Numerical Anchoring, Perceived Returns, and Asset Prices∗

Paulo Costa†

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Abstract: Investors often observe financial information in dollar amounts, even though investment performance is measured in percentage returns. I develop a model in which observing financial information in dollar amounts may distort investors’ perception of returns. When converting from dollar amounts to percentage returns and vice-versa, individuals anchor on a customary dollar amount and do not fully adjust to amounts that substantially deviate from it. Behavior of this sort leads to predictable mistakes. I empirically test two predictions of the model in one online experiment and one field experiment with more than 170,000 investors from a brokerage firm. The online experiment leverages a within-subject design to confirm the first prediction: individuals underestimate the future value of large dollar amounts relative to small dollar amounts for a given percentage return and a time horizon. I use the field experiment to confirm the second prediction: investors respond more strongly to the same percentage gains when they are described in larger dollar amounts. This simple treatment increases investor purchase of a financial product by 24.5%. Having found supportive evidence for the model, I apply it to understand the effect of share prices — quoted in dollar terms — on the behavior of stock returns. Consistent with the model, I find that stocks with similar past returns, but higher share prices, exhibit stronger return predictability and are less likely to show reversal in the long-run, controlling for size. Based on this finding, I propose a trading strategy that enhances the performance of momentum strategies in the stock market.

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†Harvard University. e-mail: paulocosta@g.harvard.edu
1 Introduction

Financial economists study the link between asset returns and investment decisions. In making these decisions, investors often process financial information quoted in dollar terms. For example, workers may want to achieve a specific retirement goal and need to decide how much to invest today given expected fund performance. In the stock market, newspapers and online media outlets often display the performance of stocks as dollar changes in price rather than percentage returns. Observing financial information in both percentage returns and dollar amounts may complicate the link between returns and investors’ behavior.

I document that describing financial information in dollar terms distorts investors’ perception of returns. When considering the performance of an investment opportunity, investors should think in percentage returns. However, since investors process information in dollar amounts (i.e., balance of retirement accounts, share prices), they may think of returns both in nominal terms (dollars) and in percentage units. Thinking about returns in dollar amounts is not a mistake per se, since the consumer can simply divide the dollar payoff by the principal to recover the percentage return. But limited cognitive resources may prompt an investor to rely on past experience, recalling a default dollar amount usually observed.

I develop a simple anchoring-and-adjustment model in which investors anchor on their customarily observed principal and do not fully adjust to amounts that substantially deviate from it. Because of this numerical anchor on the default principal, the mental representation of principals smaller than the anchor will appear larger than in reality, whereas that of a principal larger than the anchor will appear smaller. As a consequence of this numerical anchor, the model makes two predictions about investors’ mistakes: one regarding the conversion from percentage returns to dollar amounts and another regarding the conversion from dollar amounts to percentage returns.

In the model, the mental representation of large dollar amounts appears smaller than in reality. As a consequence, when converting from percentage returns to dollar information, individuals will underestimate the future value of large dollar amounts relative to that of
smaller dollar amounts, given a percentage return and a time horizon.

When rational investors convert from dollar information to percentage returns, they should just divide the dollar payoff by the principal invested to recover the percentage return. However, because the mental representation of large principals is smaller than in reality, the model predicts that investors respond more strongly to the same percentage gains when they are described in larger dollar amounts, given a percentage return and a time horizon.

This study uses both an online experiment and a field experiment to exogenously vary the dollar information observed by investors when making financial decisions. It is hard to imagine a situation in the real world in which individuals have to make the same decisions observing different financial information in dollar terms, holding constant interest rates and time horizons. For this reason, the experiments help me cleanly test the predictions of the model.

The online experiment leverages a within-subject design to ask 177 participants on the Amazon Mechanical Turk platform to convert percentage returns to dollar amounts. I exogenously vary the principal, interest rates, and time periods faced by the participants in an incentivized task. The results confirm the first prediction of the model: participants underestimate the future value of large principals relative to that of small principals, given a percentage return and a time horizon.

The field experiment was conducted with more than 170,000 experienced investors from a brokerage firm in Brazil and tests whether they respond more strongly to the same percentage gains when described in larger dollar amounts. The setting of the experiment was an email sent to investors selling a six-year government bond, which had a 9.55% fixed interest rate (APR) at the time of the experiment. I use a between-subject experimental design to vary the magnitude of the dollar payoff of the bond according to different levels of principals invested. The principals used in the experiment are R$ 1.00 ($0.27) and R$ 100.00 ($27.02). Since the bond return was fixed for six years, I also varied the framing of the return as simple (one year) or compound (six years). To the best of my knowledge, this is the first paper
to study whether framing an interest rate as compound interest changes the demand for a financial product.

I find that the take-up of the bond increases by 24.5% when investors opened the emails containing the examples using the larger principal (R$ 100.00), despite having all emails display the percentage return of 9.55%, corroborating the second prediction of the model. Surprisingly, there is no effect of framing the interest rate as compound interest on demand for the bond.

The experimental results corroborate the predictions of the model. In a nutshell, because individuals underestimate the future value of large dollar amounts compared to small dollar amounts in the online experiment, they respond more strongly to advertisement of financial products using large dollar amounts properly calculated relative to advertisement using small dollar amounts in the field experiment.

Having found supportive evidence for the model, I extend it to understand the effect of share prices — quoted in dollar terms — on the behavior of stock returns. Specifically, investors receive news about percentage changes in the fundamental value of the firm that need to be reflected in the share price. Investors anchor on a default fundamental value — the fundamental value they are used to observing in the market — to convert the news in percentage terms to a dollar amount (i.e., the implied price change). Because of the anchor on the default fundamental value, the mental representation of fundamental values larger than the default value looks smaller than in reality. As the perceived fundamental value affects prices, investors underestimate the future value of stocks with higher share prices relative to those with lower share prices, given a percentage return and time horizon. Over time, as prices return back to fundamentals, stocks with high share prices are more likely to drift towards the direction of the news.

The extension of the baseline model makes two predictions about the behavior of stock returns. First, the lower (higher) the share price, the stronger (weaker) is the initial return response following news. Second, as price returns back to fundamentals, past returns orig-
inated from the initial return reaction will have more predictive power concerning future returns for stocks with higher share prices. In other words, past returns better predict future returns for stocks with higher share prices. Therefore, both past positive and negative returns are less likely to revert for stocks with higher share prices. As a consequence, momentum strategies should be more profitable for stocks with higher share prices. I confirm these two predictions using data from the U.S. stock market.

The empirical findings of the extended model suggest a trading strategy to enhance the profitability of momentum strategies. The model predicts that stocks with larger share price tend to drift for longer than stocks with lower share price. Therefore, I pair extreme winners and losers with similar past performance but different share prices. The suggested strategy goes long on stocks with best past performance (winners) and high prices and goes short on stocks with worst past performance (losers) and high share prices. My trading strategy generates a Fama and French (1993) three-factor alpha of 26.67% (t-stat = 10.21) and enhances the profitability of momentum strategies by generating a Carhart 4-factor alpha of 8.21% (t-stat = 6.54) in annualized terms.

My paper contributes to several strands of research in finance. First, it demonstrates the importance to financial markets of a recent literature in behavioral economics on the imperfect perception of numerical magnitudes. Recently, economists have shown that people misperceive the magnitude of numbers outside of the range they usually observe (Frydman and Jin, 2019; Khaw, Li and Woodford, 2019). These findings have been applied to examine how imperfect numerical perception impacts economic choice. Most of the findings in this literature, however, are restricted to lab experiments. In this study, I present evidence that imprecision about numerical magnitudes matters in real-stake scenarios outside the lab, even for a sample of experienced financial investors.

Second, my results contribute to a literature in household finance about investment mis-

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1See Dehaene (2012) for a review from a psychological perspective and Woodford (2019) for economic applications
One widely studied phenomenon in household finance is the so-called exponential growth bias, “the tendency of individuals to systematically and dramatically underestimate the growth or decline of exponential series when asked to make intuitive assessments (without calculators)” - as described in Stango and Zinman (2009). The findings of my experiments add two caveats to this phenomenon. In the field experiment, there is no evidence of an effect of exponential growth bias on the take-up of a financial product. In addition, the online experiment shows that exponential growth bias is only present in the data for high interest rates and distant time horizons. My results suggest that another mechanism, such as an anchor on a default interest rate, may be at play instead of a simple tendency to underestimate exponential growth.

Third, the experimental results in this paper offer an important lesson to the literature on financial disclosure and financial education. In an effort to help investors make good financial decisions, regulators may be tempted to provide explanations about how interest rates work using examples containing dollar information. This paper shows that it is possible to nudge consumers toward or away from financial products by framing its dollar returns in different ways. Therefore, caution is warranted when disclosing interest rates and delivering financial education: framing of information containing dollar amounts matters.

Fourth, the results in this paper contribute to the literature on the effect of share prices on stock returns. Baker, Greenwood and Wurgler (2009) find that investors have a time-varying demand for low-priced stocks and that firms cater to investors’ preference by splitting their stocks when demand for low-priced stocks is high. Birru and Wang (2016, 2019) find that investors believe that low-priced stocks have more upside potential than high-priced stocks. As a consequence, they overestimate the return skewness of low-priced stocks. In a recent paper, Shue and Townsend (2019) hypothesize that investors in the stock market suffer from non-proportional thinking, interpreting news both in terms of percentage returns and dollar returns. While the model of this paper is similar to Shue and Townsend’s, there are

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See Campbell (2006, 2016) and Guiso and Sodini (2013) for a review on household finance.
three important distinctions worth highlighting: 1) I show that non-proportional thinking is a general financial behavior, going beyond the context of stock prices and returns; 2) I use direct experimental evidence to confirm the assumption of Shue and Townsend (2019) that people suffer from non-proportional thinking; 3) I relate non-proportional thinking to anchoring, a widely studied phenomenon since Kahneman and Tversky (1974). In this way I help unify behavioral explanations of distinct and puzzling financial behaviors.

Finally, I contribute to the literature on the returns of momentum strategies. Since the seminal paper by Jegadeesh and Titman (1993), financial economists have studied why past recent winners and losers exhibit return continuation in the near future. While we are far from reaching a consensus (Barberis, Shleifer, and Vishny, 1998; Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 2000; Jegadeesh and Titman, 2013), my paper shows that return continuation in equity markets varies systematically with the level of share prices.

The paper is organized as follows. In section 2, I make predictions about financial behavior based on a simple model of how subjects anchor on dollar terms when converting from percentage returns to dollar returns and vice-versa. Section 3 tests those predictions both in an online experiment and in a field experiment with 170,000 experienced investors. In section 4, I extend the baseline model to the stock market to study the behavior of stock returns, and more specifically to study how the predictability of past returns on future returns depend on the share price. I end section 4 applying the empirical predictions of the model to generate a trading strategy. I conclude the paper in section 5 highlighting some policy implications of my findings and suggesting future directions for research.

2 Baseline Model and Predictions

In this section, I propose a model of how the principal (n) of an investment faced by boundedly-rational consumers may distort their perception of interest rates. The key con-
tribution of the model is to account for the anchoring on the default principal and the insufficient adjustment toward the principal (Kahneman and Tversky, 1974)\(^3\) which makes calculations about interest rates biased. The modeling of the anchoring and adjustment mechanism follows from Gabaix (2014, 2019).

2.1 The Rational World

In the rational world, the decision maker perceives all variables perfectly: the principal is given by \(n\) and the true interest rate of an investment product is given by \(
\rho\), which is experienced for \(t\) years. The cumulative percentage returns \((r\%)\) and dollar amount or payoffs \((r\$)\) of the investment opportunity are, respectively:

\[
r\% = (1 + \rho)^t \tag{1}
\]

\[
r\$ = n(1 + \rho)^t \tag{2}
\]

In this scenario, thinking about the principal to be invested and the dollar returns of the investment is not a mistake, since the agent can just divide the dollar returns by the principal to recover the true interest rate.

2.2 The Boundedly-Rational World: a Model of Numerical Anchoring and Adjustment

In the boundedly-rational world, the consumers anchor on the default principal \((n^d)\) and insufficiently adjust towards the observed principal \((n)\) (Kahneman and Tversky, 1974).

\(^3\)Interestingly, the seminal Kahneman and Tversky (1974) paper presents an example of anchoring on calculations done by two groups of subjects, in a similar fashion to what I argue happens in financial decisions. The first group was asked to estimate \(1 \times 2 \times 3 \times 4 \times 5 \times 6 \times 7 \times 8\), whereas the second estimated \(8 \times 7 \times 6 \times 5 \times 4 \times 3 \times 2 \times 1\). By having started the multiplication by larger numbers (i.e., a larger default), the second group’s estimate was 4 times higher than the first group. In my paper, however, the default comes from the decision-maker’s own experiences.
This insufficient adjustment gives rise to a boundedly-rational mental representation of the principal \(n^{BR}\):

\[
n^{BR} = (n^d)^a(n)^{1-a}
\]  

(3)

where \(0 < a \leq 1\).

In this formulation, \(a = 0\) is equivalent to a rational agent, whereas \(a = 1\) represents a fully-behavioral individual. Note that since the boundedly-rational mental representation of the principal \(n^{BR}\) is a weighted average of the principal \(n\) and the default principal \(n^d\), principals lower than the default principal will seem larger than they are in reality, whereas larger principals will seem smaller. Therefore, by anchoring on the default principal, the consumers make predictable mistakes when converting from percentage returns to dollar returns and vice-versa.

### 2.2.1 Converting from percentage returns to dollar returns

When converting from percentage returns to dollar returns, the mental representation of the principal \(n^{BR}\) gives rise to a mental representation of the dollar return \(r^{\$,BR}\), similar in fashion to equation (2):

\[
r^{\$,BR} = n^{BR}(1 + \rho)^t
\]  

(4)

Given the mental representation of the dollar return \(r^{\$,BR}\), a rational observer can calculate its implied percentage return \(r^{\%,BR}_{imp}\), by dividing the dollar return \(r^{\$,BR}\) by the principal \(n\). Using (2) and (4), the implied percentage return \(r^{\%,BR}_{imp}\) can be written as:

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4I use the terms “mental representation” or “intuitive calculation” throughout the paper to denote an “as-if” phenomenon. In the model, agents do not separately think of the default principal, then the chosen principal, and do the weighting in their heads. Instead, the boundedly-rational decision-makers put together different insights about the situation and outputs the biased estimates of percentage and dollar returns as a product of their deliberation.
\[ r_{\text{imp},BR} = \frac{r_{\text{dollar},BR}}{n} = \frac{n^{BR}(1 + \rho)^t}{n} = \left(\frac{n^d}{n}\right)^a(1 + \rho)^t \] (5)

where \(0 < a \leq 1\).

Equation (5) allows me to make two predictions about over and underestimation of interest rates. The first one is about absolute under and overestimation of returns, which means that I can establish for which set of principals the implied percentage interest rate is higher or lower than the true interest rate. However, to do so, I need to be able to observe what the default principal of subjects is. In financial markets, however, it is hard, if not impossible, to determine the default principal in the mental representation of a subject, making claims about absolute under and overestimation hard to establish. That is why in this paper I will focus on a second set of predictions about relative over and underestimation of interest rates with respect to the principals faced by consumers. By relative comparison I mean determining whether higher principals lead to higher or lower perceived percentage interest rates, regardless of the true percentage interest rate. With the meaning of relative under and overestimation in mind, equation (5) allows me to hypothesize the following:

**Prediction 1 – Relative Under and Overestimation of Implied Returns**

*For any given default principal \((n^d)\), consider two principals \(n_1\) and \(n_2\), and a return \(\rho\), giving rise to their respective mental representations of dollar returns \(r_{\text{dollar},BR}^{1,SBR}\) and \(r_{\text{dollar},BR}^{2,SBR}\), and implied percentage returns \(r_{\text{imp},BR}^{1}\) and \(r_{\text{imp},BR}^{2}\). If \(n_1 < n_2\), it follows that \(r_{\text{imp},BR}^{1} > r_{\text{imp},BR}^{2}\). In other words, the higher the principal, the lower the implied percentage returns when converting from percentage returns to dollar amounts.*

\(^5\)From equation (7), I can hypothesize that for a principal \(n\), such that \(n < n^d\), the subjects will overestimate the dollar returns of the low principal amounts.

\(^6\)For example, imagine that an individual’s default principal of investment is very high, say $1,000,000.00 and that she is faced with 2 different principals $1.00 or $100.00. According to equation (5), the individual would absolutely overestimate how the 2 principals grows over time. However, regardless of whether the econometrician knows the default principal, equation (5) also allows me to say that the individual would relatively overestimate how the principal of $1.00 would grow when compared to the principal of $100.00.
2.2.2 Converting from Dollar Returns to Percentage Returns

In this scenario, the decision-maker observes the dollar return \( r^d \) of an investment opportunity. As in (1) and (2), to observe the true interest rate, a rational decision maker divides the dollar returns by the principal \( n \). However, the boundedly-rational decision-maker uses her mental representation of the principal \( n^{BR} \) instead. The implied percentage return then becomes:

\[
 r_{%,BR} = \frac{r^d}{n^{BR}} = \frac{n(1 + \rho)^t}{(n^d)^a (n)^{1-a}} = \left( \frac{n}{n^d} \right)^a (1 + \rho)^t
\]

(6)

where \( 0 < a \leq 1 \).

From equation (6), I can make the following prediction about the conversion from dollar returns to percentage returns:

**Prediction 2 – Relative Under and Overestimation of Returns**

*For any given default principal \((n^d)\), consider two principals \( n_1 \) and \( n_2 \), and dollar returns \( r^d \), giving rise to their respective mental representations of percentage returns \( r_{1%,BR} \) and \( r_{2%,BR} \). If \( n_1 < n_2 \), it follows that \( r_{1%,BR} < r_{2%,BR} \). In other words, the higher the principal, the higher the implied percentage interest rate when converting from dollar amounts to percentage returns.*

3 Experimental Tests of the Model

This section describes two experiments that test the two predictions of the baseline model. In section 3.1, I will study the conversion from percentage interest rates to dollar returns by varying the principal invested in an online experiment on MTurk. In section 3.2, for a sample of more than 170,000 investors, I designed a field experiment to study the conversion from dollar returns to percentage interest rates by varying the default principal seen by investors.
3.1 Online Experiment

MTurk is an online platform run by Amazon that allows researchers to run survey and experiments, which has been used in many recent economics and finance papers (DellaVigna and Pope 2017; Kuziemko, Norton, Saez, and Stantcheva, 2015; Lian, Ma, and Wang 2018) This experiment was run on the Amazon Mechanical Turk (MTurk) platform in 2019.

In the experiment, I asked participants to report dollar returns when presented with principals of different magnitudes, interest rates, and time horizons in a within-subject framework. These questions were designed to test prediction 1 of the baseline model, namely the lower the principal, the higher the implied percentage interest rate when converting from percentage returns to dollar returns.

3.1.1 Demographics and Sample Characteristics

I conducted this experiment with 177 adults in the United States who participate in the MTurk platform. Table 1 reports the summary statistics for the subjects. The sample is mostly comprised of men (55.4%) and is skewed towards younger and middle-aged people, with over 50% of participants reporting to be between 30 and 50 years old, whereas 39% are between 18 and 30 years old. In at least three measures, the subjects are arguably more sophisticated than the general U.S. population. First, over 70% of participants graduated from college, compared to approximately 33% of the American population (Ryan and Bauman, 2016). Second, in terms of financial literacy, 59.3% of participants correctly answer all the “Big Three” questions, as in Lusardi and Mitchell (2008), correct, compared to 30.2% in their sample. Third, in terms of numeracy (Lusardi 2012), approximately 50% of participants

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7Lusardi and Mitchell have used two financial literacy measures in their papers. The most common is known as “Big Three,” which asks subjects about interest compounding, the effect of inflation and nominal interest rates on purchasing power, and diversification. Another measure is known as “Big Five” used in the 2009 National Financial Capability Survey, adding two questions to the Big Three: one on the relationship between bond prices and interest rates and one on the comparison of rates for 15- and 30-year mortgage rates. In this paper, I exclude the question about mortgage rates and create an index of the four remaining questions. Therefore, I am able to compare the performance of my sample to theirs for the “Big Three” questions but not for the “Big Five.”
gets all of the questions correct and an additional 39.5% of them get at least half of them correct. For comparison, in a similar set of questions, only 13% of respondents in the UK were able to answer all of them correctly (Banks and Oldfield, 2007). Finally, 99.4% of participants lived in the United States for the past 10 years, alleviating any concerns that the subjects were not proficient in English and unable to answer the questions.

3.1.2 Experimental Design

The goal of this experiment is to understand how subjects intuitively assess how percentage returns are mapped onto dollar returns. So, the main task in the experiment asks the subjects to answer hypothetical questions about how money in an investment account would grow over time given a principal, an interest rate, and a time period. The design of the experiment is based on a survey run by Basu (2019) to study interest compounding in India. To test the prediction that a low principal will lead subjects to overestimate dollar returns and a high principal will lead subjects to underestimate dollar returns, I vary the questions to have principals of \{1.00; 100.00; 10,000.00\} dollars. To make sure that the results are not specific to a certain range of interest rates, I vary the interest rates to be \{2%; 10%; 20%\}. Finally, to test how the answers change with different time horizons, I vary the time periods to be \{1; 2; 5; 10; 20\} years. In total, every subject provides 45 estimates (3 principals x 3 interest rates x 5 time periods.) The questions are divided into 9 groups. For each group, the subjects see 1 principal, 1 interest rate, and 5 time period. The order of the group of questions is random. The instructions for the experiment as well as the questions are located in the Appendix 1 of the paper. The within-subject design of this experiment provides a critical comparison. It allows us to observe how the same subject behaves facing both a low and a high principal, providing a direct test of the prediction that subjects behave differently when facing high vs low principals.

One could argue that these questions are purely math tasks, suggesting that they would have no relevance to financial decision-making since subjects could solve them with enough
time and/or a calculator. While the task resembles mathematical exercises, similar questions, such as the two used to measure misperception of interest rates in the Survey of Consumer Finance (SCF) until 1983 have been shown to be correlated with a myriad of financial behaviors (Stango and Zinman, 2009). To further alleviate concerns about the questions not having much relevance for financial decision-making, I took some precautionary measures. First, the experiment is interested in studying the intuitive assessment of the conversion from percentage returns to dollar returns and not the ability of a subject to use a calculator or computer device. So, I limited the time the subjects had to answer each group of 5 questions \{1 principal x 1 interest rate x 5 time periods\} to 90 seconds, which gave participants enough time to think and use their intuition to answer the questions. Calculations and computers were not allowed during the experiment.

Second, to account for differences between subjects in math abilities, I asked them 4 numeracy questions found in Lusardi (2011). Finally, as compound interest is a relevant topic to financial markets and investing, I used four questions found in Lusardi and Mitchell (2008) and in the 2009 National Financial Capability Study to understand the influence of financial literacy in the performance of subjects.

3.1.3 Data Collection and Compensation

To ensure quality responses in the experiment, I posted the experiment on MTurk and only made it visible for subjects who were suited according to the following restrictions. First, I required the subjects to have a past satisfactory completion rate of at least 90 percent of tasks. Second, the experiment was only visible to subjects who lived in the United States, in order to avoid participants with limited English proficiency.

Another way to increase the quality of responses is to pay subjects well. Even though the average wage on MTurk is approximately $4.80 per hour (Kuziemko et al. 2015), I paid $2.50 for participation for a 20-minute study (i.e. a base compensation of $7.50/hr) and up

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The emphasis on the intuitive assessment of subjects in this paper is important because it is very likely that with calculators and enough time, the subjects would be able to answer the questions correctly.
to $1.08 in the form of incentives based on the accuracy of the answer. Given the relatively good payment of the experiment, the spots were taken up in less than 1 hour.

3.1.4 Results

To directly test the prediction that subjects will overestimate (underestimate) dollar returns for lower (higher) principals, I will plot figures of the estimates for all the principals for a given interest rate. For ease of interpretation and to keep the same order of magnitude for all estimates regardless of the principals, I will normalize the answers by their respective principals, plotting the estimates of \((1 + \rho)^t\) for each principal, given an interest rate of 2%, 10% or 20%.

[Figure 1 – Estimated Dollar Returns Over Time with Interest Rate = 2%]

[Figure 2 – Estimated Dollar Returns Over Time with Interest Rate = 10%]

[Figure 3 – Estimated Dollar Returns Over Time with Interest Rate = 20%]

The figures deliver the main findings of the experiment. To begin, subjects believe that the dollar returns of smaller principals grow faster than those of larger principals, regardless of the true percentage interest rate. As a consequence, the lower the principal, the higher the percentage interest rate implied by the perceived dollar return, corroborating the statement of prediction 1 of the baseline model.

Table 2 examines the findings in detail. Its panels A, B, and C present the estimated dollar returns and the difference in estimation for the interest rates of 2%, 10%, and 20%, respectively. In each panel, I present the mean and standard deviations of the estimated dollar returns in rows (1) to (3) for each principal, whereas columns (1) to (5) highlight the estimates over different time periods. Row (4) presents the correct answer for the task. Finally, rows (5) to (7) report the pairwise differences in estimates and their respective standard errors from rows (1) to (3).
Panel A of Table 2 shows the results for an interest rate of 2%. The results make it clear how subjects believe that the estimated dollar returns grow faster for smaller principals. For instance, under a 2% interest rate, a principal of $1.00 would grow to approximately $1.49 over 20 years, for an implied interest rate of 49% over that period of time. However, for the same time period, subjects believe that a principal of $1.00 would grow to $6.67, for an implied interest of 567%. For a principal of $100.00, the estimated dollar return over 20 years is $401.40, implying a percentage interest rate of 301%, making it substantially lower than for a principal of $1.00. Finally, for a principal of $10,000.00 over 20 years, the estimated dollar returns is approximately $26,990.00, for an implied percentage interest rate of 169%. Rows (5), (6) and (7) of panel A show that the vast majority of the differences in implied percentage returns across all time periods are positive, large, and statistically significant, corroborating the pattern of relative overestimation of smaller principals. Panels B and C, which show the estimates for interest rates of 10% and 20%, respectively, reinforce the finding that subjects believe that smaller principals grow faster, making it clear that the relative overreaction of smaller principal is a general phenomenon and not restricted to a certain range of interest rates.

Finding 1 – Relative Under and Overestimation of Implied Returns

In a within-subject experimental design, individuals underestimate the future value of large dollar amounts relative to small dollar amounts for a given percentage return and time horizon.

3.1.5 Robustness Checks

In this section, I will show that some potential confounders are not driving the main effect shown in the experiment. First, it could be the case that there are some outliers in the data that are driving the result, especially since the standard errors of the estimates are much
larger for smaller principals (i.e. $1.00) and in later time periods (10 and 20 years.) To address this issue, I perform the same analysis plotting figures of the median – instead of the mean – of the estimates. The figures A1, A2, and A3 for each interest rate are shown in Appendix 1. In each one of them, the patterns of the estimated dollar returns growing faster for lower principal holds. In fact, these figures help refute an additional concern: the rounding of small numbers (Andersen et al. 2013). It is reasonable to imagine a situation that subjects – due to the cognitive cost of reporting decimal numbers – would report only round numbers, which could create patterns seen in Figures 1, 2, and 3. However, Figures A1, A2, and A3 make it clear that decimal numbers are widely used in the experiment and that in their presence the pattern holds.

Second, subjects with low levels of numeracy and financial literacy could be driving the result, as they would be less able to perform these calculations well. Even though the experiment is aimed at testing the intuitive calculations performed by the subjects, it is reasonable to consider that subjects with stronger mathematical and financial skills should do better in these tasks. In fact, it has been shown that people with higher level of financial literacy and numeracy make better financial decisions (Lusardi, 2012). To alleviate the concern that the experimental results are not entirely driven by numeracy and financial knowledge, I plot the figures for the 55 subjects who have got a perfect score in the financial literacy questions (figures A4, A5, and A6) and for the 88 subjects who got a perfect score in the numeracy questions (figures A7, A8, and A9.) In all of these figures, the pattern showing that the estimated dollar returns over time grow faster for smaller principals remain highly robust.

Third, some subjects may be knowledgeable about some basic questions about interest rates and math but may not know how to convert percentage interest rates to dollar returns. As a consequence, they could make mistakes that are serially correlated across time. If, for some reason such as rounding, these subjects believe that a $1.00 principal grows faster after 1 year, they could anchor on this higher estimate and keep producing higher estimates for
the subsequent time periods. To alleviate the concern that people who do not know how to convert percentage interest rates to dollar returns are driving the result, I plot figures A10, A11, and A12 for the 83 subjects who have got the simple interest question correct in all 9 combinations of 3 principals and 3 interest rates. Figures A10, A11, and A12 show that despite providing the correct answer at $t = 1$ year, the subjects diverge to the hypothesized pattern in later time periods, rejecting that the result is driven by people who are not familiar with how interest calculations work.

### 3.1.6 Discussion

In light of the results of the experiment, some points are noteworthy. To begin, the pattern that subjects estimate that the dollar returns of small principal grow faster is robust across different interest rates and a myriad of robustness checks. What is surprising about these findings is not that subjects get these answers wrong, as it would be expected from questions that are computationally hard to perform in a short period of time, but that the way the subjects are biased depends on the principal.

Another interesting point is that despite always observing relative overestimation of smaller principals, for most of the experiment I also observe absolute overestimation of smaller principals, especially under low interest rates. For instance, under an interest rate of 2%, subjects always overestimate the estimated dollar returns, regardless of the principal and time period. When the interest rate is 10%, absolute overestimation happens for every principal and time period, except for the principal of $10,000 and $t = 20$ years. Finally, under an interest rate of 20%, most of the answers show absolute underestimation. In fact, all the answer for the principal of $10,000 fall short of the correct values. The same happens for most of the answers for the principal of $100. All of these examples point to a possible misperception of interest rates also influenced by the magnitude of the true interest rate. It is possible to imagine an extension of our current model to accommodate this issue. In this case, the decision-maker would also anchor on a default interest rate $\rho_d$. By anchoring on $\rho_d$
and insufficiently adjusting toward $\rho$, the mental representation of the interest rate would look larger for lower interests and smaller for higher interests, similar to equation (4) regarding the mental representation of the principal. In this extended model, the misperception of the principal and interest rate would interact to produce the patterns seen in figures 1, 2, and 3. The extension of the model is left for further research.

Given the findings of this experiment, one point that needs to be re-examined in the household finance literature is under what conditions exponential growth bias happens. In their seminal paper, Stango and Zinman (2009), on page 2818, state: “EG [Exponential Growth] bias is the tendency of individuals to systematically and dramatically underestimate the growth or decline of exponential series when asked to make intuitive assessments (without calculators).” My experimental results, which replicate the findings of Basu (2019), show that exponential growth bias does not necessarily suggest that consumers will underestimate the value of money over time. In fact, in the experiment, subjects only follow Stango and Zinman’s definition of exponential growth bias under higher principals, higher interest, and in later time periods. Both the level of the principal and the interest rate seem to be important for the question about whether subjects underestimate future monetary values. More recently, Levy and Tasoff (2016) suggest that under varying interest rates, subjects can end up overestimating exponential growth. In my experiment results, if I restrict the data to only include the first answer to a group of questions (1 principal x 1 interest x 5 time periods) given by a subject$^9$I still observe overestimation of dollar returns in the instances previously found in the experiment. Therefore, even in a situation when the interest rates have not (yet) changed, varying interest rates does not seem to be a necessary condition for overestimation of future monetary values.

Even though the results of the experiment provide many interesting insights into financial decision-making, it leaves some open questions. Even though the task was designed to test predictions of a model, does such a simple experiment capture the complexities of

$^9$These results are not reported on the paper but are available upon request.
financial decisions in the real world, where people can have calculators and computer to make computations? In other words, does the model and its predictions have any external validity? Such questions are the subject of the experiment in the next section.

### 3.2 Field Experiment

The second experiment investigates the purchase of a 6-year fixed-interest government bond to active investors of a brokerage firm. To test prediction 2 - that the magnitude of dollar returns may affect investor’s perception of percentage interest rates, - I varied the magnitude of the dollar returns in the explanation using different principals to measure changes in the demand for the bond. This experiment took place in January 2019.

#### 3.2.1 Experimental Design and Implementation

To test whether the magnitude of the principal impacts the take-up of a financial product for a given interest rate, I partnered with a brokerage firm in Brazil to randomly assign the message content of an email selling a 6-year government bond, which has a 9.55% fixed interest rate (APR) at the time of the experiment. Our main test consists in explaining the 9.55% interest rate using different principals – and as a consequence, different dollar returns - simulating an investment. I chose the principals of R$ 1.00 ($0.27) and R$ 100.00 ($ 27.02) for two reasons. First, the interest calculations involving the two values are remarkably similar. Second, the values are not extremely high to give an impression that only high net worth individuals could invest in the product. This is especially important in experiments involving the take-up of financial products, which notoriously have low power (Banerjee et al., 2015). Even if one were to consider the R$ 100.00 principal to be high for a developing country, I try to alleviate this concern by only sending the email to active investors in the firm, meaning that they have invested in either stocks, bonds, mutual, or other financial products.

101.00 USD = R$ 3.70 in January, 2019, when the data was obtained.
Since the product advertised was a 6-year bond with a fixed interest rate, it also allowed us to experimentally test the effect of framing the returns as either simple (1-year) or compound (6-year) interest. To the best of my knowledge, this is the first study to experimentally test a causal relationship between compound interest and the take-up of a financial product. Most papers that study compound interest rely on correlations between knowledge of compound interest and financial behavior, such as the seminal paper in this literature, Stango and Zinman (2009), or focus on the experiments regarding the intensive margin of contribution to retirement accounts, such as Goda et al (2014) and Song (Forthcoming). However, addressing the extensive margin of savings and investment is also important, given that many households have no emergency funds saved and end up being very vulnerable to financial shocks (Caner and Wolff, 2004; Lusardi et al., 2011)

To study both the effect of the principal magnitudes (R$ 1.00 vs R$ 100.00) and the framing of interest rates (simple vs compound interest), I implement a 2x2 factorial design for the experiment, shown in the figure below:

[Figure 4 – Description of Treatment Conditions in the Field Experiment]

In the experimental design, I also included a control group that received no explanation about the interest rates. This message was similar to the emails the brokerage firm regularly sent to its investors.

Every email was identical in its form and content, except for the line that included the treatments explaining what a 9.55% interest rate means. The email to all subjects starts with the subject line: “Guaranteed Return of 9.55% a year for 6 years with Treasury bonds.” In the body of the email, there was the logo of the partner brokerage firm, next to the picture of a black male model. Then, the email addresses the subjects by their first name followed

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11Note that the product advertised was a 6-year government bond, which means that it is possible for the investor to sell it at any time after purchase. In other words, while the explanations of the interest rate are accurate, it is possible that the investors will not hold the bond until maturity. As a consequence, they would not obtain the dollar returns as noted on the email. However, as is shown in the text of the email to the investors as well as in the disclaimer below the main text, the investors only cash the interest at the time of maturity and the explanations are meant only to provide a numerical guide of what an interest rate means.
by a short message advertising the product. All emails stated the annual return of 9.55%, followed by 5 treatments:

* **Control:** [ no explanation is shown ]

* **Treatment 1** – Low principal (R$ 1.00) and simple interest (1 year):
  “In other words, for every R$ 1.00 invested, you will have R$ 1.09 in 1 year”

* **Treatment 2** – High principal (R$ 100.00) and simple interest (1 year):
  “In other words, for every R$ 100.00 invested, you will have R$ 109.55 in 1 year”

* **Treatment 3** - Low principal (R$ 1.00) and compound interest (6 years):
  “In other words, for every R$ 1.00 invested, you will have R$ 1.72 in 6 years”

* **Treatment 4** - High principal (R$ 100.00) and compound interest (6 years):
  “In other words, for every R$ 100.00 invested, you will have R$ 172.85 in 6 years”

The email was sent in December 2018 to 177,654 investors. The full text of the email seen by the investors is in the Appendix of this paper.

### 3.2.2 Baseline Data on Sample Characteristics and Balance Checks

To help with statistical power in the experiment, the partner brokerage firm decided to promote the purchase of the bond for existing clients whom it considered most likely to want to buy it. For this reason, the experiment was only done with customers who fulfilled two criteria: 1) had an account with the brokerage firm; 2) had already purchased a financial product (stocks, bonds, and mutual funds) through the brokerage firm.

[Table 3: Baseline Variables for Sample Description and Orthogonality Checks
- Intent to Treat]

Table 3 summarizes the baseline data available for the purpose of this paper and checks the covariate balance across the different treatments. For demographic information, I have information on income (R$ 10,928 a month) and gender (28% female). This information is
collected at the time of the account opening and can be updated at any time by the client.
In terms of investment information, I was able to obtain the total amount invested with the
brokerage firm, the level of risk tolerance[12] and whether the client invests in stocks, bonds,
and mutual funds. The last column of Table 3 shows that none of the baseline variables are
correlated with treatment assignment.

[Table 4: Baseline Variables for Sample Description and Orthogonality Checks
  - Treatment on the Treated]

To increase the statistical power of the experiment, the partner brokerage firm provided
me with information about whether the client had opened the email, making it known which
subjects had been treated. In Table 4, I repeat the covariate balance done in Table 3 for
the subsample of clients that opened the email. Most of the rows show that the decision
to open the email did not interfere with treatment assignment. However, two covariates
- risk tolerance and investment stocks – are not balanced across treatments. I take two
precautionary measures to assure that this is not affecting the results of the experiment.

First, a complementary approach to testing for balance is to verify for joint orthogonality.
Therefore, for each treatment condition – principal magnitude and framing of interest rate,
- I run the following regression and report the F-test to test the joint hypothesis that all
coefficients on the covariates are zero:

\[ Treatment_i = \alpha + \beta \cdot \text{controls} + \epsilon_i \quad (7) \]

Table 5 reports the results of the regression described on (10) and shows that we cannot
reject the hypotheses that all coefficients are zero for both treatments.

[Table 5: Orthogonality Check - Treatment on the Treated]

12The Brazilian equivalent of the Security and Exchange Commission ("CVM - Comissão de Valores
Mobiliários") requires clients to answer a subset of questions to determine their risk-tolerance index, ranging
from 0 to 3. Only those subjects whose risk-tolerance index allowed them to receive advertisements about
bonds got the email.
Second, following the suggestion of Bruhn and McKenzie (2009), when showing the results of the experiment later in this section, I will run two separate regressions with and without the covariates that do not appear to be balanced. As Table 7 will show, the results are virtually the same when the covariates are added, alleviating concerns about their effects on the result.

### 3.2.3 Hypotheses, Specifications, and Results

Following equations (8) and (9), the main hypothesis of this experiment is that more clients will purchase the bond after seeing the explanations of the interest rates with higher principals because their larger dollar returns will make the implied interest rate seem larger than when the bond is explained with smaller principals.

A second hypothesis considered in this experiment is the influence of framing the interest rates as simple vs compounded interest. The hypothesis, namely exponential growth bias (Stango and Zinman, 2009), states that subjects may believe that money grows in a linear fashion, underestimating the benefits of compound interest in investments. As a consequence, more clients will purchase the bond after seeing the explanation of interest rates with compound interest.

To test the hypotheses of the effects of high principals and compound interest on the purchase of the bond, I analyze the 2 x 2 factorial experimental design estimating the following ordinary least square (OLS) regressions at the individual level, indexed by i:

\[
\text{Invested}_i = \alpha + \beta_1 \cdot \text{HighMagnitude} + \beta_2 \cdot \text{Compound} + \theta_i \cdot \text{Controls}_i + \epsilon_i \tag{8}
\]

where \( Y \) is a dummy variable for whether the client purchased the bond in the 10 days after the email was sent out. HighMagnitude and Compound are indicator variables representing whether the subjects were allocated to treatments with high principal and compound interest, respectively. Table 6 presents the number of investors allocated to each treatment.
group as well as the number of investors who opened the email and purchased the bond.

[Table 6 - Summary of Results of the Field Experiment]

[Table 7 - Effects of the Principal Magnitude and Compound Interest on Investment]

Table 7 presents the estimated effects of high principals and compound interest on the take-up of the bond. Row (1) presents the estimate of the effect of messages with the higher principal on the demand for the bond and show that they significantly increase take-up relative to messages with low principal. The magnitudes are on the order of 0.26 percentage points, which is equivalent to a 24.5% increase in the average take-up rate.

Row (2) estimates the effect of messages with compound interest on demand for the bond and finds no detectable effect. The magnitude of the coefficient on compound interest is small, negative, and statistically insignificant, which is the opposite of what would be expected if subjects underestimated the growth of money over time.

Row (3) tests both hypotheses together and finds that the coefficients remain stable, meaning that the magnitude of the principal matters for the demand for bonds, whereas the frame of interest rates as compound interest does not. Row (4) adds the baseline controls to the regression and show that the coefficients remain stable. In this specification, as suggested by Bruhn and McKenzie (2009), I added the two covariates that were not balanced when evaluating the treatment-on-the-treatment framework. The results of higher principals and compound interest remain unchanged, which alleviates any concerns about treatment assignment.

Finding 2 – Relative Under and Overestimation of Returns

Investors increase their demand by 25% for the financial product when its returns are explained using larger dollar amounts.

These results corroborate our main hypothesis for this experiment, which argues that larger dollar returns – as a consequence of higher principals – makes the implied interest
rate by the consumer larger, increasing the demand for the bond.

I argue that these results are likely economically significant for a variety of reasons. First, messaging costs were low and the increase of nearly 25% in take-up is large for such a small intervention. Second, the subjects who participated in the experiment are experienced investors, since one screening condition for participation was to have already invested in a financial product with the brokerage firm before. For instance, the well-known exponential growth bias, which is found in unsophisticated populations, was not present in these investors, suggesting that the effect of high dollar returns on investment may be unrelated to sophistication in financial markets. Finally, as Alan et al. (2018) suggests, this type of intervention captures the effects of subjects opening the email, rather than carefully reading them. It is possible that some clients opened the email, never read it, or did not read the whole email. Therefore, the effect captured here can be interpreted as a lower bound for the effects of consumers who actually read the message.

3.2.4 Discussion

In this experiment, I find that showing a percentage interest rate applied to a higher principal amount makes the implied percentage interest rate looks larger to consumers than when the same percentage interest rate is applied to a lower principal. This finding corroborates the predictions of the baseline model and show that they are also relevant to the real world outside of MTurk, since the experiment involved active retail investors from a large brokerage firm.

A surprising finding of the experiment is that correcting for exponential growth bias does not increase the demand for the bond. As mentioned before, to the best of my knowledge, this is the first paper that looks for a causal relationship between framing interest rates as simple vs compound interest and the take-up of a financial product. Other experimental studies involving interest compounding, such as Song (forthcoming, RFS) and Goda et al. (2014), aim at increasing the contribution to retirement accounts in which subjects are already
enrolled. In those studies, while the increase in retirement contributions are statistically significant, they are small in magnitude. In Goda et al (2014), the annual contribution to the retirement accounts increase by $85 annually, whereas in Song (forthcoming) the annual contributions go up by 50 RMB, approximately $9. Putting all this evidence together casts doubt on the strength of the relevance of interest compounding to investing in real-world scenarios.

The experiment also raises questions about the delivery of financial education. One way to think about the experimental conditions in the field experiment is to interpret them as an intervention on financial literacy, since interest rates and compound interest are explained to the subjects. It has been documented that even high net-worth individuals in Brazil have low levels of financial literacy (Costa, 2014). A simple comparison between the control group, which received no explanation about what the percentage interest means, and the four treatment conditions shows no effects of explaining the interest rates in the take-up of the financial product. One potential reason for the lack of result is that this particular population of investors may already be highly sophisticated, since they are active investors in a brokerage firm. If this is the case, this stresses the importance of the main finding that the framing of dollar returns for a given percentage interest rate matters for the demand of presumably sophisticated investors for a financial product. However, in a similar study (Costa, 2019), I replicate the findings of this experiment in a setting with unsophisticated borrowers and find once again that just explaining the interest rates to those customers has little impact on the demand for high-interest loans. In both field experiments, I showed that there are ways to nudge investors to make a given decision by changing the principal used to explain an interest rate. However, it is also important to keep in mind that the intervention is quite small (i.e. just one line on an email) and may not have been enough to change financial behavior in some dimensions, such as interest compounding.

Both the MTurk experiment and the field experiment make it clear that individuals have

\[\text{13}^{\text{The result is not reported on the paper but is available upon request.}}\]
trouble intuitively converting from percentage interest rates to dollar returns and vice-versa. Having seen that the predictions of the baseline model hold and that they are relevant for retail investors in the real world begs the question: are these findings also relevant for stock prices in financial markets? This is the question I answer in the next section.

4 The Effect of Share Prices on the Behavior of Stock Returns

In the previous section, I showed how financial information described in dollar terms distort investors’ perception of returns, as predicted by the baseline model in section 2. In this section, I extend the model of misperception of interest rates to study the effect of financial information in dollar terms (i.e. share prices) on the behavior of stock returns.

This section is organized as follows. First, I will construct a simple model of the effect of share prices on return responses following the arrival of news in the stock market. Second, I will use this model to make predictions about the return predictability of momentum strategies. Third, I will test these predictions using data from the U.S. stock market. Finally, in light of the evidence from the model and empirical results, I will propose a trading strategy that outperforms the standard momentum strategy first suggested by Jegadeesh and Titman (1993).

4.1 A Simple Model of Return Response in the Stock Market

To study the behavior of stock returns in a simple model of misperception of interest rates, I will assume that all investors are boundedly-rational agents misperceive interest rates equally in a 3-period world. For each time period t, I define $P_t$ and $F_t$ to be the share price of a stock and fundamental value to be the fundamental value of a firm’s share in a rational world, whereas $P_{t}^{BR}$ and $F_{t}^{BR}$ are the corresponding variables in a boundedly-rational world.

In the first period, the bounded-rational and rational agents perceive a stock price ($P$)
and its fundamental value (F) perfectly, so that $P_1 = P^{BR} = P = F = F^{BR}_1 = F_1$. Between the first and the second periods, all agents receive news that the stock prices will move by $\theta$ percentage points. In a rational world, agents would convert the news from percentage returns to dollar returns correctly, moving the firm’s fundamental value from $F$ to $F + F\theta$ and, as consequence, moving the share price from $P$ to $P + P\theta$. In the bounded-rational world, however, the investors err when converting the percentage return to dollar amounts ($r^S$) due to anchoring. As a result, they will rely on their default fundamental value ($F^d$) when they perform a calculation with the fundamental value $F$. The insufficient adjustment from the default fundamental value ($F^d$) towards the true fundamental value ($F$) gives rise to a bounded-rational mental representation of the fundamental value ($F^{BR}$):

$$F^{BR} = (F^d)^a \cdot (F)^{1-a}$$

(9)

where $0 < a \leq 1$.

In period 2, consequently, the boundedly-rational agent will believe the fundamental value of the firm to be:

$$F^{BR}_2 = F + F^{BR}_1\theta$$

(10)

Therefore, since price equals fundamental value, price will be given by:

$$P^{BR}_2 = P + P^{BR}_1\theta$$

(11)

Note that as the boundedly-rational mental representation of the fundamental value ($F^{BR}$) is a weighted average of the fundamental value ($F$) and the default fundamental value ($F^d$), fundamental values lower than the default value will seem larger than they are in reality, whereas larger values will seem smaller. As a result, by anchoring on the default fundamental value, the investor will make predictable mistakes when converting from information in percentage terms to information in dollar terms.
In line with the boundedly-rational fundamental value, the boundedly-rational agents can either overestimate or underestimate the price response to the percentage return \( \theta \) in period 2, depending on the magnitude of the default fundamental value \( F^d \):

\[
P_{2}^{BR} > P \quad \text{if} \quad F < F^d \\
N \quad P_{2}^{BR} = P \quad \text{if} \quad F = F^d \\
N \quad P_{2}^{BR} < P \quad \text{if} \quad F > F^d
\]  

(12)

In time period 3, financial analysts report their share price forecast and help correct the mispricing, bringing the price back to the rational fundamental value, such that \( F_{3}^{BR} = F + F\theta \) and \( P_{3}^{BR} = P + P\theta \). The figure below summarizes the model:

![Figure 5 - A Summary of the Model of Behavior of Stock Returns](image)

Having constructed the price responses in each period, I can derive the returns for the bounded-rational agent between time periods 1 and 2 \( (\nu_2^{BR}) \) and implicitly define the returns between time periods 2 and 3 \( (\nu_3^{BR}) \) showing that both returns will add up to \( \theta \) in this simple
Equations (13) and (14) allow me to make assessments about both absolute and relative return responses with respect to stock prices. By absolute return responses, I mean under what conditions stock prices move more or less than \( \theta \) percentage points after observing news that stock prices should move by \( \theta \) percentage points. On the other hand, by relative return responses, I mean the degree to which stock prices react more or less strongly to the same percentage return \( \theta \). For the reasons discussed in section 2, it is necessary to observe the default price \((P_d)\) in the model to make claims about absolute return responses. Since it is not feasible to make statements about investor’s default prices with aggregate data, I will focus on relative return responses with respect to stock prices.

### 4.2 Predictions about Momentum in the Stock Market

In their seminal paper, Jegadeesh and Titman (1993) document that U.S. stocks that have performed well in the past 6 to 12 months tend to outperform in the future. The evidence is robust and holds in international equity markets, as well as in different asset classes (Asness, Moskowitz, Pedersen, 2013; Fama and French, 2012). Despite strong support for the existence and prevalence of momentum, Jegadeesh and Titman (2011, p. 507), in a recent survey about momentum, state that “financial economists are far from reaching a consensus on what generates momentum profits.”

In the model, momentum arises when prices in period 2 have not fully incorporated the news that arrived between periods 1 and 2, more precisely when \( P > P^{BR} \). To compensate for example, from equation (13), I can hypothesize that for \( P^{BR} > P \), the bounded-rational agents will overestimate the return response from period 1 to period 2 \((r_2^{BR})\). If \( \theta > 0 \), that means that price will rise more than in the rational world. To correct for this mispricing, equation (14) shows that from period 2 to period 3 there would be return reversal.
for this underreaction, the stock prices will drift towards the fundamental value in period 3. However, if there is overreaction to news between periods 1 and 2 (i.e. $P < P^{BR}$), the price in period 2 will be greater than the fundamental value, and the price will revert back to fundamental value between periods 2 and 3. Therefore, the model predicts both the existence of momentum and reversal in the stock market.

The model also sheds light on the circumstances under which previous returns have greater predictive power over future returns. The difference in the predictive power of momentum over future return arises because stocks with different share prices will have different return responses following the same news. Specifically, equation (13) shows that investors are more likely to underestimate the return responses for stocks with higher share prices compared to stocks with lower share prices. As a consequence, in the presence of momentum, the model predicts that higher-priced stocks should drift for longer than stocks with low share prices following the same news. Therefore, equation (13) makes the following prediction about momentum:

**Prediction 1 – The Effect of Price on Momentum Returns**

*For any given default stock price $P^d$, the lower (higher) the stock price $P$, the stronger (weaker) is the return response between periods 1 and 2. Therefore, momentum will be more predictive of future returns for stocks with higher share prices. In other words, past returns are more predictive of future returns for stocks with higher share prices. In addition, stocks with higher share price are less likely to show reversal.*

Having laid out the model predictions about the effect of share prices on the predictive power of momentum over future returns, I now turn to the empirical tests of these predictions in the next subsection.
4.3 Empirical Tests of Momentum in the Stock Market

4.3.1 Data and Variables

To test the predictions about the effect of share prices on momentum returns and reversal, I use stock return data from the Center for Research on Security Prices (CRSP) focusing on common stocks (share code 10 or 11) starting from 1926 to 2016. Following Jegadeesh and Titman (1993, 2001) and Ali, Daniel, and Hirshleifer (2017), I restrict the sample to stocks whose prices are above $5 and market capitalization is above the 10th percentile size breakpoint, using the NYSE size breakpoints, at the time of portfolio formation. All analyses use monthly data.

Momentum is calculated as the cumulative returns from 12 months before to one month before the portfolio formation date. The most recent month is excluded to mitigate the effect of short-term reversal documented by Jegadeesh (1990) and Lehman (1990). Size is the product of price and number of shares outstanding. All prices are closing prices. The monthly time series of risk-free rates are taken from professor Ken French’s website.

One concern in the analysis is that the effect of price on returns may be driven by size. As Shue and Townsend (2019) state: “Holding the equity size of a stock constant, the nominal share price has no real meaning, because the price depends on the arbitrary number of shares a firm’s equity is divided into.” To address this issue, and I control for both size and price in the regression specifications 12 months before portfolio formation to avoid a mechanical correlation between returns, and price and size (Shue and Townsend 2019). In order to be able to compare the magnitude of the effects of momentum and its interaction with lagged price and size, I demean lagged price and size, so that all dependent variables are in the same unit. In the regression tables, I italicized them as a reminder that they have been demeaned.
4.3.2 Results

I begin by testing Prediction 3 of the model, that momentum will better predict future returns for stocks with higher share prices. To do so, I estimate Fama MacBeth (1973) regressions of natural log of the cumulative one-month-ahead excess returns on the natural log of the cumulative returns of the commonly used measure of momentum, its interaction with lagged price and size, and lagged price and size. Table 8 shows the effect of share price on the predictive power of momentum over returns one-month ahead. In all columns, the direct effect of price and size are included in the regression but are not reported, since they are mostly insignificant.

[Table 8: The Effect of Share Price on the Predictive Power of Momentum over Returns]

Column (1) shows that momentum is highly predictive of one-month-ahead excess returns in the cross-section, as expected. In column (2), when the interaction between momentum and lagged price is added, I find that the interaction terms also has substantive predictive power over future returns. One natural concern is that size – not price – is driving this effect. In column (3) I report that the interaction of momentum and lagged size also has predictive power over future returns. However, when I introduce both the interactions of lagged size and lagged price with momentum in column (4), the predictive power of the interaction with size is smaller and less statistically significant than the interaction with price. Overall, these results make clear that past returns – i.e., momentum - are more predictive of future returns for stocks with higher share prices.

It is well known that momentum returns tend to reverse in the long-run. Now, I will test that past returns are less likely to predict future reversals for stocks with higher share prices. The regression framework will be the same as when I tested Prediction 3, except that the independent variable is now excess-returns k-months ahead, where k = 1, 12, 24, 36, 48, and 60. Note that the independent variables are the same from Table 8 and measured from months $t - 12$ to $t - 2$, regardless of the dependent variable.
Column (1) of Table 9 is the same as column (5) of Table 8 and serves as a guide to the magnitude of the predictive power of the independent variables on excess return one month ahead. An interesting pattern starts to emerge in column (2). Past returns predict stronger returns 12 months after portfolio formation than after one month, having a similar magnitude to its interaction with price – but not with size. In Columns (3) - (6), past returns predict reversal in the long-run and more strongly so in columns (4) - (6). On the other hand, the interaction between lagged price and past returns stays positive and grow more strongly, showing that return reversal happens more slowly for stocks with higher share prices. Since all regressors have the same units, I can conclude that starting at 12 months, the interaction of price with past returns is more important than past returns in predicting the long-run performance of momentum returns. Meanwhile, the interaction of size with past returns also has positive returns but they are much smaller in magnitude and not always significant. In other words, past returns are less likely to predict future reversals for higher share prices controlling for size, confirming prediction 3.

Finding 3 – The Effect of Price on Momentum Returns

Stocks with similar past returns, but higher share prices, exhibit stronger return predictability and are less likely to show reversal in the long-run, controlling for size.

4.3.3 A Trading Strategy

The model hypothesizes that stock returns respond differently to news based on the stock’s share price. Following news, the model predicts that stocks with larger share price tend to drift for longer than stocks with lower share price. Therefore, I suggest a strategy that pairs stocks with similar past performance – both winners and losers - but different share prices. The suggested strategy goes long on stocks with best past performance (winners) with high prices and short on stocks with worst past performance (losers) with high share
prices, since stocks with higher share price drift for longer than those with lower share price. Even though that strategy is similar to the standard momentum strategy, there is one key difference. While momentum goes long on previous winners and short on previous losers, the strategy presented in this paper pairs stocks with similar previous large positive and negative returns and then sort those in different price terciles, going long on winners with high price and going short on losers with high price.

The details of the strategy implementation are as follows. First, in line with the data I used in this section, I exclude stocks whose price are below $5 and market capitalization are below the 10th size breakpoint, using the NYSE size breakpoints, at portfolio formation. Second, similarly to the standard momentum strategies, I sort stocks in deciles of past performances from 12 to 1 month ago for each month in the dataset, skipping the most recent month. I focus the analysis on the winners (decile 10) and losers (decile 1). Third, within each of these two deciles, I once again sort them in 5 quintiles of past performance. Fourth, within each new quintiles of winners and losers, I sort the stocks in terciles of price at portfolio formation. Fifth, I average the winner and loser portfolios by price terciles, forming 6 portfolios in total: winner-high price; winner-medium price; winner-low price; loser-high price; loser-medium price; loser-low price. Sixth, since the model predicts that high-priced stocks drifts for longer in the direction of past returns, I go long the winner-high price portfolio and go short the winner-low price portfolio. I also construct the other two portfolios using medium and low prices to compare the performance. The theory would predict that the highest price portfolio would perform best, whereas the lowest price portfolio would perform worst.

[Table 10 - Performance of Portfolios of Momentum Strategies]

\footnote{If one sorts the winner and loser deciles by price terciles, the previous return performance within each of the winner-price tercile would be vastly different. For instance, I find that the top tercile of price among winners had average past returns over the last 11 months skipping the most recent month of 111% (median = 89%), whereas the middle tercile of price among winners had an average performance of 123% (median = 97%), and the bottom tercile had an average of 166% (median = 115%). The loser-price terciles, on the other hand, have similar performance. A portfolio that goes long on winners and short on losers by price tercile would not be an appropriate application of the theory because of the different recent returns faced by each tercile of winners.}
Table 10 shows the performance of 4 different strategies based on momentum. The first row is the common momentum strategy suggested by Jegadeesh and Titman (1993). The second to the fourth row show the trading strategy suggested in this section, with particular attention to the portfolio formed by winners and losers with highest price in the last column. All strategies are followed by their average excess returns, standard deviation of returns, Sharpe ratio, and the Fama-French 3-factor alpha. Since the new portfolios are constructed in a similar fashion to a standard momentum strategy, I also report the 4-factor Fama-French-Carhart alpha.

Column (1) shows that the standard momentum strategy exhibits an average excess return of 17.18%, a 3-factor alpha of 23.14%, and a 4-factor alpha of 5.78%. The theory presented in this section suggests that stocks with lowest price would have worse performance, followed by stocks with medium price, then the stocks with highest price having the best performance. This is what columns (2), (3), and (4) report in Table 10. In all measures of performance, the strategy with the stocks with highest share price perform better. For instance, the Fama-French 3-factor alphas of the portfolios of lowest, middle, and highest price stocks are 19.40%, 23.87%, and 26.64%, respectively, in annualized terms. What is surprising is that the alpha of the highest-price portfolio is greater than that of the standard momentum strategy by over 3% a year.

[Figure 6 – Performance of Momentum Trading Strategies]

Figure 6 compares the dollar returns of a $1.00 investment from 1927 to 2016 in the 4 momentum strategies presented in Table 10. The investment in the standard momentum strategy becomes $120,788 in 2016. Meanwhile, the $1.00 invested in the highest price stocks deliver a dollar return of $623,822, whereas the medium-price portfolio delivers $76,596, and the lowest-price portfolio, $13,287.

[Figure 7 – Performance of Portfolios of Past Losers]

[Figure 8 – Performance of Portfolios of Past Winners]
Figures 7 and 8 extend the analysis to the winner and loser legs of the portfolio. Figure 7 shows the performance of the different loser portfolios. The standard momentum loser portfolio shrinks the initial $1.00 investment to $0.02, whereas the suggested high-price portfolio shrinks it to $0.003. The low-price portfolio only shrinks it to $0.09, while the medium-price portfolio does it to $0.01. In Figure 8, the standard momentum winners grow the $1.00 investment to $151,056, an amount similar to the $133,784 of the medium-priced portfolio. Meanwhile, the high-price portfolio delivers $194,781, whereas the low-price portfolio delivers $66,670. It is worth stressing the gradient of the performances shown in figures 7 and 8: high-priced winners perform best and high-priced losers perform worst. That is why the trading strategy goes both long and short on stocks with high price.

5 Conclusion

In this paper, I developed a simple anchoring-and-adjustment model in which investors anchor on their customarily observed dollar amount and do not fully adjust to amounts that substantially deviate from it. In the model, the mental representation of large dollar amounts appears smaller than in reality. As a consequence, when converting from percentage returns to dollar information, individuals will underestimate the future value of large dollar amounts relative to that of smaller dollar amounts, given a percentage return and a time horizon. Relatedly, the model predicts that investors respond more strongly to the same percentage gains when they are described in larger dollar amounts, given a percentage return and a time horizon.

The predictions are confirmed in one experiment on an online and one field experiment with over 170,000 experienced investors. Having found evidence for the model, I extend it to study the effect of share prices on the behavior of stock returns. I find that momentum strategies using stocks with higher share price exhibit stronger return predictability and are less likely to show reversal in the long-run, controlling for size. In fact, a trading strategy
that exploits this finding generates, in annualized terms, a Fama-French 3-factor alpha of 26.67% (t-stat = 10.21) and a Fama-French-Carhart 4-factor alpha of 8.21% (t-stat = 6.54), enhancing the profitability of momentum strategies.

This paper leaves multiple avenues for future research. First, this paper studied investment decisions of investors. But how well does it explain the behavior of borrowers? In a companion paper (Costa, 2019), I apply the model of misperception of interest rates to debt markets and test it in a field experiment in which I offer a loan to over 130,000 borrowers from a commercial bank. I find results in line with the predictions made in this paper. Borrowers prefer the framing of interest rates with lower principals because the amount of dollar interest looks proportionally smaller. Similarly, I also find that framing the interest rates of loans as compound interest does not affect the demand for the loans.

Second, even though the paper mostly focused on the misperception of principals of an investment opportunity, the model can be applied to the misperception of other financial variables, such as interest rates. A booming literature in psychophysics has studied for decades how people perceive numbers. This paper is just one step toward this direction.

Third, the results suggest a closer look at how financial information is disclosed to consumers. Sometimes with the best interest of the consumer in mind, examples about the relationship between interest rates and dollar amounts are used to explain what interest rates are. This paper showed that it is possible to nudge consumers toward or away from financial products by framing its dollar returns appropriately. Therefore, caution is warranted when disclosing interest rates and delivering financial education: framing of information containing dollar amounts matters. Therefore, it is crucial to keep in mind the principles of behavioral finance and economics when designing disclosures and financial education materials.

Finally, the model of how share prices affect the behavior of stock returns provides key insights into when momentum and reversal are more likely to happen in financial markets. The advantage of the simplicity of the model is that it is easily portable to study the misperception of other variables in the stock market and other asset markets. Baker, Greenwood,
and Wurgler (2009) stated that “psychology of stock price levels is unexplored.” This paper has shown that the issue of misperception of magnitudes goes beyond prices. In finance, the psychology of numerical magnitudes is still vastly unexplored.

References


Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam. ”Investor psychology and security market under-and overreactions.” the Journal of Finance 53, no. 6 (1998): 1839-


**Tables**

**Table 1: Demographics of MTurk Subjects**

This table displays the summary statistics from the MTurk experiment. In addition to presenting information on gender, education, and age, I also surveyed subjects about their investment experience, financial literacy, numeracy, and a proxy for language proficiency. The financial literacy questions are taken from Lusardi and Mitchell (2008). The numeracy questions are from Lusardi (2012). The question about where subjects lived in the past 10 years is used as a proxy for English proficiency.

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>79</td>
<td>44.6%</td>
</tr>
<tr>
<td>Male</td>
<td>98</td>
<td>55.4%</td>
</tr>
<tr>
<td><strong>Education</strong></td>
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<td></td>
</tr>
<tr>
<td>High school</td>
<td>51</td>
<td>28.8%</td>
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<tr>
<td>College</td>
<td>113</td>
<td>63.8%</td>
</tr>
<tr>
<td>Graduate school</td>
<td>13</td>
<td>7.3%</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>18-30</td>
<td>69</td>
<td>39.0%</td>
</tr>
<tr>
<td>30-50</td>
<td>94</td>
<td>53.1%</td>
</tr>
<tr>
<td>Above 50</td>
<td>18</td>
<td>10.2%</td>
</tr>
<tr>
<td><strong>Investing Experience</strong></td>
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<td></td>
</tr>
<tr>
<td>Extensive</td>
<td>7</td>
<td>4.0%</td>
</tr>
<tr>
<td>Some</td>
<td>45</td>
<td>25.4%</td>
</tr>
<tr>
<td>Limited</td>
<td>70</td>
<td>39.5%</td>
</tr>
<tr>
<td>No</td>
<td>55</td>
<td>31.1%</td>
</tr>
<tr>
<td><strong>Financial Literacy Score</strong></td>
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<td></td>
</tr>
<tr>
<td>0-1</td>
<td>25</td>
<td>14.1%</td>
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<tr>
<td>2-3</td>
<td>97</td>
<td>54.8%</td>
</tr>
<tr>
<td>4</td>
<td>55</td>
<td>31.1%</td>
</tr>
<tr>
<td><strong>Numeracy Score</strong></td>
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<td>10.7%</td>
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<tr>
<td>2-3</td>
<td>70</td>
<td>39.5%</td>
</tr>
<tr>
<td>4</td>
<td>88</td>
<td>49.7%</td>
</tr>
<tr>
<td><strong>Lived in the US for 10+ years</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>176</td>
<td>99.4%</td>
</tr>
<tr>
<td>No</td>
<td>1</td>
<td>0.6%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>177</td>
<td></td>
</tr>
</tbody>
</table>
Table 2 - Estimated Dollar Returns Over Time

Rows (1) to (3) report the mean of subject estimates for the dollar returns under different principals. In these rows, the estimates are divided by their respective principals, so that the estimates are in the same order of magnitude. Columns (1) to (5) show the estimates for each time frame: 1, 2, 5, 10, and 20 years. Standard errors of the estimates are in parentheses. Row (4) shows the correct answer for the estimation task. Rows (5) to (7) report the pairwise difference in estimates from rows (1) to (3). Standard errors of the differences are shown in parentheses. *, **, and *** indicate that the difference is statistically different from zero at the 10%, 5%, and 1% level of significance, respectively. Panel A, B, and C show the estimates and differences for the tasks with interest rate of 2%, 10%, and 20%, respectively.

### Panel A: Interest Rate = 2%

<table>
<thead>
<tr>
<th>Estimates</th>
<th>t = 1</th>
<th>t = 2</th>
<th>t = 5</th>
<th>t = 10</th>
<th>t = 20</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Principal = $ 1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1)</td>
<td>1.127</td>
<td>1.370</td>
<td>2.016</td>
<td>3.415</td>
<td>6.671</td>
</tr>
<tr>
<td></td>
<td>(0.283)</td>
<td>(0.77)</td>
<td>(1.879)</td>
<td>(4.355)</td>
<td>(9.790)</td>
</tr>
<tr>
<td>(2) Principal = $ 100.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2)</td>
<td>1.036</td>
<td>1.139</td>
<td>1.519</td>
<td>2.270</td>
<td>4.014</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.268)</td>
<td>(1.053)</td>
<td>(3.588)</td>
<td>(5.621)</td>
</tr>
<tr>
<td>(3) Principal = $ 10,000.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3)</td>
<td>1.031</td>
<td>1.114</td>
<td>1.256</td>
<td>1.617</td>
<td>2.699</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.017)</td>
<td>(0.450)</td>
<td>(1.112)</td>
<td>(3.234)</td>
</tr>
<tr>
<td>(4) Correct Value</td>
<td>1.020</td>
<td>1.040</td>
<td>1.104</td>
<td>1.219</td>
<td>1.486</td>
</tr>
</tbody>
</table>

### Differences

<table>
<thead>
<tr>
<th>Differences</th>
<th>(5) Difference: (1) - (2)</th>
<th>(6) Difference: (1) - (3)</th>
<th>(7) Difference: (2) - (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.091***</td>
<td>0.096***</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.021)</td>
<td>(0.005)</td>
</tr>
<tr>
<td></td>
<td>0.231***</td>
<td>0.256***</td>
<td>0.025</td>
</tr>
<tr>
<td></td>
<td>(0.061)</td>
<td>(0.061)</td>
<td>(0.026)</td>
</tr>
<tr>
<td></td>
<td>0.496***</td>
<td>0.759***</td>
<td>0.263***</td>
</tr>
<tr>
<td></td>
<td>(0.162)</td>
<td>(0.148)</td>
<td>(0.087)</td>
</tr>
<tr>
<td></td>
<td>1.145***</td>
<td>1.798***</td>
<td>0.653***</td>
</tr>
<tr>
<td></td>
<td>(0.377)</td>
<td>(0.339)</td>
<td>(0.205)</td>
</tr>
<tr>
<td></td>
<td>2.657***</td>
<td>3.972***</td>
<td>1.315***</td>
</tr>
<tr>
<td></td>
<td>(0.849)</td>
<td>(0.777)</td>
<td>(0.488)</td>
</tr>
</tbody>
</table>

N | 177 | 177 | 177 | 177 | 177
### Table 2 - Continued

#### Panel B: Interest Rate = 10%

<table>
<thead>
<tr>
<th>Estimates</th>
<th>Time (in years)</th>
<th>t = 1</th>
<th>t = 2</th>
<th>t = 5</th>
<th>t = 10</th>
<th>t = 20</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>(1) Principal = $1.00</td>
<td>t = 1</td>
<td>1.164</td>
<td>1.416</td>
<td>2.312</td>
<td>4.160</td>
<td>9.558</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.228)</td>
<td>(0.567)</td>
<td>(1.891)</td>
<td>(4.267)</td>
<td>(11.921)</td>
</tr>
<tr>
<td>(2) Principal = $100.00</td>
<td>t = 2</td>
<td>1.100</td>
<td>1.319</td>
<td>2.019</td>
<td>3.506</td>
<td>7.437</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.000)</td>
<td>(0.292)</td>
<td>(1.142)</td>
<td>(3.098)</td>
<td>(7.253)</td>
</tr>
<tr>
<td>(3) Principal = $10,000.00</td>
<td>t = 5</td>
<td>1.077</td>
<td>1.222</td>
<td>1.726</td>
<td>2.709</td>
<td>4.953</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.039)</td>
<td>(0.218)</td>
<td>(0.069)</td>
<td>(2.214)</td>
<td>(4.897)</td>
</tr>
<tr>
<td>(4) Correct Value</td>
<td>t = 10</td>
<td>1.100</td>
<td>1.210</td>
<td>1.611</td>
<td>2.594</td>
<td>6.728</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.017)</td>
<td>(0.048)</td>
<td>(0.166)</td>
<td>(0.382)</td>
<td>(1.049)</td>
</tr>
<tr>
<td>(5) Difference: (1) - (2)</td>
<td>t = 10</td>
<td>0.064***</td>
<td>0.097**</td>
<td>0.294**</td>
<td>0.654**</td>
<td>2.122**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.017)</td>
<td>(0.048)</td>
<td>(0.166)</td>
<td>(0.382)</td>
<td>(1.049)</td>
</tr>
<tr>
<td>(6) Difference: (1) - (3)</td>
<td>t = 10</td>
<td>0.087***</td>
<td>0.194***</td>
<td>0.587***</td>
<td>1.451***</td>
<td>4.606***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.017)</td>
<td>(0.046)</td>
<td>(0.159)</td>
<td>(0.365)</td>
<td>(0.966)</td>
</tr>
<tr>
<td>(7) Difference: (2) - (3)</td>
<td>t = 10</td>
<td>0.023***</td>
<td>0.097***</td>
<td>0.293***</td>
<td>0.797***</td>
<td>2.484***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.003)</td>
<td>(0.027)</td>
<td>(0.110)</td>
<td>(0.267)</td>
<td>(0.654)</td>
</tr>
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</table>

| N                  |                 | 177   | 177   | 177   | 177    | 177    |

---
Table 2 - Continued

Panel C: Interest Rate = 20%

<table>
<thead>
<tr>
<th>Estimates</th>
<th>Time (in years)</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>t = 1</td>
<td>t = 2</td>
<td>t = 5</td>
<td>t = 10</td>
<td>t = 20</td>
</tr>
<tr>
<td>(1) Principal = $ 1.00</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>1.456</td>
<td>(0.909)</td>
<td>2.039</td>
<td>(1.981)</td>
<td>4.095</td>
<td>(5.465)</td>
</tr>
<tr>
<td>(2) Principal = $ 100.00</td>
<td>(7)</td>
<td>(8)</td>
<td>(9)</td>
<td>(10)</td>
<td>(11)</td>
</tr>
<tr>
<td>1.200</td>
<td>(0.000)</td>
<td>1.514</td>
<td>(0.283)</td>
<td>2.483</td>
<td>(1.109)</td>
</tr>
<tr>
<td>(3) Principal = $ 10,000.00</td>
<td>(13)</td>
<td>(14)</td>
<td>(15)</td>
<td>(16)</td>
<td>(17)</td>
</tr>
<tr>
<td>1.161</td>
<td>(0.073)</td>
<td>1.377</td>
<td>(0.196)</td>
<td>2.089</td>
<td>(0.898)</td>
</tr>
<tr>
<td>(4) Correct Value</td>
<td>(19)</td>
<td>(20)</td>
<td>(21)</td>
<td>(22)</td>
<td>(23)</td>
</tr>
<tr>
<td>1.200</td>
<td>(0.000)</td>
<td>1.440</td>
<td>(0.196)</td>
<td>2.488</td>
<td>(0.898)</td>
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</table>

Differences

<table>
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<th>Differences</th>
<th>(5) Difference: (1) - (2)</th>
<th>(6) Difference: (1) - (3)</th>
<th>(7) Difference: (2) - (3)</th>
<th>(8) N</th>
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</thead>
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<td>0.526***</td>
<td>1.612***</td>
<td>6.266***</td>
</tr>
<tr>
<td></td>
<td>(0.068)</td>
<td>(0.150)</td>
<td>(0.420)</td>
<td>(1.718)</td>
</tr>
<tr>
<td></td>
<td>0.295***</td>
<td>0.662***</td>
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<tr>
<td></td>
<td>(0.069)</td>
<td>(0.150)</td>
<td>(0.416)</td>
<td>(1.717)</td>
</tr>
<tr>
<td></td>
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<td>1.492***</td>
</tr>
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<td>(0.006)</td>
<td>(0.026)</td>
<td>(0.107)</td>
<td>(0.294)</td>
</tr>
<tr>
<td></td>
<td>177</td>
<td>177</td>
<td>177</td>
<td>177</td>
</tr>
</tbody>
</table>
Table 3 - Baseline Variables for Sample Description and Orthogonality Checks - Intent to Treat

Columns (1) to (6) report averages, with standard errors in parentheses. Column (7) reports the Bonferroni p-values from the joint hypothesis that the coefficients on the treatment indicators are zero. Variables were measured in January 2019. *, **, and *** indicate statistically significant from zero at the 10%, 5%, and 1% level of significance, respectively.

<table>
<thead>
<tr>
<th>Experimental Conditions</th>
<th>Full sample</th>
<th>Control</th>
<th>Treatment 1</th>
<th>Treatment 2</th>
<th>Treatment 3</th>
<th>Treatment 4</th>
<th>Bonferroni p-values</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
</tr>
<tr>
<td>Income</td>
<td>10,928</td>
<td>10,627</td>
<td>10,857</td>
<td>11,461</td>
<td>10,890</td>
<td>10,803</td>
<td>0.702</td>
</tr>
<tr>
<td></td>
<td>(76,940)</td>
<td>(74,119)</td>
<td>(71,904)</td>
<td>(82,619)</td>
<td>(79,264)</td>
<td>(76,329)</td>
<td></td>
</tr>
<tr>
<td>Total Amount Invested</td>
<td>273,121</td>
<td>276,173</td>
<td>271,968</td>
<td>274,923</td>
<td>272,555</td>
<td>269,985</td>
<td>0.630</td>
</tr>
<tr>
<td></td>
<td>(575,877)</td>
<td>(580,902)</td>
<td>(574,022)</td>
<td>(579,348)</td>
<td>(576,873)</td>
<td>(568,160)</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>0.278</td>
<td>0.276</td>
<td>0.277</td>
<td>0.280</td>
<td>0.278</td>
<td>0.277</td>
<td>0.869</td>
</tr>
<tr>
<td></td>
<td>(0.447)</td>
<td>(0.447)</td>
<td>(0.447)</td>
<td>(0.449)</td>
<td>(0.448)</td>
<td>(0.447)</td>
<td></td>
</tr>
<tr>
<td>Risk Tolerance</td>
<td>1.186</td>
<td>1.183</td>
<td>1.186</td>
<td>1.185</td>
<td>1.183</td>
<td>1.190</td>
<td>0.732</td>
</tr>
<tr>
<td></td>
<td>(0.674)</td>
<td>(0.678)</td>
<td>(0.673)</td>
<td>(0.673)</td>
<td>(0.674)</td>
<td>(0.672)</td>
<td></td>
</tr>
<tr>
<td>Invests in Mutual Funds</td>
<td>0.429</td>
<td>0.432</td>
<td>0.429</td>
<td>0.430</td>
<td>0.425</td>
<td>0.431</td>
<td>0.319</td>
</tr>
<tr>
<td></td>
<td>(0.495)</td>
<td>(0.495)</td>
<td>(0.495)</td>
<td>(0.495)</td>
<td>(0.494)</td>
<td>(0.495)</td>
<td></td>
</tr>
<tr>
<td>Invests in Stocks</td>
<td>0.304</td>
<td>0.307</td>
<td>0.305</td>
<td>0.304</td>
<td>0.300</td>
<td>0.306</td>
<td>0.251</td>
</tr>
<tr>
<td></td>
<td>(0.460)</td>
<td>(0.461)</td>
<td>(0.460)</td>
<td>(0.460)</td>
<td>(0.458)</td>
<td>(0.461)</td>
<td></td>
</tr>
<tr>
<td>Invests in Bonds</td>
<td>0.464</td>
<td>0.467</td>
<td>0.464</td>
<td>0.465</td>
<td>0.465</td>
<td>0.461</td>
<td>0.679</td>
</tr>
<tr>
<td></td>
<td>(0.499)</td>
<td>(0.499)</td>
<td>(0.499)</td>
<td>(0.499)</td>
<td>(0.499)</td>
<td>(0.499)</td>
<td></td>
</tr>
<tr>
<td>Has Other Investments</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
<td>0.326</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.027)</td>
<td>(0.033)</td>
<td>(0.027)</td>
<td>(0.027)</td>
<td>(0.030)</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>177,654</td>
<td>35,541</td>
<td>35,381</td>
<td>35,432</td>
<td>35,654</td>
<td>35,646</td>
<td></td>
</tr>
</tbody>
</table>
Table 4 - Baseline Variables for Sample Description and Orthogonality Checks - Treatment on the Treated

Columns (1) to (6) report averages, with standard errors in parentheses. Column (7) reports the Bonferroni p-values from the joint hypothesis that the coefficients on the treatment indicators are zero. Variables were measured in January 2019. *, **, and *** indicate statistically significant from zero at the 10%, 5%, and 1% level of significance, respectively.

<table>
<thead>
<tr>
<th>Experimental Conditions</th>
<th>Full sample</th>
<th>Control</th>
<th>Treatment 1</th>
<th>Treatment 2</th>
<th>Treatment 3</th>
<th>Treatment 4</th>
<th>Bonferroni p-values</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
</tr>
<tr>
<td>Income</td>
<td>5,126</td>
<td>5,099</td>
<td>4,953</td>
<td>5,127</td>
<td>5,077</td>
<td>5,371</td>
<td>0.994</td>
</tr>
<tr>
<td></td>
<td>(53,459)</td>
<td>(50,444)</td>
<td>(50,258)</td>
<td>(50,450)</td>
<td>(53,126)</td>
<td>(61,921)</td>
<td></td>
</tr>
<tr>
<td>Total Amount Invested</td>
<td>55,019</td>
<td>55,107</td>
<td>54,481</td>
<td>56,492</td>
<td>50,773</td>
<td>57,806</td>
<td>0.196</td>
</tr>
<tr>
<td></td>
<td>(204,195)</td>
<td>(201,387)</td>
<td>(199,166)</td>
<td>(213,228)</td>
<td>(188,034)</td>
<td>(217,688)</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>0.225</td>
<td>0.232</td>
<td>0.219</td>
<td>0.224</td>
<td>0.231</td>
<td>0.222</td>
<td>0.259</td>
</tr>
<tr>
<td></td>
<td>(0.418)</td>
<td>(0.422)</td>
<td>(0.414)</td>
<td>(0.416)</td>
<td>(0.421)</td>
<td>(0.415)</td>
<td></td>
</tr>
<tr>
<td>Risk Tolerance</td>
<td>0.902</td>
<td>0.908</td>
<td>0.903</td>
<td>0.917</td>
<td>0.885</td>
<td>0.896</td>
<td>0.058*</td>
</tr>
<tr>
<td></td>
<td>(0.694)</td>
<td>(0.702)</td>
<td>(0.695)</td>
<td>(0.691)</td>
<td>(0.695)</td>
<td>(0.689)</td>
<td></td>
</tr>
<tr>
<td>Invests in Mutual Funds</td>
<td>0.271</td>
<td>0.269</td>
<td>0.282</td>
<td>0.267</td>
<td>0.266</td>
<td>0.266</td>
<td>0.158</td>
</tr>
<tr>
<td></td>
<td>(0.444)</td>
<td>(0.443)</td>
<td>(0.450)</td>
<td>(0.442)</td>
<td>(0.442)</td>
<td>(0.442)</td>
<td></td>
</tr>
<tr>
<td>Invests in Stocks</td>
<td>0.204</td>
<td>0.205</td>
<td>0.213</td>
<td>0.203</td>
<td>0.192</td>
<td>0.206</td>
<td>0.024**</td>
</tr>
<tr>
<td></td>
<td>(0.403)</td>
<td>(0.404)</td>
<td>(0.409)</td>
<td>(0.402)</td>
<td>(0.394)</td>
<td>(0.405)</td>
<td></td>
</tr>
<tr>
<td>Invests in Bonds</td>
<td>0.532</td>
<td>0.532</td>
<td>0.538</td>
<td>0.527</td>
<td>0.528</td>
<td>0.534</td>
<td>0.642</td>
</tr>
<tr>
<td></td>
<td>(0.499)</td>
<td>(0.499)</td>
<td>(0.499)</td>
<td>(0.499)</td>
<td>(0.499)</td>
<td>(0.499)</td>
<td></td>
</tr>
<tr>
<td>Has Other Investments</td>
<td>0.0002</td>
<td>0.0005</td>
<td>0.0001</td>
<td>0.0000</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.136</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.023)</td>
<td>(0.011)</td>
<td>(0.000)</td>
<td>(0.011)</td>
<td>(0.011)</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>39,535</td>
<td>7,725</td>
<td>7,853</td>
<td>7,946</td>
<td>8,016</td>
<td>7,995</td>
<td></td>
</tr>
</tbody>
</table>
Table 5 - Orthogonality Check - Treatment on the Treated

Each column presents the coefficients of a single OLS regression of the treatment conditions on the covariates available at baseline. Standard errors are reported in parentheses. The p-value of the F-test of all regression coefficients being zero is reported at the end. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Magnitude: Low (= 0) or High (= 1)</th>
<th>Framing of Interest: Simple (= 0) or Compound (= 1)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Income</td>
<td>-4.10 x 10^{-8}</td>
<td>-2.95 x 10^{-8}</td>
</tr>
<tr>
<td></td>
<td>(6.70 x 10^{-8})</td>
<td>(6.70 x 10^{-8})</td>
</tr>
<tr>
<td>Total Amount Invested</td>
<td>2.32 x 10^{-8}</td>
<td>-7.49 x 10^{-9}</td>
</tr>
<tr>
<td></td>
<td>(1.54 x 10^{-8})</td>
<td>(1.54 x 10^{-8})</td>
</tr>
<tr>
<td>Female</td>
<td>-0.0022</td>
<td>0.0054</td>
</tr>
<tr>
<td></td>
<td>(0.0072)</td>
<td>(0.0072)</td>
</tr>
<tr>
<td>Risk Tolerance</td>
<td>0.0055</td>
<td>-0.0082*</td>
</tr>
<tr>
<td></td>
<td>(0.0045)</td>
<td>(0.0045)</td>
</tr>
<tr>
<td>Invests in Mutual Funds</td>
<td>0.0021</td>
<td>-0.0109*</td>
</tr>
<tr>
<td></td>
<td>(0.0065)</td>
<td>(0.0065)</td>
</tr>
<tr>
<td>Invests in Stocks</td>
<td>0.0014</td>
<td>-0.0078</td>
</tr>
<tr>
<td></td>
<td>(0.0073)</td>
<td>(0.0073)</td>
</tr>
<tr>
<td>Invests in Bonds</td>
<td>0.0034</td>
<td>-0.0026</td>
</tr>
<tr>
<td></td>
<td>(0.0060)</td>
<td>(0.0060)</td>
</tr>
<tr>
<td>Has Other Investments</td>
<td>-0.1686</td>
<td>0.1660</td>
</tr>
<tr>
<td></td>
<td>(0.2887)</td>
<td>(0.2886)</td>
</tr>
<tr>
<td>P-Value of F-Test</td>
<td>0.6823</td>
<td>0.1580</td>
</tr>
<tr>
<td>R²</td>
<td>0.0001</td>
<td>0.0004</td>
</tr>
<tr>
<td>N</td>
<td>31,810</td>
<td>31,810</td>
</tr>
</tbody>
</table>
Table 6 – Summary of Results of the Field Experiment

This table presents the summary of the results of the field experiment by version of the treatment faced by the subjects. “Magnitude” refers to whether the subjects saw the interest rate explained using a low magnitude (R$ 1.00) or a high magnitude (R$ 100.00). “Interest” refers to whether the subjects saw the interest rate framed as simple interest (over the course of 1 year) or compound interest (over the course of 6 years). “Emails Sent” refers to the number of subjects that got an email. “Emails Opened” refers to the number of subjects that opened the email. “Number of Investors” refers to the number of subjects that purchase the bond.

<table>
<thead>
<tr>
<th>Version</th>
<th>Magnitude</th>
<th>Interest</th>
<th>Emails Sent</th>
<th>Emails Opened</th>
<th>Number of Investors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>---</td>
<td>---</td>
<td>35541</td>
<td>7725</td>
<td>77</td>
</tr>
<tr>
<td>Treatment 1</td>
<td>Low</td>
<td>Simple</td>
<td>35381</td>
<td>7853</td>
<td>79</td>
</tr>
<tr>
<td>Treatment 2</td>
<td>High</td>
<td>Simple</td>
<td>35432</td>
<td>7946</td>
<td>97</td>
</tr>
<tr>
<td>Treatment 3</td>
<td>Low</td>
<td>Compound</td>
<td>35654</td>
<td>8016</td>
<td>73</td>
</tr>
<tr>
<td>Treatment 4</td>
<td>High</td>
<td>Compound</td>
<td>35646</td>
<td>7995</td>
<td>95</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td></td>
<td><strong>177654</strong></td>
<td><strong>39535</strong></td>
<td><strong>421</strong></td>
</tr>
</tbody>
</table>
Table 7 - Effects of the Principal Magnitude and Compound Interest on Investment

Each column presents treatment effects estimate from a single OLS regression with standard errors between parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Additional controls include income, gender, and investment in mutual funds. The mean of the dependent variable on the left-hand side (LHS) is reported as well.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Magnitude</td>
<td>0.0025** (0.0012)</td>
<td>0.0025** (0.0012)</td>
<td>0.0026** (0.0012)</td>
<td></td>
</tr>
<tr>
<td>Compound</td>
<td>-0.0006 (0.0012)</td>
<td>-0.0006 (0.0012)</td>
<td>-0.0006 (0.0012)</td>
<td></td>
</tr>
<tr>
<td>Stocks</td>
<td></td>
<td>0.0040** (0.0015)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bonds</td>
<td></td>
<td>0.0189*** (0.0013)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Risk Level</td>
<td></td>
<td>-0.0030*** (0.0009)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Additional Controls</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Mean (LHS)</td>
<td>0.0106</td>
<td>0.0106</td>
<td>0.0106</td>
<td>0.0106</td>
</tr>
<tr>
<td>N</td>
<td>31,810</td>
<td>31,810</td>
<td>31,810</td>
<td>31,810</td>
</tr>
<tr>
<td>R²</td>
<td>0.0001</td>
<td>0.0000</td>
<td>0.0002</td>
<td>0.0093</td>
</tr>
</tbody>
</table>
Table 8 - The Effect of Share Price on the Predictive Power of Momentum over Returns

This table presents the result of Fama and Macbeth (1973) regression analyses of the relation between one-month ahead cumulative abnormal returns and momentum. Each column in the table presents results for a different cross-sectional regression specification. I exclude stocks with price below $5 and stocks with market capitalization below the 10th percentile size breakpoint (using size NYSE breakpoints). The dependent variable in every regression is the one-month ahead cumulative abnormal returns. The cumulative return of momentum is calculated as the cumulative return over the past eleven months skipping the most recent month. Independent variables are winsorized at the 0.5% level on a monthly basis. The variables representing the log of lagged price and lagged size are demeaned. Both the variables representing the demeaned lagged price and lagged size are also included in the regression but not reported on the table. Standard errors are in parentheses. ***, **, and * denote 10%, 5%, and 1% statistical significance.

**Sample**: CRSP (1927 - 2016)

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log (1+ CR\text{Mom})</td>
<td>0.014*** (0.002)</td>
<td>0.013*** (0.001)</td>
<td>0.013*** (0.001)</td>
<td>0.013*** (0.001)</td>
</tr>
<tr>
<td>Log (1+ CR\text{Mom}) x Log(Price_{t-12})</td>
<td>0.004*** (0.001)</td>
<td></td>
<td>0.003*** (0.001)</td>
<td></td>
</tr>
<tr>
<td>Log (1+ CR\text{Mom}) x Log(Size_{t-12})</td>
<td></td>
<td>0.003*** (0.001)</td>
<td>0.001** (0.0005)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time Periods</td>
<td>1,080</td>
<td>1,080</td>
<td>1,080</td>
<td>1,080</td>
</tr>
<tr>
<td>Observations</td>
<td>1,703,540</td>
<td>1,694,681</td>
<td>1,694,675</td>
<td>1,694,675</td>
</tr>
<tr>
<td>Average R-squared</td>
<td>0.026</td>
<td>0.046</td>
<td>0.043</td>
<td>0.054</td>
</tr>
</tbody>
</table>
Table 9 - The Effect of Share Price on the Reversal of Momentum Returns

This table presents the result of Fama and Macbeth (1973) regression analyses of the relation between k-month ahead cumulative abnormal returns and momentum. Each column in the table presents results for a different cross-sectional regression specification. I exclude stocks with price below $5 and stocks with market capitalization below the 10th percentile size breakpoint (using size NYSE breakpoints). The dependent variable in every regression is the k-month ahead cumulative abnormal returns. The cumulative return of momentum is calculated as the cumulative return over the past eleven months skipping the most recent month. Independent variables are winsorized at the 0.5% level on a monthly basis. The variables representing the log of lagged price and lagged size are demeaned. Both the variables representing the demeaned lagged price and lagged size are also included in the regression but not reported on the table. Standard errors are in parentheses. ***, **, and * denote 10%, 5%, and 1% statistical significance.

<table>
<thead>
<tr>
<th>Sample: CRSP (1927 - 2016)</th>
<th>Log (1+ k-Month CAR)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable:</td>
<td>k=1 k=12 k=24 k=36 k=48 k=60</td>
</tr>
<tr>
<td>Log (1+ CR_{Mom})</td>
<td>0.013*** 0.037*** -0.008 -0.044*** -0.072*** -0.089***</td>
</tr>
<tr>
<td></td>
<td>(0.001) (0.010) (0.016) (0.019) (0.024) (0.032)</td>
</tr>
<tr>
<td>Log (1+ CR_{Mom}) x Log(Price_{t-12})</td>
<td>0.003*** 0.039*** 0.071*** 0.082*** 0.096*** 0.030</td>
</tr>
<tr>
<td></td>
<td>(0.001) (0.007) (0.011) (0.012) (0.015) (0.080)</td>
</tr>
<tr>
<td>Log (1+ CR_{Mom}) x Log(Size_{t-12})</td>
<td>0.001** 0.011** 0.009 0.021** 0.027** 0.014</td>
</tr>
<tr>
<td></td>
<td>(0.0005) (0.004) (0.006) (0.008) (0.011) (0.011)</td>
</tr>
<tr>
<td>Time Periods</td>
<td>1,080 1,068 1,056 1,044 1,032 1,020</td>
</tr>
<tr>
<td>Observations</td>
<td>1,694,675 1,621,117 1,523,449 1,429,570 1,343,215 1,263,183</td>
</tr>
<tr>
<td>Average R-squared</td>
<td>0.054 0.06 0.069 0.071 0.073 0.072</td>
</tr>
</tbody>
</table>
Table 10 – Performance of Portfolios of Momentum Strategies

This table reports characteristics of momentum strategies of U.S. stocks over the period from 1927 to 2016, excluding stocks whose price is below $5 at portfolio formation and market capitalization is below the 10th percentile size breakpoint using the NYSE size breakpoints. Returns, standard deviation, Sharpe ratio, Fama-French 3-factor alpha, and Fama-French-Carhart 4-factor alpha are calculated with monthly data but are reported in annualized terms. In Column (1), I present the characteristics of the momentum strategy that is long the portfolio that contains the 10% of stocks with largest gains (the winner portfolio) and short the portfolio that contains the 10% of stocks with worst losses (the loser portfolio). Columns (2), (3), and (4) present the characteristics of portfolios that have had similar past returns with three different price levels at portfolio formation. To do so, I sort the winner and loser portfolios in 5 groups based on past performance, forming 10 new groups of performance (5 top, 5 bottom). Then, within each new group of performance, I sort the stocks in terciles of share price at portfolio formation. Finally, I average performance by price terciles. Column (2), (3), and (4) show the characteristics of the portfolio that had similar past performance over the past 12 months, skipping the most recent one, but different price levels of portfolio formation. Column (2), (3), and (4) contain the stocks in the tercile with lowest, middle, and highest share prices respectively. T-statistics are shown between parentheses.

<table>
<thead>
<tr>
<th>Price Terciles</th>
<th>All</th>
<th>Lowest</th>
<th>Middle</th>
<th>Highest</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td></td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Return</td>
<td>17.18%</td>
<td>14.44%</td>
<td>17.32%</td>
<td>20.27%</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>22.47%</td>
<td>22.93%</td>
<td>24.62%</td>
<td>24.66%</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>0.76</td>
<td>0.63</td>
<td>0.70</td>
<td>0.82</td>
</tr>
<tr>
<td>FF 3-Factor Alpha</td>
<td>23.14%</td>
<td>19.40%</td>
<td>23.87%</td>
<td>26.64%</td>
</tr>
<tr>
<td>(10.12)</td>
<td>(8.39)</td>
<td>(9.71)</td>
<td></td>
<td>(10.12)</td>
</tr>
<tr>
<td>FFC 4-factor Alpha</td>
<td>5.78%</td>
<td>3.66%</td>
<td>6.29%</td>
<td>8.21%</td>
</tr>
<tr>
<td>(6.25)</td>
<td>(2.68)</td>
<td>(5.01)</td>
<td></td>
<td>(6.54)</td>
</tr>
<tr>
<td>Observations</td>
<td>1080</td>
<td>1080</td>
<td>1080</td>
<td>1080</td>
</tr>
</tbody>
</table>
Figures

Figure 1 – Estimated Dollar Returns Over Time with Interest Rate = 2%

This figure reports the mean of the subject’s estimates for the dollar returns under different principals. The experiment uses a within-subject design, which implies that the same subjects faced the tasks with all different levels of principals. The estimates are divided by their respective principals, so that they are in comparable magnitudes. The interest rate of this task was 2%. The experiment was performed on Amazon Mechanical Turk (MTurk) with 177 participants.
This figure reports the mean of the subject’s estimates for the dollar returns under different principals. The experiment uses a within-subject design, which implies that the same subjects faced the tasks with all different levels of principals. The estimates are divided by their respective principals, so that they are in comparable magnitudes. The interest rate of this task was 10%. The experiment was performed on Amazon Mechanical Turk (MTurk) with 177 participants.
Figure 3 – Estimated Dollar Returns Over Time with Interest Rate = 20%

This figure reports the mean of the subject’s estimates for the dollar returns under different principals. The experiment uses a within-subject design, which implies that the same subjects faced the tasks with all different levels of principals. The estimates are divided by their respective principals, so that they are in comparable magnitudes. The interest rate of this task was 20%. The experiment was performed on Amazon Mechanical Turk (MTurk) with 177 participants.
Figure 4 – Description of Treatment Conditions in the Field Experiment

This figure shows the factorial design of the field experiment.

<table>
<thead>
<tr>
<th>Framing of Interest</th>
<th>Principal Magnitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple</td>
<td>Low (R$ 1.00)</td>
</tr>
<tr>
<td></td>
<td>High (R$ 100.00)</td>
</tr>
<tr>
<td>Compound</td>
<td>Treatment 1</td>
</tr>
<tr>
<td></td>
<td>Treatment 2</td>
</tr>
<tr>
<td></td>
<td>Treatment 3</td>
</tr>
<tr>
<td></td>
<td>Treatment 4</td>
</tr>
</tbody>
</table>
Figure 5: A summary of the model of behavior of stock returns

<table>
<thead>
<tr>
<th>Model Type</th>
<th>Time 1</th>
<th>Time 2</th>
<th>Time 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rational Fundamental</td>
<td>$F$</td>
<td>$F + F\theta$</td>
<td>$F + F\theta$</td>
</tr>
<tr>
<td>BR - Fundamental</td>
<td>$F$</td>
<td>$F + F^{BR}\theta$</td>
<td>$F + F\theta$</td>
</tr>
<tr>
<td>BR - Price</td>
<td>$P$</td>
<td>$P + P^{BR}\theta$</td>
<td>$P + P\theta$</td>
</tr>
</tbody>
</table>

$t = 1$  
$t = 2$  
$t = 3$  

$\theta$
Figure 6 – Performance of Momentum Trading Strategies

This figure illustrates the result of the trading strategies proposed in the paper. Each portfolio is created as follows. First, I exclude from the sample all stocks whose price are below $5 and whose market capitalization is below the 10th percentile of the NYSE size breakpoint. Second, I sort stocks in deciles of past performances from 12 to 1 month ago for each month in the dataset, skipping the most recent month. I focus the analysis on the winners (decile 10) and losers (decile 1). Third, within each of these two deciles, I once again sort them in 5 quintiles of past performance. Fourth, within each new quintiles of winners and losers, I sort the stocks in terciles of price at portfolio formation. Fifth, I average the winner and loser portfolios by price terciles, forming 6 portfolios in total: winner-high price; winner-medium price; winner-low price; loser-high price; loser-medium price; loser-low price. “MOM: high prices” is the portfolio that goes long on the winner-high price portfolio and goes short on the winner-low price portfolio. “MOM: medium prices” and “MOM: low prices” are constructed similarly. “MOM Strategy” is the standard momentum portfolio that goes long on the decile of winners and short on the decile of losers. The performances shown on the left reflects the value in December 2017 of $1.00 invested in January 1927.
Figure 7 – Performance of Portfolios of Past Losers

This figure illustrates the result of the trading strategies proposed in the paper. Each portfolio is created as follows. First, I exclude from the sample all stocks whose price are below $5 and whose market capitalization is below the 10th percentile of the NYSE size breakpoint. Second, I sort stocks in deciles of past performances from 12 to 1 month ago for each month in the dataset, skipping the most recent month. I focus the analysis on the winners (decile 10) and losers (decile 1). Third, within each of these two deciles, I once again sort them in 5 quintiles of past performance. Fourth, within each new quintiles of winners and losers, I sort the stocks in terciles of price at portfolio formation. Fifth, I average the winner and loser portfolios by price terciles, forming 6 portfolios in total: winner-high price; winner-medium price; winner-low price; loser-high price; loser-medium price; loser-low price. “Losers: high prices” is the portfolio that goes short on the loser-high price portfolio. “Losers: medium prices” and “Losers: low prices” are constructed similarly. “Losers Strategy” is the standard portfolio that goes short on the decile of losers. The performances shown on the left reflects the value in December 2017 of $1.00 invested in January 1927.

Dollar Value of Past Losers

- Losers strategy
- Losers: medium prices
- Losers: low prices
- Losers: high prices

Year

Dollar value of investment
$10^1, 10^0, 10^{-1}, 10^{-2}, 10^{-3}$

$-$0.09, $-$0.02, $-$0.01, $-$0.003
This figure illustrates the result of the trading strategies proposed in the paper. Each portfolio is created as follows. First, I exclude from the sample all stocks whose price are below $5 and whose market capitalization is below the 10th percentile of the NYSE size breakpoint. Second, I sort stocks in deciles of past performances from 12 to 1 month ago for each month in the dataset, skipping the most recent month. I focus the analysis on the winners (decile 10) and losers (decile 1). Third, within each of these two deciles, I once again sort them in 5 quintiles of past performance. Fourth, within each new quintiles of winners and losers, I sort the stocks in terciles of price at portfolio formation. Fifth, I average the winner and loser portfolios by price terciles, forming 6 portfolios in total: winner-high price; winner-medium price; winner-low price; loser-high price; loser-medium price; loser-low price. “Winners: high prices” is the portfolio that goes long on the winner-high price portfolio. “Winners: medium prices” and “Winners: low prices” are constructed similarly. “Winners Strategy” is the standard portfolio that goes long on the decile of winners. The performances shown on the left reflects the value in December 2017 of $1.00 invested in January 1927.
Appendix

Appendix 1 – MTurk Experimental Instructions

Thank you very much for your participation. You are being asked to take part in a survey about the relationship between people, money, and time.

This survey will take you about 20 minutes to complete. You will receive $2.50 for completing this survey. There are 4 short tasks in the survey.

The survey is incentivized. The additional incentive is up to $1.08 in addition to the $2.50 for completing the survey. In total, you can make up to $3.58

At the end of the survey, you will receive a code to paste into the box below to receive credit for taking our survey.

Click on the button below to the right to start the survey.

----------- [ Page Break ] -----------

[Consent form goes here]

----------- [ Page Break ] -----------

For each of the 54 incentivized question, the rule for payment is as follows:

If your answer is within 10% of the correct value, you will receive the full incentive amount: $0.02.
If your answer is within 11 to 25% of the correct value, you will receive half of the incentive amount: $0.01

Remember: there are 54 questions incentivized, for a bonus of up to $1.08 in addition to the $2.50 survey payment. The number of questions per task are:

Task 1: 2 questions;
Task 2: 45 questions;
Task 3: 4 questions;
Task 4: 4 questions

**Please DO NOT use a calculator or a computer to help you answer any question in this survey. Violators will be dismissed without pay.**

Example:
(Incentivized)
How much is $10 \times 10 = ?$

The correct answer is **100**, so the incentive based on the answer would be:

<table>
<thead>
<tr>
<th>Response</th>
<th>Below 75</th>
<th>75 - 89</th>
<th>90-110</th>
<th>111-125</th>
<th>Above 125</th>
</tr>
</thead>
<tbody>
<tr>
<td>Earnings</td>
<td>$0.00</td>
<td>$0.01</td>
<td>$0.02</td>
<td>$0.01</td>
<td>$0.00</td>
</tr>
</tbody>
</table>

Click on the button below to the right to start the survey

-------- [ Page Break ] ---------

**Task 1**

Task 1 has two questions. Only the second question is incentivized.

**Please DO NOT USE A CALCULATOR for any of these questions. Violators will be dismissed without pay and reported to Amazon MTURK.**

Click on the button below to the right to start Task 1.

-------- [ Page Break ] ---------

Suppose you were buying a good for a list of price of $1 and you were to repay the amount to the dealer in 12 monthly installments. How much do you think it would cost, in total, for the good after one year - including all finance and carrying charges?

Please only include numbers in your answer.

Decimals are allowed (.); Dollar signs ($) and commas (,) are NOT allowed.
What percent rate of interest do those payments imply?

Please do NOT include the % (percentage sign) in your answer.

Task 2

This is the longest task in the survey. In addition to the $2.50 for completing the survey, you can earn additional $0.90 just in this task.

In the following 9 situations, each with 5 questions, you will be asked to forecast how money grows over time when invested with no risk. You will be given the principal invested, the interest rate (per annum), and 5 time periods in each question. You will be given 1.5 minute (90 seconds) to complete each of the 9 situations. You don't need to enter the dollar sign ($) or commas (,) in each answer. You can enter decimals(.)

Please do NOT use a calculator for any of these questions. Violators will be dismissed without pay.

You will see the following information (in bold). X represent the numbers in each situation:

**Principal Amount: $X**
**Interest Rate: X % per annum**

Please do not use any calculators or computer to solve the task. If you submit your answers for each situation after more than 1.5 minute (90 seconds), you will not be paid the incentive of up to $0.10 per situation, for a total bonus of up to $0.90. You will still receive the survey fee of $2.50.

Click "Next" whenever you are ready and the clock will start counting at the bottom of the page.
Principal Amount $1
Interest Rate: 10% per annum

Please only include numbers in your answer.
Decimals are allowed (.) ; Dollar signs ($) and commas (,) are NOT allowed.

How much money the account will have after:

1 year __________
2 years __________
5 years __________
10 years __________
20 years __________

Congratulations for getting through Task 2!

Task 3 and Task 4 have only 4 questions each.

Task 3

Answer the 4 questions on the next page. For each correct answer, you will receive $0.02.

Do not use a calculator or a computer to answer these questions. Violators will be dismissed without pay.

You have 120 seconds (2 minutes) to answer these questions. If you take longer, you will not receive the bonus of $0.02 per correct answer.

Financial Literacy Questions
Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money in the account to grow:

- Less than $110
- Exactly $110
- More than $110
- Do not know
- Refuse to answer

Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, using the money that will be in the account, would you be able to buy:

- Less than what you can buy today
- Exactly what I can buy today
- More than what you can buy today
- Do not know
- Refuse to answer

Do you think that the following statement is true or false? “Buying a single company stock usually provides a safer return than a stock mutual fund.”

- True
- False
- Do not know
- Refuse to answer

If interest rates rise, what will typically happen to bond prices?

- They will rise
- They will fall
- They will stay the same
- There is no relationship between bond prices and the interest rates
- Do not know
- Refuse to answer

-------- [ Page Break ] ---------

Congratulations for getting through Task 3!
Task 4 has only 4 questions.
Task 4

Answer the 4 questions on the next page. For each correct answer, you will receive $0.02.

Do not use a calculator or a computer to answer these questions. Violators will be dismissed without pay.

The boxes to answer the questions are presented to the right of the page (on the same line as "The answer is...")

You have 120 seconds (2 minutes) to answer these questions. If you take longer, you will not receive the bonus of $0.02 per correct answer.

---------- [ Page Break ] ----------

Numeracy Questions

In this section, you will be asked 4 questions. For each correct answer, you will receive additional $0.05.

If you answer it incorrectly, you will lose $0.05 from your bonus payment. If you answer "I don't know", you do not win nor lose anything.

Your answer does not affect your show-up fee of $1.00

1) If the chance of getting a disease is 15%, how many people out of 2,000 would be expected to get the disease?

If 5 people all have the winning number in the lottery and the prize is $2,000,000, how much will each of them get?

In a sale, a shop is selling all items at half price. During the sale, the sofa cost $300. How much did the sofa cost before the sale?

A car dealer is selling a car for $6,000. This is two-thirds of what it cost new. How much did the car cost new?

---------- [ Page Break ] ----------
Demographics Questions

What is your gender?
☐ Male
☐ Female

What is your age?

What is the highest level of education you have attained?
☐ Below high school
☐ High school
☐ College
☐ Graduate school (Masters, Doctoral degrees)

Where have you been living in the past 10 years of your life?
☐ Mostly in the United States
☐ Mostly outside the United States

Do you have any experience investing in financial assets (e.g. stocks, bonds, mutual funds, pension funds, etc.)?
☐ I have extensive experience investing in financial assets
☐ I have some experience
☐ I have very limited experience
☐ I have no experience at all

If you were to make some investments with your savings, how would you describe your risk tolerance?
☐ I am very risk averse and conservative
☐ I am somewhat risk averse but I am willing to hold some risky assets.
☐ I am not very risk averse and I am willing to hold a decent amount of risky assets.
☐ I am not very risk seeking and I have strong preferences for risky assets.
Thank you so much for your participation.

In this survey, I was personally interested in understanding how people's math ability influences their perception of money growth. Thanks for helping me understand that.

**Your validation code will be on the next page**

Is there anything you would like me to know? Please write it below.

---------- [ Page Break ] ----------

Please make note of the following 7-digit code. You will input it through Mechanical Turk to indicate your completion of the study. Then **click the button on the bottom right of the page to submit your answers**. You will not receive credit unless you click this button.

code: 7312766
Appendix 2: Robustness Checks of Experiment 1

Part 1 - Median Estimates (N = 177)

Figure A1

Figure A2
Part 2 – Mean estimates for subjects with a perfect financial literacy score (N = 55)
Part 3 – Mean estimates for subjects with a perfect math score (N = 88)
Part 4 – Mean estimates for subjects who understand simple interest (N = 83)
Figure A11

Estimated Dollar Returns Over Time
Interest Rate = 10%

Mean of estimates for subjects who answered the simple interest question correctly

Figure A12

Estimated Dollar Returns Over Time
Interest Rate = 20%

Mean of estimates for subjects who answered the simple interest question correctly
Appendix 3 – Text of the Email

Subject: Guaranteed Return of 9.55% a year for 6 years with Treasury bonds

Investment Opportunity
Fixed-Interest Treasury Bond 2025

Paulo, how are you?

Did you know that you could have a return of 9.55% a year for 6 years guaranteed by the Treasury, regardless the volatility of the market? That is what the Fixed-Interest Treasury Bond 2025 offers you.

[Treatment] In other words, for every R$ 100.00 invested, you will have R$ 172.85 in 6 years.

In a savings account, however, assuming a fixed return of 4.58% a year over the same period, you would only have R$ 130.82.

What are Fixed Interest Bonds?

As the name suggests, these are bonds that have a fixed interest rate, determined at the time of the purchase of the product.

What are the advantages?

You are protected and already know how much you will have on the maturity date of your investment.

I want to invest now