It Depends Who you Ask: Context Effects in the Perception of Stock Returns

Constantinos Antoniou[†], Junyang Guo[‡] and Neil Stewart[§]

November 10, 2021

Abstract

Stock returns convey information to investors about fundamental values. But do all investors perceive a specific stock return in the same way? Using a large dataset of individual investor stock selling decisions, we show that the *same* return is perceived *differently* by different investors, and that these differences are driven by the comparison of a given return to investors' own personal and idiosyncratic experiences of returns in the small set of stocks that they own. The effect is large. When a given return is classed as extreme compared to an investor's personal history of returns, the response of investors toward that return increases by a factor of 3.5. Whereas stock returns are commonly considered to be objective, our findings suggest that there is considerable subjectivity in their perception.

We thank Vimal Balasubramaniam, Aleix Calveras, Cary Frydman, Andrea Gamba, Arie Gozluklu, Samuel Hartzmark, Andrea Isoni, Gabriele Lattanzio, Tomás Lejarraga, Redzo Mujcic, Bartolomeu Pascual, Roberto Pascual, Nattavudh Powdthavee, Jozsef Sakovics, Alex Stremme, Richard Taffler, John Thanassoulis, Elizabeth Whalley, Ania Zelewskaas, and seminar and conference participants at Warwick Business School, the University of Balearic Islands, the 7th International Young Finance Scholars' Conference and the 2021 Financial Management Association Meeting for comments and suggestions. This work was supported by Economic and Social Research Council Grants ES/P008976/1, ES/N018192/1 and ES/V004867/1.

[†]Warwick Business School, University of Warwick. Email: Constantinos.Antoniou@wbs.ac.uk

[‡]Warwick Business School, University of Warwick. Email: J.Guo.2@warwick.ac.uk

[§]Warwick Business School, University of Warwick. Email: Neil.Stewart@wbs.ac.uk

1 Introduction

Because stock prices aggregate information from many different traders, they are closely monitored by various economic agents who are trying to learn about fundamental values. For example, investors' trading decisions with specific assets are affected by the returns those assets have generated in the past (e.g. Grinblatt, Titman, and Wermers, 1995; Barber and Odean, 2008; Kaniel, Saar, and Titman, 2008; Campbell, Ramadorai, and Schwartz, 2009; Grinblatt, Jostova, Petrasek, and Philipov, 2020), and the investment decisions of corporate managers are sensitive to the stock prices of their firms (e.g. Chen, Goldstein, and Jiang, 2007; Bakke and Whited, 2010; Foucault and Fresard, 2014; Goldstein, Liu, and Yang, 2021). Thus, stock prices and stock returns play a central role in the process by which information is transmitted in equity markets.

The information transmitted by stock returns is typically assumed to be an *objective* signal, so a given return, say 3%, is perceived in the same way by all participants in financial markets. However, evidence from psychology and economics, that people do not judge magnitudes like stock returns in an *absolute* manner but *relative* to their own idiosyncratic past experiences, suggests that this assumption may in fact be systematically violated in financial markets. For example, Jesteadt, Luce, and Green (1977) exposed some subjects to a soft noise and others to a loud noise. They then asked all subjects to assess the loudness of the same noise. Jesteadt, Luce, and Green (1977) found that the subjects who previously experienced the soft noise, assessed the subsequent noise to be louder, relative to the subjects who previously experienced the louder noise. Such *context effects* in the perception of magnitudes are extremely robust phenomena, widely documented in different settings. For example, Bhargava and Fisman (2014) find context effects in mate choices using a speed-dating field experiment, and Simonsohn and Loewenstein (2006) and Simonsohn (2006) in consumer housing and commuting choices, respectively. In a finance application, Hartzmark and Shue (2018) show that context effects influence the pricing of earnings surprises.[1]

[1]For a review of the relevant literature in neuroscience and psychophysics see Wallis and Kennerley (2011), Laming (1997) and Stewart, Brown, and Chater (2005). The notion that magnitudes are evaluated subjectively and not objectively is embedded in various theories of risky choice, such as adaptation level theory (Helson, 1964), range frequency theory (Parducci, 1965), norm theory (Kahneman and Miller, 1986), support theory (Tversky and Koehler, 1994), decision by sampling (Stewart, Chater, and Brown, 2006; Noguchi and Stewart,

These findings imply that a specific return, say 3%, will not be perceived in the same way by all investors. Rather, those investors who are less accustomed to such returns will perceive it as *larger*, compared to other investors who have experienced such returns before. Essentially the argument that context effects influence the perception of stock returns implies a form of *limited attention* (e.g. Lim and Teoh, 2010), whereby investors do not monitor and internalize the entire distribution of stock returns, across all firms and all time periods, but rather asses the magnitude of a specific stock return relative to their own experiences in the stock market. Such "tunnel vision" on idiosyncratically experienced returns can arise because investors face constraints in their ability to store and process information (e.g. Hirshleifer and Teoh, 2003), or simply because ownership channels their focus toward information about owned assets as opposed to non-owned assets (Hartzmark, Hirshman, and Imas, 2021). Thus, context effects can create heterogeneity in the way a given stock return is perceived, influencing the transmission of price-based information in financial markets.

We use the portfolio-level trading data used previously by Gathergood, Hirshleifer, Leake, Sakaguchi, and Stewart (2019) and Quispe-Torreblanca, Gathergood, Loewenstein, and Stewart (2020) to examine whether context effects influence the way investors perceive stock returns. The starting point of our analysis is illustrated in Figure 1, which plots on the y-axis the probability that investor i sells stock j in day t, and on the x-axis the return generated by j in day $t-1$ (henceforth j's *1-day return*).[2] The V-shape indicates that investors are more likely to sell stocks with large returns in absolute value, perhaps because these returns are salient, and thus more likely to capture their attention (e.g. Barber and Odean, 2008). The question we ask in this study is whether the probability that investor i sells stock j in day t depends on how *subjectively extreme* the *1-day return* of j is, when compared to the daily returns investor i has experienced before, from any of the stocks in their own portfolio. The context effects hypothesis predicts that, when the *1-day return* of j is subjectively extreme, then i will be

2018), and efficient coding (Frydman and Jin, 2021).

[2]We focus our analysis on selling decisions as these can be modelled with relatively high precision. Specifically, because retail investors do not sell short–only about 1% of investors in our sample engage in short selling, consistent with prior evidence from Barber and Odean (2008)–when they want to sell a stock they only have to compare between the stocks they own, which we can observe in our data. In contrast, when investors want to buy a stock they can choose from the entire universe of publicly listed companies. However, because we do not know which stocks investors are considering, it is more difficult to model the buying decision. Nonetheless, we do conduct some analysis of buying decisions in a later section of the paper.

more likely to sell this stock.

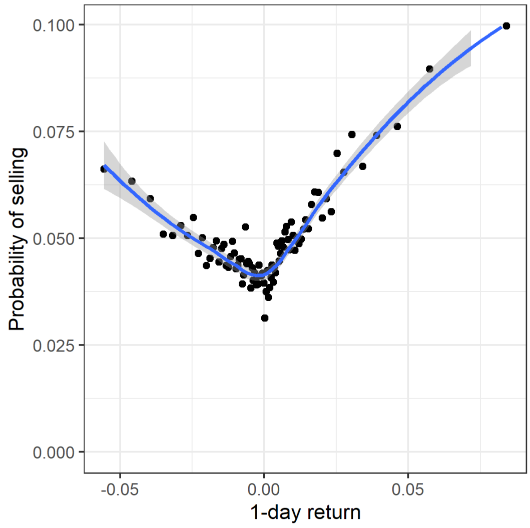

Figure 1. Probability of selling on each percentile of 1-day returns
This figure shows the probability of selling on each percentile of 1-day return. Each point represents a percentile of 1-day returns. The smoothed conditional means line (the dark blue line) and the 95% confidence interval (grey area) are generated by Local Polynomial Regression Fitting.

To test this hypothesis, we use a model that allows for different slope coefficients on 1-day returns when these returns are subjectively extreme. The dependent variable in the model is an indicator that equals 1 if investor i sells stock j in day t. To capture how extreme the return of j is in $t-1$ for investor i, we find the maximum and minimum daily return that i has previously experienced, from any of the stocks they hold in their portfolio. If the 1-day return of j is very high or very low compared to the maximum or minimum returns from i's portfolio, then it is classed as "extreme" using a dummy variable, which we interact with the 1-day return. According to the context effects hypothesis, we expect that the effect of the 1-day return on the probability of the stock being sold will be magnified, if the 1-day return is extreme for the specific investor.

The motivation to capture extremeness in this way is the finding that decision makers remember well certain salient features of the distribution of a variable, like the minimum or the maximum. For example, according to "peak-end" effects, decisions are made by comparing the final state of a variable with its peak value, as experienced by the decision maker in previous trials (Kahneman, Fredrickson, Schreiber, and Redelmeier, 1993). This finding implies that the extreme value previously experienced is retained in the memory of the decision maker, regardless of its position in the overall sequence, and affects how the magnitude of the latest realization of the variable is perceived.[3]

Our models control for the return since purchase that a specific stock has generated for the investor, thus accounting for the disposition effect (Odean, 1998; Ben-David and Hirshleifer, 2012). Moreover, we control for the rank effect (Hartzmark, 2015), and the time that the specific stock is held in the portfolio of each investor. We also control for *account* $\times$ *date* fixed effects, thus ruling out explanations based on investor sophistication, or time varying risk aversion or sentiment. Moreover, we control for time-varying firm characteristics that may be influencing investors selling decisions with a *stock* $\times$ *year-month* fixed effect.

Our main finding is illustrated in Figure 2, which plots the predicted probability of investor i selling stock j in day t as a function of j's 1-day returns. The left panel illustrates that the probability a stock is sold is higher when the 1-day return of the stock is large, either positive or negative. In line with the context effects hypothesis, investors' personal histories of 1-day returns have a large effect on their responses to 1-day returns. This is shown in the right panel of Figure 2, which plots the predicted probability of selling as a function of 1-day returns, allowing for different slopes for those 1-day returns that are subjectively extreme. The much steeper V-shape for these extreme returns indicates that, *for a given, objective 1-day return*, investors are much more likely to sell, if this return appears large compared to their own personal history of daily returns. The economic effect of extremeness is sizeable, as the coefficient on positive (negative) 1-day returns increases by a factor of two (5.5) when the return is classed as extreme.

While our findings are consistent with the context effects hypothesis, there may be other reasons for different investors responding differently to the same return. For instance, two investors may respond differently to a given stock's return depending on the overall performance of their portfolio at that time, or how this particular stock has performed for them thus far. However, such effects cannot be driving our results, since we control for the return that the stock has generated for the investor in our models. Moreover, our model includes *account* $\times$ *date* fixed effects, thus overall portfolio performance cannot be driving the heterogeneity in the responses to 1-day returns that we document.

[3] In our robustness checks, we conduct sensitivity analysis with different definitions of extremeness.

Another possible reason for investors responding differently to the same return is different priors about this stock.[4] If the extremeness variable relates to these priors, it may lead to heterogeneity in the responses to 1-day returns. We conduct several tests that examine this issue. Firstly, when modelling the decision to sell stock j, we define extremeness using all the *other* stocks in the investors' portfolio *except* j, to account for the possibility that in our baseline tests the maximum or minimum return for this investor systematically come from stock j, and therefore influence investors' prior for this stock. Secondly, we further control for the correlation of the returns of stock j with the stock that generated the maximum or minimum return for investor i, as well as the interaction between this correlation and the 1-day returns of j. This correlation captures the extent to which the two stocks are related (e.g., due to having similar characteristics, being in the same industry, supply chain links, etc), and thus controls for the possibility that the (previously experienced) extreme returns influence the priors for stock j. Finally, we draw the maximum or minimum return for the investor from stocks that where held previously, but not held any more. This test achieves to increase the "distance" between stock j and the stock that generated the extreme returns for the investor, thereby making these returns potentially less relevant for the priors for stock j. Our results continue to hold in all these tests.

A different possibility is that the relationship between the probability of selling and 1-day positive or negative returns is not linear, and that the interaction between returns and the extremeness dummy is capturing these non-linearities. Two different specifications are adopted to address this concern. First, we add a 1-day return decile fixed effect, and second by including in our baseline model controls for the squares of positive and negative 1-day returns. The context effects hold in both these specifications. Furthermore, we carry out a placebo test, whereby for investor j 1-day returns are compared to extreme returns that are randomly drawn from a portfolios with no stocks in common. If our findings merely capture a response to 1-day returns, we should continue to find similar results in the placebo test. It turns out that the actual ratio of the coefficient on the interaction between negative (positive) returns and extremeness, to the coefficient on negative (positive) returns, from our baseline findings is

[4]Bayesian agents with different priors exposed to the same signal will have different posteriors, and therefore different reactions.

32.3 (10.0) standard deviations away from the mean of the distribution of the corresponding placebo ratios. The size of these differences suggests that it is extremely unlikely that our baseline results only capture responses to 1-day returns.

We conduct several other robustness checks, including defining the extremeness dummy using different cut-offs or when using a continuous measure, using market-adjusted or portfolio-adjusted 1-day returns, controlling for public information about company j at higher frequencies, or controlling for the volatility that investors are accustomed to in their portfolios (i.e., investors with less volatile portfolios may have lower extremeness values). Our results continue to hold in all specifications. Moreover, our findings obtain when we define returns (and the corresponding subjective extremeness measures) over longer horizons (1-week, 2-weeks, 3-weeks and 1-month).

The context effects we document are strongly asymmetric, being much stronger for negative returns. This finding may reflect the generic asymmetry in the way losses and gains are perceived, perhaps in the context of Prospect Theory where *"losses loom larger than gains"* (Kahneman and Tversky, 1979), and/or the more generic notion that "*bad is stronger than good*" in many different contexts, including memory of past events e.g.,(Baumeister, Bratslavsky, Finkenauer, and Vohs, 2001). Since the vast majority of our investors have long positions, previously experienced extreme negative returns are bad news, which stand out in memory more vividly than extreme positive returns, thus leading to stronger context effects.

Moreover, in additional tests, we find that the amount of time between the day that investors experience the extreme return in their portfolio and day $t-1$ does not matter, which implies that the memory of previously experienced extreme returns is not subject to recency effects, or at least not for horizons of 1-2 years that our sample spans. One possible explanation for this finding is the "peak-end" effect, whereby decisions are made by comparing the final state of a variable with its peak value experienced in previous trials (Kahneman, Fredrickson, Schreiber, and Redelmeier, 1993). This finding implies that the extreme value previously experienced is retained in the memory of the decision maker, regardless of its position in the overall sequence.

For our final test, we conduct a test of the context effects hypothesis in a corporate finance setting, motivated from the well-known finding that firms' managers learn about the future prospects of their firms from stock prices when making their investment decisions (Bakke and Whited, 2010; Chen, Goldstein, and Jiang, 2007; Foucault and Fresard, 2014; Goldstein, Liu, and Yang, 2021). Building on this findings, we examine whether the sensitivity of investments to Tobin's q (a standardized measure of stock price) is larger when the most recent q for the company is extreme, in relation to the maximum q the specific manager has seen before. The results indeed indicate significant context effects, as we find that the sensitivity of investments to Tobin's q increases by 12.5% when q is classed as extreme. This finding suggests that even sophisticated market participants such as corporate managers exhibit context effects when responding to stock prices.

Theoretical models in asset pricing and market microstructure suggest that rational investors extract information about the fundamental values of different assets by observing their prices (e.g. Stein, 1987; Wang, 1993; Barlevy and Veronesi, 2003; Calvo, 2004; Mendel and Shleifer, 2012). In line with this view, empirical studies show that investors' trading decisions with certain stocks are affected by the returns these stocks have generated in the past (Grinblatt, Titman, and Wermers, 1995; Heath, Huddart, and Lang, 1999; Badrinath and Wahal, 2002; Barber and Odean, 2008; Kaniel, Saar, and Titman, 2008; Campbell, Ramadorai, and Schwartz, 2009; Grinblatt, Jostova, Petrasek, and Philipov, 2020). Whereas this line of work implicitly assumed that all investors perceive a given return in the same way, our analysis suggests that the perception of returns is influenced by personal experiences. This finding suggests that the distribution of personal return experiences in the investor population at any given time can affect the speed and efficiency with which price-based information percolates in financial markets.

Our work also contributes to the literature that studies how personal return experiences affect investors' trading decisions. Along these lines, the literature has shown evidence of a disposition effect and a rank effect, whereby investors are more likely to sell stocks that generated gains for them, or stocks whose returns since purchase stand-out in investors' portfolios (Odean, 1998; Hartzmark, 2015). Moreover, the literature has shown evidence of reinforcement learning, whereby investors are more likely to buy assets that performed well for them in the past (Kaustia and Knüpfer, 2008; Malmendier and Nagel, 2011; Strahilevitz, Odean, and Barber, 2011; Antoniou and Mitali, 2020). The key variable of interest in all these studies is the return that a specific stock has generated for an investor, which is a subjective variable since investors typically buy the same stocks at different times. Instead, our study highlights that personal return experiences influence the interpretation of the return, which is an "objective" variable, common to all investors.

In a related paper Hartzmark and Shue (2018) show that the stock returns for a given earning surprise in day t are higher, if large companies announced lower earning surprises in day $t-1$, in line with context effects. Our study complements theirs in various ways. First, whereas Hartzmark and Shue (2018) draw their conclusions from an event study focusing on the perception of earnings news, we bring direct, portfolio-level evidence of context effects in the perception of a *different* quantity that is ubiquitous in financial research and commonly thought to be objective: *stock returns*. Moreover, our portfolio level setting allows us to highlight several new insights. For example, whereas Hartzmark and Shue (2018) show that their effects are short-lived, obtaining only when comparing earning surprises in day t with those in day $t-1$, our results suggest that extreme returns "stick" to investors' mind, even if experienced long ago. Moreover, we document that context effects are strongly asymmetric, being much stronger for negative returns as opposed to positive returns. These new findings have important implications when modelling how information is retrieved from investors' memory (e.g. Bordalo, Gennaioli, and Shleifer, 2017; Wachter and Kahana, 2019; Nagel and Xu, 2019; Enke, Schwerter, and Zimmermann, 2020).

We also expand the literature that discusses how salience can affect trading decisions and asset prices (Klibanoff, Lamont, and Wizman, 1998; Bordalo, Gennaioli, and Shleifer, 2012; Bordalo, Gennaioli, and Shleifer, 2013; Hartzmark, 2015). In Hartzmark (2015), salience is the extent to which the total return earned by a stock in an investor's portfolio stands out relative to other stocks in the portfolio. This type of salience is subjective, because the same stock can be salient in some investors' portfolios but not salient in others' because of differences in either time of purchase or other stocks held. Bordalo, Gennaioli, and Shleifer (2013) provide a stock-level definition of salience, based on the difference between the returns of a stock with the aggregate returns of the market. Thus, in this setting, salience is based on information that is common to all investors. Our contribution is to show that the objective return, is perceived in a subjective way, which highlights that salience can be created by the interaction of personal experiences with common information.

2 Data and Methods

2.1 Data sources and sample construction criteria

We use data from a major trading platforms in the United Kingdom, where retail investors can buy or sell securities. The dataset records each transaction by each investor on a daily basis from April 2012 to June 2016. For each transaction, we can observe the customer identification, a stock identifier , the trade date, the trade price and quantity and the transaction type (e.g. buy, sell).

In order to investigate the impact of experienced past returns, it is necessary to track the trading history of investors. For investors who opened accounts before the start of the sample period, the purchase dates of many stocks of the stocks that they hold cannot be obtained, as they were purchased before April 2012, and so their experienced returns cannot be fully tracked. Therefore, the sample used in this study focuses on accounts opened after April 2012. Using transactional level data of these accounts, the portfolio data of each account on any days, an unbalanced panel data, can be retrieved. Each observation (row) presents a stock j held by an investor i on date t.

If additional shares of a stock are purchased when the stock has been held in the portfolio, the value-weighted average of the multiple purchase prices is taken as the purchase price. The unit of observation in our study is sell days, as in previous studies that use similar data (e.g. Odean, 1998; Grinblatt and Keloharju, 2001; Kaustia, 2010; Linnainmaa, 2010; Birru, 2015; Hartzmark, 2015; Chang, Solomon, and Westerfield, 2016). Any day that an investor sells at least one stock is a sell day for that investor, and our models examine whether the probability of selling a stock on these sell days depends on 1-day returns and the extremeness of these returns (622,567 observations).

We exclude investors who engaged in short-selling (567,835 observations remaining).[5] Further, to limit the effect of news-based "day-trading" and short-time holdings, we exclude from our analysis records of stocks that are held less than five working days (N = 531,710 remaining). Finally, to facilitate within subject analysis, especially at the daily portfolio level, portfolios are excluded if the number of holdings is less than five (N = 456,187 remaining), as in Hartzmark (2015).[6]

The portfolio data are then supplemented with split-adjusted stock prices at the close of each trading day, matched by SEDOL from Datastream. After these steps, we end up with 456,187 investor-day-stock observations, from 6,312 investors for 3,505 stocks. The median age of investors our dataset is 52 years, and 17.5% of them are female. The median number of holdings in a portfolio is 12, and the median holding period for a stock is 97 working days. Summary statistics on holdings and account levels are shown in Table 1.

2.2 Econometric model and variable definitions

The econometric model we use to test the hypothesis is shown below:

$$
\begin{aligned}
Sell_{ijt} = {} & \beta_1(return^-_{j,t-1}) + \beta_2(return^+_{j,t-1}) + \beta_3(I(extremeness)_{i,j,t-1}) \\
& + \beta_4(return^-_{j,t-1} \times I(extremeness)_{i,j,t-1}) + \beta_5(return^+_{j,t-1} \times I(extremeness)_{i,j,t-1}) \\
& + \beta_6(RSP^-_{i,j,t-1}) + \beta_7(RSP^+_{i,j,t-1}) + \beta_8(I(gain)_{i,j,t-1}) + \beta_9(\sqrt{holding\ days}_{ijt}) \\
& + \beta_{10}(RSP^-_{i,j,t-1} \times \sqrt{holding\ days}_{ijt}) + \beta_{11}(RSP^+_{i,j,t-1} \times \sqrt{holding\ days}_{ijt}) \\
& + \beta_{12}(variance_{i,j,t-1}) + \beta_{13}(I(loss)_{i,j,t-1} \times variance_{i,j,t-1}) \\
& + \beta_{14}(I(gain)_{i,j,t-1} \times variance_{i,j,t-1}) + \beta_{15}(I(highest\ RSP)_{i,j,t-1}) \\
& + \beta_{16}(I(lowest\ RSP)_{i,j,t-1}) + \sigma_{ijt} + \alpha_{it} + \gamma_{jt} + \epsilon_{ijt}
\end{aligned}
\tag{1}
$$

[5] Many studies exclude from their analysis short selling trades (e.g. Odean, 1998; Ben-David and Hirshleifer, 2012; Hartzmark, 2015; Chang, Solomon, and Westerfield, 2016; Grinblatt, Jostova, Petrasek, and Philipov, 2020). In this study, because we are interested in overall trading experiences, if we only drop short sale trades, then the experiences for these investors would be mis-measured. Thus, we drop the entire accounts that engage in short-selling. This filter results to a small percentage of accounts being excluded (about 1%), thus it is unlikely to be influencing our results in a material way.

[6] In the appendix we present results without applying these last two filters to our sample, and show that our key findings remain qualitatively and quantitatively unchanged.

The dependent variable $Sell_{ijt}$ equals to 1 if investor i sold stock j in sell-day t, and 0 otherwise. The quantity we refer to as 1-day return in the paper is $return_{j,t-1}$, which is calculated as the percentage change in the closing stock price of this stock from day $t-2$ to day $t-1$. Since investors attention may be drawn to large positive or large negative returns (Barber and Odean (2008)), our models incorporate separate variables for negative and positive 1-day returns for company j, $return^{-}_{j,t-1}$ and $return^{+}_{j,t-1}$, respectively. If the return of stock j in day $t-1$ is positive (negative), then $return^{-}_{j,t-1}$ ($return^{+}_{j,t-1}$) is set to 0. The coefficients β_1 and β_2 show the propensity of investors to trade after large price changes. Based on the "attention-grabbing" hypothesis, we expect that investors are more likely to sell stocks with large price changes in the previous day (i.e., $\beta_1 > 0$ and $\beta_2 < 0$). Indeed, as shown by Figure 1, this is likely to be the case, as the probability of selling displays a strong V-shape, when plotted against 1-day returns.

To test context effects in the perception of stock returns, we introduce the variable $extremeness_{i,j,t-1}$, which measures how the $return_{j,t-1}$ for stock j in $t-1$ compares to the 1-day returns that investor i has seen before. Specifically, for each investor and each trading day, we find the maximum and minimum return that they have seen before on any day (until day $t-2$), from any of the stocks they own in their portfolio. The idea here is that, investor i's perception of how large or how small the return generated by j in $t-1$ is, will be affected by the extreme returns this investor has seen before. If the $return_{j,t-1}$ is positive, $extremeness_{i,j,t-1}$ is defined as $return^{+}_{j,t-1} - max(return)_{i,t-2}$, and if $return_{j,t-1}$ is negative, it is defined as $min(return)_{i,t-2} - return^{-}_{j,t-1}$. Thus, increases in $extremeness_{i,j,t-1}$ reflect a return in $t-1$ that is very different from the daily returns the specific investor has seen before.[7]

In our models, we define the variable $I(extremeness)_{i,j,t-1}$, which equals to 1 if $extremeness_{i,j,t-1}$ is in the top quartile of the corresponding distribution in our sample, and 0 otherwise. The interaction between $I(extremeness)_{i,j,t-1}$ and $return_{j,t-1}$ tests the context-effects hypothesis, which predicts that investors respond more strongly to 1-day returns, if

[7] Take the example shown on the table in the introduction. For investor X, the maximum 1-day returns since each purchase date till day $t-2$ of stocks A, B and C are +2.0%, +1.0% and 0.0%; and the minimum are −0.5%, −3.0% and −0.9% respectively. On a random day $t-1$, the 1-day returns of them are +5.0%, −0.2% and +0.7%. The corresponding $extremeness_{i,j,t-1}$es are 3% (5.0% − 2.0%), −2.8% (−3.0% − (−0.2%)) and −1.3% (0.7% − 2.0%)) respectively.

these are classed as extreme (i.e., $\beta_4 < 0$ and $\beta_5 > 0$). We capture the effect of extremeness using a dummy, as in this way both the statistical and economic significance of context effects can be easily discernible in each table. However, in later sections of the paper, we conduct robustness checks with different definitions of extremeness, including using $extremeness_{i,j,t-1}$ as a continuous variable.

Our models control for several variables that have been shown to influence the stock selling decisions of individual investors. A robust finding documented in numerous studies is the disposition effect, whereby investors are more likely to sell a stock which has generated a gain for them since the day of purchase, relative to one that has generated a loss (Shefrin and Statman, 1985; Odean, 1998; Grinblatt and Keloharju, 2001; Shapira and Venezia, 2001; Locke and Mann, 2005). Moreover, in a more recent study Ben-David and Hirshleifer (2012)) show that the probability of selling a stock increases as returns increase (decrease) above (below) zero, but that people are more responsive to positive changes in returns.

To capture these findings, we calculate the return that the stock has generated since it was purchased by the investor for each investor-stock-sell day, by comparing its initial purchase price with its closing price on day $t-1$ ($RSP_{i,j,t-1}$). Based on this variable, we define a number of controls, closely following Hartzmark (2015): a variable that equals to $RSP_{i,j,t-1}$ if it is negative and 0 otherwise ($RSP^{-}_{i,j,t-1}$), a variable equal to $RSP_{i,j,t-1}$ if it is positive and 0 otherwise ($RSP^{+}_{i,j,t-1}$), and a dummy variable equal to 1 if $RSP_{i,j,t-1}$ is positive ($I(gain)_{i,j,t-1}$). $RSP^{-}_{i,j,t-1}$ and $RSP^{+}_{i,j,t-1}$ control for the effect documented by Ben-David and Hirshleifer (2012), whereas $I(gain)_{i,j,t-1}$ controls for the disposition effect.

To account for the effect of holding duration for specific stocks, as in Hartzmark (2015), we control for the square root of the number of days that a stock is held by the investor ($\sqrt{holding\ days}_{ijt}$), as well as interactions between returns since purchase and $\sqrt{holding\ days}_{ijt}$. To further control for the possibility that stocks which are held in the portfolio longer periods of time are more likely to reach extreme returns and be sold, a *holding day decile* fixed effect, σ_{ijt}, is added to the model.

The volatility of stock returns has been shown to affect stock trading decisions (Borsboom and Zeisberger, 2020). To account for this effect, we include as a control the variance of daily returns of a specific stock in an investors portfolio, from the purchase day until day $t-1$ ($variance_{i,j,t-1}$), as well as the interactions between $variance_{i,j,t-1}$ and $I(gain)$ and $variance_{i,j,t-1}$ and $I(loss)$.

The "rank effect" documented by Hartzmark (2015) is the tendency of investors to sell the stocks with the highest or lowest return since purchased. To control for this effect, we define the variables $I(highest\ RSP)_{i,j,t-1}$ and $I(lowest\ RSP)_{i,j,t-1}$, which are variables that flag the highest and lowest return since purchase stocks in an investor's portfolio at any given time.

To rule out the possibility that the results are driven by time-varying investor characteristics (such as portfolio return, sentiment, risk-aversion, etc) we include an *account* $\times$ *date* fixed effect, α_{it}. With this fixed effect, analysis is made using variation within each portfolio at any given day. Finally, to control for time-varying firm characteristics that may be influencing investors selling decisions (such as past returns, market values, book-to-market ratios, etc), we include a *stock* $\times$ *year-month* fixed effect.[7]

All continuous variables are winsorized at the 1% and 99% levels. We estimate the model using ordinary least squares, to avoid the incidental parameters problem when multiple fixed effects are involved in the analysis (Neyman and Scott, 1948).[8] As in An, Engelberg, Henriksson, Wang, and Williams (2019), the standard errors in all our models are triple clustered, at the account, date and stock levels.

3 Results

3.1 Baseline model

Table 2 shows the coefficients from a series of regressions based on Equation (1), where controls and fixed effects are added sequentially, and the full model results are shown in Column (7). As seen from this column, the probability of selling stock j in sell day t is significantly higher when the return of j in $t-1$ is larger (in absolute value), in line the findings in Figure 1. Specifically, the coefficient of 0.819 (-0.368) for $return^+$ ($return^-$) indicates that a 1 percentage

[7]For robustness, we also estimate the model using *stock* $\times$ *year-week* and *stock* $\times$ *date* fixed effects. We do not use the latter as the baseline, because we are interested in the coefficient on 1-day returns, which does not vary across investors in the same day.

[8]In the appendix, we show that our results hold when using a logit model without any fixed effects.

point increase (decrease) in positive (negative) daily return is associated with a 0.82% (0.37%) increase in the probability of selling the stock.

In line with the context effects hypothesis, the interactions between $I(extremeness)_{i,j,t-1} \times return^{+}_{j,t-1}$ is positive, showing that, if these returns are extreme relative to the returns they have seen before, investors are even more likely to sell stocks with high positive returns. Similarly, the interaction $I(extremeness)_{i,j,t-1} \times return^{-}_{j,t-1}$ is negative, showing that, if these drops are extreme, investors are even more likely to sell stocks after large price drops. The coefficients on these interactions are highly statistically significant (at the 0.5% level.), with an economic magnitude that is substantial. Specifically, the coefficient on $return^{-}_{j,t-1}$ increases by more than a factor of five, whereas the coefficient on $return^{+}_{j,t-1}$ increases by a factor of two. The size of the context effects can be clearly seen in Figure 2, which plots the probability of selling as predicted by the model, against 1-day returns. In the left panel, the V-shape shows that stocks with large magnitude 1-day returns, positive or negative, are more likely to be sold. However, in the right panel, the V-shape is much steeper for 1-day returns that are classed as extreme, relative to the daily returns in the personal portfolios of different investors. These findings suggest that context effects influence investors' perception of stock returns.

Another finding emanating from Column (7), is that context effects are much stronger for negative returns. To establish that the difference is statistically significant we use the estimates in Column (7) to test the restriction $\frac{\beta_4/\beta_1}{\beta_5/\beta_2} = 1$. The null hypothesis under this restriction is strongly rejected in the data, which suggests that context effects are indeed stronger for negative returns. This finding may reflect the stronger effect of negative stimuli on perception (e.g., Kahneman and Tversky (1979); Baumeister, Bratslavsky, Finkenauer, and Vohs (2001)).

In terms of controls variables, we find that a stock with a positive return since purchase is 4.5 percentage more likely to be sold than a stock with a negative return since purchase, in line with the disposition effect. The coefficients on $I(highest\ RSP)_{i,j,t-1}$ and $I(lowest\ RSP)_{i,j,t-1}$ are positive and significant, consistent with Hartzmark (2015). $RSP^{-}_{i,j,t-1}$ loads positively, indicating that people are less likely to sell, as the returns since purchase become more negative. The interactions between $RSP^{-}_{i,j,t-1}$ and $RSP^{+}_{i,j,t-1}$ with $\sqrt{holding\ days}_{ijt}$ are negative and significant, indicating that people are less likely to sell stocks with higher returns that have been held for longer periods of time.

Overall, the results in Table 2 provide strong support to the hypothesis that context effects influence the way investors perceive and respond to stock returns.

3.2 Robustness checks

In this section we conduct various robustness checks.

3.2.1 Different priors or context effects?

In our analysis, we define extremeness by comparing the return of stock j in $t-1$ to the maximum or minimum return that an investor has seen before. If the maximum or minimum returns are generated by the same stock j, then it is possible that these previously observed maximum or minimum returns influence the prior expectation that this investor has about stock j. Therefore, our results could be capturing different priors among investors, and not different perceptions of the same public signal.

To address this possibility, in this section we re-define $extremeness_{i,j,t-1}$, by drawing the maximum or minimum return for each investor using all other k stocks in the portfolio, where $k \neq j$. It is unlikely that the maximum or minimum return observed for stock k, influences the prior of the investor for stock j. The results are shown in Column (1) Table 3, and are in line with our baseline findings from Table 2.

Further, we control for the correlation between the returns of stock j and the returns of stock k which generated the maximum or minimum return for investor i, as well as the interactions between the correlation and 1-day returns of j. The correlations are calculated in a rolling fashion, using daily returns in the past 3 or 6 months ending in day $t-1$. This correlation captures the extent to which the two stocks are related (e.g., due to having similar characteristics, being in the same industry, supply chain links, etc), and thus controls for the possibility that the (previously experienced) extreme returns influence the priors for stock j. Our results continue to hold, as shown in Columns (2) and (3) Table 3.

Finally, we draw the maximum or minimum return for the investor from stocks that were held previously, but not held any more. This test achieves to increase the "distance" between stock j and the stock that generated the extreme returns for the investor, thereby making these returns potentially less relevant for the priors for stock j. Results continue to hold as shown in Column (4) Table 3.[9]

3.2.2 Non-linear responses to 1-day returns

Our models fit a linear relationship between $return^{+}_{j,t-1}$, $return^{-}_{j,t-1}$ and the probability of selling. However, it is possible that the relationship is non-linear, and the interaction between $I(extremeness)_{i,j,t-1} \times return_{j,t-1}$ is only picking up this non-linear effect. To address this concern, we conduct several tests. First, in Column (1) of Table 4, we estimate our baseline model whilst including a $return_{t-1}$ decile fixed effect. If our results are only capturing stronger responses to very large returns (in absolute value), then our coefficients on the interaction terms of interest ($return \times I(extremeness)$) should be insignificant in this setting where they are estimated using within-return decile variation. However, contrary to this notion, Column (1) shows that the context effects continue to hold.

Second, in Column (2), we add to our baseline model a control for the squared term of positive or negative 1-day returns. Again, if our findings only capture a non-linear responses to large returns, this non-linear response would be absorbed by the squared terms rendering our coefficients of interest insignificant. As shown in Column (2), the coefficients on $return \times I(extremeness)$ continue to be of a similar magnitude as the baseline model, and statistically significant, which indicates that non-linearities cannot explain our results.[10]

Third, we carry out a placebo test, whereby for investor j 1-day returns are compared to extreme returns that are randomly drawn from another portfolio in our sample that comprises totally different stocks. We use the *actual* 1-day returns of stock j in $t-1$ and these "placebo" extreme returns to calculate $I(extremeness_{i,j,t-1})$. If our findings merely capture a response to 1-day returns, then we should continue to find similar results in the placebo test, since it

[9]We also construct the $extremeness_{i,j,t-1}$ by comparing a return to returns generated by all the stocks ever held by the investors. The results continue to hold as shown in Column (3) Table A5.

[10]The significance of the squared terms indicates that there is some non-linearity in the responses. Note also that the squared terms are not only capturing non-linearities, but also the monotonic increase, which in our baseline model was captured by $return^{+}$ and $return^{-}$. That is why $return^{+}$ and $return^{-}$ are insignificant in Column (2). In unreported results, we produced a figure similar to Figure 2 for the model shown in Column (2) of Table 4 and the plots are virtually identical to Figure 2, indicating that the non-linearity is small, and that the squared terms are mainly capturing the monotonic increase.

does not matter which extreme return we assign to an investor, as the 1-day return is kept the same.

The random match is carried out 1,000 times. We estimate the baseline model in each matching, and calculate the ratio of the coefficient on the interaction (β_4 or β_5 in Equation 1) over the coefficient on returns (β_1 or β_2). The distribution of these ratios is shown in Figure 3, with the solid line depicting the corresponding actual ratio from the baseline model. The actual ratio turns out to be 32.3 (10) standard deviations away from the mean of the distribution of the placebo ratios for negative (positive) returns. These results suggest that it is highly unlikely that our baseline results are only capturing responses to 1-day returns as opposed to context effects.[11]

3.2.3 Variance of stocks and portfolios

Another possible explanation for our findings is that the $I(extremeness)$ variable is capturing the variance in the returns experienced by the investor. To illustrate, if an investor holds a portfolio with low variance, then the maximum or minimum returns experienced will not be very large. Thus, when a large 1-day return occurs, the investor responds more strongly, not because of context effects, but because this volatility is unusual given their holdings. To rule out this explanation, we estimate various indicators of the variance in returns experienced by the investor, and interact these with 1-day returns. If our results are capturing responses to unusual variance, then these interactions should absorb the effect from our variables of interest.

We calculate the experienced variance of the investor in several ways: the variance of daily returns for stock j, from the day it is purchased by the investor to day $t-1$ ($Variance_j$), or the weighted variance which accounts for the weight stock j receiveds in the investor's portfolio($WVariance_j$). We also calculate these statistics in a rolling fashion, using daily returns from $t-90$ to day $t-1$ ($Variance_{j,90}$ and $WVariance_{j,90}$, respectively). Finally, we also calculate the variance of the total portfolio returns of the investor's portfolio, from the date the account was opened until day $t-1$ ($Variance_{Port}$).

The results from these models are shown in Table 5. Our findings continue to hold in all

[11] In Figure A1 in the appendix we find similar results when doing the placebo test using the continuous variable $extremeness$.

specifications, as the interactions between $returns \times I(extremeness)$ are of similar magnitude as in our baseline models, and statistically significant throughout. These findings suggest that our results are not driven by the volatility investors are accustomed to in their portfolios.[12]

3.2.4 Different definitions for extremeness

In our baseline analysis the extremeness dummy $I(extremeness)_{i,j,t-1}$ takes the value of one when $extremeness_{i,j,t-1}$ is in the top quartile in the overall sample. To examine if the results are sensitive to this definition, we conduct our analysis by defining extremeness using different cutoff points, as well as the original continuous variable ($extremeness_{i,j,t-1}$). The results are shown in Table 6. In Columns (1) and (2) we construct the extremeness dummy using the 50th percentile and the 90th percentile, respectively, as a cutoff point. In Column (3) we use the original continuous variable $extremeness_{i,j,t-1}$, rather than further constructing a dummy. All coefficients of variables of interest show the expected signs and are highly statistically significant.

3.2.5 Public information at higher frequencies

Because we are interested in the coefficient on $return_{j,t-1}$, in our baseline models we include a *stock* $\times$ *year-month* fixed effect, which controls for all public information about a stock that varies monthly. However, it may be the case that public information at higher frequencies, such as the "hype" that surrounds earnings announcements, or various corporate events, make a specific 1-day return more salient, and thus lead to stronger responses.

To rule out this explanation, in Table 7, we replace the *stock* $\times$ *year-month* fixed effect with a *stock* $\times$ *year-week* fixed effect or a *stock* $\times$ *date* fixed effect. The full models are shown in Columns (2) and (4). All the coefficients on the variables of interest continue to show the expected signs, and are statistically significant at 0.5% level.

Overall, the results in these section show that context effects in the perception of stock returns are robust to various alternative model specifications that control for various other factors that may be relevant.[13]

[12] The variance of value weighted daily portfolio returns, $variance_{it}$, is omitted in Column (5) as it does not vary within the account-date level. Thus it is accounted by the account-date fixed effect.

[13] In other tests, presented in Tables in the appendix, we show that our results hold under different sample

4 Further Tests

In this section we conduct additional tests that pertain to our hypothesis.

4.1 Returns over different horizons

In this section we test the hypothesis using returns defined over longer horizons, specifically over three days, one week, two weeks, three weeks, and one month. Maximum and minimum experienced returns in terms of aforementioned horizons are drawn out for each portfolio, and $I(extremeness)_{i,j,t-1}$ is calculated in a similar way as in the baseline model. Equation (1) is then estimated for each of these different return definitions.

Figure 4 shows the probability of selling a stock as a function of its 1-day return, allowing for different coefficients if the 1-day return is subjectively extreme (as the right Panel of Figure 2), for different return definitions. In each panel, we find a V-shaped pattern, which becomes steeper when that return is classed as extreme in the investors' portfolios. This finding indicates that the context effect hypothesis holds true for different stock return horizons.

4.2 Context effects and time

Our definitions of extremeness do not take into account the time since the maximum or minimum return was experienced by an investor, based on findings such as the peak-end effect(e.g., (Kahneman, Fredrickson, Schreiber, and Redelmeier, 1993)). However, another finding in the research that studies memory, is that recent events are recalled more easily. If such recency effects operate here, then context effects should be larger when the extreme returns where experienced more recently. In this section, we examine whether the recency effect interacts with the context effect.

To study these interactions, we calculate the number of days between day $t-1$ and the day when the investor experienced the highest or lowest return. We then construct a dummy variable, $I(G)$, equal to 1 if the length is smaller than the sample median (74 days), in the first 30th percentile (25 days), or first decile (9 days). In additional tests $I(G)$ is set to 1 in

construction criteria (Tables A3 and A4), and when defining extremeness using market-adjusted or portfolio-adjusted returns.

cases where the maximum or minimum returns for an investor occurred one week, two weeks or one month before day $t-1$. We then estimate the model in Equation (1), whilst including interactions between $I(G)$ and the main variables of interest.

The results, presented in Columns (1)-(3) in Table 8, show no evidence of recency effects as the the triple interactions are always insignificant. This finding suggests that time does not alleviate the memory of extreme return experiences, in line with the peak-end effect (Kahneman, Fredrickson, Schreiber, and Redelmeier, 1993). (Neil, maybe some more discussion w.r.t. this finding?)

4.3 Context effects and investor characteristics

In this section, we examine whether context effects differ in the cross-section of investors. To conduct the tests, for each variable we define a dummy , $I(G)$, which takes the value of 1 if the specific investor is above median in the sample for a given characteristic, and 0 otherwise. Then, we interact this dummy with all the variables of interest, and re-estimate our baseline model.[14]

Calvet, Campbell, and Sodini (2009) show that investors who are wealthier, are more financially sophisticated. For our first set of cuts we construct four variables to capture their level of wealth: the average house price or the average weekly income at the investors' postcode,[15] the initial value of their equity portfolio at the date the investor has opened the account, or the median value of their equity portfolio over the whole period the investor is in the dataset.

The next variable we consider is the performance of investors. To conduct this split, we calculate their portfolio return ending in day $t-1$ (as the value held weighted average of the return since purchase of all the individual stocks in their portfolio), and set the dummy $I(G)$ equal to 1 if the portfolio return is positive and zero otherwise.

Next, we consider investors age, based on findings such as Korniotis and Kumar (2013) that the portfolios of older investors have worst performance than those of younger investors.

Investors' trading frequency is a variable analyzed by several studies in household finance

[14]The dummy $I(G)$ is not included in the model, as it does not entail any variation within the account-date level, thus it is absorbed by the account-date fixed effect.
[15]We use data in 2011 from Office for National Statistics.

(e.g. Barber and Odean, 2000; Grinblatt and Keloharju, 2009; Seru, Shumway, and Stoffman, 2010). Trading frequency is defined as the monthly average number of buys and sells of an investor.

The last variable we consider is login frequency, a proxy for amount of attention investors pay to their portfolio (e.g. Dierick, Heyman, Inghelbrecht, and Stieperaere, 2019). We calculate the login frequency for each investor by tallying the number of times they log in the account each month, and the average this tally across all the months the investor is in the sample.

The coefficients on $I(extremeness)_{i,j,t-1} \times return_{j,t-1}$ in Table 9 are of the expected sign and are statistically significant throughout, which indicates that the subgroup identified by $I(G) = 0$ exhibit context effects in their perception of stock returns.

Investor sophistication does not affect the context effects we document, as the coefficient on the triple interaction in Columns (1)-(4), which flags the wealthier investors, is insignificant. Moreover, login frequency does not matter, as the triple interaction in Column (8) is also insignificant. Thus, in these cases, the coefficient on $I(extremeness)_{i,j,t-1} \times return_{j,t-1}$ adequately describes the context effects for both subgroups.

The triple interactions are significant in Columns (5)-(7), showing that investors with better performing portfolios, younger investors, or investors who trade less often show stronger context effects for negative returns. The last row in Table 9 shows the "total" context effects coefficient toward negative returns exhibited by those investors who trade more (i.e., when $I(G) = 1$ in Column (7)), and its statistical significance. Frequent traders also exhibit significant context effects toward negative returns.

Overall, the analysis in this section shows that context effects in the perception of stock returns are exhibited by all the types of investors we consider.

4.4 Topping up decisions

We focus our analysis on selling decisions, as these can be modelled accurately. In this section, we examine whether context effects influence the probability of investors topping up a stock that they already hold in their portfolio. The assumption here is that investors, when topping up a stock, are only considering stocks they already own. Even though this is likely to be a simplification, as investors can be also considering other publicly listed companies that they do not own, it would be useful to see if context effects also affect certain aspects of buying decisions.

The analysis here is the same as that presented in Table 2, except that the dependent variable is now an indicator that equals 1 if investor i tops up stock j in day t, and 0 otherwise. The results are presented in Table 10. Investors are more likely to top up an existing holding when previous day return gets larger in absolute value (Column (1)), consistent with the findings in Barber and Odean (2008). The coefficient on $return^{+}_{j,t-1} \times I(extremeness)_{i,j,t-1}$ is not statistically significant, which indicates no context effects for positive returns. However, the coefficient on $return^{-}_{j,t-1} \times I(extremeness)_{i,j,t-1}$, is negative and significant across all model specifications, in line with the context effects hypothesis. The finding that context effects are stronger for negative returns, is consistent with our baseline analysis using selling decisions.

Overall, the analysis in this section suggests that context effects also influence buying decisions.

4.5 A corporate finance application

A well-known finding from corporate finance, is that corporate managers learn from stock prices when choosing their investment policies. (Chen, Goldstein, and Jiang, 2007; Bakke and Whited, 2010; Foucault and Fresard, 2014; Goldstein, Liu, and Yang, 2021). The idea here is that, even though managers are firm insiders with good information about the growth prospects of their firms, stock prices can expand their information set, as they amalgamate the signals from the many different investors who trade their stocks in equity markets.

In this section, we examine whether context effects influence the way managers learn from stock prices. The typical way that managerial learning is shown in this context, starting with the analysis of Chen, Goldstein, and Jiang (2007), is to show that a measure of investments is positively related to Tobin's q, a standardized measure of stock price. A higher q indicates more growth opportunities, and thus stimulates more investments. When the manager learns more from a given stock price, then the coefficient on q should be higher.

Our test here compares whether managers learn more from stock prices when these are extreme relative to what they have seen before, in line with context effects. We use data from Execucomp to identify the mangers of each firm in each year, and define $extremeness_{j,t}$ as the difference between the firm's latest q and the maximum q the manager of this firm has seen before in the firm, up to that date. We then define the dummy $I(G)$ that takes the value of one, if $extremeness_{j,t}$ is in the top quartile of the distribution in the sample. Our prediction is that the coefficient on $q_{j,t-1} \times I(G)$ will be positive and significant, indicating that managers are more responsive to prices when these are extreme relative to what they have seen before.

The variable definitions and sample construction criteria are based on Foucault and Fresard (2014), using data from Compustat (details in the caption of Table 11) . The dependent variable is capital expenditure (CAPX), and we include various controls typically included in such tests such as cash-flow, leverage, cash holdings, firm assets, change in sales, and return on assets. In line with our analysis in Table 4, to ensure that the interaction $q_{j,t-1} \times I(G)$ is not only capturing non-linearities in the responses of managers to q, we control for q^2 in the model.

The results are shown in Table 11. In Column (1) we include firm and year fixed effects. In column (2) we add firm-manager and year fixed effects, which capture manager-level variables, such as managerial style, ability, etc. In Column (3) we add q-decile fixed effects, in order to further control for the possibility that $q_{j,t-1} \times I(G)$ is only capturing the effect of very large q's in the cross section.[16]

As in previous literature, the coefficient on q is positive and significant. In line with the context effects, the coefficient on the interaction $q_{j,t-1} \times I(G)$ is positive and significant in all columns. The economic significance is also substantial, as the coefficient on q increases by 17% when it is extreme in Column (1), and by 12.5% in Column (2).

Overall, these results show evidence to suggest that context effects also influence the way corporate managers perceive stock prices.

5 Conclusion

Stock returns are ubiquitous in financial research and the media, and a common presumption is that all investors perceive the same return in the same way. In this paper we challenge this

[16]The q^2 control is omitted in this model as coefficients are estimated using within q-decile variation.

view, showing that a given return is perceived differently by different investors, and that these differences are driven by the comparison of a return to investors' own personal and idiosyncratic experiences of returns in the small set of stocks that they hold.

This result is robust to many different model specifications, and its magnitude is substantial. For example, the response to a negative (positive) return increases by a factor of 5.5 (2) when the return is extreme relative to an investors own portfolio. In additional analysis, we find that context effects extent beyond retail investors, and influence the way corporate managers learn from stock prices when choosing their investment policies.

Overall, whereas stock returns are commonly considered to be "objective" pieces of information, our study demonstrated that there is considerable subjectivity in their perception.

References

An, Li, Joseph Engelberg, Matthew Henriksson, Baolian Wang, and Jared Williams, 2019, The portfolio-driven disposition effect, Revise & Resubmit at *Journal of Finance*.

Antoniou, Constantinos and Shema F Mitali, 2020, Déjà vu: Do experienced returns affect mutual fund managers' investment decisions?, *Available at SSRN 3116073*.

Badrinath, Swaminathan G and Sunil Wahal, 2002, Momentum trading by institutions, *Journal of Finance* 57, 2449–2478.

Bakke, Tor-Erik and Toni M Whited, 2010, Which firms follow the market? An analysis of corporate investment decisions, *Review of Financial Studies* 23, 1941–1980.

Barber, Brad M and Terrance Odean, 2000, Trading is hazardous to your wealth: The common stock investment performance of individual investors, *Journal of Finance* 55, 773–806.

Barber, Brad M and Terrance Odean, 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors, *Review of Financial Studies* 21, 785–818.

Barlevy, Gadi and Pietro Veronesi, 2003, Rational panics and stock market crashes, *Journal of Economic Theory* 110, 234–263.

Baumeister, Roy F, Ellen Bratslavsky, Catrin Finkenauer, and Kathleen D Vohs, 2001, Bad is stronger than good, *Review of General Psychology* 5, 323–370.

Ben-David, Itzhak and David Hirshleifer, 2012, Are investors really reluctant to realize their losses? Trading responses to past returns and the disposition effect, *Review of Financial Studies* 25, 2485–2532.

Bhargava, Saurabh and Ray Fisman, 2014, Contrast effects in sequential decisions: Evidence from speed dating, *Review of Economics and Statistics* 96, 444–457.

Birru, Justin, 2015, Confusion of confusions: A test of the disposition effect and momentum, *Review of Financial Studies* 28, 1849–1873.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2012, Salience theory of choice under risk, *Quarterly Journal of Economics* 127, 1243–1285.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2013, Salience and asset prices, *American Economic Review* 103, 623–28.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2017, Memory, attention, and choice, *Quarterly Journal of Economics*.

Borsboom, Charlotte and Stefan Zeisberger, 2020, What makes an investment risky? An analysis of price path characteristics, *Journal of Economic Behavior & Organization* 169, 92–125.

Calvet, Laurent E, John Y Campbell, and Paolo Sodini, 2009, Measuring the financial sophistication of households, *American Economic Review* 99, 393–98.

Calvo, Guillermo A, 2004, Contagion in emerging markets: When Wall Street is a carrier, *Latin American Economic Crises*, Springer, 81–91.

Campbell, John Y, Tarun Ramadorai, and Allie Schwartz, 2009, Caught on tape: Institutional trading, stock returns, and earnings announcements, *Journal of Financial Economics* 92, 66–91.

Chang, Tom Y, David H Solomon, and Mark M Westerfield, 2016, Looking for someone to blame: Delegation, cognitive dissonance, and the disposition effect, *Journal of Finance* 71, 267–302.

Chen, Qi, Itay Goldstein, and Wei Jiang, 2007, Price informativeness and investment sensitivity to stock price, *Review of Financial Studies* 20, 619–650.

Dierick, Nicolas, Dries Heyman, Koen Inghelbrecht, and Hannes Stieperaere, 2019, Financial attention and the disposition effect, *Journal of Economic Behavior & Organization* 163, 190–217.

Enke, Benjamin, Frederik Schwerter, and Florian Zimmermann, 2020, Associative memory and belief formation, *National Bureau of Economic Research*.

Foucault, Thierry and Laurent Fresard, 2014, Learning from peers' stock prices and corporate investment, *Journal of Financial Economics* 111, 554–577.

Frydman, Cary and Lawrence J Jin, 2021, Efficient coding and risky choice, Forthcoming in *Quarterly Journal of Economics*.

Gathergood, John, David Hirshleifer, David Leake, Hiroaki Sakaguchi, and Neil Stewart, 2019, Naïve buying diversification and narrow framing by individual investors, *National Bureau of Economic Research*.

Goldstein, Itay, Bibo Liu, and Liyan Yang, 2021, Market feedback: Evidence from the horse's mouth, *Available at SSRN 3874756*.

Grinblatt, Mark, Gergana Jostova, Lubomir Petrasek, and Alexander Philipov, 2020, Style and skill: Hedge funds, mutual funds, and momentum, *Management Science*.

Grinblatt, Mark and Matti Keloharju, 2001, What makes investors trade?, *Journal of Finance* 56, 589–616.

Grinblatt, Mark and Matti Keloharju, 2009, Sensation seeking, overconfidence, and trading activity, *Journal of Finance* 64, 549–578.

Grinblatt, Mark, Sheridan Titman, and Russ Wermers, 1995, Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior, *American Economic Review*, 1088–1105.

Hartzmark, Samuel M, 2015, The worst, the best, ignoring all the rest: The rank effect and trading behavior, *Review of Financial Studies* 28, 1024–1059.

Hartzmark, Samuel M, Samuel D Hirshman, and Alex Imas, 2021, Ownership, learning, and beliefs, *Quarterly Journal of Economics* 136, 1665–1717.

Hartzmark, Samuel M and Kelly Shue, 2018, A tough act to follow: Contrast effects in financial markets, *Journal of Finance* 73, 1567–1613.

Heath, Chip, Steven Huddart, and Mark Lang, 1999, Psychological factors and stock option exercise, *Quarterly Journal of Economics* 114, 601–627.

Helson, Harry, 1964, *Adaptation-level theory: An experimental and systematic approach to behavior*, New York: Harper & Row.

Hirshleifer, David and Siew Hong Teoh, 2003, Limited attention, information disclosure, and financial reporting, *Journal of Accounting and Economics* 36, 337–386.

Jesteadt, Walt, R Duncan Luce, and David M Green, 1977, Sequential effects in judgments of loudness, *Journal of Experimental Psychology: Human Perception and Performance* 3, 92–104.

Kahneman, Daniel, Barbara L Fredrickson, Charles A Schreiber, and Donald A Redelmeier, 1993, When more pain is preferred to less: Adding a better end, *Psychological Science* 4, 401–405.

Kahneman, Daniel and Dale T Miller, 1986, Norm theory: Comparing reality to its alternatives, *Psychological Review* 93, 136–153.

Kahneman, Daniel and Amos Tversky, 1979, Prospect theory: An analysis of decisions under risk, *Econometrica* 47, 278.

Kaniel, Ron, Gideon Saar, and Sheridan Titman, 2008, Individual investor trading and stock returns, *Journal of Finance* 63, 273–310.

Kaustia, Markku, 2010, Prospect theory and the disposition effect, *Journal of Financial and Quantitative Analysis* 45, 791–812.

Kaustia, Markku and Samuli Knüpfer, 2008, Do investors overweight personal experience? Evidence from IPO subscriptions, *Journal of Finance* 63, 2679–2702.

Klibanoff, Peter, Owen Lamont, and Thierry A Wizman, 1998, Investor reaction to salient news in closed-end country funds, *Journal of Finance* 53, 673–699.

Korniotis, George M and Alok Kumar, 2013, Do portfolio distortions reflect superior information or psychological biases?, *Journal of Financial and Quantitative Analysis* 48, 1–45.

Laming, Donald Richard John, 1997, *The measurement of sensation*, Oxford University Press.

Lim, Sonya S and Siew Hong Teoh, 2010, Limited attention, *Behavioral finance: Investors, corporations, and markets* 6.

Linnainmaa, Juhani T, 2010, Do limit orders alter inferences about investor performance and behavior?, *Journal of Finance* 65, 1473–1506.

Locke, Peter R and Steven C Mann, 2005, Professional trader discipline and trade disposition, *Journal of Financial Economics* 76, 401–444.

Malmendier, Ulrike and Stefan Nagel, 2011, Depression babies: Do macroeconomic experiences affect risk taking?, *Quarterly Journal of Economics* 126, 373–416.

Mendel, Brock and Andrei Shleifer, 2012, Chasing noise, *Journal of Financial Economics* 104, 303–320.

Nagel, Stefan and Zhengyang Xu, 2019, Asset pricing with fading memory, *National Bureau of Economic Research*.

Neyman, Jerzy and Elizabeth L Scott, 1948, Consistent estimates based on partially consistent observations, *Econometrica* 16, 1–32.

Noguchi, Takao and Neil Stewart, 2018, Multialternative decision by sampling: A model of decision making constrained by process data, *Psychological Review* 125, 512–544.

Odean, Terrance, 1998, Are investors reluctant to realize their losses?, *Journal of Finance* 53, 1775–1798.

Parducci, Allen, 1965, Category judgment: A range-frequency model, *Psychological Review* 72, 407–418.

Quispe-Torreblanca, Edika, John Gathergood, George Loewenstein, and Neil Stewart, 2020, Investor attention, reference points and the disposition effect, *Available at SSRN 3422790*.

Seru, Amit, Tyler Shumway, and Noah Stoffman, 2010, Learning by trading, *Review of Financial Studies* 23, 705–739.

Shapira, Zur and Itzhak Venezia, 2001, Patterns of behavior of professionally managed and independent investors, *Journal of Banking & Finance* 25, 1573–1587.

Shefrin, Hersh and Meir Statman, 1985, The disposition to sell winners too early and ride losers too long: Theory and evidence, *Journal of Finance* 40, 777–790.

Shue, Kelly and Richard R Townsend, 2018, Can the Market Multiply and Divide? Non-Proportional Thinking in Financial Markets, *The Journal of Finance*.

Simonsohn, Uri, 2006, New Yorkers commute more everywhere: contrast effects in the field, *Review of Economics and Statistics* 88, 1–9.

Simonsohn, Uri and George Loewenstein, 2006, Mistake: The effect of previously encountered prices on current housing demand, *Economic Journal* 116, 175–199.

Stein, Jeremy C, 1987, Informational externalities and welfare-reducing speculation, *Journal of Political Economy* 95, 1123–1145.

Stewart, Neil, Gordon DA Brown, and Nick Chater, 2005, Absolute identification by relative judgment, *Psychological Review* 112, 881–911.

Stewart, Neil, Nick Chater, and Gordon DA Brown, 2006, Decision by sampling, *Cognitive Psychology* 53, 1–26.

Strahilevitz, Michal Ann, Terrance Odean, and Brad M Barber, 2011, Once burned, twice shy: How naive learning, counterfactuals, and regret affect the repurchase of stocks previously sold, *Journal of Marketing Research* 48, S102–S120.

Tversky, Amos and Derek J Koehler, 1994, Support theory: A nonextensional representation of subjective probability, *Psychological Review* 101, 547–567.

Wachter, Jessica A and Michael Jacob Kahana, 2019, A retrieved-context theory of financial decisions, *National Bureau of Economic Research*.

Wallis, Jonathan D and Steven W Kennerley, 2011, Contrasting reward signals in the orbitofrontal cortex and anterior cingulate cortex, *Annals of the New York Academy of Sciences* 1239, 33–42.

Wang, Jiang, 1993, A model of intertemporal asset prices under asymmetric information, *Review of Economic Studies* 60, 249–282.

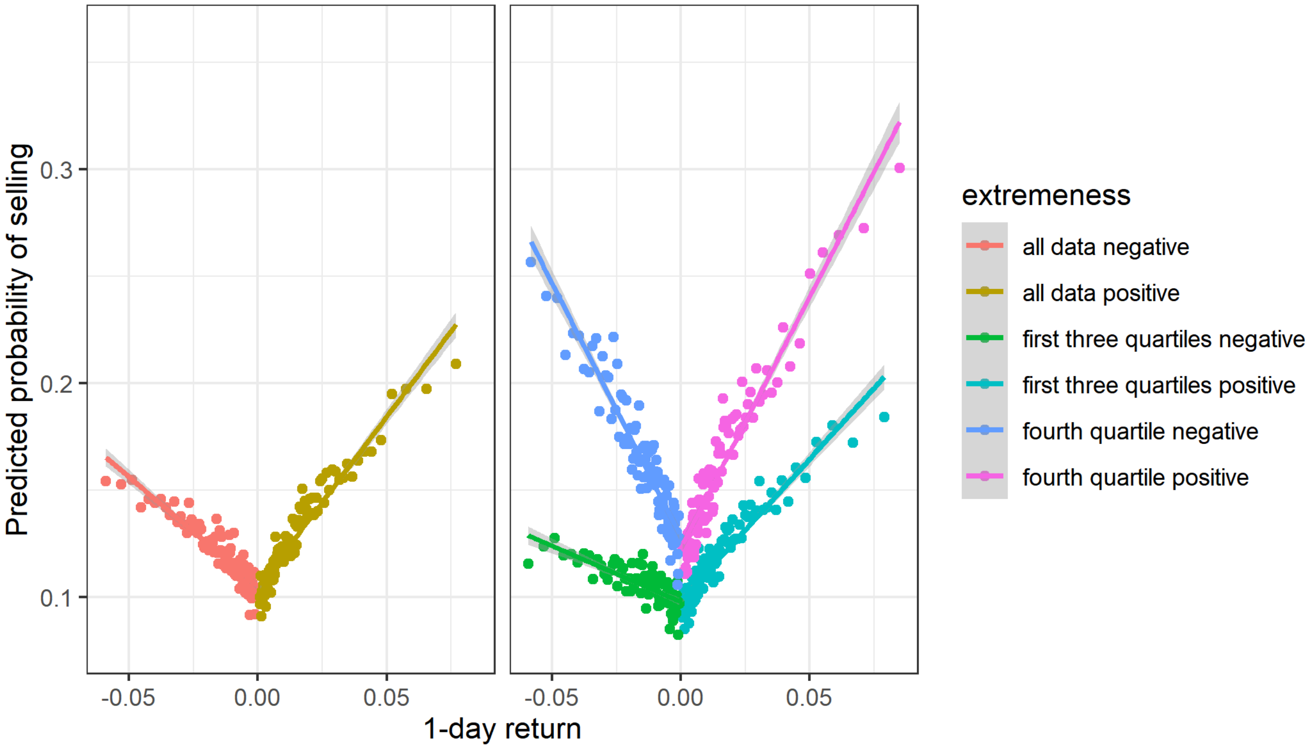

Figure 2. Predicted probability of selling on 1-day return
The figure shows the probability of selling on 1-day return, predicted by the linear model (1). In the left panel, 1-day returns are broken into 2 branches: positive 1-day returns and negative 1-day returns. Each branch contains 100 points. Each point represents the average predicted probability of selling for each percentile of 1-day returns in the branch. Lines and confidence intervals are generated by the best fitted linear models on these 100 data points. In the right panel, 1-day returns are further broken into 4 branches by the first three quartiles and the fourth quartile of *extremeness* on top of the positive/negative signs. Each branch also contains 100 points. Each point also represents the average predicted probability of selling for each percentile of 1-day returns in the branch. Lines and confidence intervals are generated in the same way as in the left panel. In the predicting model, the dependent variable is a dummy variable, equal to 1 when a holding is sold, and 0 otherwise. Explanatory variables consist: $return^{-}$, $return^{+}$, $I(extremeness)$, $return^{-} \times I(extremeness)$, $return^{+} \times I(extremeness)$, RSP^{-}, RSP^{+}, $I(gain)$, $\sqrt{holding\ days}$, $RSP^{-}\times\sqrt{holding\ days}$, $RSP^{+}\times\sqrt{holding\ days}$, $variance$, $I(loss) \times variance$, $I(gain) \times variance$, $I(highest\ RSP)$, $I(lowest\ RSP)$, the $account \times date$ fixed effect, the $stock \times year\text{-}month$ fixed effect and the $Holding\ day\ decile$ fixed effect. The definitions of variables can found in Table A1.

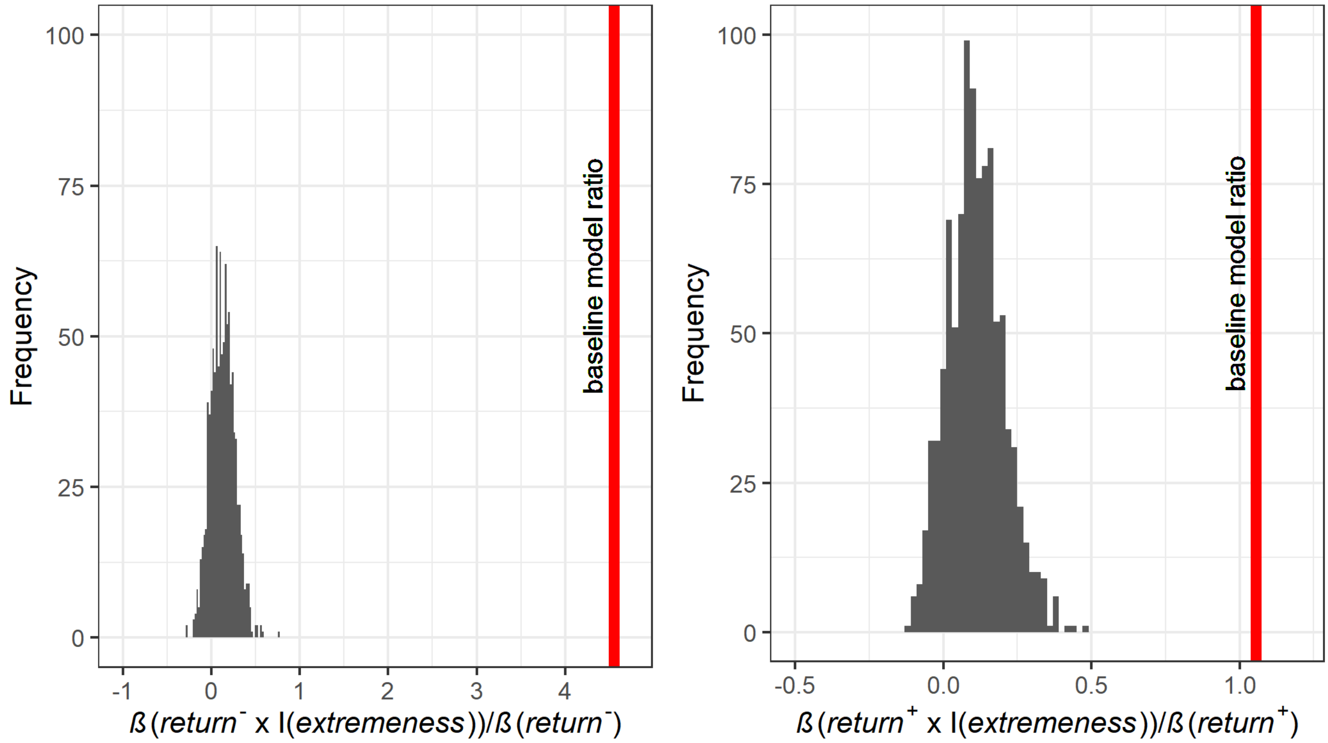

Figure 3. Results from the placebo test

The figure shows the distribution of the ratio of interest ($\beta(return^{-} \times I(extremeness))/\beta(return^{-})$ and $\beta(return^{+} \times I(extremeness))/\beta(return^{+})$) in the placebo test. In the placebo test, the *extremeness* is calculated by subtracting 1-day return by maximum/minimum return from a random portfolio without common stocks with the portfolio being considered, rather than the investors' experienced maximum/minimum return. The random match was carried out for 1,000 times and Model (1) was estimated based on each random match. The distributions of ratios of interest are shown in the figure. The predicting model is identical as column (7) in Table 2 (except the way constructing *extremeness*), containing the *account* $\times$ *date* fixed effect, the *stock* $\times$ *year-month* fixed effect, the *Holding day decile* fixed effect and following explanatory variables: $return^{-}$, $return^{+}$, $I(extremeness)$, $return^{-} \times I(extremeness)$, $return^{+} \times I(extremeness)$, RSP^{-}, RSP^{+}, $I(gain)$, $\sqrt{holding\ days}$, $RSP^{-} \times \sqrt{holding\ days}$, $RSP^{+} \times \sqrt{holding\ days}$, $variance$, $I(loss) \times variance$, $I(gain) \times variance$, $I(highest\ RSP)$ and $I(lowest\ RSP)$. The definitions of variables can found in Table A1. The baseline coefficients are taken from Column (7) Table 2.

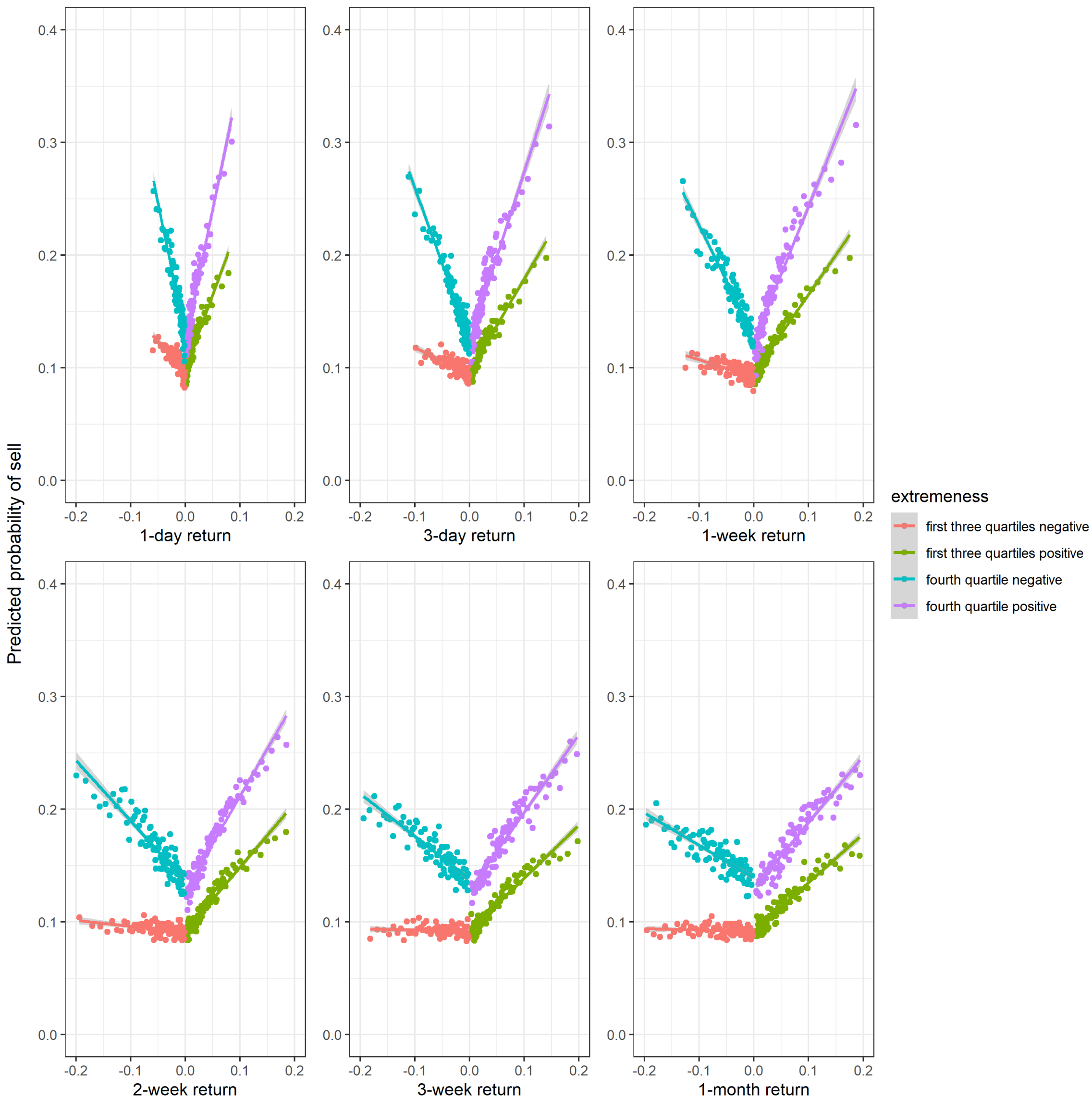

Figure 4. Predicted probability of selling on different measures of the return
The figure shows the probability of selling predicted by a linear model similar to Model (1) but replacing 1-day returns with different measures of the return: 1-day return, 3-day return, 1-week return, 2-week return, 3-week return and 1-month return. In each panel, returns are broken into 4 branches by the first three quartiles and the fourth quartile of *extremeness* as well as the positive/negative signs. Each branch contains 100 points. Each point represents the average predicted probability of selling for each percentile of returns in the branch. Lines and confidence intervals are generated by the best fitted linear models on these 100 data points.

Table 1. Summary statistics

Panel A: Summary statistics at the holding level

Statistic	N	Mean	St. Dev.	Pctl(10)	Pctl(25)	Median	Pctl(75)	Pctl(90)
return	456,187	0.0004	0.023	−0.023	−0.009	0.000	0.009	0.023
negative return	198,992	−0.016	0.016	−0.038	−0.021	−0.011	−0.005	−0.002
positive return	202,388	0.017	0.019	0.002	0.005	0.011	0.021	0.039
return since purchase	456,187	−0.021	0.226	−0.277	−0.108	−0.010	0.070	0.200
$\sqrt{holding\ days}$	456,187	10.785	5.767	3.873	6.083	9.849	14.697	19.261
variance	456,187	0.001	0.025	0.000	0.0002	0.0003	0.001	0.002
number of holdings	456,187	16.412	14.022	6	8	12	19	32
min return	456,187	−0.211	0.513	−0.407	−0.294	−0.166	−0.098	−0.067
max return	456,187	0.303	0.152	0.073	0.108	0.175	0.289	0.545
extremeness	456,187	−0.235	0.253	−0.472	−0.276	−0.156	−0.090	−0.057
extremeness (negative 1-day return)	206,762	−0.193	0.149	−0.376	−0.273	−0.148	−0.083	−0.052
extremeness (positive 1-day return)	198,992	−0.195	0.150	−0.486	−0.274	−0.150	−0.084	−0.057
sell	456,187	0.123	0.328					

Panel B: Summary statistics at the account level

Statistic	N	Mean	St. Dev.	Pctl(10)	Pctl(25)	Median	Pctl(75)	Pctl(90)
age	6,309	47.678	15.205	32	32	52	62	72
selling.rate	6,312	0.201	0.144	0.083	0.125	0.171	0.200	0.345
house price (£)	5,879	218,371.3	88,267.14	125,000	150,000	205,000	250,000	325,000
weekly income (£)	6,190	443.10	82.63	358.7	380.6	409.7	491.4	551.7
initial value (£)	6,277	11,948.09	59,135.68	487.34	1,400.00	3,931.44	9,819.55	20,958.39
median value (£)	6,312	52,966.45	59,135.68	2,226.46	6,623.87	16,911.47	41,149.46	103,820.78
% female	5,525	17.5						

This table presents summary statistics. Panel A presents information on each holding on sell days during the sample period, from March 2012 to June 2016. All the variables are winsorised at the 1% and 99% levels. Panel B reports information on the account level during the sample period. Only accounts opened after the sample period started are included. Only portfolios with at least one sell on the day are included. Portfolios with less than 5 holdings and stocks held less than 5 days are excluded from the analysis. There are 6312 accounts in the sample. House price and weekly income are matched based on postcodes. Some values are missing in house price, weekly income, age and gender, since demographic information is incomplete in some accounts. There are missing initial values because some price information in the stocks bought in the opening day is missing.

Table 2. Linear regressions on testing perceived 1-day returns

	Dependent variable:						
	Sell						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
return^-	-0.798^{***}	-0.369^{***}	-0.373^{***}	-0.674^{***}	-0.592^{***}	-0.415^{***}	-0.368^{***}
	(0.085)	(0.076)	(0.076)	(0.070)	(0.077)	(0.064)	(0.071)
return^+	1.508^{***}	1.252^{***}	1.252^{***}	1.092^{***}	1.182^{***}	0.706^{***}	0.819^{***}
	(0.072)	(0.077)	(0.077)	(0.069)	(0.078)	(0.055)	(0.064)
I(extremeness)		-0.002	-0.004	-0.009^{***}	-0.009^{**}	-0.002	-0.008^{*}
		(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
$\text{return}^- \times$I(extremeness)		-1.588^{***}	-1.588^{***}	-1.522^{***}	-1.815^{***}	-1.372^{***}	-1.675^{***}
		(0.154)	(0.154)	(0.145)	(0.160)	(0.137)	(0.156)
$\text{return}^+ \times$I(extremeness)		0.965^{***}	0.968^{***}	0.826^{***}	0.978^{***}	0.726^{***}	0.864^{***}
		(0.133)	(0.133)	(0.126)	(0.152)	(0.111)	(0.140)
RSP^-				0.190^{***}	0.188^{***}	0.272^{***}	0.292^{***}
				(0.024)	(0.027)	(0.025)	(0.033)
RSP^+				0.034	0.099^{***}	0.013	0.043
				(0.025)	(0.027)	(0.025)	(0.028)
I(gain)				0.041^{***}	0.045^{***}	0.042^{***}	0.045^{***}
				(0.004)	(0.004)	(0.003)	(0.004)
$\sqrt{\textit{holding days}}$				0.0004	-0.0001	-0.0001	-0.001
				(0.0003)	(0.001)	(0.001)	(0.001)
$\text{RSP}^- \times \sqrt{\textit{holding days}}$				-0.003^{*}	-0.002	-0.006^{***}	-0.007^{***}
				(0.001)	(0.001)	(0.001)	(0.002)
$\text{RSP}^+ \times \sqrt{\textit{holding days}}$				-0.007^{***}	-0.011^{***}	-0.006^{***}	-0.008^{***}
				(0.001)	(0.001)	(0.001)	(0.001)
variance				-1.135	-0.232	-4.005^{*}	-4.360^{**}
				(2.338)	(2.769)	(1.862)	(1.623)
I(loss)$\times$variance				1.133	0.227	3.979^{*}	4.329^{**}
				(2.338)	(2.768)	(1.861)	(1.621)
I(gain)$\times$variance				1.111	0.167	3.829^{*}	4.180^{*}
				(2.335)	(2.764)	(1.864)	(1.629)
I(highest RSP)				0.141^{***}	0.133^{***}	0.140^{***}	0.132^{***}
				(0.006)	(0.006)	(0.005)	(0.006)
I(lowest RSP)				0.050^{***}	0.055^{***}	0.056^{***}	0.056^{***}
				(0.004)	(0.004)	(0.003)	(0.004)
Account FE	Yes	Yes	Yes	Yes	No	Yes	No
Account $\times$ date FE	No	No	No	No	Yes	No	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	No	No
Stock $\times$ year-month FE	No	No	No	No	No	Yes	Yes
Holding day decile FE	No	No	Yes	Yes	Yes	Yes	Yes
Observations	456,187	456,187	456,187	456,187	456,187	456,187	456,187
R^2	0.098	0.099	0.100	0.122	0.188	0.222	0.293

This table presents the results from linear regressions testing whether investors perceive the same 1-day return differently because of past return experience. The dependent variable is a dummy equal to 1 if the stock is sold on day t. $Return^{-}_{j,t-1}$ equals to 1-day return of the stock from the end of day $t-2$ to the end of day $t-1$ if the return is negative, 0 otherwise. Similarly, $return^{+}_{j,t-1}$ equals to 1-day return of the stock if it is positive, 0 otherwise. $I(extremeness_{i,j,t-1})$ is a dummy indicating whether the corresponding return is regarded extreme by the investor. The exact definition can be found in Table A1. $RSP^{+}_{i,j,t-1}$ refers to positive return since purchase. It equals to return since purchase when it is positive, 0 otherwise. $RSP^{-}_{i,j,t-1}$ refers to negative return since purchase. It equals to return since purchase when it is negative, 0 otherwise. $I(gain)_{i,j,t-1}$ is a dummy indicating whether return since purchase is positive; $I(loss)_{i,j,t-1}$ is a dummy indicating whether return since purchase is negative. $\sqrt{Holding\ days}_{ijt}$ is the squre root of the number of business days for which the stock has been held by the investor. $Variance_{i,j,t-1}$ is the variance of the 1-day returns of the specific stock from the purchase day till day $t-1$. $I(highest\ RSP)_{i,j,t-1}$ is a dummy equal to 1 if the return since purchase is the highest in the portfolio. $I(Lowest\ RSP)_{i,j,t-1}$ is a dummy equal to 1 if the return since purchase is the lowest in the portfolio. *Account* FE indicates a fixed effect for each account. *Account* $\times$*date* FE refers to a fixed effect for each interaction of account and date. *Stock* FE indicates a fixed effect for each sedol. *Stock* $\times$ *year-month* FE refers to a fixed effect for each pair of sedol and year-month. $Holding\,day\,decile$ FE refers to a fixed effect for each decile of holding lengths. Data cover the period between March 2012 and June 2016. Only accounts opened after the sample period started are included. Only portfolios with at least one sell on the day are included. Portfolios with less than 5 holdings and stocks held less than 5 days are excluded from the analysis. Standard errors clustered on account, date and stock levels are presented in parenthese with p values indicated by $^{*}p$<0.05; $^{**}p$<0.01; $^{***}p$<0.005.

Table 3. Different priors of the stock j

Comparison set for extremeness.2	except stock j itself			ex-holding
Length of returns for ρ_{jk}		3-month	6-month	
	Dependent variable:			
	sell			
	(1)	(2)	(3)	(4)
return$^-$	-0.336^{***}	-0.381^{***}	-0.387^{***}	-1.125^{***}
	(0.072)	(0.074)	(0.076)	(0.127)
return$^+$	0.800^{***}	0.772^{***}	0.760^{***}	1.220^{***}
	(0.066)	(0.069)	(0.071)	(0.094)
I(extremeness.2)	-0.006^{*}	-0.006	-0.007^{*}	-0.001
	(0.003)	(0.003)	(0.003)	(0.007)
return$^-$×I(extremeness.2)	-1.522^{***}	-1.580^{***}	-1.592^{***}	-1.881^{***}
	(0.142)	(0.156)	(0.156)	(0.522)
return$^+$×I(extremeness.2)	0.774^{***}	0.807^{***}	0.787^{***}	0.653^{***}
	(0.123)	(0.132)	(0.132)	(0.216)
ρ_{jk}		-0.005	-0.007	
		(0.006)	(0.007)	
ρ_{jk}×return$^-$		0.362	0.686	
		(0.299)	(0.366)	
ρ_{jk}×return$^+$		0.381	0.530	
		(0.292)	(0.348)	
Controls	Yes	Yes	Yes	Yes
Account × date FE	Yes	Yes	Yes	Yes
Stock × year-month FE	Yes	Yes	Yes	Yes
Holding day decile FE	Yes	Yes	Yes	Yes
Observations	456,187	444,760	439,487	356,101
R^2	0.293	0.295	0.297	0.281

This table presents the results from linear regressionss testing wether the results come from different priors on stock j. In Column (1) - (3), $extremeness.2_{i,j,t-1}$ is recalculted by comparing the 1-day return from the stock j to the highest/lowest 1-day return from stocks in the portfolio other than the stock j itself, different from the set consisting all stocks in the portfolio when constructing $extremeness_{i,j,t-1}$; in Column (4), $extremeness.2_{i,j,t-1}$ is reconstructed using the comparison set where the highest/lowest 1-day is drawn from experienced 1-day returns of stocks that have been fully liquidated from the portfolio (ex-holding). Some observations are missing since there are not ex-holdings available. 75th percentile is used as the dummy cutoff point again when constructing $I(extremeness.2)_{i,j,t-1}$. ρ_{jk} is the 1-day return correlation between stock j and stock k, where the highest/lowest 1-day return is from. In Column (2), 1-day returns in the past 3 months (or shorter if related return information is missing) till date $t-1$ are used to calculate ρ_{jk} while in Column (3), returns in the past 6 months (or shorter if related return information is missing) are used. Some observations are missing in Columns (2) and (3) because 1) the return information is not available (new IPO or missing in Datastream) in the past 20 working days for either stock, or 2) there are no price variations for a stock during the time period. The exact definitioncan be found in Table A1. The dependent variable is a dummy equal to 1 if the stock is sold on day t. $Return^+_{j,t-1}$ equals to 1-day return of the stock from the end of day $t-2$ to the end of day $t-1$ if the return is positive, 0 otherwise. Similarly, $return^-_{j,t-1}$ equals to 1-day return of the stock if it is negative, 0 otherwise. Control variables consist of $RSP^-_{i,j,t-1}$, $RSP^+_{i,j,t-1}$, $I(gain)_{i,j,t-1}$, $\sqrt{holding\ days}_{ijt}$, $RSP^-_{i,j,t-1}\times\sqrt{holding\ days}_{ijt}$, $RSP^+_{i,j,t-1}\times\sqrt{holding\ days}_{ijt}$, $variance_{i,j,t-1}$, $I(loss)_{i,j,t-1}\times variance_{i,j,t-1}$, $I(gain)_{i,j,t-1}\times variance_{i,j,t-1}$, $I(highest\ RSP)_{i,j,t-1}$ and $I(lowest\ RSP)_{i,j,t-1}$. *Account × date* FE refers to a fixed effect for each interaction of account and date. *Stock × year-month* FE refers to a fixed effect for each pair of sedol and year-month. *Holding day decile* FE refers to a fixed effect for each decile of holding lengths. Data cover the period between March 2012 and June 2016. Only accounts opened after the sample period started are included. Only portfolios with at least one sell on the day are included. Portfolios with less than 5 holdings and stocks held less than 5 days are excluded from the analysis. Standard errors clustered on account, date and stock levels are presented in parenthese with p values indicated by $^*p<0.05$; $^{**}p<0.01$; $^{***}p<0.005$.

Table 4. Using return squre and return decile fixed effects

	Dependent variable: Sell (1)	(2)
return^-	-0.612^{***}	0.215
	(0.134)	(0.154)
$\text{return}^{-\ 2}$		9.856^{***}
		(2.520)
return^+	0.991^{***}	0.287
	(0.122)	(0.155)
$\text{return}^{+\ 2}$		7.538^{***}
		(2.070)
I(extremeness)	-0.008^{*}	-0.007^{*}
	(0.003)	(0.003)
$\text{return}^- \times$ I(extremeness)	-1.646^{***}	-1.639^{***}
	(0.155)	(0.155)
$\text{return}^+ \times$ I(extremeness)	0.841^{***}	0.837^{***}
	(0.140)	(0.141)
Controls	Yes	Yes
Account $\times$ date FE	Yes	Yes
Stock $\times$ year-month FE	Yes	Yes
Holding day decile FE	Yes	Yes
1-day return decile FE	Yes	No
Observations	456,187	456,187
R^2	0.293	0.293

This table presents results from linear regressions with 1-*day return decile* fixed effects or $return^2$ as controls. 1-*day return decile* FE refers to a fixed effect for each decile of returns. The dependent variable is a dummy equal to 1 if the stock is sold on day t. $Return^+_{j,t-1}$ equals to 1-day return of the stock from the end of day $t-2$ to the end of day $t-1$ if the return is positive, 0 otherwise. Similarly, $return^-_{j,t-1}$ equals to 1-day return of the stock if it is negative, 0 otherwise. $I(extremeness_{i,j,t-1})$ is a dummy indicating whether the corresponding return is regarded extreme by the investor. The exact definition can be found in Table A1. Control variables consist of $RSP^-_{i,j,t-1}$, $RSP^+_{i,j,t-1}$, $I(gain)_{i,j,t-1}$, $\sqrt{holding\ days}_{ijt}$, $RSP^-_{i,j,t-1}\times\sqrt{holding\ days}_{ijt}$, $RSP^+_{i,j,t-1}\times\sqrt{holding\ days}_{ijt}$, $variance_{i,j,t-1}$, $I(loss)_{i,j,t-1}\times variance_{i,j,t-1}$, $I(gain)_{i,j,t-1}\times variance_{i,j,t-1}$, $I(highestRSP)_{i,j,t-1}$ and $I(lowest\ RSP)_{i,j,t-1}$. *Account* $\times$ *date* FE refers to a fixed effect for each interaction of account and date. *Stock* $\times$ *year-month* refers to a fixed effect for each pair of sedol and year-month. *Holding day decile* FE refers to a fixed effect for each decile of holding lengths. Data cover the period between March 2012 and August 2016. Only accounts opened after the sample period started are included. Only portfolios with at least one sell on the day are included. Portfolios with less than 5 holdings and stocks held less 5 days are excluded from the analysis. Standard errors clustered on account, date and stock levels are presented in parenthese with p values indicated by $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.005$.

Table 5. Interacting return variance with returns

var	$Variance_j$	$WVariance_j$	$Variance_{j,90}$	$WVariance_{j,90}$	$Variance_{Port}$
	Dependent variable:				
	sell				
	(1)	(2)	(3)	(4)	(5)
return$^-$	−0.365***	−0.361***	−0.361***	−0.363***	−0.365***
	(0.071)	(0.071)	(0.072)	(0.072)	(0.071)
return$^+$	0.820***	0.826***	0.811***	0.819***	0.818***
	(0.064)	(0.064)	(0.065)	(0.064)	(0.064)
I(extremeness)	−0.008*	−0.008*	−0.009**	−0.008*	−0.008*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
return$^-$×I(extremeness)	−1.677***	−1.674***	−1.678***	−1.671***	−1.673***
	(0.156)	(0.156)	(0.155)	(0.156)	(0.156)
return$^+$×I(extremeness)	0.864***	0.858***	0.868***	0.864***	0.867***
	(0.140)	(0.140)	(0.141)	(0.141)	(0.140)
var	−4.365**	−194.202	−1.355***	−244.628	
	(1.625)	(116.826)	(0.397)	(131.399)	
return$^-$×var	−0.666	−0.112	−2.468***	−86.475	−0.892
	(0.667)	(48.474)	(0.869)	(106.331)	(11.879)
return$^+$×var	−0.035	−50.305	1.950	58.625*	−0.885
	(0.265)	(39.602)	(1.934)	(28.675)	(11.879)
I(gain)	0.045***	0.045***	0.045***	0.045***	0.045***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
I(loss)×var	4.326**	199.349	0.398***	245.588	−0.892
	(1.623)	(116.562)	(0.140)	(131.401)	(11.879)
I(gain)×var	4.180*	198.439	0.391***	244.220	−0.885
	(1.631)	(116.752)	(0.068)	(131.054)	(11.879)
Other variables	Yes	Yes	Yes	Yes	Yes
Account × date FE	Yes	Yes	Yes	Yes	Yes
Stock × year-month FE	Yes	Yes	Yes	Yes	Yes
Holding day decile FE	Yes	Yes	Yes	Yes	Yes
Observations	456,187	455,904	456,187	455,904	456,187
R^2	0.293	0.293	0.293	0.293	0.293

This table presents the results from linear regressionss controlling interactions between (weighted) stock return variance or portfolio return variance and returns. In Column (1), $var_{i,j,t-1}$ equals to the variance of 1 day returns of stock j from the purchase day to day $t-1$ ($Variance_j$); in Column (2), $var_{i,j,t-1}$ equals to the variance of 1 day returns of stock j from the purchase day to day $t-1$, multiplied by the square of the value weight of stock j in the portfolio at the end of day $t-2$ ($WVariance_j$); in Column (3), $var_{i,j,t-1}$ equals to the variance of returns of stock j from the day $t-90$ to day $t-1$ ($Variance_{j,90}$); in Column (4), $var_{i,j,t-1}$ equals to the variance of returns of stock j from the day $t-90$ to day $t-1$, multiplied by the square of the value weight of stock j in the portfolio at the end of day $t-2$ ($WVariance_{j,90}$); in Column (5), $var_{i,t-1}$ equals to the variance of 1-day returns of the portfolio from the portfolio open day to day $t-1$ ($Variance_{Port}$). $Variance$ is interacted with $return^-_{j,t-1}$, $return^+_{j,t-1}$, $I(loss)_{i,j,t-1}$ and $I(gain)_{i,j,t-1}$. The dependent variable is a dummy equal to 1 if the stock is sold on day t. Other variables consist of $RSP^-_{i,j,t-1}$, $RSP^+_{i,j,t-1}$, $\sqrt{holding\ days}_{ijt}$, $RSP^-_{i,j,t-1}\times\sqrt{holding\ days}_{ijt}$, $RSP^+_{i,j,t-1}\times\sqrt{holding\ days}_{ijt}$, $I(highest\ RSP)_{i,j,t-1}$ and $I(lowest\ RSP)_{i,j,t-1}$. *Account* × *date* FE refers to a fixed effect for each interaction of account and date. *Stock* × *year-month* FE refers to a fixed effect for each pair of sedol and year-month. *Holding day decile* FE refers to a fixed effect for each decile of holding lengths. Data cover the period between March 2012 and June 2016. Only accounts opened after the sample period started are included. Only portfolios with at least one sell on the day are included. Portfolios with less than 5 holdings and stocks held less than 5 days are excluded from the analysis. Standard errors clustered on account, date and stock levels are presented in parenthese with p values indicated by $^*p<0.05$; $^{**}p<0.01$; $^{***}p<0.005$.

Table 6. Using different extremeness dummy cutoff points and the continuous *extremeness* variable

Extremeness variants	50th percentile as dummy cutoff point	90th percentile as dummy cutoff point	original continuous variable
	Dependent variable:		
	Sell		
	(1)	(2)	(3)
return^-	-0.282^{***}	-0.492^{***}	-1.434^{***}
	(0.079)	(0.071)	(0.125)
return^+	0.743^{***}	0.859^{***}	1.266^{***}
	(0.071)	(0.064)	(0.093)
I(extremeness)	-0.009^{***}	-0.010^{*}	
	(0.003)	(0.005)	
extremeness			-0.001
			(0.005)
$\text{return}^- \times$I(extremeness)	-1.166^{***}	-1.953^{***}	
	(0.134)	(0.210)	
$\text{return}^+ \times$I(extremeness)	0.702^{***}	1.130^{***}	
	(0.117)	(0.187)	
$\text{return}^- \times$extremeness			-3.060^{***}
			(0.417)
$\text{return}^+ \times$extremeness			0.723^{***}
			(0.143)
Controls	Yes	Yes	Yes
Account × date FE	Yes	Yes	Yes
Stock × year-month FE	Yes	Yes	Yes
Holding day decile FE	Yes	Yes	Yes
observations	456,187	456,187	456,187
R^2	0.292	0.293	0.292

This table presents robustness check using different extremeness dummy cutoff points and the continuous *extremeness* variable. Instead of using the 75th percentile as a cutoff point when constructing $I(extremeness)_{i,j,t-1}$, the 50th percentile is used in Column (1); the 90th percentile is used in Column (2); and the original continuous $extremeness_{i,j,t-1}$ is adopted in Column (3). The dependent variable is a dummy equal to 1 if the stock is sold on day t. $Return^+_{j,t-1}$ equals to 1-day return of the stock from the end of day $t-2$ to the end of day $t-1$ if the return is positive, 0 otherwise. Similarly, $return^-_{j,t-1}$ equals to 1-day return of the stock if it is negative, 0 otherwise. Control variables consist of $RSP^-_{i,j,t-1}$, $RSP^+_{i,j,t-1}$, $I(gain)_{i,j,t-1}$, $\sqrt{holding\ days}_{ijt}$, $RSP^-_{i,j,t-1}\times\sqrt{holding\ days}_{ijt}$, $RSP^+_{i,j,t-1}\times\sqrt{holding\ days}_{ijt}$, $variance_{i,j,t-1}$, $I(loss)_{i,j,t-1}\times variance_{i,j,t-1}$, $I(gain)_{i,j,t-1}\times variance_{i,j,t-1}$,$I(highest\ RSP)_{i,j,t-1}$ and $I(lowest\ RSP)_{i,j,t-1}$. *Account* × *date* FE refers to a fixed effect for each interaction of account and date. *Stock* × *year-month* FE refers to a fixed effect for each pair of sedol and year-month. *Holding day decile* FE refers to a fixed effect for each decile of holding lengths. Data cover the period between March 2012 and June 2016. Only accounts opened after the sample period started are included. Only portfolios with at least one sell on the day are included. Portfolios with less than 5 holdings and stocks held less than 5 days are excluded from the analysis. Standard errors clustered on account, date and stock levels are presented in parenthese with p values indicated by $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.005$.

Table 7. Using stock×year-week fixed effects and stock×date fixed effects

	Dependent variable:			
	Sell			
	(1)	(2)	(3)	(4)
return^{-}	0.225***	0.041		
	(0.078)	(0.075)		
return^{+}	0.328***	0.205***		
	(0.071)	(0.070)		
I(extremeness)	−0.005	−0.005	−0.006	−0.006
	(0.003)	(0.003)	(0.004)	(0.004)
return^{-} × I(extremeness)	−1.480***	−1.378***	−1.628***	−1.475***
	(0.163)	(0.160)	(0.230)	(0.223)
return^{+} × I(extremeness)	0.745***	0.510***	0.821***	0.534***
	(0.148)	(0.142)	(0.194)	(0.188)
Controls	No	Yes	No	Yes
Account × date FE	Yes	Yes	Yes	Yes
Stock × year-week FE	Yes	Yes	No	No
Stock × date FE	No	No	Yes	Yes
Holding day decile FE	Yes	Yes	Yes	Yes
Observations	456,187	456,187	456,187	456,187
R^2	0.436	0.447	0.695	0.702

This table presents results from linear regressions with *stock × year-month* fixed effects and *stock × date* fixed effects. The dependent variable is a dummy equal to 1 if the stock is sold on day t. $Return^{+}_{j,t-1}$ equals to 1-day return of the stock from the end of day $t-2$ to the end of day $t-1$ if the return is positive, 0 otherwise. Similarly, $return^{-}_{j,t-1}$ equals to 1-day return of the stock if it is negative, 0 otherwise. $I(extremeness)_{i,j,t-1}$ is a dummy indicating whether the corresponding return is viewed as being extreme by the investor. The exact definition can be found in Table A1. Control variables consist of $RSP^{-}_{i,j,t-1}$, $RSP^{+}_{i,j,t-1}$, $I(gain)_{i,j,t-1}$, $\sqrt{holding\ days}_{ijt}$, $RSP^{-}_{i,j,t-1} \times \sqrt{holding\ days}_{ijt}$, $RSP^{+}_{i,j,t-1} \times \sqrt{holding\ days}_{ijt}$, $variance_{i,j,t-1}$, $I(loss)_{i,j,t-1} \times variance_{i,j,t-1}$, $I(gain)_{i,j,t-1} \times variance_{i,j,t-1}$, $I(highest\ RSP)_{i,j,t-1}$ and $I(lowest\ RSP)_{i,j,t-1}$. *Account × date* FE refers to a fixed effect for each interaction of account and date. *Stock × year-week* refers to a fixed effect for each pair of sedol and year-week. *Stock × date* FE refers to a fixed effect for each pair of sedol and date. *Holding day decile* FE refers to a fixed effect for each decile of holding lengths. Data cover the period between March 2012 and June 2016. Only accounts opened after the sample period started are included. Only portfolios with at least one sell on the day are included. Portfolios with less than 5 holdings and stocks held less than 5 days are excluded from the analysis. Standard errors clustered on account, date and stock levels are presented in parenthese with p values indicated by $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.005$.

Table 8. Recency effect

I(G) cutoff point	10th percentile	30th percentile	50th percentile
		Dependent variable:	
		Sell	
	(1)	(2)	(3)
return$^-$	-0.360^{***}	-0.379^{***}	-0.390^{***}
	(0.072)	(0.081)	(0.096)
return$^+$	0.788^{***}	0.898^{***}	0.882^{***}
	(0.066)	(0.071)	(0.081)
I(extremeness)	-0.009^{*}	-0.009^{*}	-0.012^{*}
	(0.003)	(0.004)	(0.005)
return$^-$×I(extremeness)	-1.671^{***}	-1.703^{***}	-1.634^{***}
	(0.171)	(0.183)	(0.224)
return$^+$×I(extremeness)	0.916^{***}	0.874^{***}	1.006^{***}
	(0.158)	(0.186)	(0.217)
I(G)	0.004	0.005	0.001
	(0.004)	(0.003)	(0.003
I(G)×return$^-$	−0.094	0.047	0.045
	(0.213)	(0.130)	(0.122)
I(G)×return$^+$	0.350	-0.272^{*}	−0.135
	(0.186)	(0.119)	(0.113)
I(G)×I(extremeness)	0.002	0.0007	0.005
	(0.009)	(0.006)	(0.006)
I(G)×return$^-$×I(extremeness)	−0.003	0.051	−0.076
	(0.432)	(0.270)	(0.281)
I(G)×return$^+$×I(extremeness)	−0.465	0.070	−0.180
	(0.352)	(0.226)	(0.241)
Controls	Yes	Yes	Yes
Account × date FE	Yes	Yes	Yes
Stock × year-month FE	Yes	Yes	Yes
Holding day decile FE	Yes	Yes	Yes
Observations	456,187	456,187	456,187
R^2	0.293	0.293	0.293

This table presents the results from linear regressions exploring the recency effect. The length between current day and the day one experienced the corresponding max/min 1-day return is calculated and 10th, 30th, 50th percentiles are 9 days, 25 days, 74 days respectively. In Coumn (1)-(3), $I(G)$ equals to 1 when the length is smaller than 9 days, 25 days and 74 days respectively, 0 otherwise. The table presents the results from in Equation (1), whilst interacting $I(G)$ with the variables of interest ($return^-_{j,t-1}$, $return^+_{j,t-1}$, $I(extremeness)_{i,j,t-1}$, $I(extremeness)_{i,j,t-1} \times return^-_{j,t-1}$, $I(extremeness)_{i,j,t-1} \times return^+_{j,t-1}$). The dependent variable is a dummy equal to 1 if the stock is sold on day t. Control variables consist of $RSP^-_{i,j,t-1}$, $RSP^+_{i,j,t-1}$, $I(gain)_{i,j,t-1}$, $\sqrt{holding\ days}_{ijt}$, $RSP^-_{i,j,t-1} \times \sqrt{holding\ days}_{ijt}$, $RSP^+_{i,j,t-1} \times \sqrt{holding\ days}_{ijt}$, $variance_{i,j,t-1}$, $I(loss)_{i,j,t-1} \times variance_{i,j,t-1}$, $I(gain)_{i,j,t-1} \times variance_{i,j,t-1}$, $I(highest\,RSP)_{i,j,t-1}$ and $I(lowest\,RSP)_{i,j,t-1}$. *Account × date* FE refers to a fixed effect for each interaction of account and date. *Stock × year-month* FE refers to a fixed effect for each pair of sedol and year-month. *Holding day decile* FE refers to a fixed effect for each decile of holding lengths. Data cover the period between March 2012 and June 2016. Only accounts opened after the sample period started are included. Only portfolios with at least one sell on the day are included. Portfolios with less than 5 holdings and stocks held less 5 days are excluded from the analysis. Standard errors clustered on account and date are presented in parenthese with p values indicated by $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.005$.

Table 9. Subsample analysis

G =	House price	Weekly income	Initial value	Median value	Portfolio RSP	Age	Trading frequency	Login frequency
	Dependent variable: Sell							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$return^{-}$	−0.469***	−0.446***	−0.466***	−0.603***	−0.086	−0.174	−0.546***	−0.531***
	(0.105)	(0.099)	(0.090)	(0.126)	(0.080)	(0.113)	(0.106)	(0.103)
$return^{+}$	0.769***	0.854***	0.909***	0.961***	0.946***	0.815***	0.914***	0.918***
	(0.101)	(0.094)	(0.098)	(0.108)	(0.078)	(0.096)	(0.096)	(0.104)
I(extremeness)	−0.006	−0.005	−0.009	−0.011	−0.001	−0.010	−0.019***	−0.014***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.004)	(0.005)
$return^{-}\times$I(extremeness)	−1.465***	−1.461***	−1.803***	−1.290***	−0.688***	−1.264***	−2.183***	−1.481***
	(0.235)	(0.218)	(0.238)	(0.277)	(0.203)	(0.245)	(0.228)	(0.223)
$return^{+}\times$I(extremeness)	0.961***	0.836***	0.909***	0.637**	0.860***	0.953***	1.033***	0.697***
	(0.210)	(0.196)	(0.224)	(0.246)	(0.195)	(0.230)	(0.183)	(0.205)
I(G)$\times return^{-}$	0.210	0.185	0.200	0.333*	−0.842***	−0.295*	0.297*	0.296*
	(0.141)	(0.135)	(0.132)	(0.152)	(0.147)	(0.136)	(0.125)	(0.127)
I(G)$\times return^{+}$	0.046	−0.088	−0.171	−0.204	−0.326*	0.007	−0.161	−0.182
	(0.139)	(0.130)	(0.130)	(0.138)	(0.137)	(0.133)	(0.135)	(0.134)
I(G)$\times$I(extremeness)	−0.004	−0.008	0.001	0.003	−0.015*	0.002	0.022***	0.011
	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)
I(G)$\times return^{-}\times$I(extremeness)	−0.269	−0.413	0.166	−0.560	−1.290***	−0.643*	1.087***	−0.367
	(0.319)	(0.326)	(0.322)	(0.328)	(0.289)	(0.316)	(0.303)	(0.319)
I(G)$\times return^{+}\times$I(extremeness)	−0.144	0.087	−0.058	0.329	0.122	−0.124	−0.370	0.308
	(0.277)	(0.270)	(0.257)	(0.275)	(0.269)	(0.269)	(0.257)	(0.258)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Account × date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock × year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holding day decile FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	420,278	443,936	453,702	456,187	456,187	454,698	456,187	456,187
R^2	0.299	0.295	0.293	0.293	0.293	0.293	0.293	0.293
I(G)$\times return^{-}\times$I(extremeness)+ $return^{-}\times$I(extremeness)					−1.978***	−1.907***	−1.066***	

This table presents the subsample analysis testing whether the context effect varies in different groups of investors. $I(G)$ is a dummy indicating whether it is in a higher group. For Columns (1) - (4) and (6), $I(G)$ equals to 1 if the account characteristics are above the median at the account level. For Columns (5), (7) and (8), I(G) equals to 1 if the characteristics are above the median across all accounts on day $t-1$. Age (except three subjects) is available in the dataset. House price and weekly income are data in 2011 downloaded from Office for National Statistics and merged into dataset based on postcode. Some obeservations are missing because of the lack of investors' postcodes. The table presents the results from in Equation (1), whilst interacting $I(G)$ with the variables of interest ($return^{-}_{j,t-1}$,$return^{+}_{j,t-1}$, $I(extremeness)_{i,j,t-1}$, $I(extremeness)_{i,j,t-1}\times return^{-}_{j,t-1}$, $I(extremeness)_{i,j,t-1}\times return^{+}_{j,t-1}$). The dependent variable is a dummy equal to 1 if the stock is sold on day t. Control variables consist of $RSP^{-}_{i,j,t-1}$, $RSP^{+}_{i,j,t-1}$, $I(gain)_{i,j,t-1}$, $\sqrt{holding\ days}_{ijt}$, $RSP^{-}_{i,j,t-1}\times\sqrt{holding\ days}_{ijt}$, $RSP^{+}_{i,j,t-1}\times\sqrt{holding\ days}_{ijt}$, $variance_{i,j,t-1}$, $I(loss)_{i,j,t-1}\times variance_{i,j,t-1}$, $I(gain)_{i,j,t-1}\times variance_{i,j,t-1}$, $I(highest\,RSP)_{i,j,t-1}$ and $I(lowest\,RSP)_{i,j,t-1}$. *Account* × *date* FE refers to a fixed effect for each interaction of account and date. *Stock* × *year-month* FE refers to a fixed effect for each pair of sedol and year-month. *Holding day decile* FE refers to a fixed effect for each decile of holding lengths. Data cover the period between March 2012 and June 2016. Only accounts opened after the sample period started are included. Only portfolios with at least one sell on the day are included. Portfolios with less than 5 holdings and stocks held less than 5 days are excluded from the analysis. Standard errors clustered on account, date and stock levels are presented in parenthese with p values indicated by*p<0.05;**p<0.01; ***p<0.005.

Table 10. Context effect and probability of topping up

	Dependent variable:						
	Top Up						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
return$^-$	-1.261^{***}	-1.141^{***}	-1.159^{***}	-1.294^{***}	-1.363^{***}	-0.930^{***}	-0.975^{***}
	(0.059)	(0.056)	(0.055)	(0.057)	(0.063)	(0.047)	(0.053)
return$^+$	0.628^{***}	0.633^{***}	0.640^{***}	0.736^{***}	0.748^{***}	0.411^{***}	0.413^{***}
	(0.047)	(0.052)	(0.051)	(0.051)	(0.054)	(0.041)	(0.044)
I(extremeness)		-0.001	-0.009^{***}	-0.009^{***}	-0.011^{***}	-0.005^{***}	-0.010^{***}
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
return$^-$ $\times$ I(extremeness)		-0.479^{***}	-0.515^{***}	-0.433^{***}	-0.637^{***}	-0.364^{***}	-0.548^{***}
		(0.112)	(0.111)	(0.108)	(0.114)	(0.101)	(0.108)
return$^+$ $\times$ I(extremeness)		-0.036	0.003	-0.014	0.075	-0.011	0.109
		(0.082)	(0.081)	(0.081)	(0.090)	(0.075)	(0.081)
RSP$^-$				0.239^{***}	0.244^{***}	0.462^{***}	0.485^{***}
				(0.015)	(0.017)	(0.021)	(0.022)
RSP$^+$				-0.212^{***}	-0.193^{***}	-0.362^{***}	-0.364^{***}
				(0.013)	(0.014)	(0.016)	(0.016)
I(gain)				-0.009^{***}	-0.009^{***}	-0.005^{***}	-0.005^{***}
				(0.002)	(0.002)	(0.002)	(0.002)
I(highest RSP)				-0.0001	-0.001	-0.002	-0.003
				(0.002)	(0.002)	(0.002)	(0.002)
I(lowest RSP)				-0.001	0.002	-0.001	-0.0001
				(0.002)	(0.002)	(0.002)	(0.002)
Other variables	No	No	No	Yes	Yes	Yes	Yes
Account FE	Yes	Yes	Yes	Yes	No	Yes	No
Account $\times$ date FE	No	No	No	No	Yes	No	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	No	No
Stock $\times$ year-month FE	No	No	No	No	No	Yes	Yes
Holding day decile FE	No	No	Yes	Yes	Yes	Yes	Yes
Observations	703,718	703,718	703,718	703,718	703,718	703,718	703,718
R^2	0.068	0.068	0.070	0.075	0.157	0.143	0.226

This table presents the results testing whether the context effect influences topping up decisions. The dependent variable is a dummy equal to 1 if a stock is topped up on day t. $Return^+_{j,t-1}$ equals to 1-day return of the stock from the end of day $t-2$ to the end of day $t-1$ if the return is positive, 0 otherwise. Similarly, $return^-_{j,t-1}$ equals to 1-day return of the stock if it is negative, 0 otherwise. $I(extremeness_{i,j,t-1})$ is a dummy indicating whether the corresponding return is regarded extreme by the investor. The exact definition can be found in Table A1. $RSP^+_{i,j,t-1}$ equals to the return since purchase when the return since purchase is positive, 0 otherwise. Similarly, $RSP^-_{i,j,t-1}$ equals to return since purchase when if it is negative, 0 otherwise. $I(gain)_{i,j,t-1}$ is a dummy indicating whether return since purchase is positive. $I(highest\ RSP)_{i,j,t-1}$ is a dummy equal to 1 if the return since purchase is highest in the portfolio. $I(lowest\ RSP)_{i,j,t-1}$ is a dummy equal to 1 if the return since purchase is lowest in the portfolio. Other variables include $\sqrt{holding\ days}_{ijt}$, $RSP^-_{i,j,t-1} \times \sqrt{holding\ days}_{ijt}$, $RSP^+_{i,j,t-1} \times \sqrt{holding\ days}_{ijt}$, $variance_{i,j,t-1}$, $I(loss)_{i,j,t-1} \times variance_{i,j,t-1}$ and $I(gain)_{i,j,t-1} \times variance_{i,j,t-1}$. *Account* $\times$ *date* FE refers to a fixed effect for each interaction of account and date. *Stock*$\times$*year-month* FE refers to a fixed effect for each pair of sedol and year-month. *Holding day decile* FE refers to a fixed effect for each decile of holding lengths. Data cover the period between March 2012 and June 2016. Only accounts opened after the sample period started are included. Only portfolios with at least one top up on the day are included. Portfolios with less than 5 holdings and stocks held less than 5 days are excluded from the analysis. Standard errors clustered on account, date and stock levels are presented in parenthese with p values indicated by $^*p<0.05$; $^{**}p<0.01$; $^{***}p<0.005$.

Table 11. Context effects in managers' decisions on investment

	Dependent variable:		
	Capital expenditure (CAPX)		
	(1)	(2)	(3)
$Q_{i,t-1}$	0.066***	0.081***	0.014*
	(0.008)	(0.009)	(0.007)
I(extremeness)	−0.004	−0.019	−0.021
	(0.010)	(0.010)	(0.010)
$Q_{i,t-1}\times$ I(extremeness)	0.011*	0.014***	0.014***
	(0.004)	(0.005)	(0.004)
$CF_{i,t-1}$	0.207***	0.253***	0.246***
	(0.034)	(0.034)	(0.034)
$Q^2_{i,t-1}$	−0.004***	−0.005***	
	(0.001)	(0.000)	
$LEV_{i,t-1}$	−0.129***	−0.155***	−0.155***
	(0.001)	(0.025)	(0.025)
$ROA_{i,t-1}$	0.242***	0.269***	0.262***
	(0.042)	(0.043)	(0.042)
$CASH_{i,t-1}$	0.261***	0.280***	0.279***
	(0.033)	(0.037)	(0.038)
$\Delta Sales_{i,t-1}$	0.120***	0.102***	0.099***
	(0.012)	(0.012)	(0.012)
$InvAssets_{i,t-1}$	−0.038***	−0.040***	−0.039***
	(0.005)	(0.007)	(0.007)
Tobin's Q decile FE	No	No	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	No	No
Firm-manager FE	No	Yes	Yes
Observations	22,089	21,722	21,722
R^2	0.506	0.537	0.538

This table presents estimates from a yearly panel regression of investments (capital expenditure (CAPX)) on Tobin's Q ([Book value of assets – book value of equity + market value of equity] / book value of assets) and several control variables. Investment is measured at year t, and is divided by lagged assets. *Extremeness* is equal to $Q_{i,t-1} - max(Q)$, where $max(Q)$ is the maximum Q that the manager of company i at time t has seen from any companies he managed up until year $t-2$. $I(extremeness)$ is a dummy variable that equals 1 if *extremeness* is in the top 30% of the distribution in our sample. The control variables are cash flow (CF) defined as income before extraordinary items plus depreciation divided by total assets, Q^2, return on assets (ROA) defined as income before extraordinary items scaled by total assets, leverage (Lev) defined as total liabilities divided by total assets, the change in sales from $t-1$ to t divided by sales in $t-1$ ($\Delta Sales$), the inverse of total assets ($InvAssets$), the number of years in the company (*experienc*) and its interaction with Tobin's Q ($experience \times Q$). All the control variables are lagged. We drop firms in industries with SIC codes between 6000-6999 and 4000-4999. All continuous variables are winsorized at the 1% and 99% percentile. Data on the history of CEOs and their age is from Execucomp, and the remaining data are from Compustat. $Year$ FE indicates a fixed effect for each year. $Firm$ FE indicates a fixed effect for each firm. $Firm - manager$ FE refers to a fixed effect for each interaction of firm and manager. $Tobin's\ Q\ decile$ FE indicates a fixed effect for each decile of Tobin's Q. Our sample is from 1980-2020. The standard errors are double clustered at the firm and year levels. ***, ** and * indicate statistical significance at the 0.5%, 1% and 5% levels, respectively.

Appendices

Table A1. Variable definitions

Variable	Definition
$return_{j,t-1}$	The 1-day return of stock j on day $t-1$, calculated by $(price_{j,t-1} - price_{j,t-2})/price_{j,t-2}$.
$return^{-}_{j,t-1}$	Negative 1-day return. It equals to $return_{j,t-1}$ when it is negative, 0 otherwise.
$return^{+}_{j,t-1}$	Positive 1-day return. It equals to $return_{j,t-1}$ when it is positive, 0 otherwise.
$RSP_{i,j,t-1}$	The return since purchase of stock j on day $t-1$, calculated by $(price_{j,t-1} - average\ purchase\ price_{i,j,t-1})/average\ purchase\ price_{i,j,t-1}$.
$RSP^{-}_{i,j,t-1}$	Negative return since purchase. It equals to $RSP_{i,j,t-1}$ when it is negative, 0 otherwise.
$RSP^{+}_{i,j,t-1}$	Positive return since purchase. It equals to $RSP_{i,j,t-1}$ when it is positive, 0 otherwise.
$I(gain)_{i,j,t-1}$	A dummy indicating whether the corresponding return since purchase is positive. It equals to 1 if $RSP_{i,j,t-1} > 0$, 0 otherwise.
$I(loss)_{i,j,t-1}$	A dummy indicating whether the corresponding return since purchase is negative. It equals to 1 if $RSP_{i,j,t-1} < 0$, 0 otherwise.
$holding\ days_{i,j,t}$	The number of business days of stock j held by i on day t.
$extremeness_{i,j,t-1}$	It measures how extreme a 1-day return compared to other extreme 1-day returns experienced by j. If $return_{j,t-1} > 0$, it is defined as the difference between it and the highest of the highest 1-day returns of holdings in j's portfolio since purchase; if $return_{j,t-1} < 0$, it is defined as the lowest of the lowest 1-day returns of holdings in$j$'s portfolio since purchase minus the 1-day return: $return_{j,t-1} - max_j(max_t(return_{j,t-p}, ..., return_{j,t-2}))$ when $return_{j,t-1} > 0$; $min_j(min_t(return_{j,t-p}, ..., return_{j,t-1})) - return_{j,t-2}$ when $return_{j,t-1} < 0$; $t-p$ is the time when stock j was first purchased.
$I(extremeness)_{i,j,t-1}$	It is a dummy which equals to 1 if, the corresponding 1-day return is positive and the $extremeness_{i,j,t-1}$ is in the top quartile among others

Continued on next page

Table A1 Variable definitions (Continued)

Variable	Definition
	with corresponding positive 1-day returns, or, the corresponding 1-day return is negative and the $extremeness_{i,j,t-1}$ is in the top quartile among others with corresponding negative 1-day returns; 0 otherwise.
$variance_{i,j,t-1}$	The variance of 1-day returns of stock i from day $t-p$ to day $t-1$; $t-p$ is the time when stock j was first purchased.
$I(highest\ RSP)_{i,j,t-1}$	A dummy, equal to 1 when return since purchase of j is highest in the portfolio held by i at the end of day $t-1$; 0 otherwise.
$I(lowest\ RSP)_{i,j,t-1}$	A dummy, equal to 1 when return since purchase of j is lowest in the portfolio held by i at the end of day $t-1$; 0 otherwise.
ρ_{jk}	The correlation between 1-day returns of stock j and stock k. It equals to the pearson correlation of 1-day returns of two stocks in the past 3 months (or 6 months). If the return history is incomplete during the calculation period for either of the stocks, it equals to the pearson correlation of 1-day returns of two stocks in the past 20 working days. It is taken as a missing value if 1-day return history in the past 20 working days is incomplete, or there are no variations in returns during the calculation period.

Table A2. Logit regression and marginal effects

	Logit Regression	Marginal Effects
	Dependent variable:	
	sell	
	(1)	(2)
return^{-}	-9.573^{***}	-0.945^{***}
	(0.721)	(0.072)
return^{+}	11.804^{***}	1.166^{***}
	(0.570)	(0.057)
I(extremeness)	0.154^{***}	0.016^{***}
	(0.034)	(0.064)
$\text{return}^{-}\times$I(extremeness)	-7.973^{***}	-0.787^{***}
	(1.010)	(0.102)
$\text{return}^{+}\times$I(extremeness)	2.103^{**}	0.208^{**}
	(0.799)	(0.080)
RSP^{-}	2.140^{***}	0.211^{***}
	(0.228)	(0.023)
RSP^{+}	0.150	0.015
	(0.171)	(0.017)
I(gain)	0.294^{***}	0.029^{***}
	(0.032)	(0.003)
$\sqrt{holding\ days}$	-0.012^{***}	-0.001^{***}
	(0.003)	(0.000)
$\text{RSP}^{-}\times\sqrt{holding\ days}$	-0.005^{***}	-0.005^{***}
	(0.228)	(0.001)
$\text{RSP}^{+}\times\sqrt{holding\ days}$	-0.004^{***}	-0.004^{***}
	(0.171)	(0.001)
variance	-6.981	-0.689
	(15.037)	(1.486)
I(loss)$\times$variance	6.846	0.676
	(15.030)	(1.485)
I(gain)$\times$variance	6.362	0.628
	(15.028)	(1.485)
I(highest RSP)	1.112^{***}	0.154^{***}
	(0.031)	(0.005)
I(lowest RSP)	0.785^{***}	0.099^{***}
	(0.037)	(0.005)
Observations	456,187	
Log Likelihood	$-161{,}208.900$	

This table presents results from logit regression and marginal effects. The dependent variable is a dummy equal to 1 if the stock is sold on day t. $Return^{+}_{j,t-1}$ equals to 1-day return of the stock from the end of day $t-2$ to the end of day $t-1$ if the return is positive, 0 otherwise. Similarly, $return^{-}_{j,t-1}$ equals to 1-day return of the stock if it is negative, 0 otherwise. $I(extremeness_{i,j,t-1})$ is a dummy indicating whether the corresponding return is regarded extreme by the investor. The exact definitioncan be found in Table A1. Control variables consist of $RSP^{-}_{i,j,t-1}$, $RSP^{+}_{i,j,t-1}$, $I(gain)_{i,j,t-1}$, $\sqrt{holding\ days}_{ijt}$, $RSP^{-}_{i,j,t-1}\times\sqrt{holding\ days}_{ijt}$, $RSP^{+}_{i,j,t-1}\times\sqrt{holding\ days}_{ijt}$, $variance_{i,j,t-1}$, $I(loss)_{i,j,t-1}\times variance_{i,j,t-1}$, $I(gain)_{i,j,t-1}\times variance_{i,j,t-1}$,$I(highest\,RSP)_{i,j,t-1}$ and $I(lowest\,RSP)_{i,j,t-1}$. Data cover the period between March 2012 and June 2016. Only accounts opened after the sample period started are included. Only portfolios with at least one sell on the day are included. Portfolios with less than 5 holdings and stocks held less than 5 days are excluded from the analysis. Standard errors clustered on account and date levels are presented in parenthese with p values indicated by $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.005$.

Table A3. Main results with the sample containing holdings held longer than 1 holding day

	Dependent variable:						
	Sell						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
return$^-$	-0.815^{***}	-0.383^{***}	-0.384^{***}	-0.707^{***}	-0.618^{***}	-0.418^{***}	-0.357^{***}
	(0.086)	(0.078)	(0.077)	(0.070)	(0.078)	(0.063)	(0.072)
return$^+$	1.615^{***}	1.338^{***}	1.334^{***}	1.134^{***}	1.211^{***}	0.733^{***}	0.826^{***}
	(0.073)	(0.077)	(0.077)	(0.069)	(0.077)	(0.057)	(0.065)
I(extremeness)		-0.0002	-0.003	-0.008^{***}	-0.008^{*}	-0.001	-0.008^{*}
		(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
return$^-$×I(extremeness)		-1.530^{***}	-1.529^{***}	-1.496^{***}	-1.772^{***}	-1.345^{***}	-1.651^{***}
		(0.153)	(0.153)	(0.144)	(0.160)	(0.138)	(0.157)
return$^+$×I(extremeness)		1.015^{***}	1.017^{***}	0.845^{***}	0.992^{***}	0.722^{***}	0.883^{***}
		(0.134)	(0.134)	(0.127)	(0.152)	(0.114)	(0.146)
Controls	No	No	No	Yes	Yes	Yes	Yes
Account FE	Yes	Yes	Yes	Yes	No	Yes	No
Account × date FE	No	No	No	No	Yes	No	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	No	No
Stock × year-month FE	No	No	No	No	No	Yes	Yes
Holding day decile FE	No	No	Yes	Yes	Yes	Yes	Yes
Observations	480,890	480,890	480,890	480,890	480,890	480,890	480,890
R^2	0.099	0.100	0.100	0.124	0.188	0.221	0.289

This table presents the main results using the sample containing holdings held longer than 1 holding day. The dependent variable is a dummy equal to 1 if the stock is sold on day t. $Return^+_{j,t-1}$ equals to 1-day return of the stock from the end of day $t-2$ to the end of day $t-1$ if the return is positive, 0 otherwise. Similarly, $return^-_{j,t-1}$ equals to 1-day return of the stock if it is negative, 0 otherwise. $I(extremeness_{i,j,t-1})$ is dummy indicating whether the corresponding return is viewed as being extreme by the investor. The exact definitioncan be found in Table A1. $RSP^+_{i,j,t-1}$ refers to positive return since purchase. It equals to return since purchase when it is positive, 0 otherwise.$RSP^-_{i,j,t-1}$ refers to negative return since purchase. It equals to return since purchase when it is negative, 0 otherwise. $I(gain)_{i,j,t-1}$ is a dummy indicating whether return since purchase is positive; $I(loss)_{i,j,t-1}$ is a dummy indicating whether return since purchase is negative.$\sqrt{Holding\ days}_{ijt}$ is the squre root of the number of business days held by the investor. $Variance_{i,j,t-1}$ is the variance of the 1-day returns of the specific stock from the purchase day till day $t-1$. $I(highest\ RSP)_{i,j,t-1}$ is a dummy equal to 1 if the return since purchase is highest in the portfolio. $I(Lowest\ RSP)_{i,j,t-1}$ is a dummy equal to 1 if the return since purchase is lowest in the portfolio. *Account* ×*date* FE refers to a fixed effect for each interaction of account and date. *Stock* × *year-month* FE refers to a fixed effect for each pair of sedol and year-month. *Holding day decile* FE refers to a fixed effect for each decile of holding lengths. Data cover the period between March 2012 and June 2016. Only accounts opened after the sample period started are included. Only portfolios with at least one sell on the day are included. Portfolios with less than 5 holdings and stocks held less than (or equal to) 1 days are excluded from the sample. Standard errors clustered on account, date and stock levels are presented in parenthese with p values indicated by $^*p<0.05$; $^{**}p<0.01$; $^{***}p<0.005$.

Table A4. Main results with the sample containing portflios with at least 3 holdings

	Dependent variable:						
	Sell						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
return^-	-0.836^{***}	-0.412^{***}	-0.419^{***}	-0.738^{***}	-0.675^{***}	-0.442^{***}	-0.405^{***}
	(0.087)	(0.081)	(0.080)	(0.072)	(0.079)	(0.061)	(0.072)
return^+	1.655^{***}	1.345^{***}	1.346^{***}	1.125^{***}	1.237^{***}	0.716^{***}	0.827^{***}
	(0.076)	(0.079)	(0.080)	(0.070)	(0.077)	(0.052)	(0.064)
I(extremeness)		0.001	-0.002	-0.009^{***}	-0.015^{***}	-0.001	-0.015^{***}
		(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
$\text{return}^- \times$I(extremeness)		-1.431^{***}	-1.435^{***}	-1.452^{***}	-1.843^{***}	-1.321^{***}	-1.750^{***}
		(0.138)	(0.138)	(0.130)	(0.154)	(0.125)	(0.152)
$\text{return}^+ \times$I(extremeness)		1.114^{***}	1.120^{***}	0.962^{***}	1.274^{***}	0.845^{***}	1.176^{***}
		(0.131)	(0.131)	(0.122)	(0.146)	(0.107)	(0.136)
Controls	No	No	No	Yes	Yes	Yes	Yes
Account FE	Yes	Yes	Yes	Yes	No	Yes	No
Account × date FE	No	No	No	No	Yes	No	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	No	No
Stock × year-month FE	No	No	No	No	No	Yes	Yes
Holding day decile FE	No	No	Yes	Yes	Yes	Yes	Yes
Observations	531,403	531,403	531,403	531,403	531,403	531,403	531,403
R^2	0.126	0.128	0.128	0.154	0.227	0.245	0.323

This table presents the main results using the sample containing portflios with at least 3 holdings. The dependent variable is a dummy equal to 1 if the stock is sold on day t. $Return^+_{j,t-1}$ equals to 1-day return of the stock from the end of day $t-2$ to the end of day $t-1$ if the return is positive, 0 otherwise. Similarly, $return^-_{j,t-1}$ equals to 1-day return of the stock if it is negative, 0 otherwise. $I(extremeness_{i,j,t-1})$ is dummy indicating whether the corresponding return is viewed as being extreme by the investor. The exact definitioncan be found in Table A1. $RSP^+_{i,j,t-1}$ refers to positive return since purchase. It equals to return since purchase when it is positive, 0 otherwise.$RSP^-_{i,j,t-1}$ refers to negative return since purchase. It equals to return since purchase when it is negative, 0 otherwise. $I(gain)_{i,j,t-1}$ is a dummy indicating whether return since purchase is positive; $I(loss)_{i,j,t-1}$ is a dummy indicating whether return since purchase is negative.$\sqrt{Holding\ days}_{ijt}$ is the squre root of the number of business days held by the investor. $Variance_{i,j,t-1}$ is the variance of the 1-day returns of the specific stock from the purchase day till day $t-1$. $I(highest\ RSP)_{i,j,t-1}$ is a dummy equal to 1 if the return since purchase is highest in the portfolio. $I(Lowest\ RSP)_{i,j,t-1}$ is a dummy equal to 1 if the return since purchase is lowest in the portfolio. *Account* ×*date* FE refers to a fixed effect for each interaction of account and date. *Stock* × *year-month* FE refers to a fixed effect for each pair of sedol and year-month. *Holding day decile* FE refers to a fixed effect for each decile of holding lengths. Data cover the period between March 2012 and June 2016. Only accounts opened after the sample period started are included. Only portfolios with at least one sell on the day are included. Portfolios with less than 3 holdings and stocks held less than 5 days are excluded from the analysis. Standard errors clustered on account, date and stock levels are presented in parenthese with p values indicated by $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.005$.

Table A5. Regressions using extremeness constructed by market adjusted returns, portfolio adjusted returns and 1-day returns from all stocks and a regression controlling returns measured in pounds

I(extremeness.2)	portfolio adjusted	market adjusted	all stocks	-
	Dependent variable:			
	sell			
	(1)	(2)	(3)	(4)
return^-	−0.463***		−0.622***	−0.056
	(0.075)		(0.102)	(0.088)
return^+	0.846***		0.874***	0.380***
	(0.068)		(0.067)	(0.074)
$\text{market.ad.return}^-$		−0.419***		
		(0.070)		
$\text{market.ad.return}^+$		0.869***		
		(0.071)		
I(extremeness)				−0.008*
				(0.003)
$\text{return}^- \times$I(extremeness)				−1.609***
				(0.155)
$\text{return}^+ \times$I(extremeness)				0.760***
				(0.143)
I(extremeness.2)	−0.007*	−0.006*	−0.007***	
	(0.003)	(0.003)	(0.003)	
$\text{return}^- \times$I(extremeness.2)	−1.404***	−1.618***	−0.342***	
	(0.163)	(0.164)	(0.121)	
$\text{return}^+ \times$I(extremeness.2)	0.785***	0.808***	0.712***	
	(0.142)	(0.143)	(0.146)	
abs(return£)				0.0001***
				(0.00001)
$\text{return}^- \times$abs(return£)				−0.0001
				(0.0003)
$\text{return}^+ \times$abs(return£)				0.001***
				(0.0002)
Other variables	Yes	Yes	Yes	Yes
Account × date FE	Yes	Yes	Yes	Yes
Stock × year-month FE	Yes	Yes	Yes	Yes
Holding day decile FE	Yes	Yes	Yes	Yes
Observations	456,187	454,009	456,187	456,187
R^2	0.292	0.293	0.292	0.293

This table presents further robustness checks. Columns (1) to (3) present the results from regressions using extremeness constructed by market adjusted returns, portfolio adjusted returns and 1-day returns from all stocks (currently held and liquidated). In Columns (1) and (2), when extracting maximum and minimum returns from the past return history to construct *extremeness*, the return history is adjusted by market returns and portfolio return on that day. For the portfolio adjusted return, positive 1-day returns are adjusted by subtracting the mean of other positive 1-day returns generated by other holdings in the portfolio (subtracting 0 if all the other stocks all generated negative returns). Negative portfolio-adjusted 1-day returns are calculated in a similar manner. For the market adjusted return, 1-day returns are subtracted by FTSE all-share return on that day. In Column (3), when constructing *extremeness*, the comparison set includes returns from all stocks in corresponding holding periods held by investors, different from the baseline model where only stocks currently held are considered. In Column (4), the regression controls for returns measured in pounds and its interactions with 1-day returns. The dependent variable is a dummy equal to 1 if the stock is sold on day t. $Return^+_{j,t-1}$ equals to 1-day return of the stock from the end of day $t-2$ to the end of day $t-1$ if the return is positive, 0 otherwise. Similarly, $return^-_{j,t-1}$ equals to 1-day return of the stock if it is negative, 0 otherwise. Control variables consist of $RSP^-_{i,j,t-1}$, $RSP^+_{i,j,t-1}$, $I(gain)_{i,j,t-1}$, $\sqrt{holding\ days}_{ijt}$, $RSP^-_{i,j,t-1}\times\sqrt{holding\ days}_{ijt}$, $RSP^+_{i,j,t-1}\times\sqrt{holding\ days}_{ijt}$, $variance_{i,j,t-1}$, $I(loss)_{i,j,t-1}\times variance_{i,j,t-1}$, $I(gain)_{i,j,t-1}\times variance_{i,j,t-1}$,$I(highest\,RSP)_{i,j,t-1}$ and $I(lowest\,RSP)_{i,j,t-1}$. *Account × date* FE refers to a fixed effect for each interaction of account and date. *Stock × year-month* FE refers to a fixed effect for each pair of sedol and year-month. *Holding day decile* FE refers to a fixed effect for each decile of holding lengths. Data cover the period between March 2012 and June 2016. Only accounts opened after the sample period started are included. Only portfolios with at least one sell on the day are included. Portfolios with less than 5 holdings and stocks held less than 5 days are excluded from the analysis. Standard errors clustered on account, date and stock levels are presented in parenthese with p values indicated by $^*p$<0.05; $^{**}p$<0.01; $^{***}p$<0.005.

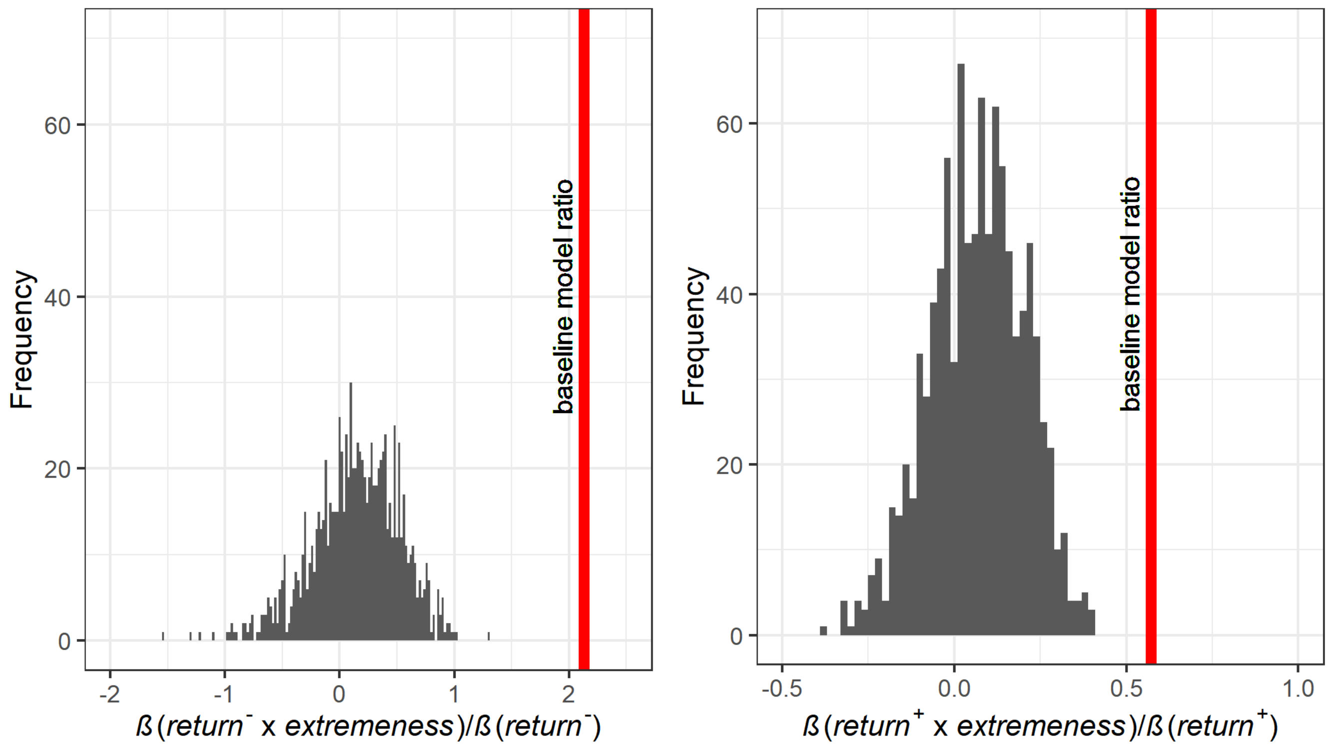

Figure A1. Results from the placebo test (using the continuous variable $extremeness$**)**
The figure shows the distribution of the ratio of interest ($\beta(return^{-} \times extremeness)/\beta(return^{-})$ and $\beta(return^{+} \times extremeness)/\beta(return^{+})$) in the placebo test. In the placebo test, the $extremeness$ is calculated by subtracting 1-day return by maximum/minimum return from a random portfolio without common stocks with the portfolio being considered, rather than the investors' experienced maximum/minimum return. The random match was carried out for 1,000 times. The distributions of ratios of interest are shown in the figure. The predicting model is identical as Column (3) Table 6 (except the way constructing $extremeness$), containing the $account \times date$ fixed effect, the $stock \times year\text{-}month$ fixed effect, the $Holding\ day\ decile$ fixed effect and following explanatory variables: $return^{-}$, $return^{+}$, $I(extremeness)$, $return^{-} \times I(extremeness)$, $return^{+} \times I(extremeness)$, RSP^{-}, RSP^{+}, $I(gain)$, $\sqrt{holding\ days}$, $RSP^{-} \times \sqrt{holding\ days}$, $RSP^{+} \times \sqrt{holding\ days}$, $variance$, $I(loss) \times variance$, $I(gain) \times variance$, $I(highest\ RSP)$ and $I(lowest\ RSP)$. The definitions of variables can found in Table A1. The baseline coefficients are taken from Column (3) Table 6.