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In the Red: The Effects of Color on Investment Behavior

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Abstract

Financial decisions in today's society are made in environments that involve color stimuli. In this paper, we perform an empirical analysis of the effects of color on investment behavior. First, we find that when investors are displayed potential losses in red, risk taking is reduced. Second, when investors are shown past negative stock price paths in red, expectations about future stock returns are reduced. Consistent with red causing "avoidance behavior," red color reduces investors' propensity to purchase stocks. The findings are robust to a series of checks involving colorblind investors and alternative colors to control for salience effects. Finally, the effects are muted in a cultural setting, e.g., China, where red is not used to visualize financial losses. A contribution of this study is to introduce hypotheses from color psychology and visual science to enhance our understanding of the behavior of individual investors.

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"As to what I have done as a poet,... I take no pride in it... But that in my century I am the only person who knows the truth in the difficult science of colours ... I am not a little proud."

—Johann Wolfgang von Goethe

I Introduction

The use of color to visually represent data and information has a long history in the finance industry. Platforms catering to professional investors, e.g., the Bloomberg Terminal, have used color since the 1980s. Fueled by an expanding FinTech industry, many individual investors in today's society make important financial decisions on online platforms (e.g, brokerage or retirement savings websites) that involve color stimuli. Emerging research in *color psychology* suggests that color stimuli carry communication values, e.g., a "red-danger association," which have been found to affect human behavior in non-finance domains. In particular, color automatically initiates biologically ingrained evaluation processes in the human visual system, which may be moderated by social learning and the cultural setting in which decisions are made. In this paper, we therefore argue that it is important to perform a systematic empirical analysis of the effects of color in the domain of financial decision-making and investment behavior.

The effects of color on human behavior in a broad sense is a research field that is currently attracting interest among many different social scientists. While interest in a relation between color and human behavior may be traced back at least to Johann Wolfgang von Goethe's (1810) Theory of Colours, it is in the last decade that rigorous scientific work on color has emerged, resulting in publications in top scientific journals (e.g., Hill and Barton (2005) and Mehta and Zhu (2009)). Eight of the articles that have appeared in the Annual Review of Psychology over the years have been about color, but the most recent one is the first to examine the influence of color on human behavior (Elliot and Maier (2014)). Because of the large volume of recent contributions related to this field, the first edition of the Handbook of Color Psychology was recently published (Elliot, Fairchild, and Franklin (2016)). This paper is among the first to perform an in-depth examination of the effects of color in the domain of financial decision-making.

From a theoretical perspective, there are two explanations for why colors carry communication values that may be expected to affect investment behavior. First, an evolutionary biology explanation implies that color associations emerge from genetically ingrained responses to critical fitness-relevant color stimuli in an individual's environment. As a concrete example, red is the color of many objectively dangerous phenomena that humans encountered in early societies, such as blood or fire, and a red face may be caused by a testosterone surge in an attack-ready opponent. Second, a social learning explanation implies that color associations emerge from repeated pairings of a color with particular concepts and an individual's experiences. Such social learning by color associations may interact with, and moderate, biologically based propensities. As a concrete example, in China, the color red is a symbol of good fortune, the color of important festivals, and the primary color of the flag and the Communist Party.

Because colors carry communication values, red is the prototypical color of alarms and stop signs that convey danger and command enhanced attention.[1] Consequently, red is used as a word in many languages, in a non-literal way and even in the absence of any color per se, to refer to dangers that humans must avoid. Prominent examples from the domain of finance and investments include "in the red" to describe a company reporting financial losses, "red flags" to refer to various warning signs, e.g., in the aftermath of investment frauds, or "red herring" to characterize the preliminary prospectus a company uses when issuing securities to the U.S. public. That is, there are many real-world examples from the finance industry where red is the color used to communicate caution or other danger-relevant concepts.

Our results can be straightforwardly summarized. First, we examine to what extent color influences investors' financial risk preferences. We find that when investors are displayed potential financial losses in red, the propensity of taking risk is reduced significantly. Specifically, investors take approximately a quarter less risk when shown potential losses in red color. This relation can not be explained by heterogeneity with respect to a set of standard individual characteristics which may potentially be correlated with risk taking propensity. That is, individuals who were ex ante similar made systematically different risky financial choices when potential financial losses were

[1] For example, red was used to signal "severe risk" in the U.S. Homeland Security's color-coded terrorism threat advisory system, the "Tzeva Adom" (which means red color in Hebrew) is the early-warning system used in Israel to communicate information about incoming missiles, and the Moscow-Washington hotline was referred to as the "red phone" during the Cold War, though a red phone was never used.

visualized in red color.

Second, we examine whether color affects investors' beliefs about expected future stock returns. We document that when investors are shown past negative stock price paths in red, expectations about future stock returns are reduced significantly. Such behavior has the potential of contributing to momentum beliefs as investors who view past negative returns in red believe that the stock price will continue to decline. In addition, we find that red color exacerbates investors' prediction errors, i.e., result in relatively more biased beliefs. We also find that red color reduces investors' propensity to purchase stocks, by about 20%, all else equal.

The evidence is broadly consistent with what color psychologists characterize as "red-danger associations" and that red color is causing "avoidance behavior." In addition, we show that the effects are robust to a series of checks involving, e.g., colorblind investors, and other colors commonly used on online investment platforms (e.g., blue) to control for salience effects. Importantly, we find that the effects of red color are significantly muted in a cultural setting (e.g., China) where red is generally not used to visualize financial losses.

This study involves inter-disciplinary research – spanning finance, color psychology, visual science, and judgment and decision-making – and contributes to these fields. First, from the perspective of standard theories in financial economics, the color used to visually represent financial data is a "supposedly irrelevant factor," to employ a term dubbed by Thaler (2016) in his Presidential Address for the American Economic Association. It should not have any impact on investor behavior whether financial losses are represented in red color, blue color, or any other color. In contrast, evidence in color psychology predicts a systematic relation between color and human behavior.

Second, with only a few exceptions, finance research has so far not confronted the hypothesis that representation of financial information, as opposed to the information per se, may influence investor behavior. Prior research has primarily focused on whether the display of different lengths of return intervals affect investment behavior (e.g., Benartzi and Thaler (1999), Haigh and List (2005), Shaton (2016), and Beshears, Choi, Laibson, and Madrian (2017)).[2] Only a select few

[2] Additional studies in financial economics which examine the relation between information display and investment behavior include Hirshleifer and Teoh (2003), Barber and Odean (2008), Anagol and Gamble (2013), Stango and Zinman (2014), and Ladika and Sautner (2016).

studies in economics and psychology have so far explored effects of color in the finance domain (e.g., Kliger and Gilad (2012) and Gnambs, Appel, and Oeberst (2015)).

Finally, a considerable amount of research in financial economics during the past couple of decades has uncovered a large number of different explanations for individuals' investment behaviors and biases.[3] Our evidence contributes by introducing visual representation, and specifically color, as a new and important explanation for the behavior of individual investors.

The rest of the paper is organized as follows. Section II reviews the use of color on prominent U.S. online investment platforms and pre-existing scientific contributions in color psychology and visual science. Section III describes the experimental research methods used to compile our data sets in the U.S. and China. Section IV reports our empirical evidence and several robustness checks. Section V reports further evidence and extensions. Section VI concludes.

II Color Psychology and Investment Behavior

In this section, we report new data from a review of the use of color on online investment platforms in the U.S. We also introduce pre-existing contributions in color psychology which are relevant for our hypotheses related to the effects of color in the domain of financial decision-making.

A Color and Online Investment Platforms

We examine the use of color on the most prominent online investment platforms that cater to individual investors in the U.S. In particular, we review: (i) the largest specialized brokerages (e.g., E*Trade, Interactive Brokers, Schwab, Scottrade, and TD Ameritrade), (ii) a large retirement savings platform (Vanguard), (iii) an emerging multimedia platform for brokerage services and trading (Robinhood), (iv) the most visited financial information providers (e.g., CNN Money, Google Finance, Morningstar, MSN Money, and Yahoo! Finance), (v) the largest online financial newspaper (Wall Street Journal), (vi) stock exchange websites (Nasdaq and NYSE), and (vii) the primary

[3]For comprehensive reviews of research related to individual investor behavior, we refer to Campbell (2006, 2016), Benartzi and Thaler (2007), Barber and Odean (2013), and Cronqvist and Jiang (2017).

account aggregator to consolidate financial information across platforms (Mint).[4]

Table 1 reports the evidence of our review and there are several conclusions. First, we find that red, green, and blue are the most common colors on the platforms. Interestingly, some colors (e.g., yellow) that are commonly used to signal caution in some other domains (e.g., traffic signs) are not used in the specific domain we study. Second, we examine the use of colors for returns and graphs, respectively. For returns, we find that the vast majority of platforms use a combination of red color for negative returns and green color for positive returns.[5] For graphs, we find that red/green is still very commonly used, though blue is also a common color. Finally, there is heterogeneity across platforms with respect to the use of color. While it is beyond the scope of this study to explain such variation, we note that it may reflect that different platforms have different objective functions. For example, some platforms have fiduciary responsibilities and are required to prioritize clients' objectives, while those who profit from clients' cash positions and trading may use colors and visualizations differently.

The conclusion that emerges from our review is that only a select few colors (red, green, and blue) are commonly used on the most prominent online investing platforms that cater to individual investors in the U.S. As a result, we argue that it is important to perform a systematic empirical analysis of the effects of color in the domain of financial decision-making.

B Color, Communication Values, and Human Behavior

Researchers in color psychology argue that there are two non-mutually exclusive theoretical explanations for why colors carry communication values and therefore may affect human behavior: (i) An evolutionary biology explanation and (ii) A social learning explanation.[6] Both are potentially relevant for explaining why color may affect investment behavior.

[4]Platforms that cater primarily to institutional and other professional investors, e.g., Bloomberg and S&P Capital IQ, were not reviewed.

[5]The Wall Street Journal is the only platform we review that uses white numbers on a black background, but with triangles next to the returns in red/green color.

[6]For more comprehensive reviews of research related to color psychology, we refer to Elliot and Maier (2014), Elliot (2015), and Elliot, Fairchild, and Franklin (2016). While we restrict our review to color psychology, there also exist research focusing on other aspects of color, including color physics, color physiology, color linguistics, and so on.

B.1 Evolutionary Biology Explanation

An evolutionary biology explanation implies that color associations emerge from genetically ingrained responses to critical fitness-relevant color stimuli in an individual's environment (e.g., Mollon (1989)). As a concrete example, red is the color of many objectively dangerous phenomena that humans encountered in early societies, such as blood or fire (e.g., Changizi, Zhang, and Shimojo (2006)). In addition, in humans, red on the skin signals anger and serves as a testosterone-based signal of aggressiveness (e.g., Archer (2006)).[7] Therefore, a *red-danger association* may originate because humans in early societies who did not avoid dangerous phenomena in red would not propagate their genes. As a result of such standard evolutionary processes, humans in today's society may be endowed with a genetic predisposition to associate red with elevated awareness. In other words, red is associated with what color psychologists refer to as *avoidance behavior*.

Evidence from non-human species suggests that such a red-danger association is at least partly genetically ingrained. Specifically, Khan, Levine, Dobson, and Kralik (2011) study rhesus macaques, an Old World monkey that is sensitive to red, green, and blue. When provided an opportunity to steal food from two human experimenters, the monkeys systematically avoided the experimenter wearing red, regardless of the sex of the experimenter. The evidence that monkeys avoid the color red in a market setting strengthens an argument that avoiding red stems from an evolutionary adaptation among human beings. That is, the aversion to red seems to have deep evolutionary origins and can not be easily explained as entirely cultural.

We also want to emphasize that color stimuli automatically starts evaluation processes in the human visual system. In fact, color computations are executed at an early level within the visual system, and these evaluation processes are so fundamental that they are found in many animals as well (e.g., Schneirla (1959)). That is, the process from evaluation of color stimuli to activation, and thus human behavior, is evoked without conscious awareness. From a physiological perspective, color affects the release of hormones. Specifically, color stimulates the neural portion of the optical pathway to the hypothalamic brain region and into the pineal and pituitary glands, which control

[7] Color psychologists have argued that color vision evolved so that humans may sense changes in blood flow beneath the skin that convey information about the emotional and physical condition of another human being. For example, as reddish skin color, caused by blood oxygenation, signals attack-readiness of an opponent, color vision significantly may improve genetic fitness and also various forms of social interactions in a society.

the entire endocrine system (e.g., Mahnke (1996)). This automatic evaluation process, started by color stimuli, may result in differential behaviors, depending on the communication value of a particular color.

B.2 Social Learning Explanation

A social learning explanation implies that color associations emerge and affect human behavior because of repeated pairings of a color with particular concepts and an individual's experiences. Such social learning by color associations may interact with, and moderate, biologically based propensities. As a result, individuals may become "prepared" to respond to a particular color in a specific way, and at least some color associations may represent a cognitive moderation or shaping of biologically ingrained responses. That is, the physical and psychological context in which color is perceived influences its meaning and human responses to it (e.g., Elliot and Maier (2012)).

Cultural setting may be expected to moderate any genetically ingrained communication values of color. First, in many cultures, conditioning of red color and experiences starts in early schooling as students receive feedback regarding academic errors in red (e.g., Elliot, Maier, Binser, Friedman, and Pekrun (2009)). In addition, red is associated with alarms and stop signs that convey danger and command enhanced attention. That is, a red-danger association may originate through such a social learning process and may strengthen evolutionarily ingrained human predispositions.[8]

Second, color associations vary significantly across cultures. As a concrete example, in China, the color red is used to symbolize good fortune, as evident from, e.g., the use of "red envelopes" for monetary gifts. Lanterns are colored in red during the Chinese New Year and the other important festivals. Red is also the primary color of China's flag as well as the governing Communist Party. While red is the color of many objectively dangerous phenomena also in China, the cultural setting may be expected to weaken any effects of color in the domain of investment behavior.

[8] Color psychologists have pointed out that color associations may be context-dependent. A concrete example is "romantic red," i.e., the notion that red results in men viewing women as more attractive and more sexually desirable. In other words, in some contexts, red may be expected to result in approach behavior rather than avoidance behavior (e.g., Meier, Dagostino, Elliot, Maier, and Wilkowski (2012)).

III Data and Experimental Research Methods

While experimental methods are well-established and widely used in research in economics (e.g., Smith (1994, 2010), and List (2011)), they have emerged in research in financial economics more recently, and are still considered non-standard. One concern among some financial economists is with respect to the external validity of the experiments, but in our setting the external validity is very high, particularly because we provide the review of the colors commonly used on online investment platforms. In this section, we describe the experimental methods used to compile our data sets, and discuss some challenges of the research methods we use.

A Data from the U.S.

A.1 The Mechanical Turk Platform

We implement the data collection using Mechanical Turk (MTurk), an Internet platform by Amazon, which provides researchers relatively low cost access to online experiment participants. Using the MTurk platform is quickly becoming the norm in business school disciplines that rely more or less exclusively on experiments, e.g., consumer behavior research in marketing. MTurk has also been used in research in economics (e.g., Olea and Strzalecki (2014) and Kuziemko, Norton, Saez, and Stantcheva (2015)), and more recently by finance researchers (e.g., Duarte, Siegel, and Young (2012), D'Acunto (2015), and Kumar, Niessen-Ruenzi, and Spalt (2015)).

The MTurk platform enables "Requesters," e.g., researchers, to post "Human Intelligence Tasks" (HITs) to "Workers," i.e., registered MTurk participants (e.g., Mason and Suri (2012)). MTurk participants are required to register, i.e., receive a WorkerID, and provide taxpayer information, including Social Security Number and a permanent residence address in the U.S. As a result, all MTurk experiment participants are U.S. residents. As is standard practice among researchers using MTurk, we do not disclose the nature and objectives of our experiments to the participants.

On the MTurk platform, Workers complete the HITs for compensation from the Requester. While concerns have emerged about the effects of the small amount of compensation to MTurk experiment participants, the compensation has not been found to be critical for MTurk experiments.

For example, in their study "The Effect of $1 Stakes," Amir, Rand, and Gal (2012) show that experiments implemented on the MTurk platform result in comparable evidence to those implemented in standard laboratories, even when using small compensation amounts. In our experiments, we compensate each experiment participant a normal and market-based amount of compensation on the MTurk platform, i.e., about 10 cents per minute (the equivalent of $6 per hour).

A.2 Data Quality

As the reliance on the MTurk platform has increased among researchers, concerns have emerged about the quality of the data. Intuitively, the challenges of not monitoring experiment participants directly may result in moral hazard, and thus reduce the data quality. It is important to emphasize that in contrast with laboratory participants, the MTurk platform has an incentive structure that is conducive to contentiousness. When a Worker submits a HIT, a Requester can choose to reject it. As a result, experiment participants are incentivized to follow instructions and pay attention to the experiment, e.g., carefully consider a stimulus prior to answering questions. In addition, researchers commonly require participants to have a high approval rate, implying that more rejections will make fewer HITs available. That is, sub-standard data quality affects participants' immediate as well as future compensation. Because of this incentive structure, it is not surprising that MTurk data have consistently been found to be of high quality.

We rely on pre-existing scientific guidelines that have recently been developed in order to conduct high-quality research using the MTurk platform (e.g., Goodman and Paolacci (2017)). First, we use quality filters and measure ex post attrition. Specifically, we restrict our experiments to participants with MTurk ratings of 95% or above. We also restrict participants from repeat participation to reduce concerns about "non-naïvité" and to increase the independence of the participants who constitute our sample. Second, we use various attention checks at certain points of the experiments, and we exclude participants who do not pass these checks. For example, experiment participants were requested to select "Asia" from a set of choices that included (in random order): "Asia," "Europe," and "South America." We also exclude participants who completed the experiments in an unrealistically short period of time. Finally, we are careful in identifying and excluding outliers, as they may appear more commonly in experimental data, particularly related to experiment participants' estimates about the future.

A.3 Selection Bias

In a recent paper, Goodman, Cryder, and Cheema (2013) review research which uses the MTurk platform and compare MTurk participants with standard laboratory samples. The conclusion is that there are, with few exceptions, no significant differences in the size of estimated effects among MTurk participants versus standard samples. We also want to emphasize that the attrition rate for our experiments is very low (3.1%) and does not differ significantly among the treatment and control conditions. That is, the quality of data compiled from the MTurk platform is comparable to the quality of standard laboratory samples, reducing concerns about selection bias (e.g., Paolacci, Chandler, and Ipeirotis (2010) and Casler, Bickel, and Hackett (2013)).

Some differences between MTurk data and standard samples are worth recognizing. First, MTurk participants are less attentive during experiments, resulting in data with reduced statistical power in studies that rely on MTurk data. Second, MTurk participants are slightly more introvert (as expected from those who derive utility from performing solitary tasks on the Internet) and express somewhat lower self-esteem, presenting challenges in some research domains, though we do not expect this difference to be relevant for our study. If there is a relation between financial risk preferences and personality (e.g., Borghans, Heckman, Golsteyn, and Meijers (2009)), then our research method with treatment and control conditions significantly reduces this concern.

We want to emphasize that MTurk data have several advantages compared to standard laboratory samples. First, MTurk participants have significant heterogeneity with respect to individual characteristics. Although about half of the Workers on MTurk are younger than 30, older participants are also well-represented. In contrast, laboratory samples are commonly constrained to students of age 18 to 22 with some college education. That is, despite a common belief that working on MTurk implies being very poor and uneducated, a considerable proportion of Workers have above-average incomes and much more heterogeneous education than student samples. Second, MTurk participants are from a diverse set of regions across the U.S. In contrast, samples of students are often concentrated to one specific educational institution and region, and therefore not representative of all U.S. individual investors. Finally, MTurk is a double-blind platform which enables participants to participate without concerns of being identified by the experimenter, and vice versa.

B Data from China

Compiling similar quality data from China, to examine the impact of cultural setting, is more challenging. Specifically, MTurk platform alternatives in China are not expected to produce the same quality of data as for the U.S. Therefore, we had to use an alternative, and more labor-intense, data collection method in China. First, the same description as the one on MTurk was used to recruit potential experiment participants on Chinese social network sites. Second, we compiled a data set with similar individual characteristics as the U.S. experiment participants. Finally, these individuals were provided a single-use code to participate in the experiment, which was implemented online using the same software as used on the MTurk platform. As a result, the quality of the data from China is comparable to the quality of the data from the U.S.

Following the practices of previous research that involve cross-cultural experiments, we use a standard back-translation method to ensure the quality of our data (e.g., Brislin (1970)). In particular, one translator translated the experiments used in the U.S. from English to Chinese.[9] Another translator, who had no prior understanding of the nature and objectives of the study, translated the experiments back to English. Using a normal reconciliation method, the original experiments were compared to this back-translation. In the very few cases where any discrepancies were found, they were traced back to find out why they occurred and what steps, if any, should be taken to change them.

[9]The translators are from China Europe International Business School's Department of Translation, which employs the most experienced team of business translators among Chinese business schools.

IV Empirical Evidence

In this section, we report empirical evidence on the effects of color in the domain of financial decision-making and investment behavior. First, we examine to what extent color influences investors' financial risk preferences. Second, we analyze whether color affects investors' beliefs about expected future stock returns.

A Color and Financial Risk Preferences

A.1 Research Design

We estimate an individual's financial risk preference using a standard research design which involves a selection among pairs of risky financial choices (e.g., Holt and Laury (2002)). Table A1 in Appendix II shows the series of 10 pairs of risky choices that were displayed one by one to each experiment participant in random order. Each pair consists of a lower-risk option and a higher-risk option, as measured by the variance in the payoffs. For example, for Pair #3 in the table, "70% chance of $2.00; 30% chance of -$1.50" is the lower-risk option, while "70% chance of $4.00; 30% chance of -$5.00" constitutes the higher-risk option. For pairs at the top of the table, the expected payoff is higher for the higher-risk option, while the expected payoff is higher for the lower-risk option for pairs towards the end of the table.[10] When the expected payoff of the higher-risk option is reduced sufficiently, an individual may cross over to the lower-risk option. For example, a risk-neutral individual would cross over at Pair #4. The point at which such a cross-over occurs is a measure of the individual's risk aversion in a Holt and Laury style risky choice setting. Within each pair, each choice consists of a potential profit and a potential loss, respectively, with different probabilities. Each individual selected either the lower-risk option or the higher-risk option for each of the 10 pairs of risky choices.[11]

As a measure of an individual's financial risk preference, we compute the proportion of selected higher-risk options. This is equivalent to estimating the point of cross-over. As a result, the variable

[10] The expected payoffs were not reported to the experiment participants.

[11] The Holt and Laury (2002) style risky choice setting has been subject to some criticism related to order effects (e.g., Harrison, Johnson, McInnes, and Rutström (2005)), but our specific research design with random ordering of choices addresses such concerns (e.g., Holt and Laury (2005)).

Financial Risk Preference varies from 0% to 100% in 10 percentage point increments. The most risk averse experiment participants in our data are those who selected the lowest proportion of higher-risk options, i.e., they cross over from the higher-risk to the lower-risk option early on.[12]

Prior to making any of these selections, each experiment participant was randomly assigned to one of two color conditions: (i) Red, i.e., the treatment condition, for which all potential financial losses were displayed in red color, but all the other information in black color, and (ii) Black, i.e., the control condition, for which all the information was displayed in black. We employ such a between-individuals research design to ensure that an individual viewed all potential losses either in red color or in black color. Figure A1 in Appendix II contains an example of the way a risky financial choice pair was displayed to the individuals who were assigned to the treatment condition (Panel A) versus in the control condition (Panel B). That is, the only difference is with respect to the color used to visualize potential financial losses.

The hypothesis we test is whether viewing the potential financial losses in red color systematically reduces an individual's financial risk taking propensity.

A.2 Evidence on Color and Financial Risk Preferences

Figure 1 shows that individuals randomly assigned to the red condition avoid the higher-risk options more frequently than those in the black condition. In the red condition, the higher-risk options were selected only 29.1% of the time. In contrast, the higher-risk options were selected 34.6% of the time in the black condition. The difference (5.5 percentage points) is economically sizable and statistically significant at the 10%-level (p-value = 0.072). In other words, visualizing potential financial losses in red color results in avoidance behavior in investors, in the sense that it significantly elevates their risk aversion.

Our research design assigns each experiment participant randomly to one of the two color conditions, but if those assigned to the red condition were more risk averse for some exogenous reason, then the previous inferences may be biased. For example, if the red condition oversampled

[12] As examples of our efforts to ensure appropriate quality of our experimental data, we exclude participants who (i) selected a certain loss of $5.00 over a certain loss of $1.50 (i.e., the higher-risk option in Pair #10) or (ii) crossed over from the lower-risk option to the higher-risk option.

women, who on average prefer less risk compared to men (e.g., Croson and Gneezy (2009)), then our estimates are confounded. We address such a concern using two complementary empirical approaches. First, we check for differences in means of individual characteristics. Table 2 Panel A shows that we find no evidence of systematic and statistically significant differences between the individuals in the red and black color conditions. This evidence means that individuals were indeed assigned randomly to the treatment and control conditions. Second, we estimate a parametric model specification in which we control for several individual characteristics.[13]

A.3 Controlling for Individual Characteristics

Table 3 shows that the effect of red color on an individual's financial risk taking propensity persists after we control for a set of standard individual characteristics (e.g., Barsky, Juster, Kimball, and Shapiro (1997)): *Male*, *Age Group*, *Education*, *Income Group*, and *Risk Aversion*. While these variables are self-reported, it is not clear why any noise in our data would produce a systematic relationship between red color and financial risk preferences.[14]

Column (1) reports that the point estimate on *Red Color* is -0.070 (p-value = 0.080). In columns (2) to (6), we include the variables one by one to control for heterogeneous individual characteristics. The point estimate on *Red Color* is stable and varies only slightly, from -0.068 to -0.083, across these model specifications. Column (7) includes all control variables simultaneously. This model specification therefore isolates the effect of the color red on financial risk taking behavior because we control for several individual characteristics as potential confounds. We find that the point estimate on *Red Color* is -0.082 and statistically significant at the 5%-level. That is, the propensity of making a risky financial choice is reduced by about 8.2 percentage points among those in the red condition.

It is noteworthy that the ex ante *Risk Aversion* variable correlates with the financial risk preference as predicted, but does not explain away the effect of red color. This measure is based on Weber, Blais, and Betz (2002), and we find that it is similar among individuals randomly

[13]The results are robust to using a non-parametric model specification.

[14]Because a small number of experiment participants select not to reveal some of the individual characteristics, the number of observations vary slightly across the reported model specifications.

assigned to the treatment and control conditions. Including this control variable does not affect our conclusions.

A.4 Evidence from Alternative Treatment Conditions

Table 4 reports evidence from experiments involving alternative treatment conditions. So far, the treatment condition has been to display all potential financial losses in red color, but we also consider several alternatives. Column (1) reports the previous treatment condition as a benchmark, i.e., "Red Loss, Black Profit" condition. Column (2) reports results for a model specification where the treatment condition is to display all potential financial profits in red color, i.e., "Black Loss, Red Profit" condition. That is, we perform what amounts to basically a placebo analysis as we do not expect any effect of this specific treatment condition. We find that the point estimate on *Red Color* is positive (0.043) and statistically insignificant. Column (3) reports results for a model specification where the treatment condition is to display all potential financial losses as well as profits in red color, i.e., "Red Loss, Red Profit" condition. We find that the point estimate on *Red Color* is -0.075 and statistically significant at the 10%-level. That is, the effect is very close to the previously reported benchmark effect of -0.082.

We conclude from these alternative treatment conditions that it is critical for the effect of color on financial risk preferences whether the potential financial losses are in red color, but not relevant whether or not the potential financial profits are in red color.

A.5 Discussion

Several conclusions emerge from our evidence. First, red color systematically influences investors' financial risk preferences. When individuals are displayed potential financial losses in red color, the propensity of taking financial risk is reduced by 23.7% ($= -0.082/0.346$). All else equal, investors' risk aversion is significantly elevated when shown potential losses in red color. In other words, red color causes avoidance behavior in individual investors, consistent with predictions from research in color psychology.

Second, the relationship between red color and reduced financial risk taking behavior can not be easily explained away by heterogeneity with respect to a set of standard individual characteristics, which may potentially be correlated with risk aversion. In particular, individuals who were ex ante similar with respect to, e.g., gender or risk aversion made systematically different risky financial choices when potential financial losses were visualized in red color.

Finally, the results suggest that investors who view potential financial losses in red color require a higher risk premium. Such behavior has the potential of contributing to time-varying risk premiums in financial market: During periods of substantial losses in financial markets, the color red is often used to visualize losses, thus potentially elevating investors' risk aversion, and therefore the required risk premium. Assuming a piece-wise linear relationship between risk aversion and the risk premium, we estimate that investors who view potential financial losses in red may require about a quarter higher risk premium.

B Color and Stock Return Beliefs

B.1 Research Design

We estimate an individual's beliefs about future stock returns from their estimates of future stock prices. Specifically, we randomly selected three stocks from the set of S&P 500 constituents and identified separate 12-month periods over which a negative cumulative return was experienced.[15] This empirical approach was selected to use real stock price paths which real investors had experienced. Figure A2 in Appendix II shows the stock price paths that were displayed one by one to each individual in random order. Each individual estimated the price of each stock half a year into the future for three different scenarios: (i) Most-likely scenario, (ii) Best-case scenario, and (iii) Worst-case scenario. As a measure of an individual's *Stock Return Beliefs*, we compute the average estimated stock return across the stocks for each of the three scenarios.[16]

Prior to making these estimations, each experiment participant was randomly assigned to one of two color conditions: (i) Red, i.e., the treatment condition, for which all the past negative stock price paths were displayed in red, and (ii) Black, i.e., the control condition, for which all the stock

[15] The identities of the stocks were not provided to the experiment participants.

[16] As an example of our efforts to ensure appropriate quality of our data, we exclude participants who provide stock return estimates two standard deviations away from the mean.

price paths were displayed in black. Again, we employ such a between-individuals research design to ensure that an individual viewed all stock price paths either in red or black color.[17] Figure A3 in Appendix II contains an example of the way the stock price paths were displayed to the individuals who were assigned to the treatment condition (Panel A) and the control condition (Panel B). That is, the only difference is with respect to the color used to visualize past stock price paths.

The hypothesis we test is whether viewing the past negative stock price paths in red color systematically reduces an individual's expectations about future stock returns.

B.2 Evidence on Color and Stock Return Beliefs

Figure 2 shows that individuals assigned to the red condition on average expect lower future returns across each of the three scenarios compared to those in the black conditions. For the most likely scenario, those in the red condition on average expect the stock to experience a -3.9% return per month. In contrast, those in the black condition on average expect the stock to experience a zero percent return per month. In other words, individuals in the red and black conditions come to opposite conclusions as to whether the stock price will continue to decrease. The difference (3.9 percentage points) is economically sizeable and statistically significant at the 1%-level.

The evidence shows that investors who were displayed past negative stock price paths in the color red on average form expectations consistent with a continuing stock price decline, and as a result exhibit "momentum beliefs." That is, after a period of negative returns, red color contributes to investors' long-recognized extrapolation of past stock returns (e.g., Tversky and Kahneman (1974) and Benartzi (2001)). In contrast, when shown the very same past stock price paths in black color, investors form "reversal beliefs," i.e., they exhibit an increased propensity to expect the stock price path to reverse in the future.

The evidence that red color results in beliefs of lower future stock returns is found also for the other two scenarios. For the worst case scenario, individuals in each color condition expect lower future returns (compared to the most likely scenario), but individuals in the red condition expect lower, i.e., even more negative, returns compared to those in the black condition. Specifically,

[17]The between-individuals research design addresses concerns related to research showing that elicitation mode, i.e., prices versus returns, may affect an individual's beliefs (e.g., Glaser, Langer, Reynders, and Weber (2007)).

individuals randomly assigned to the red condition expect 7.2 percentage points lower future returns per month. For the best case scenario, individuals in each condition estimated higher future returns (compared to the most likely scenario), but those in the red condition expect significantly lower returns compared to those in the black condition. In particular, individuals randomly assigned to the red condition expect 2.2 percentage points lower future returns per month. Importantly, red color has a particularly significant effect for worst case scenario stock return estimates.

Our research design assigned each individual randomly to one of the two color conditions, but if those assigned to the red condition systematically estimate different stock returns for some exogenous reason, then the previous inferences may be biased. We address such a concern using two empirical approaches. First, we check for differences in means of individual characteristics. Table 1 Panel B shows that we find no evidence of systematic and statistically significant differences between the individuals in the red and black color conditions. Second, we estimate a parametric model specification in which we control for individual characteristics.

B.3 Controlling for Individual Characteristics

Table 5 shows that the effect of the red condition on an individual's future stock return estimates persists after controlling for a set of standard individual characteristics: *Male*, *Age Group*, *Education*, and *Stock Market Participant*. While these variables are self-reported, it is not clear why any noise in the data would produce a systematic relationship between red color and expectations about future stock returns.

Column (1) reports that the point estimate on *Red Color* is -0.039. This corresponds to the unconditional difference in stock return estimates in the red versus black color conditions. In columns (2) to (5), we include these variables one by one to control for heterogeneous individual characteristics. The point estimate on *Red Color* is stable and varies only slightly, from -0.035 to -0.039, across these columns. Column (6) includes all the control variables simultaneously. This model specification therefore isolates the effect of the color red on beliefs about future stock returns because we control for several individual characteristics as potential confounders. We find that the point estimate on *Red Color* is -0.035, and statistically significant at the 1%-level, i.e., similar to the unconditional estimate of the effect. In other words, when investors are shown past negative stock price paths in red, expectations about future stock returns are reduced by about 3.5%.

B.4 Evidence on Color and Stock Return Prediction Errors

The evidence reported so far raises the question of whether red color eliminates or exacerbates the difference between investors' expected returns and subsequently realized returns. That is, does red color result in more or less biased beliefs compared to black color? We note that the previous evidence does not speak to whether red color results in systematically biased investor beliefs. As a result, we compute an individual-level prediction error for each individual in the data. The variable *Stock Return Prediction Error* is the difference between the expected stock return and the ex post realized stock return. That is, a positive (negative) prediction error indicates that the expected return is higher (lower) than the ex post realized return.

Figure 3 shows that the color red results in more negative prediction errors, i.e., more biased beliefs. In Table 6, we control for heterogeneity in individual characteristics. Column (1) reports that the point estimate on *Red Color* is -0.045, and statistically significant at the 1%-level. That is, red color results in individuals estimating significantly lower returns than realized ex post. Column (2) includes all control variables for heterogeneous individual characteristics. We find that the point estimate is -0.041, and still statistically significant at the 1%-level, i.e., similar to the unconditional estimate of the effect. In other words, individuals in the red condition expect the stock return to be 4.1 percentage points lower per month than the ex post realized return, i.e., we find evidence of systematically negative prediction errors related to red color. Our interpretation of this evidence is that the expectations about future stock returns are excessively low among the individuals in the red condition, i.e., resulting in biased beliefs.

B.5 Evidence on Color and Propensity to Purchase Stocks

We also examine whether the propensity to purchase a stock is reduced by the red color of the negative past stock price path. Specifically, investors rated their propensity to purchase each stock on a Likert scale from 1 to 9. Figure 4 shows that individuals randomly assigned to the red condition exhibit, on average, a lower propensity to purchase a stock compared to those in the black condition. The difference is economically sizeable: The propensity to purchase a stock is 2.7 among those in the red condition versus 3.1 among those in the black condition. The difference (0.5) is statistically significant at the 5%-level (p-value = 0.040). That is, an investor's propensity to purchase a stock is reduced when past negative returns are shown in red color. A similar conclusion emerges from Table 7, in which we control for heterogeneity across individuals. Specifically, we find that the propensity of an investor to purchase stocks is reduced by 17.6% (= 0.545/3.1) when negative stock price paths are displayed in red color.

B.6 Discussion

Several conclusions emerge from our evidence. First, color affects investors' beliefs about future stock returns. When ex ante similar individuals are displayed past negative stock price paths in red color, the expectations about future stock returns are reduced by 3.9 percentage points per month. Such behavior has the potential of contributing to momentum beliefs as investors who view past negative returns in red color exhibit an increased propensity to expect the stock price to continue to decline. That is, red color seems to exacerbate an extrapolation bias among investors. Red color has a particularly significant effect for worst case scenario stock return estimates. In addition, red color results in negative prediction errors. That is, investors' expectations about future stock returns are excessively low, compared to ex post realized returns, in the red condition. Red color exacerbates the difference between investors' expected returns and subsequently realized returns, i.e., red color steers investors in a direction of less rational expectations.

Second, red color reduces investors' propensity to purchase stocks. The propensity of purchasing the stock is reduced by 17.6% among individuals who are displayed past negative stock price paths in red color. In other words, visualizing past negative stock price paths in red color results in avoidance behavior in investors, in the sense that it significantly reduces the propensity to purchase a stock. That is, red color has the potential of adversely affecting stock market liquidity.

Finally, the evidence raises questions of whether the effects of red color arise by way of a discount rate effect or a cash flow effect. The financial risk preference results suggest that red color increases investors' required rate of return, i.e., there is a discount rate effect. The results for beliefs about future stock returns show that investors expect lower returns. Collectively, this evidence suggests that investors who view financial data in red color consider stocks to be riskier (denominator effect) and at the same time less cash flow producing (numerator effect).

V Further Evidence and Extensions

In this section, we report further empirical evidence on the effects of color in the domain of financial decision-making and investment behavior.

A Evolutionary Biology vs. Social Learning Explanation: Evidence from China

Research in color psychology argues that there are two theoretical explanations for why colors carry communication values and therefore may affect human behavior: An evolutionary biology explanation and a social learning explanation. As a result, we extend the previously reported analysis by examining which of these explanations are relevant in explaining why red color may affect financial decision-making and investment behavior. As they are not mutually exclusive, both explanations may be relevant.

Color associations are found to vary systematically across cultures. As a concrete example, in China, the color red symbolizes good fortune, is the color of important festivals, and is the primary color of the flag and the Communist Party. While red is the color of many objectively dangerous phenomena also in China, social learning and the cultural setting may be expected to moderate any effects of red color in China.

The differences in communication values of color across cultures extend to the financial decision-making domain. While red is used to represent financial losses in the U.S., it is used for the opposite, i.e., to represent positive stock returns, in China. As a result, the cross-cultural heterogeneity between the U.S. and China offers a setting to further analyze the explanation of the effects of red color. Specifically, an evolutionary biology explanation suggests that U.S. and Chinese investors behave similarly with respect to red color. A social learning explanation suggests that the effect of red color among Chinese investors may be muted, or potentially even reversed, compared to the effect among U.S. investors.

We employ the same research design as we used to analyze if color affects investors' beliefs about future stock returns. Table 8 shows that Chinese investors randomly assigned to the red condition do not expect significantly different future returns compared to those in the black condition. Column (1) reports that the point estimate on *Red Color* is -0.011. Column (2) includes all control variables for heterogeneous individual characteristics, but the point estimate is still small (-0.014) and statistically insignificant. This effect is only about a third ($= -0.014/-0.039$) of the previously reported point estimate. These results contrast sharply with the previously reported evidence for U.S. individuals. We also report estimates from a PSM model, in which we match Chinese individuals in the red color condition to U.S. individuals in the red color condition based on a set of standard individual characteristics: *Male*, *Age Group*, and *Education*. In the PSM model, *U.S. Investor* is an indicator variable that is one if the individual is from the U.S., and zero if the individual is from China. Column (3) reports that U.S. investors, who are otherwise similar to Chinese individuals, estimate 6.4 percentage points lower future stock returns, in the red condition.

We conclude that humans in today's society are endowed with a biological predisposition to associate red with elevated awareness, i.e., avoidance behavior. Importantly, as the evidence from China shows, social learning may significantly weaken such ingrained communication values of color. That is, the cultural setting may moderate evolutionary human predispositions.

B Evidence on Salience Effects

Recent research in economics emphasizes the importance of salience in several domains, including financial decision-making (e.g., Bordalo, Gennaioli, and Shleifer (2012, 2013) and Frydman and Mormann (2016)). As a result, one concern related to the previously reported evidence is that it is not red color per se that causes the behavioral differences, but it is simply representing a salience effect. That is, while red contrasts, i.e., "sticks out," compared to black, another color may cause a similar salience effect. In particular, visual science researchers would characterize this as "absolute salience" effects (e.g., Wolfe and Horowitz (2004)).

We perform several extensions to examine salience effects. First, we use the same research design as we used to analyze if color affects investors' financial risk preferences, with the only difference being that we completely invert the colors. In the red condition, all potential financial losses were displayed in black color, but all the other information in red color. As a result, the contrast between the potential losses and the other information is exactly the same as previously. We find that the point estimate on *Red Color* is small, and not statistically significant.

Second, we substitute red color for blue color and re-examine the previous effects. Blue color was chosen because several online investment platforms use blue color to visualize financial information. We employ the exact same research design as previously, with the only difference being that each individual was randomly assigned to either the blue or the black color condition. Figure 5 reports that individuals randomly assigned to the blue condition do not exhibit significantly different behavior compared to those in the black condition. Panel A shows that 39.6% of those in the blue condition select the higher-risk options, compared to 39.4% of those in the black condition. Panel B reports an average return estimate of -1.3% per month among those in the blue condition compared to 0.0% among those in the black condition. Panel C shows that the propensity to purchase a stock is 3.1 among those in the blue as well as black conditions.

We conclude that using another color than red does not influence the behavior of investors in a similar way as red color. This evidence is further support for the conclusion that it is the color red in the domain of financial losses that causes the previously reported effect of color on investment behavior, rather than a more general salience effect caused by a different color that sticks out. That is, we find that only red color produces avoidance behavior in the domain of investments.[18]

C Evidence from Colorblind Investors

One empirical approach to validate the previously reported effects of color on investment behavior is to "switch off" the underlying characteristic that supposedly explains the behavior. We do this by studying a sample of colorblind individuals. If we find similar effects after such the switch off, we would be concerned that the previously reported effects of color were in fact attributable to

[18] As a robustness check, we have examined the effect of yellow color as it is commonly used to signal caution in some domains (e.g., traffic signs). We find no statistically significant effect of yellow color. This result is perhaps not surprising because online investment platforms generally do not use yellow color to represent potential financial losses or past negative stock price paths.

omitted variable bias and an individual characteristic we do not control for.

We employ the same research design as we used to analyze if color affects investors' beliefs about future stock returns. Table 9 shows that colorblind investors randomly assigned to the red condition do not expect significantly different future returns compared to those in the black condition. Column (1) reports that the point estimate on *Red Color* is -0.008, and statistically insignificant. Column (2) includes all control variables for heterogeneous individual characteristics. The point estimate is still small (-0.013) and statistically insignificant. This effect is only about a third ($= -0.013/-0.039$) of the previously reported point estimate. These results contrast sharply with the previously reported evidence for individuals who are not colorblind.

An appropriate sample of colorblind investors comprises of individuals with similar characteristics as our original sample. We find statistically significant differences for gender in that males are overrepresented in our sample of colorblind individuals (77% versus 61%). This is to be expected as colorblindness is more common in males in the population (e.g., Wong (2011)). As we include *Male* as a control variable, this is not likely to cause any omitted variable bias. As an additional empirical approach, we also report estimates from a propensity score matching (PSM) model, in which we match colorblind individuals in the red color condition to non-colorblind individuals in the red color condition based on a set of standard individual characteristics: *Male*, *Age Group*, and *Education*. In the PSM model, *Non-Colorblind* is an indicator variable that is one if the individual is not colorblind, i.e., has full color vision, and zero otherwise. Column (3) reports that *Non-Colorblind* individuals, who are otherwise similar to colorblind individuals, estimate 4.5 percentage points lower future stock returns, in the red condition. The size of the PSM effect is comparable, and slightly stronger, than the originally estimated effect.

We conclude that red color does not influence the expectations about future stock returns among colorblind individuals. Switching off the underlying characteristic has the effect that colorblind individuals are immunized to the effect of color on investment behavior. Importantly, this evidence provides further validation of the conclusion that it is the color red, as opposed to some omitted individual characteristic, which causes the previously reported effects of color on investment behavior.

D Evidence on Fast vs. Slow Decisions

Researchers have long recognized that different psychological approaches are involved in decision-making (e.g., Stanovich and West (2000) and Kahneman (2011)). In particular, Dual Process Theory research suggests that "System 1" is the more automatic system, while "System 2" is the more analytic system. It is ambiguous a priori whether the individuals randomly assigned to the red condition make financial decisions significantly faster or slower. On the one hand, a red-danger association may result in a faster decision because of avoidance behavior. On the other hand, because there is not imminent danger in these experiments, red color may be expected to result in elevated awareness and more analysis by an investor prior to making any financial decisions. The MTurk platform provides researchers with detailed data on the *Time to Decision* for each experiment participant.

Table 10 reports our evidence related to *Time to Decision.* Column (1) reports that the point estimate on *Red Color* is 0.2, and statistically insignificant, for the experiments involving *Financial Risk Taking.* The average decision time is 8.8 seconds. That is, individuals in the red condition made their decisions about 0.2 seconds (1.9%) slower. Column (2) includes all control variables for heterogeneous individual characteristics. The point estimate is 0.4 and still statistically insignificant. The remaining columns of the table involve time to decision and the *Stock Return Beliefs* experiments. The average decision time is 30.4 seconds. Column (3) reports that the point estimate on *Red Color* is 2.6, and statistically insignificant, for the *Financial Risk Taking.* That is, individuals in the red condition made their decisions about 2.6 seconds (8.6%) slower. Column (4) includes all control variables for heterogeneous individual characteristics. The point estimate is 2.0 and still statistically insignificant.

We conclude that there is no evidence of faster decisions among individuals in the red color condition. If anything, there is some evidence that red color may cause elevated awareness and more analysis by an investor prior to making financial decisions.[19]

[19] One caveat is that some individuals think relatively more in System 1 while others more in System 2 (e.g., Epstein, Pacini, Denes-Raj, and Heier (1996), but we are not measuring heterogeneity in "thinking styles."

VI Conclusions

A review of prominent online investment platforms in the U.S. catering to individual investors shows that financial decisions in today's society are made in environments involving color. Such color stimuli carry communication values which have been found to affect human behavior in non-finance domains. Specifically, color automatically initiates biologically ingrained evaluation processes in the human visual system, which may be moderated by social learning and the cultural setting in which decisions are made. In this paper, we therefore performed a systematic empirical analysis of the effects of color in the domain of investment behavior.

We find that when investors are displayed potential financial losses in red, the propensity of taking risk is reduced significantly. This relation can not be explained by heterogeneity with respect to a set of standard individual characteristics which may potentially be correlated with risk taking. In addition, we document that when investors are shown past negative stock price paths in red, expectations about future stock returns are reduced significantly. Such behavior has the potential of contributing to momentum beliefs as investors who view past negative returns in red believe that the stock price will continue to decline. We also find that red reduces investors' propensity to purchase stocks. The effects are robust to a series of checks involving colorblind investors and alternative colors to control for salience effects. Importantly, we find that the effects of red color are significantly muted in a cultural setting (e.g., China) where red is generally not used to visualize financial losses. The evidence is broadly consistent with what color psychologists characterize as "red-danger associations" and that red color is causing "avoidance behavior."

Our evidence has implications for (i) research in financial economics, (ii) the finance industry, and (iii) public policy makers. Finance research has so far largely not confronted the hypothesis that representation of financial information, as opposed to the information per se, may influence financial decision-making and investor behavior. We find that color influences very fundamental characteristics of investors, including their preferences and beliefs. Our evidence has implications for profit-maximizing finance industry entities that are interested in scientific inferences with respect to visualization of financial information and its impact on investors' behavior. Public policy makers and regulators may infer from our evidence that color may be an important, and implementationwise relatively inexpensive, "nudge," in the domain of financial decision-making.

This research contributes to a new field in financial economics which may be dubbed "Visual Finance." We identify several directions in the future for such an emerging field. First, while our evidence is based on well-recognized research methods in experimental economics, a next and natural step would be to expand the evidence to the field. One alternative is to perform experiments on online investment platforms, though ethical concerns combined with fiduciary responsibilities will make it challenging, particularly if large investment portfolios are potentially affected. Second, an alternative is to examine behavior in a quasi-experimental setting. For example, most financial and other newspapers (e.g., Wall Street Journal) have switched to color editions in the past few decades, which suggests a difference-in-difference analysis of investment behavior around such exogenous changes, caused by technological innovation. Finally, while color is an important dimension of visual representation of financial data and information, there are several others that future research may examine in more depth (e.g., Schwabish (2014)).

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Table 1: Color and Online Investment Platforms

The table reports an examination of the use of color on the most prominent online investment platforms that cater to individual investors in the U.S. In particular, we review: (i) the largest specialized brokerages (e.g., E*Trade, Interactive Brokers, Schwab, Scottrade, and TD Ameritrade), (ii) a large retirement savings platform (Vanguard), (iii) an emerging multimedia platform for brokerage services and trading (Robinhood), (iv) the most visited financial information providers (e.g., CNN Money, Google Finance, Morningstar, MSN Money, and Yahoo! Finance), (v) the largest online financial newspaper (Wall Street Journal), (vi) stock exchange websites (Nasdaq and NYSE), and (vii) the primary account aggregator to consolidate financial information across platforms (Mint). We report the use of color to represent stock returns and the color used in graphs of stock prices. All sites were accessed in June 2017.

Online Investment Platform	Returns	Graphs
CNN Money	Red/Green	Blue
E*Trade	Red/Green	Blue
Google Finance	Red/Green	Blue
Interactive Brokers	Red/Green	Red/Green
Mint	Red/Green	Red/Green
Morningstar	Red/Green	Blue
MSN Money	Red/Green	Blue
Nasdaq	Red/Green	Blue
NYSE	Red/Green	Blue
Robinhood	Red/Green	Red/Green
Schwab	Red/Green	Red/Green
Scottrade	Red/Green	Red/Green
TD Ameritrade	Red/Green	Red/Green
Vanguard	Red/Green	Blue
Wall Street Journal	White	Blue
Yahoo! Finance	Red/Green	Red/Green

Table 2: Summary Statistics

The table reports experiment participant level summary statistics for the treatment (Red) and control (Black) conditions. Panel A reports characteristics for the sample of participants used to estimate the effects of red color on *Financial Risk Preferences*. Panel B reports characteristics of the participants used to estimate the effects of red color on *Stock Return Beliefs*. The final column reports p-values from two-sample t-tests which compare the means for each variable across the treatment and control conditions. All variables are defined in Appendix I.

Panel A: Color and Financial Risk Preferences

	Red			Black			
	Mean	St. Dev.	N	Mean	St. Dev.	N	p-value
Male	0.51	0.50	160	0.49	0.50	160	0.330
Age Group	5.88	2.57	160	6.43	2.82	160	0.069
Education	3.76	1.20	160	3.88	1.19	157	0.361
Income Group	3.20	1.64	157	3.46	1.74	154	0.170
Risk Aversion	3.90	0.53	160	3.88	0.46	160	0.777

Panel B: Stock Return Beliefs

	Red			Black			
	Mean	St. Dev.	N	Mean	St. Dev.	N	p-value
Male	0.61	0.49	87	0.57	0.50	98	0.604
Age Group	4.44	2.22	87	3.99	2.06	98	0.159
Education	3.82	1.17	87	3.73	1.10	98	0.628
Income Group	2.91	1.55	85	3.04	1.68	95	0.572
Stock Market Participant	0.22	0.41	83	0.30	0.46	96	0.195

Table 3: Evidence on Color and Financial Risk Preferences

The table reports estimates from Tobit models of estimated financial risk preferences. *Financial Risk Preferences* is the dependent variable and is the proportion of the higher-risk options chosen by the experiment participant. *Red Color* is an indicator variable that is one if the individual was randomly assigned to the red color condition, and zero otherwise. The other variables are defined in Appendix I. Standard errors are reported within parentheses and are White (1980) heteroskedasticity-robust. ***, **, * means that the point estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Red Color	-0.070*	-0.069*	-0.083**	-0.075*	-0.070*	-0.068*	-0.082**
	(0.040)	(0.040)	(0.038)	(0.040)	(0.041)	(0.039)	(0.039)
Male		-0.018					-0.044
		(0.039)					(0.040)
Age Group			-0.025***				-0.020**
			(0.008)				(0.008)
Education				-0.014			-0.008
				(0.015)			(0.017)
Income Group					-0.010		-0.003
					(0.012)		(0.013)
Risk Aversion						-0.128***	-0.111***
						(0.042)	(0.041)
Intercept	0.325***	0.334***	0.483***	0.384***	0.357***	0.821***	0.949***
	(0.031)	(0.035)	(0.052)	(0.071)	(0.057)	(0.167)	(0.177)
N	320	320	320	317	311	320	310
Pseudo R-sq.	0.009	0.010	0.043	0.012	0.010	0.040	0.069

Table 4: Evidence from Alternative Treatment Conditions

The table reports estimates from Tobit models of estimated financial risk preferences. *Financial Risk Preferences* is the dependent variable and is the proportion of the higher-risk options chosen by the experiment participant. Column (1) reports estimates from the primary red treatment condition as a benchmark, i.e., "Red Loss, Black Profit" condition. Column (2) reports results for a model specification where the treatment condition is to display all potential financial profits in red color, i.e., "Black Loss, Red Profit" condition. Column (3) reports results for a model specification where the treatment condition is to display all potential financial losses as well as profits in red color, i.e., "Red Loss, Red Profit" condition. *Red Color* is an indicator variable that is one if the individual was randomly assigned to the red color condition, and zero otherwise. The other variables are defined in Appendix I. Standard errors are reported within parentheses and are White (1980) heteroskedasticity-robust. ***, **, * means that the point estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Condition	Red Loss, Black Profit	Black Loss, Red Profit	Red Loss, Red Profit
Red Color	-0.082**	0.043	-0.075*
	(0.039)	(0.056)	(0.043)
Intercept	0.949***	0.813***	0.927***
	(0.177)	(0.246)	(0.202)
Controls	Yes	Yes	Yes
N	310	263	253
Pseudo R-sq.	0.069	0.017	0.049

Table 5: Evidence on Color and Stock Return Beliefs

The table reports estimates from OLS models of estimated beliefs about future stock returns. *Stock Return Belief* is the dependent variable and is the average monthly stock return based on each participant's price estimates. *Red Color* is an indicator variable that is one if the individual was randomly assigned to the red color condition, and zero otherwise. The other variables are defined in Appendix I. Standard errors are reported within parentheses and are White (1980) heteroskedasticity-robust. ***, **, * means that the point estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Red Color	-0.039***	-0.039***	-0.038***	-0.039***	-0.035***	-0.035***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)
Male		0.015				0.004
		(0.011)				(0.012)
Age Group			-0.001			-0.001
			(0.002)			(0.002)
Education				0.003		0.0002
				(0.004)		(0.004)
Stock Market Participant					0.040***	0.040***
					(0.011)	(0.012)
Intercept	-0.000	-0.009	0.004	-0.011	-0.012*	-0.010
	(0.006)	(0.009)	(0.012)	(0.016)	(0.007)	(0.019)
N	185	185	185	185	179	179
Adj. R-sq.	0.067	0.073	0.063	0.064	0.127	0.114

Table 6: Evidence on Color and Stock Return Prediction Errors

The table reports estimates from OLS models of stock return prediction errors. *Stock Return Prediction Error* is the dependent variable and is the average difference between *Stock Return Beliefs* and the ex post realized returns. *Red Color* is an indicator variable that is one if the individual was randomly assigned to the red color condition, and zero otherwise. The other variables are defined in Appendix I. Standard errors are reported within parentheses and are White (1980) heteroskedasticity-robust. ***, **, * means that the point estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Red Color	-0.045***	-0.041***
	(0.012)	(0.012)
Intercept	-0.017***	-0.030
	(0.006)	(0.022)
Controls	No	Yes
N	185	179
Adj. R-sq.	0.070	0.112

Table 7: Evidence on Color and the Propensity to Purchase Stocks

The table reports estimates from Tobit models of propensity to purchase stocks. *Propensity to Purchase Stocks* is the dependent variable and is the average of the purchase ratings, on a one to nine Likert scale, across the stocks. *Red Color* is an indicator variable that is one if the individual was randomly assigned to the red color condition, and zero otherwise. The other variables are defined in Appendix I. Standard errors are reported within parentheses and are White (1980) heteroskedasticity-robust. ***, **, * means that the point estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Red Color	-0.593**	-0.594**	-0.616**	-0.606**	-0.590**	-0.618**	-0.494**	-0.545**
	(-2.28)	(-2.25)	(-2.27)	(-2.33)	(-2.23)	(-2.38)	(-2.01)	(-2.04)
Male		0.019						-0.158
		(0.07)						(-0.59)
Age Group			0.049					0.016
			(0.75)					(0.26)
Education				0.178				0.098
				(1.47)				(0.85)
Income Group					0.134			-0.006
					(1.59)			(-0.07)
Risk Aversion						0.540*		0.440
						(1.72)		(1.42)
Stock Market Participant							1.404***	1.345***
							(4.67)	(4.44)
Intercept	3.057***	3.046***	2.863***	2.391***	2.648***	2.118***	2.639***	1.552**
	(17.79)	(14.57)	(10.80)	(5.40)	(8.46)	(3.98)	(16.06)	(2.00)
N	185	185	185	185	180	185	179	175
Pseudo R-sq.	0.008	0.008	0.009	0.011	0.012	0.014	0.043	0.051

Table 8: Evolutionary Biology vs. Social Learning Explanation: Evidence from China

The table reports estimates from OLS and propensity score matching (PSM) models of estimated beliefs about future stock returns involving Chinese individuals. *Stock Return Belief* is the dependent variable and is the average monthly stock return based on each participant's price estimates. *Red Color* is an indicator variable that is one if the individual was randomly assigned to the red color condition, and zero otherwise. In the PSM model, we match Chinese individuals in the red color condition to U.S. participants in the red color condition based on a set of standard individual characteristics: *Male*, *Age Group*, and *Education*. *U.S. Investor* is an indicator variable that is one if the individual resides in the U.S., and zero if the individual resides in China. The other variables are defined in Appendix I. Standard errors are reported within parentheses and are White (1980) heteroskedasticity-robust. ***, **, * means that the point estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Model	OLS	OLS	PSM
Red Color	-0.011	-0.014	
	(0.018)	(0.021)	
U.S. Investor			-0.064***
			(0.010)
Intercept	-0.058***	-0.093**	
	(0.009)	(0.042)	
Controls	No	Yes	NA
N	139	116	148
Adj. R-sq.	-0.005	0.062	NA

Table 9: Evidence from Colorblind Investors

The table reports estimates from OLS and propensity score matching (PSM) models of estimated beliefs about future stock returns involving colorblind individuals. *Stock Return Belief* is the dependent variable and is the average monthly stock return based on each participant's price estimates. *Red Color* is an indicator variable that is one if the individual was randomly assigned to the red color condition, and zero otherwise. In the PSM model, we match colorblind individuals in the red color condition to non-colorblind individuals in the red color condition based on a set of standard individual characteristics: *Male*, *Age Group*, and *Education*. *Non-Colorblind* is an indicator variable that is one if the individual is not colorblind, i.e., has full color vision, and zero otherwise. The other variables are defined in Appendix I. Standard errors are reported within parentheses and are White (1980) heteroskedasticity-robust. ***, **, * means that the point estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Model	OLS	OLS	PSM
Red Color	-0.008	-0.013	
	(0.012)	(0.012)	
Non-Colorblind			-0.045***
			(0.015)
Intercept	-0.005	-0.063*	
	(0.008)	(0.037)	
Controls	No	Yes	NA
N	136	130	130
Adj. R-sq.	-0.004	-0.002	NA

Table 10: Evidence on Fast vs. Slow Decisions

The table reports regressions of the time taken by participants to provide stock price forecasts. *Time to Decision* is the dependent variable and is the equally-weighted average, across all experiments, of the amount of time (in seconds) the participant viewed the screen when conducting the experiment. *Red Color* is an indicator variable that is one if the individual was randomly assigned to the red color condition, and zero otherwise. Columns 1 and 2 report estimates related to participants' *Financial Risk Preferences*. Columns 3 and 4 reports estimates related to participants' *Stock Return Beliefs*. The other variables are defined in Appendix I. Standard errors are reported within parentheses and are White (1980) heteroskedasticity-robust. ***, **, * means that the point estimate is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable:	*Financial Risk Preferences*		*Stock Return Beliefs*	
Red Color	0.168	0.437	2.574	2.020
	(0.693)	(0.668)	(3.580)	(3.500)
Intercept	8.805***	3.761	30.449***	34.261***
	(0.437)	(2.778)	(2.652)	(9.890)
Controls	No	Yes	No	Yes
N	320	310	185	179
Adj. R-sq.	-0.003	0.022	-0.003	0.014

Figure 1: Evidence on Color and Financial Risk Preferences

The figure reports estimates of the effects of red color on financial risk preferences by color condition. The bars show the mean *Financial Risk Preferences* for the treatment (Red) and control (Black) conditions. *Financial Risk Preferences* is the proportion of the higher-risk options chosen by the experiment participant. Error bars show the mean $\pm$ one standard error.

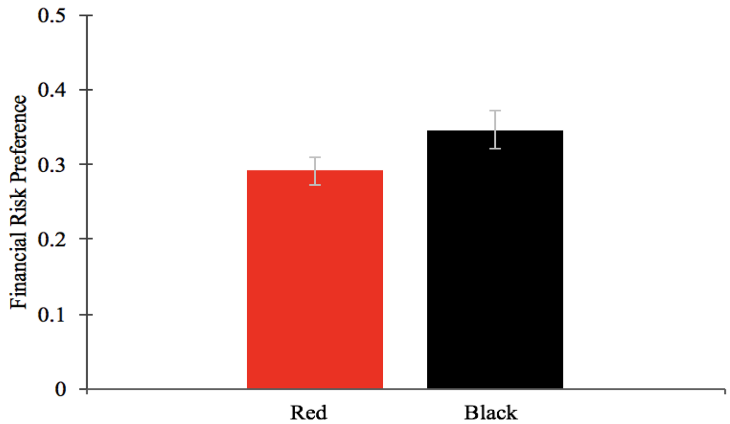


Figure 2: Evidence on Color and Stock Return Beliefs

The figure reports estimates of the effects of red color on stock return beliefs. The figure contains univariate estimates of stock return beliefs by color condition. The bars show the mean *Stock Return Beliefs* for the treatment (Red) and control (Black) conditions. *Stock Return Beliefs* is the average monthly stock return based on each participant's price estimates. Error bars show the mean ± one standard error.

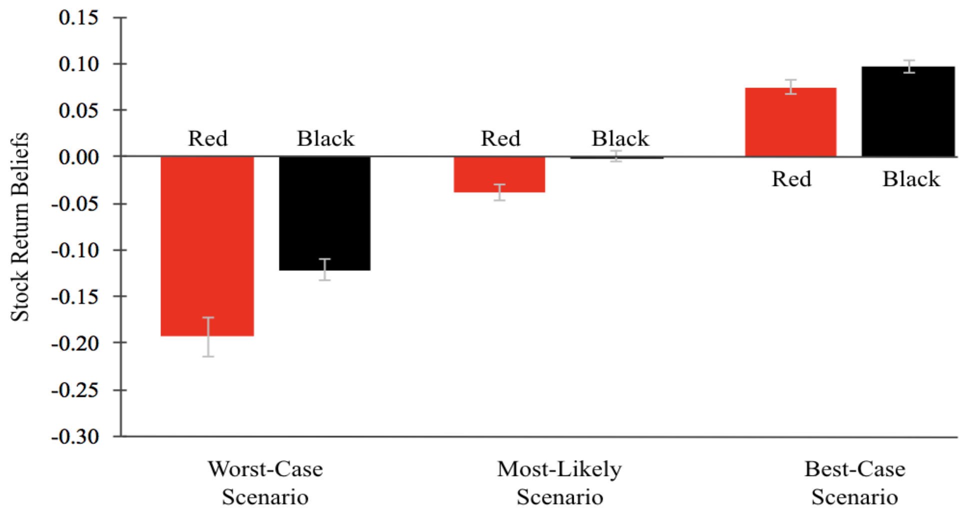


Figure 3: Evidence on Color and Stock Return Prediction Errors

The figure reports estimates of the effects of red color on stock return prediction errors. The figure contains univariate estimates of stock return prediction errors by color condition. The bars show the mean *Stock Return Prediction Error* for the treatment (Red) and control (Black) conditions. *Stock Return Prediction Error* is the average difference between *Stock Return Beliefs* and the ex post realized returns. Error bars show the mean ± one standard error.

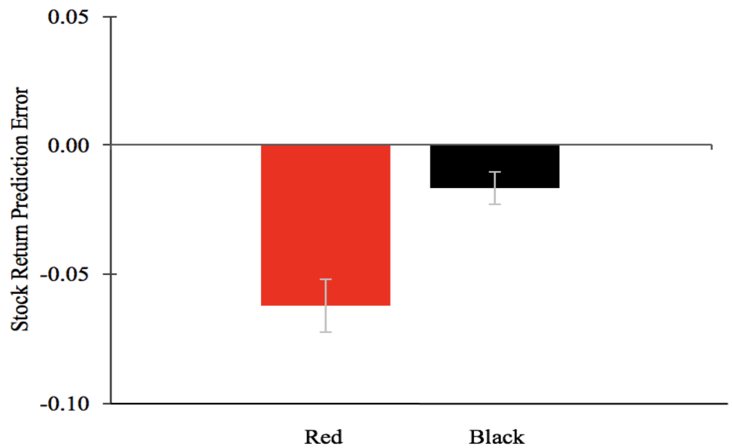


Figure 4: Evidence on Color and the Propensity to Purchase Stocks

The figure reports univariate estimates of participants' likelihood of investing in the stocks. The bars show *Propensity to Purchase* across the treatment (Red) and control (Black) conditions. *Propensity to Purchase* is the average of the purchase ratings, on a one to nine Likert scale, across the stocks. Error bars show the mean ± one standard error.

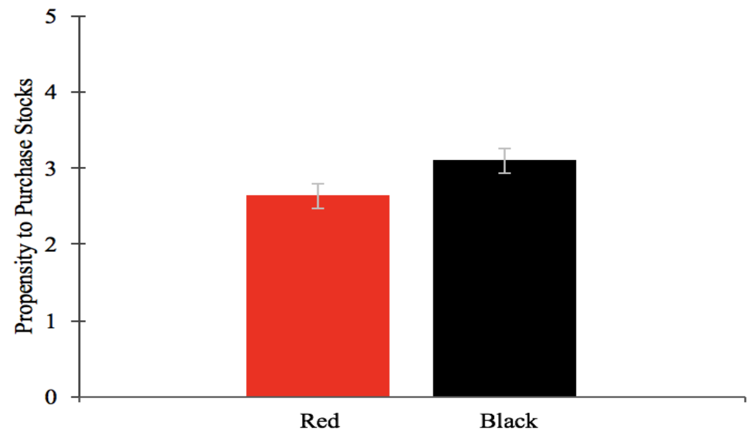
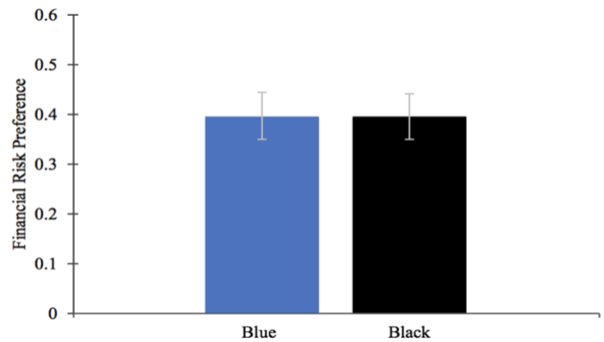


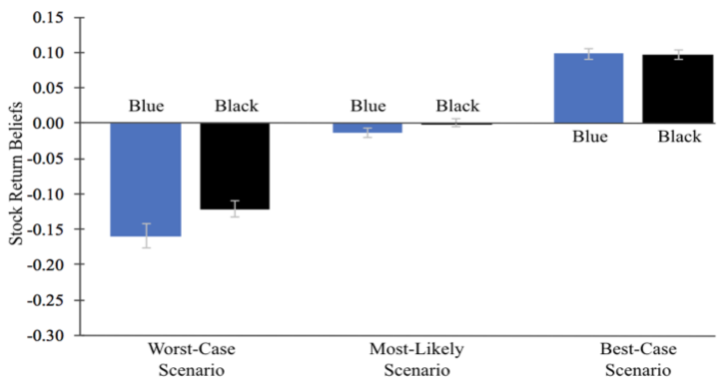
Figure 5: Evidence on Salience Effects

The figure reports estimates of salience effects from using blue color. Specifically, Panel A presents univariate estimates of elicited financial risk preferences by color condition. The bars show the mean *Financial Risk Preferences* for the salience treatment (Blue) and control (Black) conditions. *Financial Risk Preferences* is the proportion of the higher-risk options chosen by the experiment participant. Panel B presents univariate estimates of participants' future expected returns for the stocks. The bars show *Stock Return Belief* for each forecast scenario across the salience treatment (Blue) and control (Black) conditions. *Stock Return Beliefs* is the average monthly stock return based on each participant's price estimates. Panel C presents univariate estimates of participants' likelihood of investing in the stocks. The bars show *Propensity to Purchase* across the salience treatment (Blue) and control (Black) conditions. *Propensity to Purchase* is the average of the purchase ratings, on a one to nine Likert scale, across the stocks. Error bars show the mean ± one standard error.

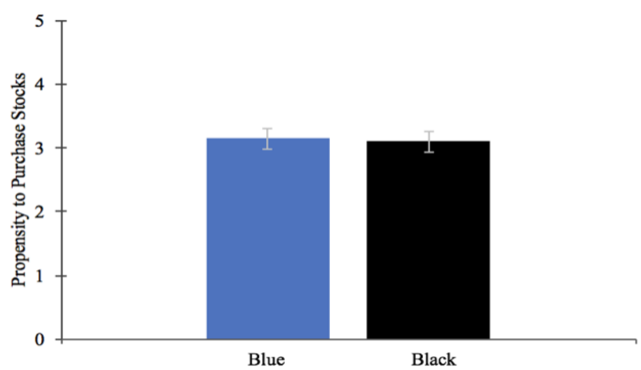
Panel A: Financial Risk Preferences



Panel B: Stock Return Beliefs



Panel C: Propensity to Purchase Stocks



Appendix I: Definitions of Variables

This table describes the variables used in the empirical analysis.

Color Variables	Definition
Red Color	An indicator variable that is one if the experiment participant was randomly assigned to the Red treatment condition, and zero otherwise.
Blue Color	An indicator variable that is one if the experiment participant was randomly assigned to the Blue treatment condition, and zero otherwise.
Dependent Variables	**Definition**
Financial Risk Preference	The proportion of higher-risk options chosen by the experiment participant (e.g., Holt and Laury (2002)).
Stock Return Beliefs	The average monthly stock return based on each experiment participant's price estimates.
Stock Return Prediction Error	The average difference between *Stock Return Beliefs* and the ex post realized returns.
Propensity to Purchase Stocks	The average of the purchase ratings, on a Likert scale from 1 to 9, across the stocks.
Time to Decision	The equally-weighted average, across all experiments, of the time (in seconds) the participant viewed the screen during the experiment.
Control Variables	**Definition**
Male	An indicator variable that is one if the experiment participant is male, and zero otherwise.
Age Group	The age of the experiment participant. Categorical variable: 1 if 18 - 20; 2 if 21 - 25; 3 if 26 - 30; 4 if 31 - 35; 5 if 36 - 40; 6 if 41 - 45; 7 if 46 - 50; 8 if 51 - 55; 9 if 56 - 60; 10 if 61 - 65; and 11 if above 65 years old.
Education	The highest level of education of the experiment participant. Categorical variable: 1 if some high school; 2 if high school graduate; 3 if some college; 4 if undergraduate degree; 5 if professional degree; 6 if master's degree; and 7 if doctoral degree.
Income Group	The income of the experiment participant. Categorical variable: 1 if $0 - 25,000; 2 if $25,001 - 40,000; 3 if $40,001 - 60,000; 4 if $60,001 - 80,000; 5 if $80,001 - 100,000; 6 if $100,000 - 150,000; and 7 if above $150,000.
Risk Aversion	An index composed of the "Gambling and Investing" risk assessment questions in Weber et al. (2002).
Stock Market Participant	An indicator variable that is one if the experiment participant reports investing in the stock market, and zero otherwise.
Non-Colorblind	An indicator variable that is one if the experiment participant is not colorblind, and zero if the individual is colorblind.
U.S. Investor	An indicator variable that is one if the experiment participant resides in the U.S., and zero if the individual resides in China.

Appendix II: Research Design

Table A1: Estimating Financial Risk Preferences

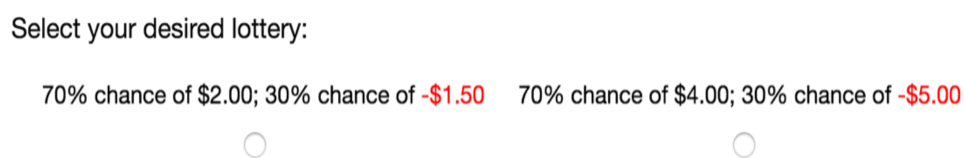
Individuals' financial risk preferences were estimated using a standard method involving risky choices (e.g., Holt and Laury (2002)). The table shows the series of 10 pairs of risky financial choices that were displayed one by one to each individual in random order. Each pair consists of a lower-risk option and a higher-risk option, as measured by the variance in the payoffs. For example, for Pair #3 in the table, "70% chance of $2.00; 30% chance of -$1.50" is the lower-risk option while "70% chance of $4.00; 30% chance of -$5.00" is the higher-risk option. Within each pair, each choice consists of a potential profit and a potential loss, respectively, with differential probabilities. Each individual selected either the lower-risk option or the higher-risk option for each of the 10 pairs. We then compute the proportion of selected higher-risk choices as a measure of an individual's revealed financial risk taking propensity. As a result, the variable *Financial Risk Preference* varies from 0% to 100% in 10 percentage point increments. The most risk averse individuals in our sample are those who selected the lowest proportion of higher-risk options.

Pair #	Lower-Risk Option	Higher-Risk Option
1	90% chance of $2.00; 10% chance of -$1.50	90% chance of $4.00; 10% chance of -$5.00
2	80% chance of $2.00; 20% chance of -$1.50	80% chance of $4.00; 20% chance of -$5.00
3	70% chance of $2.00; 30% chance of -$1.50	70% chance of $4.00; 30% chance of -$5.00
4	60% chance of $2.00; 40% chance of -$1.50	60% chance of $4.00; 40% chance of -$5.00
5	50% chance of $2.00; 50% chance of -$1.50	50% chance of $4.00; 50% chance of -$5.00
6	40% chance of $2.00; 60% chance of -$1.50	40% chance of $4.00; 60% chance of -$5.00
7	30% chance of $2.00; 70% chance of -$1.50	30% chance of $4.00; 70% chance of -$5.00
8	20% chance of $2.00; 80% chance of -$1.50	20% chance of $4.00; 80% chance of -$5.00
9	10% chance of $2.00; 90% chance of -$1.50	10% chance of $4.00; 90% chance of -$5.00
10	0% chance of $2.00; 100% chance of -$1.50	0% chance of $4.00; 100% chance of -$5.00

Figure A1: Color and Financial Risk Preferences

Each experiment participant was randomly assigned to one of two color conditions: (i) Red, i.e., the treatment condition, for which all potential financial losses were displayed in red color, but all the other information in black color, and (ii) Black, i.e., the control condition, for which all the information was displayed in black. The figure contains an example of the way a risky financial choice pair was displayed to the individuals who were in the treatment group (Panel A) and the control group (Panel B). That is, the only difference was with respect to the color used to visualize potential financial losses.

Panel A: Red (Treatment) Condition



Panel B: Black (Control) Condition

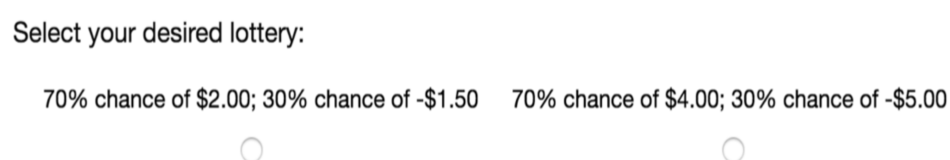
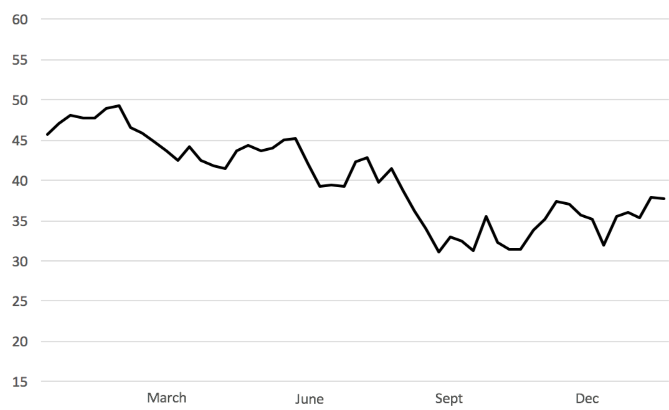


Figure A2: Estimating Stock Return Beliefs

Individuals' beliefs about future stock returns were estimated from their estimates of future stock prices. Specifically, we randomly selected three stocks from the set of S&P 500 constituents and identified separate 12-month periods over which a negative cumulative return was experienced for each stock. Panels A, B, and C shows the stock price paths that were displayed one by one to each individual in random order. Each individual estimated the price of each stock half a year into the future for three different scenarios: (i) Most-likely scenario, (ii) Best-case scenario, and (iii) Worst-case scenario. As a measure of an individual's *Stock Return Belief*, we compute the average estimated stock return across the stocks for each of the three scenarios.

Panel A: Stock 1



Panel B: Stock 2

Panel C: Stock 3

Figure A3: Color and Stock Return Beliefs

Each individual was randomly assigned to one of two color conditions: (i) Red condition, i.e., the treatment condition, for which stock price paths were displayed in red color, and all the other information in black color, and (ii) Black condition, i.e., the control condition, for which all the information was displayed in black. The figure contains an example of the way a stock price path was displayed to the individuals who were in the treatment group (Panel A) and the control group (Panel B). That is, the only difference was with respect to the color used to visualize the stock price paths.

Panel A: Red (Treatment) Condition

Panel B: Black (Control) Condition