avoid the possibility of users taking advantage of knowing the market prices beforehand. However, immediate transactions were only made possible in recent years thanks to technological advancements, so the simulator represents the stock market relatively well.

Each starting player is given 100,000$ starting capital[4] and can trade stocks and options on the US stock market with few limitations. Firstly, there is no opportunity to sell options contracts short; the options are not exercised at the expiration but only award their price at expiration. Secondly, option trades are only executed when the algorithm estimates enough tradeable contracts exist on the stock market to mimic the lower liquidity in option markets. And lastly, each user can use margin trading since every account is automatically a margin account. The maximum buying power is calculated as follows:

$$Buying\ power = Total\ Cash\ +\ (Long\ Stocks\ *\ 50\%)\ -\ (Shorted\ Stock\ *\ 150\%) \quad (1)$$

If the buying power decreases below zero, the trader will be issued a margin call and notified by email. After that, the user has two days to sell some assets to make his buying power positive. Otherwise, part of their portfolio will be automatically liquidated, with the most volatile positions being closed first. Using the formula above, we can see that the maximum available margin is 50% of the current market value of long stocks, but the user needs to hold 150% of the current market value of shorted stocks as collateral[5].

[4] All conditions mentioned only apply to the official Investopedia games listed there. Other games can have different rules that are decided on inception by the game organizer.

[5] The user is, therefore, defined as using a margin when either his cash is negative or if the difference between cash and one and a-half the value of shorted stocks is negative, with the maximum available margin being half the value of long stocks.

3.2 Available information and data verification

We collected trading data for the official Investopedia 2020 and 2021 trading competition from January 2, 2020, to July 18, 2021. we chose to focus on the two games for several reasons. Firstly, they are both official competitions that everyone can enter, even with the delay, and the game does not have an official end, meaning that the player can continue for as long as they want[6]. This setup attracts a lot of users and ensures that the simulator does not have end-of-the-game problems. Since there are no monetary rewards, the users are not incentivized to change their trading strategy. Secondly, Investopedia only allows past trades to be visible for two years, meaning that any competition starting earlier does not allow us to construct the users' holdings or observe the initial transactions.

For each of the users, we can identify the user id, and for each of their trades, we know the date and the time of the transaction, the direction of the trade, the executed price, commissions, if there are any, the quantity, the ticker and the current market value of the portfolio. Regarding options, we have all the identifying information, including type, expiration date, and strike price, which allows for unique identification. Therefore, it is possible to calculate the current market value of their portfolio and each asset type or position separately using stock and option prices. This approach allows us to decompose each portfolio shock into shocks to each asset type's holdings. Furthermore, we can track the ratio of the current market value of each asset type to the total portfolio value, as well as the number of opened positions. Each variable of interest is defined in the next section and in the Appendix.

One potential concern is whether the stock market simulator data corresponds to retail investors' actual behavior. While there is no direct monetary incentive in the paper competition,

[6] There are many users active in competitions that started in 2012.

an indirect incentive is present and visible. Success in the trading simulator increases the likelihood of having a profitable investment strategy, which means we should expect users in the game to perform as well as they can. One of the papers supporting the use of simulated data in the analysis of trading behavior is a paper by Sui and Wang (2022). They show that transaction activity in simulated accounts is very similar to real accounts.

Nevertheless, it is essential to empirically confirm that the stock market simulator activity corresponds to real retail trading.[7] To verify this, we use the approach of Boehmer, Jones, Zhang, and Zhang (2020) using TAQ data. They classify trades with TAQ exchange code “D” and prices just below a round penny (fraction of a cent between 0.6 and one) as retail purchases. Conversely, trades with exchange code “D” and prices just above a round penny (fraction of a cent between zero and 0.4) are classified as retail sales. It is important to note that these estimates are conservative since they omit retail trades that occur on exchanges as well as limit orders that are not executed immediately. However, this approach has a negligible type 1 error (i.e., trades classified as retail are very likely to be retail). Using this data, we can calculate the correlation between the number of accounts purchasing and selling each ticker using monthly data. This analysis is available in Table 1.

(Insert Table 1)

We can see that the average correlation between the retail activity and the stock market simulator is 75%, showing that there are considerable similarities between retail traders and simulator users[8]. It is important to note that this high correlation is observed even though retail investors are also

[7] It is an indirect test that the sample of simulator users is comparable to retail investors.
[8] Currently, we only have access to 10 months of 2020 data. After we obtain more recent data, we plan on conducting more detailed analysis using the entire sample of 2020-2021.

exposed to personal shocks and have varying levels of investing capital, whereas simulator users are all given 100,000$ at the start of the game. This result suggests that the Investopedia stock simulator is not far from actual retail activity, suggesting that further research using stock simulator data may uncover details of retail activity.

4. Methodology

4.1 Shock measures and behavior response proxies

The central hypotheses are focused on the shocks to the individual traders and the trader's response to them. Therefore, we need to identify the shocks and how to measure the response/change in investors' behavior. Furthermore, we need to define measures and proxies capturing the subsequent changes in the investor's portfolio, namely the portfolio-associated risk.

Since the data was obtained from the stock market simulator, there is no need to control for personal shocks to the individual, such as the need for liquidity, because the game serves as an example of the close economy. Money in the account cannot be refilled or withdrawn; cash and portfolio values are used to keep track of progress and provide a comparison to other traders in the game. Therefore, following prospect theory (Kahneman and Tversky, 1979), we will focus only on account/portfolio value shocks.

To measure the individual response to shocks, we need a proxy for the risk sought at the time of the investment. Therefore, we will employ beta-weighted deltas of the portfolio to approximate the portfolio risk, using the market as the baseline (e.g., Sebastian, 2017). Additionally, the weights of the asset types and their changes after the shock are good proxies for capturing an individual's portfolio risk adjustment. Furthermore, we plan to decompose the account shock into partial shocks to individual asset types. This will provide better and deeper data for analysis of the trader's response.[9]

As the access to complete stock market data information is not available in this version of the paper, we use several other variables to proxy an individual's portfolio risk. Given conventional wisdom (e.g., Engelberg et al., 2018), we can classify the main asset types by their associated risk: the least risky asset type is a long stock holding followed by short positions. The riskiest investment type is represented by option trading[10]. Thus, we suggest analyzing the ratio of dollar amount invested in long positions divided by the total amount invested in all asset types, which we dub the ratio of the long holding, which should proxy for any possible increase or decrease in the risk sought. Note that any significant change in the long-holding ratio should be interpreted as a change in the investment profile. It means that the investor is decreasing his exposure and risk sought, or increasing other investment assets, thus increasing the risk sought.

However, it is not clear whether a decrease in the ratio of long positions to the total number of positions is the result of trying to decrease the exposure on the stock market or of the trader increasing the number of positions in shorted stocks or options. Thus, we also analyze other ratios and variables, which could help disentangle the results of the long ratio.

Additional variables depicting the risk exposure of the individual investor are associated with the use of margin[11]. First, we define a dummy variable *marginD* equal to 1 during the trading

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[9] Unfortunately, at this moment, the full stock information data (prices, dividends, ticker changes) for 2021 are not yet available, and more critically, we do not have access to options data. After January 2022, we should have available complete stock market information, including options data for both of the two years.

[10] While options can be used to hedge, which would not classify them as risky, most of the option holdings are on stocks where the users do not hold the underlying asset.

[11] Note that the stock market simulator defines the available margin as 50% of the current value of long stocks in the portfolio. However, there is also a requirement to keep 150% value of shorted stocks in cash as collateral. If the margin increases above this level, there is a margin call and automatic selling of some assets with the highest exposure.

days when an investor is using margin to trade, and variable *marginU is* defined as the ratio of margin used to total available margin[12].

This version primarily uses a diversification/concentration measure based on portfolio weights associated with the purchasing prices. To describe the level of diversification, we use the Herfindahl-Hirschman Index (HHI) applied to the portfolio weights. The HHI (Hirschman, 1980) is defined as

$$HHI = \sum_{i=1}^{n} w_i^2 \tag{2}$$

Where w_i is the portfolio weight of asset *i*. Therefore, HHI equal to 10,000 implies that the trader only holds one asset in their portfolio, and lower numbers imply higher diversification. HHI is primarily used as a measure of market concentration in the case of the M&A[13], but it has been used as a measure of portfolio diversification (e.g., Goetzmann and Kumar, 2008; Blume and Friend, 1975).

However, HHI does not account for cross-correlations between particular stocks and options. While there is a generalized version of HHI that does account for cross-correlation (Vaibhav and Ramasubramanian, 2015), the measure is not widely used. Therefore, we will focus on a beta-weighted delta of portfolio risk in future versions to better measure each trader's risk. we will use the formulation of Sebastian (2017):

$$Beta\ Weighted\ Delta = \delta_1 \times \beta_1 \times \frac{(Stock\ price)_1}{Index\ price} + \delta_2 \times \beta_2 \times \frac{(Stock\ price)_2}{Index\ price} + \cdots \tag{3}$$

[12] Note that because of missing stock market prices, the extent of margin use, the variable *marginU*, cannot be properly evaluated and we temporarily use only the margin dummy *marginD*.

[13] From the regulatory stand point an HHI of less than 1,500 is associated with a competitive marketplace, an HHI of 1,500 to 2,500 is considered moderately concentrated, and an HHI of 2,500 or greater defines a highly concentrated market.

Where the δ_i is equal to 1, if the asset is a stock, or equal to option delta and β_i is the asset beta to the specified index. This measure allows us to directly compare the entire portfolio, including shorted stocks and options, with the specified index as a baseline for risk. Using this approach, we can capture the investment and risk profile of the trader that is not captured by the HH index, to evaluate better the changes caused by shocks to the portfolio value.

4.2 Identification and estimation strategy

Estimation and testing of the hypotheses of the various responses of the shock to the account value can be addressed using two different data structures. First, we can construct a time series panel of daily portfolio values using the daily stock market and option data, including asset type partitioning. This data can be used to properly model risk adjustment on a daily basis. We implicitly assume that the retail investor does not trade if he does not possess new information and/or if the portfolio value and risk are within the expected or anticipated patterns or boundaries. The reaction to the shock, and subsequent investor's risk adjustment over time, can be studied using time series dynamics, speed of adjustment (SOA), trend tests and change point detection, stationarity test, etc. Additionally, the data structure could shed light on testing the rational inattention hypotheses by analyzing when individual investors return to the market for active trading.[14] Furthermore, using daily data should allow us to test and control for lower user retention to verify the robustness of the results.

The second approach, used primarily in this version of the draft, is based on observations and variable values coming from the game, i.e., the data structure is represented only by the dates of active trading. In other words, the account value, asset structure, and portfolio riskiness measures are available only during active trading. Note that an investor usually makes several

[14] As we mentioned early, daily stock market and option prices are not yet available.

trades per day. We propose using the data value from the last trade of each investor's trading day. We implicitly assume that the day's last transaction anchors the new portfolio structure and close the reaction to the previous market and portfolio development. For this data structure, we will primarily use the difference-in-difference (DID) approach, represented first by the fixed effect regressions, improved version using regression adjustments methods, or average treatment effect on treated (ATET) estimation.

Using Active trading data, DID and ATET

Regression fixed effects models for shock responses

First, we use regression models with fixed effects corresponding to a different sequence of shocks. Employed specifications aim to model the behavior of investors following negative and positive shocks and test for a time decay after the respective shock(s).

To estimate the immediate effect of the shock and the time decay/personality persistence, we propose the following set of specifications:

$$\begin{aligned} y_i = {} & \alpha_0 + \beta_1 psDecay + \beta_2 psValue + \beta_3 nsDecay + \beta_4 nsDValue + \delta_1 nTrades + \\ & \delta_2 nTrades^2 + \tau_1 Year_i + \tau_2 Month_i + \upsilon_1 Time + \upsilon_2 Time^2 + \vartheta MarginD \end{aligned} \tag{4}$$

$$\begin{aligned} y_i = {} & \alpha_0 + \gamma_1 PP + \gamma_2 PN + \gamma_3 NP + \gamma_4 NN + \delta_1 nTrades + \delta_2 nTrades^2 + \tau_1 Year_i \\ & + \tau_2 Month_i + \upsilon_1 Time + \upsilon_2 Time^2 + \vartheta MarginD \end{aligned} \tag{5}$$

$$\begin{aligned} y_i = {} & \alpha_0 + \beta_1 psDecay + \beta_2 psValue + \beta_3 nsDecay + \beta_4 nsValue + \gamma_1 PP + \gamma_2 PN \\ & + \gamma_3 NP + \gamma_4 NN + \delta_1 nTrades + \delta_2 nTrades^2 + \tau_1 Year_i + \tau_2 Month_i \\ & + \upsilon_1 Time + \upsilon_2 Time^2 + \vartheta MarginD \end{aligned} \tag{6}$$

and a full specification with the individual fixed effects:

$$\begin{aligned} y_i = {} & \alpha_0 + \beta_1 psDecay + \beta_2 psValue + \beta_3 nsDecay + \beta_4 nsValue + \gamma_1 PP + \gamma_2 PN \\ & + \gamma_3 NP + \gamma_4 NN + \delta_1 nTrades + \delta_2 nTrades^2 + \tau_1 Year_i + \tau_2 Month_i \\ & + \upsilon_1 Time + \upsilon_2 Time^2 + \vartheta MarginD + \alpha_i \end{aligned} \tag{7}$$

For the sake of simplicity, we omit the standard error term in all specifications.

The dependent variable y_i is a proxy/measure of the riskiness of the individual investor. As discussed in the previous section y_i stands for *HHI* (Herfindahl-Hirschman Index), *max_prtfW* (Max portfolio weight), and *longR* (amount invested in long stocks, divided by total invested amount). The explanatory variables $psDecay$ and $nsDecay$ contain a positive (negative) shock decay series. This is equal to 0 before the first shock occurs and is equal to 1 in the time of the first shock. It then increases by one for each subsequent trading day until the next shock, when it turns again to 1. Similarly, the variables $psValue$ and $nsValue$ consist of the value of the positive (negative) portfolio change exceeding the threshold of 10 percent, again equal to zero before the first shock.

The set of dummy variables PP, PN, NP, and NN aim to capture the effect of a different combination of subsequent shocks. We use the following mnemonics: PP stands for two positive(P) shocks in the row, while NP is equal to one if the second to last shock was negative(N) while the last shock was positive, etc. This set of dummy variables allows us to estimate and control for differing effects of losing or winning streaks since, for example, the negative impact might be washed out by ensuing gains or amplified by ensuing losses, as pointed out by Kahneman and Tversky (1979). Year and $Month$ are dummy variables controlling time trading fixed effects for market conditions, while $nTrades$ ($nTrades^2$) controls for individual trading activity represented by the number of trades conducted during a given trading day. Similarly, the variable $Time$ ($Time^2$) controls for experience, the quadratic time effect linked to the number of active trading days of the individual investor since the first trade day. Finally, $MarginD$ is a dummy variable equal to 1 if the investor is currently using margin.

The specifications (4)-(6) can be used to test hypotheses developed in the previous section in the following sense. In terms of parameters hypotheses (2)-(4) correspond to the following:

Hypothesis H2 **H_0:** Shock does not cause any change

H_A: Shock causes a change in behavior

H_0: $\beta_2 = 0,\ \beta_4 = 0,\ \gamma_1 = 0\ ,\ \gamma_2 = 0,\ \gamma_3 = 0,\ \gamma_4 = 0$

H_1: $\beta_2 \neq 0,\ \beta_4 \neq 0,\ \gamma_1 \neq 0\ ,\ \gamma_2 \neq 0,\ \gamma_3 \neq 0,\ \gamma_4 \neq 0$

Hypothesis H3 **H_0:** Time decay has no effect

H_A: Time decay is in the opposite direction to the shock

H_0: $\beta_1 = 0, \beta_3 = 0,$

H_1: $\beta_1 > -\gamma_1,\ \beta_1 > -\gamma_3,\ \beta_1 > -\beta_2, \beta_3 > -\gamma_2,\ \beta_3 > -\gamma_4, \beta_3 > -\beta_4$

Corollary 1. **H_0:** Shock size dominates the sequence of shocks

H_1: Shock sequence dominates the size of shocks

H_0: $\beta_2 \geq \gamma_1, \beta_2 \geq \gamma_3, \beta_4 \geq \gamma_2, \beta_4 \geq \gamma_4$ H_1: $\beta_2 < \gamma_1, \beta_2 < \gamma_3, \beta_4 < \gamma_2, \beta_4 < \gamma_4$

Hypothesis 4. **H_0:** Following a negative shock, investors increase risk seeking

H_4: Following a negative shock, investors decrease risk seeking

H_0: $\gamma_2 \geq 0,\ \gamma_4 \geq 0$ H_0: $\gamma_2 < 0,\ \gamma_4 < 0$

Approach using control sample, matching techniques, and ATET

To strengthen the causal interpretation of the results, we perform a matching analysis of the behavior of traders experiencing a sequence of positive/negative shock(s). The idea is to compare the risk exposure of similar traders after the shock(s), where affected traders are in the treatment group, and those without a shock are in the control group. To evaluate the "causal" effect of the shock, we will use estimates of the so-called treatment effect on the treated (ATET).[15] The ATET

[15] See Heckman, Ichimura, & Todd (1997), Dehejia & Wahba (1999) for a starting point and introduction to this method.

approach controls for selection on observable differences across individuals; the estimated impacts of positive(negative) shocks or their sequence are based on comparisons of treated individuals experiencing the shock with their closest non-treated neighbors in the control group. Therefore, the methodological strength of the matching approach lies precisely in the weakness of the regression-fixed-effects estimators and vice versa. These methods are complementary, and if their estimated effects are similar, they would reinforce each other and enhance the credibility of the finding.[16]

Following the standard matching notation, let $D = 1$ if the individual experienced the first negative shock in his/her portfolio value and $D = 0$ if the portfolio value did not change more than the value defining the shock. In our specification, we define a shock when there is more than a 10% change in the portfolio value between two trade days of the individual. Similarly, Y_1 is the value of an individual with the shock and Y_0 is the portfolio value of changing gradually, with no shocks. Then an observed individual portfolio value is equal to

$$Y = DY_1 + (1 - D)\, Y_0 \tag{7}$$

The difference in portfolio value could be attributed to the treatment effect (i.e., to the shock) if the individual simultaneously has two portfolios – one with the shock and the other without a shock.

$$\Delta Y = Y_1 - \ Y_0 \tag{8}$$

Obviously, we only observe an individual with a shock in his/her portfolio or without a dramatic change in portfolio value. Mimicking the randomized laboratory experiment, ATET defines the best approximation of the difference. Ideally, we need to find a "twin," the nearest

[16] we refer to Abadie and Imbens, (2006, 2011) for the underlying theory, discussions and starting application guidance and Hitt & Frei (2002), Davies & Kim (2009), Wamser (2014) among others for finance applications.

neighbor for each treated individual – similar in the other characteristics (coordinates), yet not experiencing the shock in his portfolio. To address potential concerns that a change in individual portfolio risk could primarily be driven by the market idiosyncratic shocks, we need to match treated and control groups in exactly the same period, measured by year and month of the trading days.

Using this sorting and classification, we can calculate ATET for the riskiness of individuals with the shock in portfolio value. This design of the matching procedure ensures that we properly measure the effect of the shock in portfolio value on risk exposure while filtering out the effect of the change in market idiosyncratic risk.

In implementing the ATET procedure, we will always split the sample into two subsamples. The treatment group is represented by a negative (positive) shock or a specific sequence of shocks. The control group consists of individuals not experiencing any dramatic changes in their portfolio value within their trading days.[17] In estimating causal effects using observational data, one needs to carefully construct the control group so that the paired individuals would have similar covariate distributions and resemble as closely as possible a randomized experiment. We strive to achieve this by choosing well-matched samples of the treated and control groups, thereby reducing bias due to the covariates (e.g., Rosenbaum, 1999; Rubin, 2006).

The following scheme summarizes the Target and control groups and matching covariates for estimating the causal effects of specific sequences of shocks in an individual's portfolio value.

[17] See Heckman, Ichimura and Todd (1997), Dehejia and Wahba (1999) for a starting point and Hitt and Frei (2002), Davies and Kim (2009), Wamser (2014) among others for a finance application.

Scheme 1. Target and control group definitions for the randomized experiment, ATET

Effect	Treatment group	Control group
FN 1st negative shock	Individuals experiencing the first NEGATIVE shocks in the period after the shock, until the end of the game, or until the next shock (t-1)	Individuals without any shocks in portfolio value (comparing the same period)
FP 1st positive shock	Individuals experiencing the first POSITIVE shocks in the period after the shock, until the end of the game, or until the next shock (t-1)	
FN SN 1st negative shock 2nd positive shock	Individuals experiencing first NEGATIVE and second NEGATIVE shock. Period after the second shock, until the end of the game or until the next shock (t-1)	
FP SN 1st negative shock 2nd positive shock	Individuals experiencing first POSITIVE and second NEGATIVE shock. Period after the second shock, until the end of the game or until the next shock (t-1)	
….		
FP SP 1st negative shock 2nd positive shock	…	
…		

In each ATET, we would match individuals primarily on their frequency of market interactions variables t and t^2 which controls for the time effect measured by the active trading day of the individual investor. We would require an exact match in terms of the year and month of the trade(s) conducted.

5. Sample Construction and descriptive statistics

5.1 Sample Construction

Our starting sample consists of over 33 thousand users who made more than one trade and spanned the period from January 2, 2020, to July 18, 2021. In the starting sample, the average trader has made 6 (median) / 21 (mean) trades, and the time difference between his first and last trade was 4 (median) / 38 (mean). Our data has two limitations. Firstly, there is lower user retention, and many users leave after the first day of trading. While this may be consistent with reality, since many traders prefer passive investing (Stambaugh, 2014), this is beyond the scope of the paper since our hypotheses are for active traders. As a result, we will restrict the sample to only those traders who have traded on at least 15 different days. Secondly, there are several users whose accounts have made an enormous number of trades[18]. These outliers suggest that some individuals use the simulator to test their algorithmic bots, which exploit either a particular market or simulator insufficiency. Therefore, we restrict the sample to users who have made less than 20 trades per trade day on average. The final sample consists of 1,886 traders who meet the criteria. The median trader in our constructed sample has made 67 different trades over 156 days (i.e., the time difference between his first and last trade day).

5.2 Descriptive statistics and stylized facts

First, we need to analyze the asset preferences of users to understand the average investor in the sample. This analysis is available in Table 2 below:

(Insert Table 2)

In the entire sample (Panel A), we observe that most users (more than 75%) have only bought stocks long and never traded options or sold stocks short. Furthermore, we can see that there is a larger share of users who have only made 1 type of trade than those who have made mixed trades. However, this changes for the constructed sample. We can see that users who only traded long stocks decreased to 43%, which is even more drastic for other singular asset traders. Additionally, we can see that in the whole sample, we have many more users who were interested only in high-risky asset types, as more individuals were focused only on shorting stocks and/or buying options contracts. However, we can see that while the number of users who have tried option contracts is

[18] For example, one trader has made 54,325 trades, averaging 220 trades per calendar day.

similar in both the entire sample and the constructed sample, the number of users who have shorted at least once is much higher in the constructed sample. Similarly, we see a much higher fraction of individuals who have traded all three asset types. This suggests that traders who stay in the sample long enough are bound to experience shocks, which lead to them trying different asset types. However, it seems that in the constructed sample, users seem to prefer shorting stocks as opposed to options trading.

Nevertheless, Table 2 does not paint the complete picture because it is static, and we do not see how traders behave day after day. Therefore, in Table 3 below, we analyze the subsequent trade days and the decomposition based on the number of positions in each asset type.

(Insert Table 3)

We can see huge volumes and positions in the first two trade days, but the number of positions and trades begins to stabilize quickly, and the percentages stay consistent through the first ten days. Furthermore, we see that while in the beginning, the number of options positions is larger than the number of short positions, it switches on the 8^{th} trade day, with short positions having a larger trend. This is consistent with the idea that users decide to change their investment strategy and risk-seeking after the shocks occur. Short selling is preferred to stock options if the user wants to increase risk. On the other hand, users who start trading options contracts on the first day could be traders with a demand for lottery-like returns, as described by Kumar (2009). It is important to note that while the number of total positions is increasing for all observed days, which could suggest that there is no equilibrium, the trend may level out in the long run. Additionally, the traders in the sample are, on average, performing well, which means that their accounts are larger. This means that they would have to rebalance and change their portfolios to keep their desired levels of risk and exposure, which we could observe.

However, to understand the decision about when to change the investment strategy, i.e., asset type, we need to see the decomposition based on the profitability of users in the sample, which is detailed in Table 4.

(Insert Table 4)

We can see that even the median investor is making significant profits, again suggesting that retail investors could be skilled, consistent with (Bradley et al., 2022). We further see that there are far more significant outliers with positive returns, again consistent with this finding. It is not completely clear whether this skewness is caused by the fact that players in the competitions are more skilled, whether this is caused by the different passages of times between trades for each trader, or simply caused by the bull market in 2020 and 2021. In future versions of this paper, after stock price data becomes available, we will focus on constructing a test using daily data to check whether this is caused by the fact that less successful traders decide to quit the game and perhaps start again. However, it is important to note that leaving investing after losing a large portion of capital is not inconsistent with reality, as documented by Gurun et al. (2017).

To thoroughly analyze the returns, we must examine the cumulative returns after each trade and the profitability after each trade decision separately. These results are presented in Table 5.

(Insert Table 5)

This table reports the number of traders in the different returns categories. Interestingly, we see that after the first trade day, the number of traders in each category became reasonably stable, even in the outlier categories. We again see that the number of traders in the positive groups is larger than in the negative ones, but, in contrast to Table 4, the differences are not as large. Furthermore, we see that once we analyze the returns after each successive trade day, the number of traders in outlier groups is not as large as Table 4 would suggest, with the majority of traders earning returns between -5% and 5%.

6. Results

This section is structured as follows. First, Section 6.1 presents the results from testing Hypothesis 2 and 3, which analyzes both the immediate effect and the time decay. Section 6.2 presents the results from testing Corollary 1, decomposing the impact of shocks into the positive/negative sequences and the size effects. Finally, Section 6.3 presents the results of robustness checks, where we use the matched samples and the average treatment effect on the treated to verify the results.

6.1. Time decay tests

We estimate regression models of the time decay and immediate effect after the shocks on different measures of traders' risk. The models are described in Section 3 with models (3)-(6), which include an extensive list of standard control variables, but the focus is on the positive and negative time decay and the shock sequence variables, which test the specified hypotheses. The results are shown in Table 6.

(Insert Table 6)

In Table 6, we study the immediate effect of the shock based on both sizes and past sequences of shocks. We also study the time decay effect of the shock on three different dependent variables capturing various measures of risk. The first dependent variable is the Herfindahl-Hirschman (HH) index, which measures the level of asset diversification, with larger values implying lower diversification. We can see that both positive and negative shocks positively affect the dependent variable, which goes against the negative time trend. Since we are analyzing traders who have stayed in the competition, they are more likely to be successful, meaning that their portfolio value is in an uptrend on average, explaining the propensity to diversify, which leads to a positive time trend. However, we see that a shock will disrupt this trend, while the more time there is from the negative shock, the lesser the impact.

This is in line with our hypothesis of the persistence of behavior since we can see that while the shock does play a large role and can be disruptive in the short run, the trader will revert to their default investment strategy and level of risk. One important result that is apparent from the table is that the shock size is economically non-significant since the unit of size of the last shock is in decimal numbers. On the other hand, the sequence of shocks is much more significant. This suggests that either investor is resistant to the shock size after a certain level is reached or treats shocks the same way past a certain level, not focusing on the size. This is in line with Corollary 1 and the findings of Kahneman and Tversky (1979).

The interpretation for the first column is that as time goes on, the diversification level rises for each trader. However, if any shock occurs, there is a decrease in diversification since the higher the HH index, the less diversified the portfolio is. The negative shocks cause a stronger reaction than the positive ones, but both cause a decrease in diversification, with the least disruptive being two consequent positive shocks. After the shock, there is apparent time decay, going in the direction of the time trend, opposite to the shock’s immediate effect. This suggests that as time passes from the negative shock, the investor starts reverting back to his/her previous behavior. However, it is important to note that it is not yet clear whether the shock leads to an increase or decrease in risk since the change in the HH index after a positive shock could be the result of profit taking, and after a negative shock, it could be the investor reducing his/her smaller positions on the market, while keeping the major ones. Therefore, both of these effects could be the result of a decrease in risk sought. We will work on disentangling these effects in future versions.

However, the HH index only measures one type of portfolio risk. In the previous section, we could see that almost all traders trade long stocks, which is consistent with reality and the common knowledge that long stocks are viewed as the least risky asset type on the stock market (Engelberg et al., 2018). As a result, we could view deviations from purchasing stocks into other asset types as an increase in risk-seeking behavior. The second dependent variable we analyze is the ratio of the dollar amount invested in long stocks divided by the dollar amounts of all types of equity.

We can again see that a shock causes a strong reaction, in this case lowering the amount invested in long stocks, but as time passes from the shock, the effect is canceled out. Furthermore, we again see that omitting the sequence of shocks leads to investors underestimating the shock's immediate impact and that the shock's size is economically insignificant. However, unlike the HH index, we can see that the time effect, in this case, is opposite to the time trend. While this may be puzzling, it is important to note that this may suggest there is an equilibrium that can be reached for the individual and that for a sufficient time after the shock, the trends cancel out. These results again support our hypothesis for the persistence of behavior and also for the existence of a baseline, which the trader wants to keep.

The last variable analyzed is the maximum portfolio weight, which captures a different risk-seeking type. The investor decides to maximize his return by focusing only on the most profitable position he observes. We can see that following any shock, there is an increase in concentration, and, again, the resulting effect is driven by the sequence rather than the size. Interestingly, here we first see that following two positive shocks, there is a decrease in the holding of the most concentrated position, suggesting that there might be a decrease in this kind of risk after a win.

It is important to note that while in all estimations, we see that the time trend is both statistically and economically significant, the question remains whether it is simply significant because we cannot control for the size of the account without absorbing the effect of the shock. The user might have a specified level of diversification, which he is simply trying to keep and has to readjust based on the level of his buying power. We will work on disentangling these effects in a future version once stock and option data prices become available.

6.2. Shock sequence tests

This section is focused on testing how the sequence of shocks affects the immediate effect, using regression models on restricted data samples. When analyzing the effect of the first shock, we restrict the regression sample up to when the second shock occurs. Similarly, when analyzing the second shock, we restrict the sample until the third shock occurs. Furthermore, when analyzing the effect after the second shock, we split the sample based on the direction of the first shock. This allows us to study the effect of the negative shock if the trader has already suffered a negative shock.

However, we need to analyze the sequence more closely and separately to understand the immediate effect of shocks better. The result of this analysis is available in Table 7:

(Insert Table 7)

When again analyzing the HH index, we can see that the first negative shock causes a strong decrease in diversification, while the positive shock does not cause any reaction. However, when we study the second shock, we can see that the reaction after a negative shock, if the first one was positive, is economically much larger than for the first negative shock. This is consistent with past research (Gervais and Odean, 2001), since investors will be overconfident in their abilities after a positive shock, and the negative shock will be more damaging. Interestingly, we can see that a positive shock following a negative shock leads to increased diversification. Taken together with the first column, this again supports our hypothesis. After the first negative shock, the user decides to decrease diversification, going against the time trend, but after he "gets even", he increases his diversification.

The margin interaction with the sequence variables controls for a different measure of risk. We can see that the interaction goes in the opposite direction of the sequence variable, which may be explained by the fact that the user does not increase risk in only one dimension. The user might decide to decrease diversification slightly but starts using margin, which is a sign of an increase in risk-seeking. However, because of limited data availability, a deeper analysis of the use of margin will be conducted in a future version of this paper.

It is again important to mention that an increase in the HH index does not necessarily mean the user is seeking more risk. It could be the result of them exiting non-major positions, which would actually be the result of a decrease in risk sought. We will work on disentangling the effects in future versions.

In the second section, we again analyze the maximum portfolio weight as another proxy for the user's risk profile. Similarly, we can see that following a negative shock, there is an increase in the concentration of the portfolio, but following a positive shock, there is a decrease. Both of these observations are in line with the hypotheses, again showing that the shocks cause a reaction but that time trend and time after the shocks will eventually absorb the effect. Interestingly, we again see that a negative shock following a positive shock causes a very strong reaction. In this model, the effect is twice as large as when the first shock is negative. Similarly, we also see that the decrease in the maximum weight when the user suffers a positive shock preceded by a negative shock is much larger than when the first shock was negative. This is consistent with the idea that the user wants to return to their preferred risk level and only change their behavior based on shocks. However, this change of behavior is not permanent and only lasts until the next shock erases the effect of the first or when sufficient time passes, as is observable both in this table with the time trend or in the previous table with the time decay variable.

6.3. Estimating reactions to the shock(s) using ATET

In this section, we present the results of estimated shocks and their sequence using a randomized experiment approach – ATET. The target group is always defined as the group of individuals experiencing positive/negative shocks or their sequence. We focus solely on the first two shocks for clarity of definition and identification. This approach has an advantage for interpretation as we observe the individuals from the beginning, and their first reaction to the shock could be the best candidate for randomization and mimicking the laboratory-controlled experiments. Also, given the size of the data for this setup, we can control for the exact same period of trading, and the covariates *Time* (*Time*^{2}) and *MarginD*, used for the "closeness" of the match, convey the relevant information regarding additional controls for the traders' experience, the interaction of the market and control for the risk attitude.

Precise definitions of the target and control groups for each shock and sequence of shocks are defined in Scheme 1. The results of the estimations are summarized in Table 8 below. In the interest of space, details of the covariates balancing tests are not presented here but are available on request. Instead, we show in Figure 1 a graphical comparison of the statistical distribution of the covariates for the raw and matched samples.

(Insert Figure 1)

Figure 1 shows a relatively good pattern in balancing the used covariates. Statistical summaries reveal satisfactory closeness in means; however, the variance of the covariates in some cases shows a variance ratio exceeding the recommended bound of 1.2.[19]

(Insert Table 8)

In Panel A of Table 8, we can see the different reactions after the first positive and negative shocks, respectively. While the reactions are the same in terms of signs, they differ statistically in terms of magnitudes. Note that the reactions are with respect to those individuals not experiencing any shocks, and they hold primarily long positions, as we can see from Panel C. We can compare the estimated ATET with the corresponding coefficients presented in Table 6 and see that the directions (signs) of the effects do not change. A negative shock generally implies a shock in the direction of increased risk, which is the opposite direction of the time trend, while a positive shock is either in the same direction but of lesser magnitude or in the opposite direction.

For example, the first variable of interest, the HH index, shows an increasing effect after negative and positive shocks; however, the effect of the positive shock is about 65 percent lower than the negative one. The result of the increased maximum portfolio weight confirms the reaction after the first shock. Again, the positive shock causes an increase in maximum portfolio weight, but about 77 percent lower. However, the reasons for these adjustments are not clear. While the increase in the concentration measure after the negative shock could be primarily driven by selling other non-performing assets, the positive shock likely increases the confidence of the individual and leads to an increase in the core asset(s) position; the effects are not yet certain. We will analyze

[19] This control check will be more scrutinized when complete data, including access to 2021 stock market data and options become available. The resulting dataset would contain more users and data points and would allow for more robust controls in the randomized experimental design.

these effects further in future versions. The last variable, the share of long holdings, decreases significantly after the negative shock, which could again indicate the increase in risky positions by adjusting the portfolio structure more towards short positions and options representing riskier assets. The first positive shock does not imply any asset structure change; after the first positive shock, the individuals keep the same ratio of the long stock positions as the individuals without any shocks.

More complex results can be seen in Panel B, Table 8. Let us first analyze the reaction to the second shock in the same direction. We expect that the second subsequent negative shock will magnify the effects observed after the first negative shock. Therefore, the second shock could be driving individuals to sell losing assets. We observe an increase in the weights of the core assets and a dramatic reduction of the long holdings, potentially leading to a large increase in the portfolios' riskiness. The second positive shock confirms the increase in the investors' confidence as the portfolio's concentration is reduced. This step could mostly be driven by an increase in cash invested and by using the margin to trade. The lower ratio of long stock position could be explained by an increase in confidence and the addition of options, mimicking the direction of their successful investment strategies.

Mixed shocks reveal opposite adjustments, which certainly reflect similar patterns to those seen for the first shocks. Following the first negative shock, the second positive shock likely brings back the investors' lost confidence. Primarily the concentration measures are slightly increased, but the increase is not statistically significant. We can see an additional increase in the portfolios' riskiness, although by about 75 percent lower than that after two negative shocks. We can speculate that this increase primarily extends the use of riskier assets in the direction of the positive shock. We consider it to be particularly interesting that if the sequence was first positive and second negative, the effect is the strongest for the concentration measures, even stronger than both negative. This could result in an investor reducing non-major positions and only focusing on smaller groups of assets. However, the risky structure proxied by the long holding ratio remains unchanged with respect to the control group. This is consistent with Gervais and Odean (2001), who show that investors can become overconfident after a success, meaning that a significant negative shock can be more damaging.

7. Conclusion

This paper analyzes the behavior of retail investors after suffering shocks to their portfolios and whether the consistency of behavior leads to investors reverting to the default levels of risk. The analysis is conducted using data from paper trading competitions on Investopedia, which are stock market simulators for individuals to learn about stock market trading without the risk of losing money. Using both difference-in-difference and treatment effects on the treated approaches, we show that while there is an immediate reaction after the user suffers a shock, the shock is absorbed after sufficient time passes. The negative shock causes much stronger responses. However, similarly to Kahneman and Tversky (1979), we observe that the sequence of shocks dominates the effect of the size of the shock. Furthermore, the strongest reaction is observed when the first shock the user experiences is a positive shock and the second one is negative. This is consistent with Gervais and Odean (2001), who show that investors can become overconfident in their abilities, which means that negative shocks can be more impactful.

While the explanations for the behavior of retail investors are not yet clear, our results suggest that the overall effects of shocks on their portfolios could be overestimated. Data limitations of other studies observing individuals only for a short period could explain our findings (e.g., Frydman et al., 2018; Thaler and Johnson. 1990). Once the time decay effect of the shock is accounted for, there is evidence that each investor has a default investment and risk profile that they return to after every shock. This is consistent with the behavioral consistency theory since psychological research shows that behavior and personality are highly stable over time (e.g., Costa & McCrae, 1988; Digman, 1989). Furthermore, Sui and Wang (2022) show that individuals tend to be more rational and exhibit fewer biases in their simulated trading accounts compared to their real accounts. This would suggest that individuals might exhibit an even stronger tendency to return to their default trading strategy when they trade using real money. This paper's results show that retail investors' behavior is not yet clearly understood, and the area warrants more research.

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Appendix 1 - Variable description

Variables	Descriptions
Measures of Risk	
Long Invested Ratio	The dollar amount invested in long stocks, divided by the total dollar amount invested in all asset types, is reported in percentages. Equal to 0 when the trader only holds cash. Source: Investopedia
HH index	Herfindahl-Hirschman Index (HHI) was applied on the portfolio weights, using the amounts invested in each different position. Calculated as $HHI = \sum_{i=1}^{n} w_i^2$, where w_i is the weight of the position in the portfolio, in percentage. The lower the number, the higher the diversification, while the max of 10,000 means that the user only has one position. Source: Investopedia
Max portfolio weight	The maximum portfolio weight is calculated using the amounts invested in each position. Reported in percentages. Source: Investopedia
Beta-weighted delta	The beta of the portfolio, using the approach by Sebastian (2017), using the following formula: $$Beta\ Weighted\ Delta = \sum \delta_i \times \beta_i \times \frac{(Stock\ price)_i}{Index\ price}$$ Where the δ_i is equal to 1, if the asset is a stock, or equal to option delta and β_i is the asset beta to the specified index. Source: CRSP and CBOE. **To be done**.
Long Holdings Ratio	The current market value of long stocks position, divided by total dollar amount invested in all asset types. Equal to 0 when the trader only holds cash. Source: CRSP. **To be done**.
MarginU	The amount of margin the investor is currently using, is divided by the total margin available to the investor. The maximum margin available is defined by the competition as 50% of the current market value of long stocks held by the investor. Source: CRSP. **To be done**.
Shock Time Variables	
Shock Indicator	The dummy variable is equal to one if the percentage change in portfolio value since the last day the user has traded is either greater than +10% or lower than -10%. Source: Investopedia
(ng/ps) Decay	The time variable indicates the number of days the trader has traded since the last shock occurred. The series starts with a value equal to 1 at the day of the shock, increasing until another shock happens, after which it starts again at 1. Before the first shock, the series is equal to 0. This series is also calculated separately for the time since last negative shock (Ng Decay) and the last positive shock (Ps Decay). Source: Investopedia.
(ng/ps) Value	Variable indicating the size change that occurred during the last shock. Values are reported in percentages. Before the first shock, this variable

	is equal to 0. This variable is also generated for only negative shocks (ng Value) and only positive shocks (ps Value). Source: Investopedia.
Shock Sequence Variables	
BF	The dummy variable is equal to one Before the First (BF) shock occurs. Source: Investopedia.
AF (*AFN*, *AFP*)	The dummy variable is equal to one After the First (AF) shock but before the second shock, including the day of the first shock. Similarly defined for After First Negative (AFN) shock and After First Positive (AFP) shock. Source: Investopedia
AS (*ASN*, *ASP*)	The dummy variable is equal to one After the Second (AS) shock but before the third shock, including the day of the second shock. Similarly defined for After Second Negative (ASN) shock and After Second Positive (ASP) shock. Source: Investopedia
AT (*ATP*, *ATN*)	The dummy variable is equal to one After the Third (AT) shock but before the fourth shock, including the day of the third shock. Similarly defined for After the Third Negative (ATN) shock and After the Third Positive (ATP) shock. Source: Investopedia
PP	The dummy variable indicates that the two preceding shocks were both positive. Source: Investopedia
PN	The dummy variable indicates that the second to last shock was positive and the last shock was negative. Source: Investopedia
NP	The dummy variable indicates that the second to last shock was negative and the last shock was positive. Source: Investopedia
NN	The dummy variable indicates that the two preceding shocks were both negative. Source: Investopedia
Control Variables	
Time	Calculated as the number of days the user has traded since the start to the specified day. Source: Investopedia
Cash to Invested ratio	The dollar amount of cash the user holds is divided by the total amount invested in all asset types. Source: Investopedia
Cash Holdings ratio	The dollar amount of cash the user is holding is divided by the current account market value. Source: CRSP. **To be done**.
MarginD	The dummy variable is equal to one if the trader is currently utilizing margin. Source: Investopedia
NTrades	The number of trades the user has conducted on the given day. Source: Investopedia

Table 1 – Stock market simulator correlation with actual data

Table 1 shows the correlation between the number of purchases and sales in the stock market simulator and retail activity. Using TAQ data, the retail activity was estimated using the approach by of Boehmer, Jones, Zhang, and Zhang (2020). They classify trades with TAQ exchange code “D” and prices just below a round penny (fraction of a cent between 0.6 and one) as retail purchases. Conversely, trades with exchange code “D” and prices just above a round penny (fraction of a cent between zero and 0.4) are classified as retail sales. The number in the table corresponds to the correlation between the stocks traded in the given month in both databases. Due to data limitations, we only have January to October 2020.

	January	February	March	April	May	June	July	August	September	October	Mean
Number of retail purchases	77.00%	84.10%	70.80%	71.10%	69.80%	65.80%	68.00%	82.30%	90.60%	76.10%	75.56%
Number of retail sales	71.90%	85.50%	68.90%	68.80%	73.30%	68.10%	71.40%	78.40%	90.10%	77.90%	75.43%

Table 2 – Trader type decomposition

Table 1 decomposes each trader based on his trading history and preferences for trading different types of assets. The first row shows the number of traders for the given combination of trading types, the second row shows the percentage of the total sample, and the row percentage is in parentheses. Cells for each crossing of row and diagonal strategies count the number (percentages) of investors keeping these strategies. Diagonal cells correspond to investors who never change their strategies, i.e., always investing in long stocks, shorting the stocks, and buying the long options. Marginal distributions are described in the right column and in the last row, with the previous value representing the total number of users who have traded only two asset types at most.

Panel A: Full Sample

	Trading types			
	Long stock	Short stock	Long Option	Total
Long stock	25,246	3,628	2,262	31,136
	75.61% (81.08%)	10.87% (11.65%)	6.77% (7.26%)	93.25%
Short stock	3,628	149	106	3,883
	10.87% (93.43%)	0.45% (3.84%)	0.32% (2.73%)	11.63%
Long Option	2,262	106	1,127	3,495
	6.77% (64.72%)	0.32% (3.03%)	3.38% (32.25%)	10.47%
Total	31,136	3,883	3,495	32,518
	93.25%	11.63%	10.47%	97.39%

Panel A presents the results for the entire sample of users who have traded more than once, consisting of 33,390 users. The users who have traded all three types of assets are the difference between the reported total and the sample size, which is 872 individuals, corresponding to 2.61% of the sample.

Panel B: Constructed Sample

	Trading types			
	Long stock	Short stock	Long Option	Total
Long stock	816	583	186	1,585
	43.27% (51.48%)	30.91% (36.78%)	9.86% (11.74%)	84.04%
Short stock	583	5	5	593
	30.91% (98.31%)	0.27% (0.84%)	0.27% (0.84%)	31.44%
Long Option	186	5	25	216
	9.86% (86.11%)	0.27% (2.31%)	1.33% (11.57%)	11.45%
Total	1,585	593	216	1,620
	84.04%	31.44%	11.45%	85.90%

Panel B corresponds to a reduced sample of 1,886 users who have traded on at least 15 days with removed bots. The users who have traded all three types of assets are the difference between the reported total and the sample size, which is 266 individuals, corresponding to 14.10% of the sample.

Table 3 – Dynamic Sequence of Trade Days

This table shows the decomposition of opened positions for each individual's first ten trade days. The decomposition is done for all three asset types (stock long, stock short, and option short), as well as the total number of positions currently opened on the day and the total number of trades conducted on the given day. For every asset type, the first row shows the number of positions, and the second row shows the percentage of total positions opened.

	Number of Long positions	Number of Short positions	Number of Option positions	Total number of positions	Total number of trades
Trade day 1	8,675	334	410	9,419	11,856
	92.10%	3.55%	4.35%		
Trade day 2	11,764	501	616	12,881	8,675
	91.33%	3.89%	4.78%		
Trade day 3	13,266	585	676	14,527	7,665
	91.32%	4.03%	4.65%		
Trade day 4	14,280	666	711	15,657	7,302
	91.21%	4.25%	4.54%		
Trade day 5	15,023	646	762	16,431	7,280
	91.43%	3.93%	4.64%		
Trade day 6	15,634	739	771	17,144	6,779
	91.19%	4.31%	4.50%		
Trade day 7	15,988	768	774	17,530	6,665
	91.20%	4.38%	4.42%		
Trade day 8	16,296	844	790	17,930	6,835
	90.89%	4.71%	4.41%		
Trade day 9	16,722	875	797	18,394	6,938
	90.91%	4.76%	4.33%		
Trade day 10	17,081	872	796	18,749	6,629
	91.10%	4.65%	4.25%		

This table corresponds to the reduced sample of 1,886 users who traded on at least 15 days, with removed bots.

Table 4 – Cumulative portfolio return analysis

This table shows the different statistics for cumulative return after each of the first ten trade days, including mean, median, standard deviations, and the different quantiles. The values in the table are in percentages, and the return is measured from the individual's game start, where the starting capital is 100,000$.

	Cumulative return up to the trade								
Trade number	Mean	Standard deviation	5%	10%	25%	Median	75%	90%	95%
Trade day 1	0.17%	3.47	-1.37%	-0.75%	-0.16%	-0.01%	0.08%	0.67%	1.58%
Trade day 2	3.92%	55.8	-6.24%	-2.95%	-0.61%	0.08%	1.94%	7.05%	14.9%
Trade day 3	14.9%	119	-7.62%	-4.04%	-0.68%	0.62%	4.51%	15.90%	37.4%
Trade day 4	22.7%	173	-8.87%	-4.86%	-0.63%	1.35%	7.54%	24.30%	59.2%
Trade day 5	47.3%	590	-9.68%	-4.45%	-0.566%	2.27%	10.4%	38%	107%
Trade day 6	83.8%	1885	-9.89%	-4.4%	-0.287%	3.29%	13.5%	45.6%	117%
Trade day 7	107%	2390	-9.96%	-4.63%	-0.291%	4.19%	17.9%	60.1%	153%
Trade day 8	131%	2870	-11.10%	-4.11%	0.10%	5.63%	22.00%	77.80%	184.00%
Trade day 9	156%	2628	-10.20%	-4.55%	0.21%	6.68%	27.20%	99.30%	223.00%
Trade day 10	179%	2638	-10.60%	-4.52%	0.57%	8.45%	32.60%	114.00%	286.00%

This table corresponds to the reduced sample of 1,886 users who traded on at least 15 days, with removed bots.

Table 5 – Dynamic portfolio return

The table shows the decomposition of the profitability of the entire portfolio for the first ten trade days, where the profitability of the portfolio is calculated as the return until the following trade. The first column corresponds to traders with a loss greater than 10%, while the next column corresponds to traders with losses between 10 and 5 %. For each trade, we report the number of traders in the first row and the row percentage in the second row.

	Period return				
Trade	$< -10\%$	$< -5\%$	0	$> 5\%$	$> 10\%$
1.->2.	50	68	1520	120	128
	2.65%	3.61%	80.59%	6.36%	6.79%
2.->3.	46	73	1476	118	173
	2.44%	3.87%	78.26%	6.26%	9.17%
3.->4.	56	70	1459	140	161
	2.97%	3.71%	77.36%	7.42%	8.54%
4.->5.	53	74	1451	133	175
	2.81%	3.92%	76.94%	7.05%	9.28%
5.->6.	57	88	1430	142	169
	3.02%	4.67%	75.82%	7.53%	8.96%
6.->7.	50	97	1398	154	187
	2.65%	5.14%	74.13%	8.17%	9.92%
7.->8.	63	92	1395	143	193
	3.34%	4.88%	73.97%	7.58%	10.23%
8.->9.	62	90	1394	143	197
	3.29%	4.77%	73.91%	7.58%	10.45%
9.->10.	64	81	1386	147	208
	3.39%	4.29%	73.49%	7.79%	11.03%
10.->11.	60	86	1396	163	181
	3.18%	4.56%	74.02%	8.64%	9.60%

This table corresponds to the reduced sample of 1,886 users who traded on at least 15 days, with removed bots.

Table 6 – Time decay effects after the shocks

	Dependent variable					
	HH index		Long Invested Ratio		Max portfolio weight	
Ps Decay	-1.971	-0.486	0.166***	0.148***	-0.021*	-0.003
	(1.217)	(1.194)	(0.014)	(0.013)	(0.012)	(0.012)
Ps Value	0.117***	0.132***	0.001***	0.001***	0.001***	0.001***
	(0.029)	(0.029)	(0.000)	(0.000)	(0.000)	(0.000)
Ng Decay	-4.775***	-6.385***	0.078***	0.088***	-0.031**	-0.051***
	(1.182)	(1.162)	(0.013)	(0.013)	(0.012)	(0.012)
Ng Value	-0.079**	-0.070*	-0.001***	-0.001***	-0.001**	-0.001**
	(0.037)	(0.037)	(0.000)	(0.000)	(0.000)	(0.000)
PP	9.330		-3.494***		-0.805**	
	(33.962)		(0.376)		(0.346)	
PN	301.5***		-5.529***		2.813***	
	(45.1)		(0.493)		(0.460)	
NP	151.6***		-1.646***		1.135**	
	(43.8)		(0.485)		(0.447)	
NN	345.0***		-6.984***		2.938***	
	(72.2)		(0.794)		(0.736)	
Time	-9.565***	-8.364***	-0.278***	-0.316***	-0.152***	-0.147***
	(1.346)	(1.302)	(0.015)	(0.014)	(0.014)	(0.013)
$Time^2$	0.022***	0.016***	0.001***	0.001***	0.000***	0.000***
	(0.006)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	3343.3***	3300.6***	82.870***	84.017***	45.355***	45.073***
	(55.7)	(55.1)	(0.615)	(0.609)	(0.567)	(0.561)
R^2	0.414	0.413	0.588	0.587	0.417	0.416
Observations (N)	56,277	56,277	56,863	56,863	56,277	56,277

Each regression contains the following control variables: Number of trades, Number of Trades squared, MarginD, Year and month effects, and individual fixed effects. The number of observations corresponds to the size of the constructed sample. Variable definitions are provided in Appendix 1. we report the standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.

Table 7 – Sequence and size of shocks

	Portfolio HH			Max weight		
Subsample	1st shock	2nd shock	2nd shock	1st shock	2nd shock	2nd shock
Sequence		FP	FN		FP	FN
AFP	-0.449			-1.777***		
	(50.803)			(0.517)		
AFN	338.477***			2.759**		
	(112.290)			(1.143)		
ASP		-13.270	-233.674**		0.020	-3.707***
		(61.120)	(106.328)		(0.624)	(1.069)
ASN		597.287***	-165.574		7.245***	-2.583
		(123.691)	(319.588)		(1.263)	(3.212)
AFP x MarginD	19.913			2.271***		
	(72.358)			(0.737)		
AFN x MarginD	-106.623			0.617		
	(157.776)			(1.606)		
ASP x MarginD		-74.181	380.787**		-1.445	6.190***
		(94.137)	(173.556)		(0.961)	(1.744)
ASN x MarginD		-309.273**	629.787		-2.070	5.372
		(155.827)	(512.517)		(1.591)	(5.151)
Time	-16.420***	-13.742***	-5.145	-0.221***	-0.207***	-0.184***
	(2.658)	(2.380)	(5.264)	(0.027)	(0.024)	(0.053)
Time^2	0.037**	0.024*	-0.049	0.001***	0.001***	0.001**
	(0.016)	(0.014)	(0.040)	(0.000)	(0.000)	(0.000)
Cash Ratio	0.813***	0.425***	1.350***	0.010***	0.004***	0.021***
	(0.095)	(0.054)	(0.316)	(0.001)	(0.001)	(0.003)
MarginD	-596.692***	-585.499***	-646.342***	-6.977***	-5.891***	-7.399***
	(45.326)	(40.885)	(77.463)	(0.461)	(0.417)	(0.779)
Constant	2933.626***	3019.611***	3095.907***	43.349***	43.221***	44.723***
	(109.555)	(91.852)	(210.439)	(1.115)	(0.938)	(2.115)
R^2	0.458	0.442	0.489	0.474	0.453	0.503
Observations (N)	22,567	23,111	5,513	22,567	23,111	5,513

Each regression contains the following control variables: Number of trades, Number of Trades squared, MarginD, Year and month effects, and individual fixed effects. For each section, the first column corresponds to observations only up to the second shock, while the other two columns correspond to a sample from the beginning until the third shock occurs. Variable definitions are provided in Appendix 1. we report the standard errors in parentheses. ***, **, and * denote statistical significance at 1%, 5% and 10%, respectively.

Table 8: Change of Individual Riskiness after Shocks using the Average Treatment Effect on the Treated (ATET)

This table reports the results of the nearest neighbor matching (Abadie and Imbens, 2006, 2011), computed using the Stata procedure *teffect*. The treated group is defined as those with the first negative (positive) shock *after* the shock in a given sequence. Matching was done in exactly the same trading period (year, month). Other matching covariates were $Time$ ($Time^2$) the active trading day of the individual investor and $MarginD$ - the dummy equal to 1 if the investor is currently using margin. The first row of the difference contains ATET; robust standard errors are in parentheses below. For the interest of space, balancing summaries are not presented here but are available upon request. Variable definitions are provided in Appendix 1. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Panel A: Average Treatment Effect on the Treated (ATET) for the First Shocks

Variable	1st Negative	1st Positive
Difference, HHI Individuals after the sequence of shocks – Individuals without a shock)	765.9*** (139.7)	268.6*** (68.6)
Difference, Max Portfolio Weight Individuals after the sequence of shocks – Individuals without a shock)	6.98** (1.56)	1.57*** (0.69)
Difference, Long Invested Ratio Individuals after the sequence of shocks – Individuals without a shock)	-4.31* (2.41)	-0.76 (0.72)
Number of matched (/pair) observations	4,170 / 2,116	18,246 /12,276

Panel B: Average Treatment Effect on the Treated (ATET) for the Sequence of Two Shocks

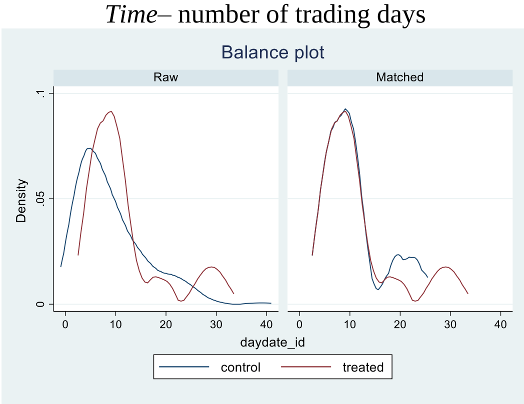
	1st Negative		1st Positive	
Variable	2nd Negative	2nd Positive	2nd Negative	2nd Positive
Difference, HHI Individuals after the sequence of shocks – Individuals without a shock)	1063.6** (423.1)	137.7 (139.1)	1339.7*** (188.8)	-48.9 (71.1)
Difference, Max Portfolio Weight Individuals after the sequence of shocks – Individuals without a shock)	10.30** (4.27)	1.13 (1.40)	17.39*** (2.03)	-1.39** (0.72)
Difference, Long Invested Ratio Individuals after the sequence of shocks – Individuals without a shock)	-19.44*** (4.29)	-4.86*** (1.89)	0.45 (1.34)	-3.35** (0.74)
Number of matched (/pair) observations	421 /146	4,170 /2,116	4,093 /1,610	12,033 /5,972

Figure 1: Covariate Balance Summary

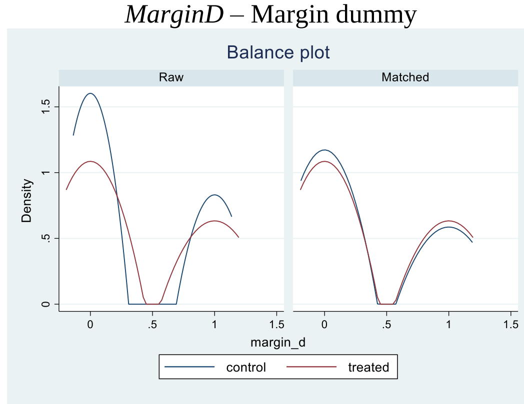
This figure shows the kernel density graphs for the covariates in the matching procedure from Table *. Below is the graphical summary for the variables Time (number of trading days) and MarginD (dummy equal to 1 if the individual uses a margin account). Panel A contains a covariates summary for the matched variables after the first negative shock. Analogously, Panel B contains the same comparison after the first positive shock. The control group consists of individuals without any shock in their portfolio value. Variable definitions are provided in Appendix I.

Panel A: After the First *Negative* Shock

Time– number of trading days

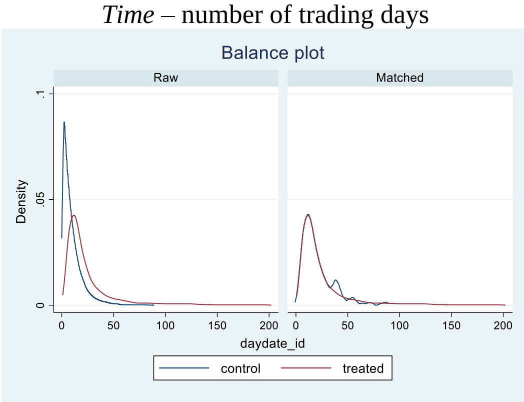


MarginD – Margin dummy

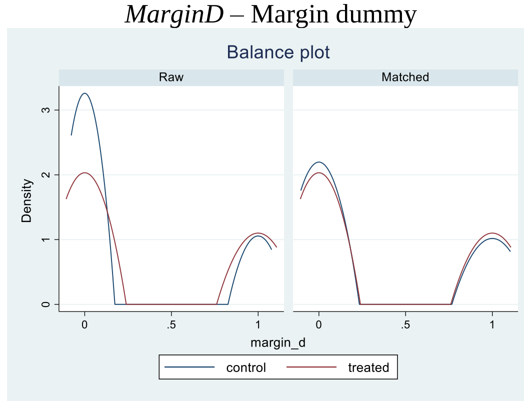


Panel B: After the First *Positive* Shock

Time – number of trading days



MarginD – Margin dummy



Appendix 2: How is the Volume Rule Calculated for Options?

The options volume rule exists to try and make options trading as realistic as possible. The basic idea is that we don't want to fill trades in our simulation that wouldn't be filled in real life because of volume. For example, you might be able to buy 1000 contracts in a frequently traded company like Cisco or Microsoft. However, this same trade would be unrealistic in a smaller company that trades a few dozen contracts daily. Even if there was another side to take the trade in real life (which is doubtful), the price would surely change because of the size of the trade. There is no way for us to determine what the end price would end up being, so we don't allow the trade to go through. In our volume rule, we first consider the total number of contracts tradable. This is calculated as the greater of:

Volume Today * Options Tradable **or** Ask/Bid Size

- "Volume Today" is the current number of contracts traded today
- "Options Tradable" is a variable defined by your administrator when the group was created. This represents the percentage of daily volume you can trade. By default, this is 25%.
- "Ask/Bid Size" is the number of contracts market makers have committed to trading at the ask/bid price. On the quote screen, this will be written as "5.00 [20]" where 5.00 would be the ask/bid price and 20 would be the size. Second, we have to take into account the number of contracts a user has already purchased today. Otherwise, you could beat the rule by making many small trades that would have the same effect on your portfolio as one big trade.

Total Contracts = Contracts Bought Today + Attempted Contract Size

This brings us to the final calculation:

If "Total Contracts" is less than or equal to "Contracts Tradable."
    Then the order is possible
Else
    Order is not possible.[20]

[20] Note: The contract tradable number is displayed when attempting the trade, therefore the user knows in advance whether the order is possible.