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"Rational" or "Intuitive": Are Behavioral Biases Correlated Across Stock Market Investors?

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ABSTRACT Human judgments are systematically affected by various biases and distortions. The main goal of our study is to analyze the effects of five well-documented behavioral biases—namely, the disposition effect, herd behavior, availability heuristic, gambler's fallacy and hot hand fallacy—on the mechanisms of stock market decision making and, in particular, the correlations between the magnitudes of the biases in the cross-section of market investors. Employing an extensive online survey, we demonstrate that, on average, active capital market investors exhibit moderate degrees of behavioral biases. We then calculate the cross-sectional correlation coefficients between the biases and find that all of them are positive and highly significant for both professional and non-professional investors and for all categories of investors, as classified by their experience levels, genders, and ages. This finding suggests that an investor who is more inclined to employ a certain intuitive decision-making technique will most likely accept other techniques as well. Furthermore, we determine that the correlation coefficients between the biases are higher for more experienced investors and male investors, indicating that these categories of investors are likely to behave more consistently, or, in other words, are more likely to decide for themselves whether to rely on simplifying decision-making techniques in general or to reject all of them. Alternatively, this finding may suggest that these investors develop more sophisticated "adaptive toolboxes", or collections of heuristics, and apply them more systematically.

KEY WORDS: availability heuristic; disposition effect; gambler's fallacy; herd behavior; hot hand fallacy

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Introduction

People are not rational utility-optimization machines. Our decisions are affected by a variety of systematic biases and distortions that may result in "incorrect" patterns of behavior and inferior performance (for an overview, see, for example, Kahneman et al., 1982; Stracca, 2004). In this study, we analyze the effects of five well-documented behavioral biases on market investors' decision-making:

- Disposition effect (Shefrin, & Statman, 1985) – an investor's tendency to sell stocks that gained value and to hold on to stocks that lost value.
- Herd behavior (for a recent survey, see, e.g., Hirshleifer, & Teoh, 2003) – the behavior of an investor imitating the observed actions of others or the movements of the market instead of following her own beliefs and information.
- Availability heuristic (Tversky, & Kahneman, 1973) – the phenomenon of determining the likelihood

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of an event according to the easiness of recalling similar instances.

- Gambler's fallacy (Laplace, 1796) – the incorrect belief in the negative autocorrelation of non-autocorrelated random sequences.
- Hot hand fallacy (Gilovich et al., 1985) – the incorrect belief that certain random sequences may in fact be non-random (human-related) and therefore positively autocorrelated.

A continuously growing body of contemporaneous financial literature clearly demonstrates that investors' behaviors are influenced by all of these biases (see, for example, Barber, & Odean, 2008; Hon-Snir et al., 2012; Kliger, & Kudryavtsev, 2008; Park, & Sabourian, 2011; Sundali, & Croson, 2006). However, is an investor who is affected by one of the biases more likely to be affected by others? Formally, are the magnitudes of behavioral biases correlated in the cross-section? To the best of our knowledge, this question is not addressed by previous literature, and the major goal of the present paper is to fill this gap.

We perform an online survey asking stock market investors, both professional and non-professional, a number of questions concerning their personal ways of making investment decisions. The questions are formulated to detect whether the participants are affected by the above-mentioned biases. For each participant, we calculate her personal "bias grades", each of which is higher the more her reported behavior, as discerned from her answers, is consistent with the respective behavioral effect. On average, our survey participants exhibit moderate degrees of behavioral biases.

The major focus of our research is calculating the cross-sectional correlation coefficients between the "bias grades". All of the correlations are positive (in fact, close to one) and highly significant for both professional and non-professional investors. Therefore, we infer that if an investor accepts a certain intuitive decision-making technique, she will likely accept other techniques as well.

Furthermore, we perform a subsample analysis of the correlations. We document that the correlation coefficients between the biases are higher for more experienced investors and male investors, indicating that these categories of investors likely behave more consistently, or, in other words, are more likely to decide for themselves whether to rely on simplifying decision-making techniques in general or to reject all of them. Alternatively, this finding may suggest that more experienced investors manage to develop (everyone for herself) a more sophisticated "adaptive toolbox" or collection of heuristics (Gigerenzer, & Selten, 2001) and apply it more systematically, possibly arriving at better investment results. We also find that the correlation coefficients for the most experienced non-professional investors are lower than those for the professional investors, likely suggesting that the latter group, though not necessarily more rational (as shown by Hon-Snir et al., 2012), at least behaves more consistently, or based on a more ample collection of decision-making rules. Conversely, the correlations appear to be independent from investors' ages. Importantly, all of the correlation coefficients we obtain for all of the subsamples and categories of participants are positive and highly significant, providing a strong robustness check for our major finding.

The rest of the paper is structured as follows. In Section 2, we review the literature on behavioral biases, featuring both psychological aspects and economic applications. In Section 3, we describe our survey design and research approach. Section 4 defines our hypotheses and provides the empirical tests and the results. Section 5 concludes and provides a brief discussion.

Psychological biases in finance: Literature review

Recent literature demonstrates that economic and financial behavior and decision making may be affected by various psychological effects. These effects, often referred to as "biases" or "fallacies", are based on feelings, emotions and intuition, rather than rational considerations, and often result in inferior financial performance. In the present research, we concentrate on five well-documented effects.

Disposition effect

One of the most striking behavioral patterns is the tendency of investors to sell "winners" (stocks that gained value) and to hold on to "losers" (stocks that lost value). The term "disposition effect" was first dubbed by Shefrin and Statman (1985), who also offer a behavioral explanation for it, based on the combination of loss aversion (Kahneman, & Tversky, 1979) and mental accounting (Thaler, 1985). In essence, the disposition effect is a reflection of investors keeping a separate mental account for each stock and, according to prospect theory, maximizing an S-shaped (concave for gains and convex for losses), reference-level-based, value function within that account. Three different types of data are applied for studying the disposition effect: aggregate (on the level of stock exchanges), individual (on the level of individual investors) and experimental.

The first to employ aggregate data are Lakonishok and Smidt (1986). Using historical stock prices as possible reference points, they find that winners tend to have a higher abnormal volume than losers. A similar technique is employed by Ferris et al. (1988) and Bremer and Cato (1996), yielding comparable results. Huddart et al. (2007) find a significantly higher volume when stock prices are above (below) their fifty-two week highs (lows). Kaustia (2004) uses the price and volume information on US initial public offerings (IPOs) and finds that for negative initial return IPOs, trading below the offer price (which is assumed to be the reference point) is suppressed in comparison to trading above the offer price and there is an increase in trading volume as their stock prices reach new record highs.

The second major group of papers studying the disposition effect is based on individual data. The reference point in these studies is taken to be the stocks' purchase prices. In a comprehensive study, Odean (1998) takes the average purchase price (for each investor and stock) as a reference point and then distinguishes between paper and realized gains and losses. For each day and investor, he calculates the Proportion of Gains Realized (PGR) and the Proportion of Losses Realized (PLR), taking the ratio of PGR to PLR as a measure of the disposition effect. Odean's main findings include the observation that individual investors demonstrate significant preferences for selling winners and holding losers. Dhar and Zhu (2002) find that the disposition effect is mainly pronounced by low-income and non-professional investors. Goetzmann and Massa (2003) argue that investors' disposition biases affect firms' returns. Grinblatt and Han (2005) were the first to connect the disposition effect and momentum, showing, both theoretically and empirically, that the disposition effect may account for the tendency of past winning stocks to subsequently outperform past losing stocks. Frazzini (2006) finds that in the presence of disposition-prone investors, prices under-react to news, thereby generating a post-event price drift. Locke and Mann (2005) find that the average holding period for losing trades is longer than for winning trades. They argue that while all traders hold losers longer than winners, the least successful traders hold losers the longest, whereas the most successful hold losers for the shortest amount of time. Shapira and Venezia (2000) compare the durations of winning and losing round trips and document the disposition effect for all groups of accounts, finding that it is less pronounced for managed accounts than for independent ones. Kliger and Kudryavtsev (2008) discover that investors update their reference points on stocks based on the perception of stock exchange-listed firms' quarterly earnings announcements as "good" or "bad surprises" and subsequently exhibit the disposition effect with respect to these reference points.

The third group of papers that sheds light on the disposition effect consists of papers employing experimental design. Weber and Camerer (1998) conduct a multi-stage experiment examining different characteristics and determinants of the disposition effect and find that subjects tend to sell fewer shares when the price falls than when it rises and also sell less when the price is below the purchase price than when it is above. Similarly to Weber and Camerer (1998), Oehler et al. (2002) use the purchase price and the last period price as alternative reference points. The disposition effect is found to be stronger when the purchase price is taken as a reference point.

Herd behavior (herding)

In financial markets, herding is usually termed as the behavior of an investor imitating the observed actions of others or the movements of the market instead of following her own beliefs and information. Herd behavior is possibly among the most mentioned but least understood terms in the financial lexicon. Difficulties in measuring and quantifying the existence of the behavior form obstacles to extensive research. Even so, there are at least two points people tend to unanimously agree upon. First, as one of the founding pillars in the newly developed behavioral asset pricing area, herd behavior helps explain market-wide anomalies. Because individual biases are not influential enough to move market prices and returns, they only have real anomalous effects if they create social contamination with a strong emotional content, leading to more widespread phenomena such as herd behavior. Second, it is generally accepted that the flood of herding may lead to a situation in which the market price fails to reflect all relevant information; therefore, the market becomes unstable and moves towards inefficiency.

Theoretical and empirical research on herd behavior has been conducted in an isolated manner. The theoretical work (e.g., Avery, & Zemsky, 1998; Cipriani, & Guarino 2008; Lee, 1998; Park, & Sabourian, 2011) tries to identify the mechanisms that can lead traders to herd. Papers in this strand of literature emphasize that in financial markets, the fact that prices adjust to the order flow makes it more difficult for herd behavior to arise than in the other setups studied in social learning literature in which there are no price mechanisms. Nevertheless, it is possible that rational traders herd because there are different sources of uncertainty in the market, traders have informational and non-informational (e.g., liquidity or hedging) motives to trade or trading activity is affected by reputation concerns.

Empirical studies of herd behavior employ either laboratory or market data. In all the models, "herding" means making the same decision independently of the private information that one receives. The problem for the empiricist is that there are no data on the private information available to traders; therefore, it is difficult to understand whether traders make similar decisions because they disregard their own information and imitate (as opposed, for instance, to reacting to the same piece of public information). To overcome this problem, some authors (e.g., Cipriani, & Guarino, 2005; 2009; Drehman et al., 2005) test herd behaviors in laboratory financial markets and document the types of behavior consistent with herd motives.

A series of empirical studies make an effort to detect and measure herd behavior in real market situations. Lakonishok et al. (1992) measure herd behavior as the average tendency of a group of money managers to buy or sell particular stocks at the same time, relative to what could be expected if the managers made their decisions independently. Wermers (1995) proposes a portfolio-change measure, by which herd behavior is measured by the extent to which portfolio weights assigned to the various stocks by different money managers move in the same direction. Christie and Huang (1995) document lower volatility of individual security returns in the periods of extremely positive and extremely negative market returns, which is in line with herding behavior and contradicts rational asset pricing. Hwang and Salmon (2004) and Wang and Canela (2006) employ cross-sectional variance of the betas to study herd behavior towards market indices in major developed and emerging financial markets. They find higher levels of herding in emerging markets than in developed markets and higher correlations of herding between two markets from the same group compared to those between two markets from different groups. They also argue that herd behavior shows significant movements and persistence independently from market conditions.

Availability heuristic

The availability heuristic (Tversky, & Kahneman, 1973) refers to the phenomenon of determining the likelihood of an event according to the easiness of recalling similar instances. In other words, the availability heuristic may be described as a rule of thumb, which occurs when people estimate the probability of an outcome based on how easy that outcome is to imagine. As such, vividly described, emotionally charged possibilities will be perceived as being more likely than those that are harder to picture or difficult to understand. Tversky and Kahneman (1974), provide examples of ways availability may provide practical clues for assessing frequencies and probabilities. They argue that "recent occurrences are likely to be relatively more available than earlier experiences" (p. 1127) and thus conclude that people assess probabilities by overweighting current information, as opposed to processing all relevant information.

A number of papers discuss the influence of the availability heuristic on market investors. Shiller (1998) argues that investors' attention to investment categories (e.g., stocks versus bonds or real estate; investing abroad versus investing at home) may be affected by alternating waves of public attention and inattention. Similarly, Barber and Odean (2008) find that when choosing which stock to buy, investors tend to consider only those stocks that have recently caught their attention (stocks in the news, stocks experiencing high abnormal trading volume, stocks with extreme one day returns). Daniel et al. (2002) conclude that investors and analysts are, on average, too credulous.

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That is, when examining an informative event or a value indicator, they do not discount adequately for the incentives of others to manipulate this signal. Credulity may be explained by limited attention and the fact that availability of a stimulus causes it to be more heavily weighted. Frieder (2004) finds that stock traders seek to buy after large positive earnings surprises and sell after large negative earnings surprises and explains this tendency by the availability heuristic, assuming that the salience of an earnings surprise increases in its magnitude. Ganzach (2001) brings support for a model in which analysts base their judgments of risk and return for unfamiliar stocks upon a global attitude. If stocks are perceived as good, they are judged to have high return and low risk, whereas if they are perceived as bad, they are judged to be low in return and high in risk. Lee et al. (2007) discuss the "recency bias", which is the tendency of people to make judgments about the likelihood of events based on their recent experience. They find that analysts' forecasts of firms' long-term growth in earnings per share tend to be relatively optimistic when the economy is expanding and relatively pessimistic when the economy is contracting. This finding is consistent with the availability heuristic, indicating that forecasters overweight the current state of the economy in making long-term growth predictions. Kliger and Kudryavtsev (2010) find that positive stock price reactions to analyst recommendation upgrades are stronger when accompanied by positive stock market index returns and negative stock price reactions to analyst recommendation downgrades are stronger when accompanied by negative stock market index returns. They dub this finding "outcome availability effect" and explain it by higher availability of positive (negative) outcomes on days of market index rises (declines). Moreover, Kliger and Kudryavtsev (2010) document weaker (stronger) reactions to recommendation upgrades (downgrades) on days of substantial stock market moves. They dub this finding the "risk availability effect" and explain it by higher availability of risky outcomes on such "highly volatile" days.

Gambler's fallacy

The gambler's fallacy is defined as an (incorrect) belief in the negative autocorrelation of a non-autocorrelated random sequence. For example, individuals who believe in the gambler's fallacy believe that after three red numbers appearing on the roulette wheel, a black number is "due", or, in other words, is more likely to appear than a red number.

The first published account of the gambler's fallacy is from Laplace (1951). Gambler's fallacy-type beliefs are first observed in the laboratory (under controlled conditions) in the literature on probability matching. In these experiments, subjects are asked to guess which of two colored lights will next illuminate. After seeing a string of one outcome, subjects are significantly more likely to guess the other, an effect referred to in that literature as *negative recency* (see Estes, 1964; Lee, 1971, for reviews). Ayton and Fischer (2004) also demonstrate the existence of gambler's fallacy beliefs in the lab when subjects choose which of two colors will appear next on a simulated roulette wheel. Gal and Baron (1996) show that gambler's fallacy behavior is not simply caused by boredom. They ask participants in their experiments how they would best maximize their earnings and receive responses based on gambler's fallacy-type logic.

The gambler's fallacy is usually thought to be caused by the representativeness heuristic (Kahneman, & Tversky, 1972; Tversky, & Kahneman, 1971). Here, chance is perceived as "a self-correcting process in which a deviation in one direction induces a deviation in the opposite direction to restore the equilibrium" (Tversky, & Kahneman, 1974, p. 1125). Thus, after a sequence of three red numbers appears on the roulette wheel, black is more likely to occur than red because a sequence "red-red-red-black" is more representative of the underlying distribution than a sequence "red-red-red-red". Recently, a number of alternative explanations for this bias have been proposed. For example, Hahn and Warren (2009) suggest that the gambler's fallacy may reflect the subjective experience of a finite data stream for an agent with a limited short-term memory capacity. In other words, this effect may result not from the limitations of people's intuitive statistics, but rather from the extent to which the human cognitive system is finely attuned to the statistics of the environment. In line with Hahn and Warren (2009), Sun and Wang (2010) demonstrate that in finite data streams, streak patterns have longer waiting times—that is, times it takes them to first occur from the time at which monitoring begins—than the patterns with reversals, making the former seem more probable in the eyes of people, whose personal experience is naturally limited.

A number of researchers demonstrate the existence of the gambler's fallacy empirically, in lottery and horse and dog racing settings. For example, Clotfelter and Cook (1991; 1993) and Terrell (1994) show that soon after a lottery number wins, individuals are significantly less likely to bet on it. This effect diminishes over time; months later, the winning number is as popular as the average number. Papachristou and Karamanis (1998) demonstrate that the participants in the Greek National Lottery bet significantly more on "overdue" numbers, that is, on the numbers that have not been drawn during some relatively long periods of time. Subsequently, Papachristou (2004) reports a weaker evidence of the same type for the British Lotto. Hauser-Rethaller and Konig (2002) and Roger and Broinanne (2007) also present evidence that people taking part in the Austrian and French Lotto, respectively, appear not to choose lottery numbers randomly. Metzger (1984), Terrell and Farmer (1996) and Terrell (1998) show the gambler's fallacy in horse and dog racing. Croson and Sundali (2005) and Sundali and Croson (2006) use videotapes of play of a roulette table in the casino and document a significant gambler's fallacy in betting. That is, following a sequence of one color outcome, people are more likely to place their bets on the other color.

Zielonka (2004) asks a group of stock market professionals a number of questions aimed at detecting their ways of making decisions and finds that market "signals" considered by technical analysts are consistent with a number of behavioral biases, including the gambler's fallacy.

Overall, the gambler's fallacy is well-documented both in the laboratory and in the real world, including money-related behavior. However, there seems to be little evidence of this pattern in financing, including stock market decision making.

Hot hand fallacy

As people exhibit the gambler's fallacy, which is a tendency to predict the opposite of the last event (negative recency), they may also express beliefs that certain events will be repeated (positive recency). The latter tendency is known as the hot hand fallacy, and unlike the gambler's fallacy, it refers to people's belief that a particular *person*, rather than a particular *outcome*, is hot. For example, if an individual has won in the past, *whatever* numbers she chooses to bet on are likely to win in the future, not only the numbers she had won with previously.

Gilovich, Vallone and Tversky (1985) were the first to use the term "hot hand". They demonstrate that individuals believe in the hot hand in basketball shooting and that these beliefs are not correct (i.e., basketball shooters' probability of success is serially uncorrelated). They suggest that the hot hand also arises out of the representativeness heuristic just as the gambler's fallacy. They write, "A conception of chance based on representativeness produces two related biases. First, it induces a belief that the probability of heads is greater after a long sequence of tails than after a long sequence of heads — this is the notorious gambler's fallacy. Second, it leads people to reject the randomness of sequences that contain the expected number of runs because even the occurrence of, say, four heads in a row — which is quite likely in a sequence of 20 tosses — makes the sequence appear non-representative". Another potential explanation for the hot hand fallacy may be related to Langer (1975) dealing with the illusion of control, or people's tendency to believe that they (or others) exert control over events that are in fact randomly determined. Rabin and Vayanos (2010) develop a theoretical model to examine the link between the gambler's fallacy and the hot-hand fallacy. They show that because of the gambler's fallacy, an individual who observes a sequence of signals that depend on an unobservable underlying state is prone to exaggerate the magnitudes of changes in the state but underestimate their duration. By contrast, they demonstrate that long sequences of similar signals may cause people to believe that a type of "momentum" is present in the underlying state itself and, in line with the hot-hand fallacy, to expect sequence continuation.

Other experimental evidence shows that subjects in a simulated blackjack game bet more after a series of wins than they do after a series of losses, both when betting on their own play and on the plays of others (Chau, & Phillips, 1995). Further evidence of the hot hand in a laboratory experiment comes from Ayton and Fischer (2004), who document both the gambler's fallacy and the Hot hand fallacy and conclude that the former is attributed to "randomly looking" processes

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and to inanimate chance mechanisms, whereas the latter refers to processes that seem to be non-random and related to human skilled performance.

Field evidence for the hot hand is weaker. Camerer (1989) compares odds in the betting market for basketball teams with their actual performance and finds that bettors do appear to believe in the “hot team”. Croson and Sundali (2005) and Sundali and Croson (2006) document hot hand-consistent behavior in casinos. Clotfelter and Cook (1989) note the tendency of gamblers to redeem winning lottery tickets for more tickets rather than for cash. This behavior is also consistent with hot hand beliefs because the individuals who have recently won seem to believe they are more likely to win again.

Overall, similarly to the gambler’s fallacy, the hot fallacy is widely discussed in different branches of literature but is not sufficiently documented in financial research, possibly because it is quite difficult to establish the hot hand feelings particular investors may have at certain moments of time.

In the present study, we first wish to shed additional light on the effects of the above-discussed psychological patterns on financial decision-making. This understanding may be especially valuable for the case of the gambler’s fallacy and the hot hand fallacy, whose potential effects on the field of finance are not sufficiently studied in previous literature. However, the major goal of this study is to analyze the cross-sectional correlations between the magnitudes of different behavioral biases in stock market decision-making, a matter that is, to our best knowledge, not at all discussed in previous literature.

Survey design and research approach

We gathered the data for this study in the framework of a computerized survey, consisting of two stages:

- First, we asked a group of professional portfolio managers (41 managers) at one of the major Israeli investment houses to fill out a short questionnaire. This stage of the survey took place in January 2011.
- Second, we conducted online surveys via one of the leading financial websites in Israel - the “Bizportal” (http://www.bizportal.co.il/). This website is widely recognized for being regularly visited by market investors, not necessarily professional. This stage of the survey took place in March-April 2011. We received responses from 305 users.

We asked all of the respondents to indicate their gender, age, and number of years of active experience in the capital market. Table 1 (in Appendix 1) reports the basic descriptive statistics of our sample. The majority of our participants were males (78.05% and 74.10% in the professionals and non-professionals groups, respectively), 30 to 40 years old (53.66% and 55.08%, respectively), and had more than 10 years of experience in stock market investments (39.02% and 40.98%, respectively).

Our survey questionnaire consisted of 10 questions, which are presented in Appendix 2. In each question, participants were asked to rate the appropriateness of a statement on a Likert scale between 1 (strongly disagree) and 5 (strongly agree).

The goal of the questionnaire was to detect if stock market investors were affected by different psychological biases. In this respect, the statements were formulated so that questions 1 and 2 referred to the disposition effect, questions 3 and 4 to the gambler’s fallacy, questions 5 and 6 to the hot hand fallacy, questions 7 and 8 to herd behavior, and questions 9 and 10 to the availability heuristic. Neither the names of the behavioral effects nor any type of description were included in the questionnaire. The questions were in fact formulated in the form of a “dialogue” allowing the participants to express their general beliefs with respect to the stock markets, in general, and their trading philosophies, in particular. Including two questions for each of the biases allowed the questionnaire to better capture the participants’ actual opinion about each of them.[1] According to the definition of the biases and the formulation of the questions, for all of our questions, except question 2, a higher grade provided by a participant would be consistent with a stronger effect of the respective bias on her.

To capture the effect of each of the behavioral biases on each of our participants, we calculate their personal “bias grades”. To do so, we first control for the cross-sectional correlations of grades given by the participants within the “pairs” of the questions we employed for each of the biases. The correlation coefficients between the grades within the pairs are reported in Table 2. The table clearly demonstrates that the correlations within all of the pairs are highly significant for both the professional and non-professional participants. We also note that the sign of the correlation between the grades on questions 1 and 2 is negative, which is because investment behavior consistent with the disposition effect requires a high grade on question 1 and a low grade on question 2.

Strong correlations within the pairs of questions allow us to aggregate the bias grades for each participant *i* and for each of the biases in the following way:

- Disposition grade (DG_i):
  $$DG_i = G\_1_i + 6 - G\_2_i \quad (1)[2]$$
  where G_N_i is the grade (answer) given by participant *i* for question (statement) N.
- Gambler's grade (GG_i):
  $$GG_i = G\_2_i + G\_3_i \quad (2)$$
- Hot-hand grade (HG_i):
  $$HG_i = G\_5_i + G\_6_i \quad (3)$$
- Herd (behavior) grade (BG_i):
  $$BG_i = G\_7_i + G\_8_i \quad (4)$$
- Availability grade (AG_i):
  $$AG_i = G\_9_i + G\_10_i \quad (5)$$

According to this approach, the resulting personal bias grades we attain for each participant *i* and for each question N range from 2, meaning that the respective bias has virtually no effect on the respective participant, or, in other words, that the participant's behavior is fully "rational", to 10, meaning that the respective participant tends to make decisions that are completely based on the respective simplifying decision-making rule (bias), or, in other words, that the participant's behavior is completely "intuitive".

Testable hypotheses and results

First, we look at the general picture of the bias grades in our sample. Table 3 concentrates the descriptive statistics in this respect, and shows some general results:

All of the bias grades for both groups range from 2 (minimal possible grade) to 9-10 (maximal possible grade). In other words, in our sample, we have both participants who seem to be fully affected and those who seem to be completely unaffected by the respective behavioral patterns.

The mean bias grades range from 4.927 to 5.646, and the majority of the participants have bias grades lower than 6. Therefore, we may infer that our participants are, on average, moderately affected by behavioral biases.

However, the major goal of our paper is to analyze the cross-sectional correlations between the magnitudes of different psychological biases in stock market behavior, a matter that is, to our best knowledge, not discussed at all in previous financial literature.

Cross-sectional correlations between the behavioral biases: Total sample

A considerable number of psychological effects in stock market behaviors have been already documented in the literature, as discussed above. A relatively small number of studies address the individual differences in the magnitudes of these effects (see Hon-Snir et al., (2012) for a series of results, short literature review, and discussion[3]). However, there are no studies that analyze if there exist cross-sectional correlations between the effects, or, in other words, if an investor who is affected by one of the biases is more likely to be affected by others. The present study makes an effort to fill this gap.

We suggest that investors tend to rely either on purely rational considerations or on their feelings and intuition. That is, we expect "rational" investors to remain rational in all of the decisions they make and "intuitive" investors to employ not simply one or two, but various simplifying decision-making rules. Therefore, we hypothesize that:

Hypothesis 1: The magnitudes of the behavioral effects are positively correlated in the cross-section.

Table 4 presents cross-sectional correlation coefficients between the personal bias grades for the professional portfolio managers (Panel A) and for the non-professional investors (Panel B). The results strongly support Hypothesis 1. *All* of the correlations are positive (in fact, close to 1) and highly significant. That is, we may conclude that if an investor accepts a certain intuitive decision-making technique, she will most likely accept others as well. This result may be especially valuable because the matter of cross-sectional correlations *between* different behavioral biases is, to our best knowledge, not discussed in previous economic and financial literature. This finding implies that investors tend to behave in a consistently "rational" or "intuitive" way. Based on this, one may be able to better predict future decisions to be made by an investor, or even a group of investors, with relatively scarce information about their past decisions. We may also note that at first glance, the fact that the Gambler's grades and the Hot-hand grades are positively correlated in the cross-section might seem puzzling. However, as we have noted in Section 2, these two behavioral biases do not contradict each other and may well co-exist within one person because they refer to people's beliefs with respect to different types of processes. For example, Ayton and Fischer (2004) experimentally document both the gambler's fallacy and the hot hand fallacy and conclude that the former is attributed to "randomly looking" processes and to inanimate chance mechanisms, whereas the latter refers to processes that seem to be non-random and related to human skilled performances.

Finally, we may note that personal bias grades seem to be equally strongly correlated for both professional and non-professional investors, as demonstrated by the two panels of Table 4.[4]

Subsample analysis

Having documented high correlations between the behavioral biases within both major groups of our participants, we now proceed to analyzing the nature of the correlations within different subsamples. We classify our survey participants by a number of personal characteristics.

Trading experience is a characteristic one should obviously address in this respect. This aspect clearly has strong effects on the ways investors make decisions. In Hon-Snir et al. (2012), we find that investors' trading experience makes them less influenced by behavioral biases. Now, we are interested in establishing if the correlations between the biases also change with experience. We expect more experienced investors to behave more consistently, in any case. In other words, we suggest that more experienced investors are more likely to decide for themselves whether to rely on simplifying decision-making techniques in general or to reject all of them.

Moreover, we may consider the same matter from a different angle. Studies by Gigerenzer and Selten, systematized in Gigerenzer and Selten (2001), put forward the concept of bounded rationality and suggest that heuristics do not represent systematic deviations from rational behavior, but rather a collection of useful rules of decision-making developed during the process of evolution and people making rapid and, though not mathematically calculated and proven, usually correct decisions. They dub this collection of heuristics an "adaptive toolbox" and mention that it is not universal but rather developed and amplified during each of our lives depending on the types of situations and problems we face. In this context, we may expect more experienced investors to possess more ample "adaptive toolboxes" and to employ the heuristics (or the rational criteria for investment decisions) in a more systematic way. In other words, we (again) expect that more experienced investors are more likely to decide whether to employ "rational" or "intuitive" decision-making techniques.

Thus, we hypothesize the following:

Hypothesis 2: The correlations between the behavioral effects are higher for more experienced investors.

To test this hypothesis, we calculate correlation coefficients between the biases separately by the categories of investors' reported market experiences. Because the subsample of professional investors is relatively small, we employ only the subsample of website visitors for this analysis. Table 5 reports the correlation coefficients by categories of experience and for each of the biases and also compares (in Panel D) the correlation coefficients for the most and least experienced investors.[5] The results in general support Hypothesis 2. Though the correlations between the biases do not increase continuously with stock trading experience, the clearly lowest correlation coefficients for all the biases are obtained within the category of the least experienced investors (with reported experience of less than 3 years). We perform a statistical comparison of the correlations between the extreme experience categories, employing the Fisher r-to-z transformation to convert correlation coefficients (Pearson's correlations) to normally distributed variables (z) and compare the latter between the subsamples. This comparison reveals that 8 out of 10 coefficients are higher for the most experienced investors, 6 of them significantly at the 5% level, including 5 at the 1% level. In other words, as expected, non-experienced traders are more likely to behave inconsistently or possess more limited "adaptive toolboxes", that is, to rely on certain simplifying behavioral techniques while rejecting others. We may also note that the correlation coefficients for the most experienced non-professional investors are still lower than those we obtained in the previous subsection for the group of professional investors[6], indicating that it is likely that the latter group, though not necessarily more rational (as shown by Hon-Snir et al., 2012), at least behaves more consistently, or, in other words, has more professional experience and employs more ample sets of decision-making rules. Finally, we should mention that all of the correlation coefficients for all of the investor categories are still significantly positive, providing an important robustness check for Hypothesis 1.

Furthermore, we wish to analyze the correlations between the behavioral effects separately for male and female investors. Psychological differences between men and women are evident and well-documented in previous literature (see, for example, Feingold, 1994; Fritz, & Helgeson, 1998; Helgeson, 1994; Helgeson, 2003; Hyde, 2005). In Hon-Snir et al (2012), we document that male investors are less likely to employ simplifying decision-making rules. In the framework of the present study, we expect male investors to employ more sophisticated sets of decision-making techniques, and therefore, hypothesize the following:

Hypothesis 3: The correlations between the behavioral effects are higher for male investors.

To test the hypothesis, we once again employ only the non-professional investors' responses. Table 6 comprises the correlation coefficients and their averages, separately for male and female investors. The results support Hypothesis 3. As reported in Panel B, 9 out of 10 coefficients are higher for male investors (or lower for female investors), 6 of them significantly at the 5% level, including 3 at the 1% level. These findings indicate that it is likely that male investors are more consistent in employing behavioral decision-making techniques or, alternatively, possess more ample "adaptive toolboxes".

Finally, we compare the correlations between the biases for different groups of ages. Again, the literature dealing with age differences in the magnitudes of behavioral biases is rather scarce. Kudryavtsev and Cohen (2010, 2011a, 2011b) report that younger people are slightly less affected by anchoring bias[7] and hindsight bias[8] when recalling financial information. Therefore, we might expect them, in general, to use more ample collections of decision-making rules. That is, we hypothesize the following:

Hypothesis 4: The correlations between the behavioral effects are higher for younger investors.

In Table 7, we divide the subsample of non-professional investors into three categories of age—18-30 years old, 30-40 years old, and older than 40[9]—and calculate the correlations between the biases for each of the categories. The results do not support Hypothesis 4. The correlation coefficients are very similar for all of the age categories, and the differences between the correlations for the youngest and the oldest investors are of different signs, the majority of them being non-significant, as demonstrated by Panel C. Therefore, investors' ages most likely do not significantly affect the consistency of the decisions. However, the very high and strongly significant correlation coefficients we obtain for all of the age categories serve as important robustness checks for our general Hypothesis 1.

Conclusions and Discussion

Our paper explores the effects of behavioral biases—namely, the disposition effect, herd behavior, availability heuristic, gambler's fallacy and hot hand fallacy—on the mechanism of stock market decision-making and, in particular, the cross-sectional correlations between the magnitudes of the biases.

Employing an extensive online survey, we demonstrate that on average, active stock market investors exhibit moderate degrees of behavioral biases. We then calculate cross-sectional correlation coefficients between the biases, and as a major contribution of our study, confirm that all of them are positive and highly significant for both professional and non-professional investors. This finding shows that if an investor accepts certain intuitive decision-making technique, she will most likely accept others as well.

Furthermore, we perform a subsample analysis of the correlations and determine that the correlation coefficients between the biases are higher for more experienced investors and male investors, indicating that these categories likely behave more consistently, or, in other words, are more likely to decide for themselves whether to rely on simplifying decision-making techniques in general or reject all of them. Alternatively, this finding may suggest that the more experienced investors manage to develop (everyone for herself) more sophisticated "adaptive toolboxes", or collections of heuristics, and apply them more systematically, possibly arriving at better investment results. We also find that the correlation coefficients for the most experienced non-professional investors are lower than those for the professional investors, suggesting that it is likely that the latter group, though not necessarily more rational, at least makes more consistent decisions, or possesses more ample "adaptive toolboxes". However, the correlations appear to be independent from investors' ages. Importantly, all of the correlation coefficients we obtain for all of the subsamples and categories of participants are positive and highly significant, providing a strong robustness check for our major finding.

Our results may have a number of interesting implications. First of all, according to our main finding, stock market investors are likely to "run to extremes", that is, to either be skeptical towards behavioral decision-making techniques in general or follow at least a few of them. This result may be applicable for both academic researchers and stock market practitioners. From the research point of view, it makes investors' behaviors more predictable. That is, if the real market, survey, or even experimental data one employs indicate that an investor or group of investors exhibits one or several behavioral biases, one might assume that these specific investors are affected by other biases as well. Financial consultants, in their turn, might find it simpler to convince an investor who appears to be affected by one of the biases to make a decision consistent with another bias or biases[10] or, on the contrary, to convince a "rational" investor to remain rational "all along the way". Both "sides of the game" might pay attention to this finding.

With regards to the higher correlations between the biases for more experienced investors and for male investors, this finding implies that the latter group, being in general less inclined to employ "intuitive" decision-making techniques, may also find it easier to "heal themselves" of all the behavioral biases knowing that one of them may result in inferior investment performances. They, and actually all the investors, simply have to be aware of as many known biases as possible to avoid them and choose appropriate investment strategies.

References

Avery, C., & Zemsky, P. (1998). Multidimensional Uncertainty and Herd Behavior in Financial Markets. *American Economic Review*, 88(4), 724–48.

Ayton, P., & Fischer, I. (2004). The Hot Hand Fallacy and the Gambler's Fallacy: Two Faces of Subjective Randomness? *Memory and Cognition*, 32(8), 1369-1378.

Barber, B. M., & Odean, T. (2008). All that Glitters: The Effect of Attention and News on the Buying behavior of Individual and Institutional Investors. *Review of Financial Studies*, 21(2), 785-818.

Bremer, M., & Kato K. (1996). Trading Volume for Winners and Losers on the Tokyo Stock Exchange. *Journal of Financial and Quantitative Analysis*, 31(1), 127-142.

Camerer, C. (1989). Does the Basketball Market Believe in the 'Hot Hand'?" *American Economic Review*, 79(5), 1257–1261.

Chau, A., & Phillips, J. (1995). Effects of Perceived Control upon Wagering and Attributions in Computer Blackjack. *The Journal of General Psychology*, 122(3), 253–269.

Christie, W. G., & Huang, R. D. (1995). Following the Pied Piper: Do Individual Returns Herd Around the Market? *Financial Analysts Journal,* 51(4), 31–37.

Cipriani, M., & Guarino, A. (2005). Herd Behavior in a Laboratory Financial Market. *American Economic Review*, 95(5), 1427-1443.

Cipriani, M., & Guarino, A. (2008). Herd Behavior and Contagion in Financial Markets. *The B.E. Journal of Theoretical Economics (Contributions)*, 8(1), Retrieved from: http://www.degruyter.com/view/j/bejte.2008.8.1/bejte.2008.8.1.1390/bejte.2008.8.1.1390.xml

Cipriani, M., & Guarino, A. (2009). Herd Behavior in Financial Markets: A Field Experiment with Financial Market Professionals. *Journal of the European Economic Association,* 7(1), 206-233.

Clotfelter, C. T., & Cook, P. J. (1989). Selling Hope: State Lotteries in America. Cambridge, MA: Harvard University Press.

Clotfelter, C. T., & Cook, P. J. (1991). Lotteries in the Real World. *Journal of Risk and Uncertainty,* 4(3), 227–232.

Clotfelter, C. T., & Cook, P. J. (1993). The 'Gambler's Fallacy' in Lottery Play. *Management Science,* 39(12), 1521–1525.

Croson, R., & Sundali, J. (2005). The Gambler's Fallacy and the Hot Hand: Empirical Data from Casinos. *Journal of Risk and Uncertainty*, 30(3), 195-209.

Daniel, K., Hirshleifer, D. &, Teoh, S. H. (2002). Investor Psychology in Capital Markets: Evidence and Policy Implications. *Journal of Monetary Economics,* 49(1), 139-209.

Dhar, R., & Zhu, N. (2002). Up Close and Personal: An Individual Level Analysis of the Disposition Effect (ICF Working Paper No. 02-20). Yale School of Management.

Drehmann, M., Oechssler, J., & Rider, A. (2005). Herding and Contrarian Behavior in Financial Markets - An Internet Experiment. *American Economic Review*, 95(5), 1403-1426.

Estes, W. (1964). Probability Learning. In A. W. Melton (Ed.), *Categories of Human Learning* (pp. 89-128). New York, NY: Academic Press.

Feingold, A. (1994). Gender Differences in Personality: A Meta-Analysis. *Psychological Bulletin*, 116(3), 429–456.

Ferris, S. P, Haugen, R. A. & Makhija, A. K. (1988). Predicting Contemporary Volume with Historic Volume at Differential Price Levels: Evidence Supporting the Disposition Effect. *Journal of Finance*, 43(3), 677-697.

Frazzini, A. (2006). The Disposition Effect and Underreaction to News. *Journal of Finance*, 61(4), 2017-2046.

Frieder, L. (2004). Evidence on Behavioral Biases in Trading Activity (EFA 2004 Maastricht Meetings Paper No. 5085). Retrieved from SSRN: http://ssrn.com/abstract=479983

Fritz, H. L. & Helgeson, V. S. (1998). Distinctions of Unmitigated Communion from Communion: Self-Neglect and Overinvolvement with Others. *Journal of Personality and Social Psychology*, 75(1), 121–140.

Gal, I. & Baron, J. (1996). Understanding Repeated Simple Choices. *Thinking and Reasoning*, 2(1), 81-98.

Ganzach, Y. (2001). Judging Risk and Return of Financial Assets. *Organizational Behavior and Human Decision Processes*, 83(2), 353-370.

Gigerenzer, G. & Selten, R. (Eds.). (2001). Bounded Rationality: The Adaptive Toolbox. Cambridge, MA: MIT Press.

Gilovich, T., Vallone, R. & Tversky, A. (1985). The Hot Hand in Basketball: On the Misperception of Random Sequences. *Cognitive Psychology*, 17(3), 295–314.

Goetzmann, W. N., & Massa, M. (2003). Disposition Matters: Volume, Volatility and Price Impact of a Behavioral Bias (Working Paper, No. 9499). Retrieved from NBER website: http://www.nber.org/papers/w9499.pdf

Grinblatt, M. & Han, B. (2005). Prospect Theory, Mental Accounting and Momentum. *Journal of Financial Economics*, 78(2), 311-339.

Hahn, U. & Warren, P. A. (2009). Perceptions of Randomness: Why Three Heads are Better than Four. *Psychological Review,* 116(2), 454–461.

Hauser-Rethaller, U. & Konig, U. (2002). Parimutuel Lotteries: Gamblers' Behavior and the Demand for Tickets. *German Economic Review*, 3(2), 223-245.

Helgeson, V. S. (1994). Relation of Agency and Communion to Well-Being: Evidence and Potential Explanations. *Psychological Bulletin*, 116(3), 412–428.

Helgeson, V. S. (2003). Unmitigated Communion and Adjustment to Breast Cancer: Associations and Explanations. *Journal of Applied Social Psychology*, 33(8), 1643–1661.

Hirshleifer D. & Teoh, S. H. (2003). Herd Behavior and Cascading in Capital Markets: A Review and Synthesis. *European Financial Management*, 9(1), 25-66.

Hon-Snir, S., Kudryavtsev, A. & Cohen, G. (2012). Stock Market Investors: Who Is More Rational, and Who Relies on Intuition? *International Journal of Economics and Finance*, 4(5), 56-72.

Huddart, S., Lang, M. & Yetman, M. (2007). Psychological Factors, Stock Price Paths, and Trading Volume. (Unpublished Paper).

Hwang, S. & Salmon, M. (2004). Market Stress and Herding. *Journal of Empirical Finance*, 11(4), 585–616.

Hyde, J. S. (2005). The Gender Similarities Hypothesis. *American Psychologist*, 60(6), 581–592.

Kahneman, D. & Tversky, A. (1972). Subjective Probability: A Judgment of Representativeness. *Cognitive Psychology,* 3(3), 430–454.

Kahneman, D. & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, 46(2), 171-185.

Kahneman, D., Slovic, P. & Tversky, A. (Eds.). (1982). Judgment under Uncertainty: Heuristics and Biases. New York, NY: Cambridge University Press.

Kaustia, M. (2004). Market-Wide Impact of the Disposition Effect: Evidence from IPO Trading Volume. *Journal of Financial Markets*, 7(2), 207-235.

Kliger, D. & Kudryavtsev, A. (2008). Reference Point Formation by Market Investors. *Journal of Banking and Finance*, 32(9), 1782-1794.

Kliger, D. & Kudryavtsev, A. (2010). The Availability Heuristic and Investors’ Reaction to Company-Specific Events. *Journal of Behavioral Finance*, 11(1), 50-65.

Kudryavtsev, A. & Cohen, G. (2010). Anchoring and Pre-Existing Knowledge in Economic and Financial Settings. *American Journal of Social and Management Sciences*, 1(2), 164-180.

Kudryavtsev, A. & Cohen, G. (2011a). The Less I Remember, the More Confident I Feel: Hindsight Bias in Economic and Financial Knowledge. *International Research Journal of Applied Finance*, 2(2), 50-81.

Kudryavtsev, A. & Cohen, G. (2011b). Behavioral Biases in Economic and Financial Knowledge: Are They the Same for Men and Women? *Advances in Management and Applied Economics*, 1(1), 15-52.

Lakonishok, J. & Smidt, S. (1986). Volume for Winners and Losers: Taxation and Other Motives for Stock Trading. *Journal of Finance*, 41(4), 951–974.

Lakonishok, J. Shleifer, A., & Vishny, R. W. (1992). The Impact of Institutional Trading on Stock Prices. *Journal of Financial Economics*, 32(1), 23-43.

Langer, E. J. (1975). The Illusion of Control. *Journal of Personality and Social Psychology*, 32(2), 311–328.

Laplace, P. S. (1951). *A Philosophical Essay on Probabilities*. New York, NY: Dover

Lee, W. (1971). Decision Theory and Human Behavior. New York, NY: Wiley.

Lee, I. H. (1998). Market Crashes and Informational Avalanches. *Review of Economic Studies*, 65(4), 741-759.

Lee, B., O’Brien, J., & Sivaramakrishnan, K. (2007). An Analysis of Financial Analysts’ Optimism in Long-term Growth Forecasts. *Journal of Behavioral Finance,* 9(3), 171-184.

Locke, P. R., & Mann, S. C. (2005). Professional Trader Discipline and Trade Disposition. *Journal of Financial Economics*, 76(2), 401-444.

Metzger, M. (1984). Biases in Betting: An Application of Laboratory Findings. *Psychological Reports*, 56(3), 883–888.

Odean, T. (1998). Are Investors Reluctant to Realize Their Losses? *Journal of Finance*, 53(5), 1775-1798.

Oehler, A., Heilmann, K., Lager, V., & Oberlander, M. (2002). Dying Out or Dying Hard? Disposition Investors in Stock Markets EFA 2002 Berlin Meetings Presented Paper. Retrieved from SSRN: http://ssrn.com/abstract=314139 or http://dx.doi.org/10.2139/ssrn.314139

Papachristou, G. (2004). The British Gambler’s Fallacy. *Applied economics*, 36(18), 2073-2077.

Papachristou, G., & Karamanis, D. (1998). Investigating Efficiency of Betting Markets: Evidence from the Greek 6/49 Lotto. *Journal of Banking and Finance*, 22(12), 1597–1615.

Park, A., & Sabourian, H. (2011). Herding and Contrarian Behavior in Financial Markets. Econometrica, 79(4), 973-1026.

Rabin, M., & Vayanos, D. (2010). The gambler’s and hot-hand fallacies: Theory and applications. *Review of Economic Studies*, 77(2), 730-778.

Roger, P., & Broihanne, M. H. (2007). Efficiency of Betting Markets and Rationality of Players: Evidence from the French 6/49 Lotto. *Journal of Applied statistics*, 34(6), 645-662.

Shapira, Z., & Venezia, I. (2001). Patterns of Behavior of Professionally Managed and Independent Investors. *Journal of Banking and Finance*, 25(8), 1573-1587.

Shefrin, H. & Statman, M. (1985). The Disposition to Sell Winners Too Early and Ride Losers Too Long. *Journal of Finance*, 40(3), 777-790.

Shiller, R. J. (1998). Human Behavior and the Efficiency of the Financial System (NBER Working Paper No. 6375). National Bureau of Economic Research.

Stracca, L. (2004). Behavioral Finance and Asset Prices: Where Do We Stand? *Journal of Economic Psychology*, 25(3), 373-405.

Sun, Y. & Wang, H. (2010). Gambler’s Fallacy, Hot Hand Belief, and the Time of Patterns. *Judgment and Decision Making*, 5(2), 124-132.

Sundali, J. & Croson, R. (2006). Biases in Casino Betting: The Hot Hand and the Gambler’s Fallacy. *Judgment and Decision Making*, 1(1), 1-12.

Terrell, D. (1994). A Test of the Gambler’s Fallacy: Evidence from Pari-Mutuel Games. *Journal of Risk and Uncertainty*, 8(3), 309–317.

Terrell, D. (1998). Biases in Assessments of Probabilities: New Evidence from Greyhound Races. *Journal of Risk and Uncertainty*, 17(2), 151–166.

Terrell, D., & Farmer, A. (1996). Optimal Betting and Efficiency in Parimutuel Betting Markets with Information Costs. *The Economic Journal*, 106(437), 846–868.

Thaler, R. (1985). Mental Accounting and Consumer Choice. *Marketing Science*, 4(3), 199-214.

Tversky, A., & Kahneman, D. (1971). Belief in the Law of Small Numbers. *Psychological Bulletin,* 76(2), 105–110.

Tversky, A., & Kahneman, D. (1973). Availability: A Heuristic for Judging Frequency and Probability. *Cognitive Psychology,* 5(2), 207-232.

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science,* 185(4157), 1124-1131.

Wang, D., & Canela, M. (2006). Herd Behavior towards the Market Index: Evidence from 21 Financial Markets (Working Paper No. 776). IESE Business School.

Weber, M., & Camerer, C. F. (1998). The Disposition Effect in Securities Trading: An Experimental Analysis. *Journal of Economic Behavior and Organization*, 33(2), 167-184.

Wermers, R. (1995). Herding, Trade Reversals, and Cascading by Institutional Investors. (Unpublished Paper), University of Colorado, Boulder.

Zielonka, P. (2004). Technical Analysis as the Representation of Typical Cognitive Biases. *International Review of Financial Analysis*, 13(2), 217-225.

Endnotes

1. *There was one more reason for limiting the number of questions referring to each of the biases to two. Our goal was to refer to a relatively large number of biases while not making the questionnaire too long (resulting in potentially uninformative answers). Making our questionnaire relatively short (we have explicitly stated that it was going to take no more than 3-4 minutes) most likely allowed us to recruit more participants among the website visitors.*
2. *We subtract the grade on question 2 because it is negatively correlated with the magnitude of the disposition effect exhibited by the respective participants. The number "6" is added to reduce the disposition grade to the same "2-to-10" scale as the rest of the bias grades.*
3. *In Hon-Snir, Kudryavtsev, and Cohen (2011), we discuss individual differences in the magnitudes of these five behavioral biases. We observe that all the effects are significantly more weakly pronounced for more experienced investors and for male investors. However, the magnitudes of the effects do not significantly differ between the professional portfolio managers and non-professional investors. Moreover, the latter appear to be significantly more strongly affected by the behavioral biases than the most experienced non-professional investors.*
4. *Six out of 10 correlation coefficients are higher for the non-professional investors, and the other 4 are lower. None of the differences are significant. The detailed results are available upon request from the authors.*
5. *We employ the Fisher r-to-z transformation to convert correlation coefficients (Pearson's correlations) to normally distributed variables (z) and compare the latter between the subsamples.*
6. *All of the 10 correlation coefficients are higher for the professional investors, 7 of them significantly at the 1% level. The detailed results are available upon request from the authors.*
7. *Anchoring bias refers to people's tendency to form their estimates for different categories, starting from a particular available, and often irrelevant, value and insufficiently adjusting their final judgments from this starting value.*
8. *Hindsight bias denotes people's tendency to overestimate in hindsight how predictable an outcome was in foresight.*
9. *Due to the small number of participants in the last three age categories according to Table 1, we combine them into one category – older than 40.*
10. *If, for some reason, that is what certain financial consultants are interested in doing.*
11. *Index that tracks the prices of the shares of the 100 companies with the highest market capitalization on the Tel Aviv Stock Exchange.*

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Appendix 1: Tables

Table 1. Sample descriptive statistics

Panel A: Portfolio managers (41 respondents)		
Category	Number	Percent of total
1. Gender:		
Men	32	78.05
Women	9	21.95
2. Age:		
18-30	9	21.95
30-40	22	53.66
40-50	9	21.95
50-60	1	2.44
60+	0	0.00
3. Capital market investor for:		
Less than 3 years	5	12.20
3 to 5 years	10	24.39
5 to 10 years	10	24.39
More than 10 years	16	39.02
Panel B: Market investors (305 respondents)		
Category	Number	Percent of total
1. Gender:		
Men	226	74.10
Women	79	25.90
2. Age:		
18-30	76	24.92
30-40	168	55.08
40-50	49	16.07
50-60	11	3.61
60+	1	0.33
3. Capital market investor for:		
Less than 3 years	107	35.08
3 to 5 years	29	9.51
5 to 10 years	44	14.43
More than 10 years	125	40.98

Table 2. Cross-sectional correlation coefficients of grades within the bias-related pairs of questions

Pair of questions	Cross-sectional correlation coefficient between the question grades
Panel A: Portfolio managers (41 respondents)	
Questions 1 & 2 (Disposition effect)	-0.924***
Questions 3 & 4 (Gambler's fallacy)	0.928***
Questions 5 & 6 (Hot hand fallacy)	0.877***
Questions 7 & 8 (Herd behavior)	0.827***
Questions 9 & 10 (Availability heuristic)	0.842***
Panel B: Market investors (305 respondents)	
Pair of questions	Cross-sectional correlation coefficient between the question grades
Questions 1 & 2 (Disposition effect)	-0.937***
Questions 3 & 4 (Gambler's fallacy)	0.917***
Questions 5 & 6 (Hot hand fallacy)	0.862***
Questions 7 & 8 (Herd behavior)	0.841***
Questions 9 & 10 (Availability heuristic)	0.842***

Note
Asterisks denote 1-tailed p-values: *p<0.10; **p<0.05; ***p<0.01

Table 3. Basic descriptive statistics of "bias grades
The table reports, by groups of participants, basic statistics of the "bias grades" calculated as follows:
$DG_i = G\_1_i + 6 - G\_2_i$; $GG_i = G\_2_i + G\_3_i$; $HG_i = G\_5_i + G\_6_i$;
$BG_i = G\_7_i + G\_8_i$; $AG_i = G\_9_i + G\_10_i$
where: G_N_i is the grade (answer) given by participant ***i*** for question (statement) N.

Statistics	Disposition grade (DG_i)	Gambler's grade (GG_i)	Hot-hand grade (HG_i)	Herd (behavior) grade (BG_i)	Availability grade (AG_i)
Panel A: Portfolio managers (41 participants)					
Mean	5.463	4.927	5.122	5.000	5.171
Median	4	4	4	4	4
Standard Deviation	2.873	3.045	2.750	2.739	2.801
Maximum	10	9	9	10	9
Minimum	2	2	2	2	2
Grade $\in$[6,10], percent	41.46	41.46	39.02	39.02	41.46
Panel B: Market investors (305 participants)					
Statistics	Disposition grade (DG_i)	Gambler's grade (GG_i)	Hot-hand grade (HG_i)	Herd (behavior) grade (BG_i)	Availability grade (AG_i)
Mean	5.646	5.105	5.331	5.243	5.416
Median	4	4	4	4	4
Standard Deviation	2.851	3.049	2.920	2.889	2.923
Maximum	10	10	10	10	10
Minimum	2	2	2	2	2
Grade $\in$[6,10], percent	43.93	41.64	41.64	41.64	42.62

Table 4. Cross-sectional correlations between behavioral biases: Total sample
The table reports, by groups of participants, correlation coefficients between the "bias grades".
Last column reports average correlation coefficients for each "bias" grade" with other grades, by groups of participants.

Panel A: Portfolio managers (41 participants)

	Correlation coefficients between "bias grades"				
	Disposition grade (DG_i)	Gambler's grade (GG_i)	Hot-hand grade (HG_i)	Herd (behavior) grade (BG_i)	Availability grade (AG_i)
Disposition grade (DG_i)		0.904***	0.901***	0.906***	0.891***
Gambler's grade (GG_i)			0.948***	0.932***	0.934***
Hot-hand grade (HG_i)				0.936***	0.942***
Herd (behavior) grade (BG_i)					0.932***
Availability grade (AG_i)					

Panel B: Non-professional investors (305 participants)

	Correlation coefficients between "bias grades"				
	Disposition grade (DG_i)	Gambler's grade (GG_i)	Hot-hand grade (HG_i)	Herd (behavior) grade (BG_i)	Availability grade (AG_i)
Disposition grade (DG_i)		0.903***	0.907***	0.905***	0.889***
Gambler's grade (GG_i)			0.949***	0.936***	0.938***
Hot-hand grade (HG_i)				0.948***	0.943***
Herd (behavior) grade (BG_i)					0.935***
Availability grade (AG_i)					

Note
Asterisks denote 1-tailed p-values: *p<0.10; **p<0.05; ***p<0.01

Table 5. Cross-sectional correlations between behavioral biases: Subsample analysis by categories of reported stock market experience.

The table compares the correlation coefficients between the "bias grades" for different categories of investors according to their reported investment experience.

In Panel D, the second row in each square reports the z-statistic according to the Fisher r-to-z transformation for the comparison of correlation coefficients between investors with more than 10 years of experience and those with less than 3 years of experience (in this order).

Panel A: Reported stock market investment experience of less than 3 years (107 participants)

	Correlation coefficients between "bias grades"				
	Disposition grade (DG_i)	Gambler's grade (GG_i)	Hot-hand grade (HG_i)	Herd (behavior) grade (BG_i)	Availability grade (AG_i)
Disposition grade (DG_i)		0.312***	0.392***	0.405***	0.253***
Gambler's grade (GG_i)			0.850***	0.750***	0.808***
Hot-hand grade (HG_i)				0.761***	0.770***
Herd (behavior) grade (BG_i)					0.691***
Availability grade (AG_i)					

Panel B: Reported stock market investment experience of 3 to 5 years (29 participants)

	Correlation coefficients between "bias grades"				
	Disposition grade (DG_i)	Gambler's grade (GG_i)	Hot-hand grade (HG_i)	Herd (behavior) grade (BG_i)	Availability grade (AG_i)
Disposition grade (DG_i)		0.873***	0.863***	0.835***	0.878***
Gambler's grade (GG_i)			0.903***	0.887***	0.907***
Hot-hand grade (HG_i)				0.909***	0.943***
Herd (behavior) grade (BG_i)					0.940***
Availability grade (AG_i)					

Table 5. (continued)

Panel C: Reported stock market investment experience of 5 to 10 years (44 participants)

	Correlation coefficients between "bias grades"				
	Disposition grade (DG_i)	Gambler's grade (GG_i)	Hot-hand grade (HG_i)	Herd (behavior) grade (BG_i)	Availability grade (AG_i)
Disposition grade (DG_i)		0.745***	0.774***	0.761***	0.730***
Gambler's grade (GG_i)			0.911***	0.892***	0.852***
Hot-hand grade (HG_i)				0.882***	0.891***
Herd (behavior) grade (BG_i)					0.860***
Availability grade (AG_i)					

Panel D: Reported stock market investment experience of more than 10 years (125 participants)

	Correlation coefficients between "bias grades" *Comparison of correlations: Investors with experience of more than 10 years versus investors with experience of less than 3 years: z-statistic according to the Fisher r-to-z transformation*				
	Disposition grade (DG_i)	Gambler's grade (GG_i)	Hot-hand grade (HG_i)	Herd (behavior) grade (BG_i)	Availability grade (AG_i)
Disposition grade (DG_i)		0.743*** *4.75****	0.764*** *4.43****	0.760*** *4.25****	0.753*** *5.40****
Gambler's grade (GG_i)			0.794*** *-1.30*	0.762*** *0.21*	0.772*** *-0.72*
Hot-hand grade (HG_i)				0.872*** *2.57****	0.804*** *0.67*
Herd (behavior) grade (BG_i)					0.816*** *2.21***
Availability grade (AG_i)					

Note
Asterisks denote 1-tailed p-values: *p<0.10; **p<0.05; ***p<0.01

Table 6. Cross-sectional correlations between behavioral biases: Male versus female investors
The table compares the correlation coefficients between the "bias grades" for male and female investors.
In Panel B, the second row in each square reports the z-statistic according to the Fisher r-to-z transformation for the comparison of correlation coefficients between women and men (in this order).

Panel A: Male investors (226 participants)

	Correlation coefficients between "bias grades"				
	Disposition grade (DG_i)	Gambler's grade (GG_i)	Hot-hand grade (HG_i)	Herd (behavior) grade (BG_i)	Availability grade (AG_i)
Disposition grade (DG_i)		0.874***	0.881***	0.874***	0.857***
Gambler's grade (GG_i)			0.931***	0.925***	0.912***
Hot-hand grade (HG_i)				0.934***	0.924***
Herd (behavior) grade (BG_i)					0.924***
Availability grade (AG_i)					

Panel B: Female investors (79 participants)

	Correlation coefficients between "bias grades" *Comparison of correlations: Female versus Male: z-statistic according to the Fisher r-to-z transformation*				
	Disposition grade (DG_i)	Gambler's grade (GG_i)	Hot-hand grade (HG_i)	Herd (behavior) grade (BG_i)	Availability grade (AG_i)
Disposition grade (DG_i)		0.842*** *-0.92*	0.784*** *-2.44****	0.790*** *-2.10***	0.778*** *-1.82***
Gambler's grade (GG_i)			0.929*** *-0.11*	0.860*** *-2.48****	0.931*** *0.95*
Hot-hand grade (HG_i)				0.889*** *-2.05***	0.909*** *-0.71*
Herd (behavior) grade (BG_i)					0.839*** *-3.00****
Availability grade (AG_i)					

Note
Asterisks denote 1-tailed p-values: *p<0.10; **p<0.05; ***p<0.01

Table 7. Cross-sectional correlations between behavioral biases: Subsample analysis by investors' age
The table compares the correlation coefficients between the "bias grades" for different categories of participants' age. In Panel C, the second row in each square reports the z-statistic according to the Fisher r-to-z transformation for the comparison of correlation coefficients between investors older than 40 years old and investors 18-30 years old (in this order).

Panel A: Investors 18-30 years old (76 participants)

	Correlation coefficients between "bias grades"				
	Disposition grade (DG_i)	Gambler's grade (GG_i)	Hot-hand grade (HG_i)	Herd (behavior) grade (BG_i)	Availability grade (AG_i)
Disposition grade (DG_i)		0.908***	0.925***	0.907***	0.906***
Gambler's grade (GG_i)			0.932***	0.930***	0.925***
Hot-hand grade (HG_i)				0.944***	0.932***
Herd (behavior) grade (BG_i)					0.959***
Availability grade (AG_i)					

Panel B: Investors 30-40 years old (168 participants)

	Correlation coefficients between "bias grades" *Comparison of correlations: Female versus Male: z-statistic according to the Fisher r-to-z transformation*				
	Disposition grade (DG_i)	Gambler's grade (GG_i)	Hot-hand grade (HG_i)	Herd (behavior) grade (BG_i)	Availability grade (AG_i)
Disposition grade (DG_i)		*0.892****	0.893***	0.894***	0.874***
Gambler's grade (GG_i)			*0.952****	0.940***	*0.937****
Hot-hand grade (HG_i)				0.950***	*0.939****
Herd (behavior) grade (BG_i)					0.925***
Availability grade (AG_i)					

Table 7. (continued)

Panel C: Investors older than 40 years old (61 participants)

	Correlation coefficients between "bias grades" *Comparison of correlations: Investors older than 40 years old versus Investors 18-30 years old: z-statistic according to the Fisher r-to-z transformation*				
	Disposition grade (DG_i)	Gambler's grade (GG_i)	Hot-hand grade (HG_i)	Herd (behavior) grade (BG_i)	Availability grade (AG_i)
Disposition grade (DG_i)		0.922*** *0.49*	0.913*** *-0.44*	0.923*** *0.56*	0.901*** *-0.15*
Gambler's grade (GG_i)			0.958*** *1.41**	0.931*** *0.04*	0.955*** *1.50**
Hot-hand grade (HG_i)				0.947*** *0.16*	0.964*** *1.85***
Herd (behavior) grade (BG_i)					0.928*** *-1.65***
Availability grade (AG_i)					

Note
Asterisks denote 1-tailed p-values: *p<0.10; **p<0.05; ***p<0.01

Appendix 2

Research questionnaire (translated):

1. I prefer to sell stocks whose prices recently increased. (Disposition effect)
2. I prefer to keep holding on to stocks if their current market price is higher than the price I had purchased them for. (Disposition effect)
3. If in each of the last six months, the TA-100 Index[11] value increased, I would expect the value of the Index to decrease in the next month. (Gambler’s fallacy)
4. If in each of the last six months, the TA-100 Index value decreased, I would expect the value of the Index to increase in the next month. (Gambler’s fallacy)
5. After I manage to realize a profit on my stock portfolio, I increase the sum of my stock market holdings. (Hot hand fallacy)
6. If I find out that the market price of one of the stocks I hold decreased dramatically, I decrease the sum of my stock market holdings. (Hot hand fallacy)
7. I prefer to buy stocks if many “buy” orders were submitted for them from the beginning of the trading session. (Herd behavior)
8. If in the last month, the aggregate trading volume in the stock market was higher than usual, I would increase the sum of my stock market holdings. (Herd behavior)
9. I prefer to buy stocks on the days when the value of the TA-100 Index increases. (Availability heuristic)
10. I prefer to sell stocks on the days when the value of the TA-100 Index decreases. (Availability heuristic)