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

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

August 23, 2021

Abstract

We use a large dataset of individual investor stock trades to demonstrate that investors are more likely to sell stocks with larger price changes in the previous day. This is consistent with investors trying to learn about the firms' fundamentals from stock returns. Our core contribution is to show that the *same* return elicits a much larger selling response when that return is extreme compared to the individual investor's own personal portfolio history of returns. The effect is large. When a return is extreme compared to an investor's personal history of returns, the coefficient on negative returns increases by a factor of 5.5 and the coefficient on positive returns increases by a factor of 2.0. Whereas stock returns are commonly considered to be "objective", here we have demonstrated considerable subjectivity in their perception.

[†]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

This work was supported by Economic and Social Research Council Grants ES/P008976/1, ES/N018192/1 and ES/V004867/1.

Stock price changes are signals about fundamental values to investors, thus play an important role in the transmission of information in equity markets. A large empirical literature demonstrates that investors' trading decisions with specific assets are affected by the returns these assets have generated in the past, which indicates that investors are indeed trying to learn from stock returns (e.g. Grinblatt, Titman, and Wermers, 1995; Grinblatt and Keloharju, 2000; Grinblatt and Keloharju, 2001; Badrinath and Wahal, 2002; Sias, 2007; Barber and Odean, 2008; Kaniel, Saar, and Titman, 2008; Campbell, Ramadorai, and Schwartz, 2009; Grinblatt, Jostova, Petrasek, and Philipov, 2020).

The question we ask in this study is whether *different* investors learn differently by observing the *same* stock return. Our hypothesis is motivated by research in psychology, which documents that the perception of a magnitude (like a stock return) is to some extent *subjective*, as it depends on previous experiences of a decision maker. For example, Jesteadt, Luce, and Green (1977) exposed some of their subjects to a soft noise and some others ones to a loud noise. Then, both groups are asked to assess the loudness of the same noise. Jesteadt, Luce, and Green (1977) found that the subjects who previously experienced the soft noise, assess the loudness of 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, shown to influence the sequential evaluations of various quantities in different contexts,[1] and are incorporated in several theories of risky choice.[2]

Motivated by these findings, we examine whether context effects influence how investors perceive stock returns. Our hypothesis can be illustrated with the following example: Two investors, X and Y, hold the portfolios shown in the table below. All stocks were purchased on day $t-4$. Both investors hold stock A. Suppose that both investors tend to sell shares in companies whose stock prices experienced large changes in the previous day. Thus Stock A is

[1]For a review in related neuroscience studies see Wallis and Kennerley (2011). For reviews of the literature in psychophysics see Laming (1997) and Stewart, Brown, and Chater (2005). For examples of context effects in behavioral economics see Brown, Gardner, Oswald, and Qian (2008) and Card, Mas, Moretti, and Saez (2012).

[2]This principle is embedded in theories of magnitude perception by adaptation level theory (Helson, 1964) and range frequency theory (Parducci, 1965), and in decision by sampling (Stewart, Chater, and Brown, 2006; Noguchi and Stewart, 2018). More generally, contextual evaluation is a well established phenomenon (e.g., norm theory, Kahneman and Miller (1986); support theory, Tversky and Koehler (1994)). Frydman and Jin (2019) present a theory of risky choice based on the principle of efficient coding, which predicts that decision makers will process more frequently encountered stimuli more efficiently.

a candidate for sale for both investors, as the 5.0% return on day $t-1$ is large.

(a) Investor X holds stock A, B and C

Day	A	B	C
t-4	−0.5%	+0.6%	−1.0%
t-3	+1.0%	−3.0%	0.0%
t-2	+2.0%	+1.0%	−0.9%
t-1	**+5.0%**	−0.2%	+0.7%

(b) Investor Y holds stock A, D, E and F

Day	A	D	E	F
t-4	−0.5%	−0.3%	+1.1%	+5.6%
t-3	+1.0%	+1.2%	−7.0%	+0.6%
t-2	+2.0%	+6.5%	+0.6%	−1.0%
t-1	**+5.0%**	−0.7%	−0.3%	+0.6%

However, it may be the case that Investor X is more likely to sell A compared to Investor Y. Why is this? For Investor X, the 1-day return for stock A on day $t-1$ is one of the largest returns she has experienced in her own portfolio. Stock A's return seems *extreme* for Investor X. But Investor Y does not sell stock A on day t, because Stock A's return does not seem particularly extreme for Investor Y. This is because Investor Y holds different stocks, and these stocks happen to have a history of larger magnitude returns. That is, sales are driven by the *perception* of the magnitude of the return, and not the objective magnitude of the return.

We test the hypothesis using portfolio-level trading data of 6,312 investors from a major brokerage platform in the United Kingdom from April 2012 to June 2016, used previously by Gathergood, Hirshleifer, Leake, Sakaguchi, and Stewart (2019) and Quispe-Torreblanca, Gathergood, Loewenstein, and Stewart (2020). In our models, building on the results of Barber and Odean (2008), we examine whether the probability of investors selling a specific stock is affected by the return that this stock has generated in the previous day.[3] The key innovation in our estimations is to allow the effect of the 1-day return on the probability of selling to depend upon the returns a specific investor has seen in the past. Specifically, for each investor, we find the maximum and minimum 1-day return that they have previously experienced (from any of the stocks they hold) and then compare the 1-day return with these previously experienced returns. If a specific 1-day return is very high or very low, compared to those which the investor has seen before, then it is classed as "extreme" using a dummy variable, which is interacted 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.

[3]We focus our analysis on the selling decisions of these investors, which can be modelled with relatively

Our models control for the return since purchase that a specific stock has generated for the investor, thus account 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* × *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* × *year-month* fixed effect.

We find that investors' personal histories of 1-day returns have a large effect on their selling behaviour. This is shown clearly in Figure 1, which plots the probability that a stock is sold against the 1-day return. The V-shape indicates that sales are more likely after large-magnitude 1-day returns, consistent with the attention grabbing hypothesis in Barber and Odean (2008). Figure 2 plots 1-day returns that are extreme compared to an investors' personal histories of 1-day returns separately. The much steeper V-shape when a return is extreme indicates that, for a given, objective 1-day return, investors are much more likely to sell if the return appears large compared to their own personal experience of 1-day 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.

A series of robustness checks is carried out. First, when modelling the decision to sell stock j, we define extremeness using all other stocks in the portfolio except j, to account for the possibility that the maximum or minimum return for this investor comes from stock j, and therefore it influences the "prior" of the investor for this stock (as opposed to the perception of the 1-day return generated by j). Our results continue to hold with this alternative way of measuring extremeness. Moreover, our results hold when defining the extremeness dummy using different cut-offs, or when using a continuous measure.

Second, we consider alternative econometric specifications. To account for public informa-

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 since we know the composition of investors' portfolios at any given day. 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.

tion for firms at frequencies higher than monthly, we replace the *stock* × *year-month* fixed effect with a *stock* × *year-week* fixed effect or a *stock* × *date* fixed effect. Our results continue to hold in all specifications. Another concern is that the model is misspecified by using linear relationship to capture the link between probability of selling and 1-day positive or negative returns. Two different specifications are adopted to address the concern: 1) adding a 1-day return decile fixed effect and 2) including square terms of 1-day returns and interactions between square terms and extremeness. The context effects persist in all these specifications.

Third, we carry out a placebo test to check whether the effect is from past experience. Instead of comparing 1-day returns to personal experienced extreme returns, they are compared to extreme returns recorded from a random portfolio, in which there are no stocks in common. The random match is carried out 100 times and the context effects disappear most of the time, which confirms that the effect revealed comes from personal experience.

In additional cross-sectional analysis, we find that, whereas all the types of investors we consider (e.g., age, wealth, performance, trading frequency) are affected by context effects, certain groups show the effect more strongly. We also find that context effects influence investors' buying decisions. Specifically, investors are more likely to top up an existing position, if the 1-day negative return generated by this stock is extreme.

We also explore whether the context effects influence more sophisticated investors. It has been shown that managers can learn from information revealed by their own firm's stock prices when making investment decisions (Bakke and Whited, 2010; Chen, Goldstein, and Jiang, 2007; Foucault and Fresard, 2014). Using the history of a standardized measure of stock price, Tobin's q, experienced by a manager, we find that managers are more sensitive to Tobin's q when it is extreme compared to past experience. An extreme Tobin's q is associated with a 10% increase in the investment.

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.

Our work also contributes to the literature which 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 overall 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.

The paper that is closest to our work is by Hartzmark and Shue (2018), who show that the returns after an earnings announcement today are higher if a large company announced lower earnings the day before. This finding suggests that investors' perception of how good an earnings announcement depends on other earnings announcements, in line with context effects. Whereas Hartzmark and Shue (2018) draw their conclusions based on a market-level event study of how stock prices assimilate information from earnings announcements in the previous day, our study contributes to the literature by showing direct, portfolio-level evidence that context effects influence investors' perception of stock returns.

1 Data and methods

1.1 Data source and sample construction criteria

This study employs transaction data from Barclays, one of the large retail trading platforms in the United Kingdom. The dataset records each transaction by each investor on the daily basis from April 2012 to June 2016. For each transaction, we can observe the customer identification, the stock identification code (Stock Exchange Daily Official List (SEDOL)), the execution date, the execution price, the transaction type (e.g. buy, sell), the executed quantity and the total cost.

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 cannot be obtained. As a result, the experienced returns before the sample period cannot be 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 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).[4] Further, to limit the effect of "day-trading" and some 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),[5] which is consistent with Hartzmark (2015).

The portfolio data is supplemented by price and split data matched by SEDOL from Datastream. 1-day return is calculated between the closing price of the stock on day $t-2$ and the closing price on day $t-1$. Return since purchase is calculated as the difference between the purchase price and the closing price on day $t-1$.

After applying all the selection criteria, 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 the holdings and account levels are shown in Table 1.

[4] 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 mismeasured. 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.

[5] We also carry out all analysis using the sample with portfolio with at least 3 holdings (with 531,403 observations). All the results reported hold qualitatively.

1.2 Econometric model and variable definitions

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

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

The dependent variable $Sell_{ijt}$ equals to 1 if investor i sold stock j in day t, and 0 otherwise. To capture the attention attracting effect from Barber and Odean (2008), that investors are more likely to focus stocks that experienced large drops or large increases in value in the previous day, our models incorporate different variables for negative and positive returns for company j, in day $t-1$, $return^-_{j,t-1}$ and $return^+_{j,t-1}$, respectively.[6] 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, which based on the findings of Barber and Odean (2008), we expect to be negative and positive, respectively.

To test for 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

[6] $Return_{j,t-1}$ captures the 1-day return of stock j from the end of day $t-2$ to the end of day $t-1$.

$min(return)_{i,t-2} - return^{-}_{j,t-1}$. Thus, increases in $extremeness_{i,j,t-1}$ reflect a return that is very different from what the 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 past day returns, if these are classed as extreme (i.e., $\beta_4 < 0$ and $\beta_5 > 0$). The benefit of testing the hypothesis using a dummy, is that the economic significance of context effects is 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 control for a series of variables, closely following Hartzmark (2015): a variable that equals to the return since purchase if it is negative and 0 otherwise ($RSP^{-}_{i,j,t-1}$), a variable equal to the return since purchase if it is positive and 0 otherwise ($RSP^{+}_{i,j,t-1}$), and a dummy variable equal to 1 if the corresponding return since purchase 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 standard disposition effect.

To account for the effect of holding duration for specific stocks, 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

[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.

interactions between returns since purchase and $\sqrt{holding\ days}_{ijt}$. To rule out the mechanical effect that stocks which are held for longer are more likely to reach extreme returns and be sold at the same time more robustly, 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 1-day returns of a holding, from the purchase day until day $t-1$ ($variance_{i,j,t-1}$), the interaction between the $variance_{i,j,t-1}$ and $I(gain)$ and the interaction between the $variance_{i,j,t-1}$ and $I(loss)$.

We also control for the rank effect documented by Hartzmark (2015), whereby stocks with the highest and lowest return since purchased are more likely to be sold. To this end, we control for $I(highest\,RSP)_{i,j,t-1}$ 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 introduce an *account* $\times$ *date* fixed effect, α_{it}. With this fixed effect, analysis is made within each portfolio at any given day. To control for time-varying firm characteristics that may be influencing investors selling decisions (such as past returns, market values, book-to-market ratios), we include a *stock* $\times$ *year-month* fixed effect.[8]

All continuous variables are winsorized at 1% and 99%. 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). 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.

[8]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 for different investors in the same day.

2 Results

2.1 Main results

Figure 2 plots the probability of selling, predicted from Equation (1), against the 1-day return. First, the clear V-shape is consistent with the attention grabbing hypothesis in Barber and Odean (2008), in which stocks with large magnitude 1-day returns, positive or negative, are more likely to be sold. Second, the V-shape is much steeper for stocks that are perceived as extreme in their 1-day return, consistent with the context effect hypothesis in which a given 1-day return is perceived as larger when an investor's personal 1-day return history contains smaller returns.

Table 2 shows the coefficients from a series of regressions based on Equation (1). We add controls and fixed effects sequentially. In Column 1 we use $return^{-}_{i,j,t-1}$ and $return^{+}_{i,j,t-1}$ as explanatory variables, together with *account* fixed effects and *stock* fixed effects. The probability of selling is significantly higher when the previous-day return is larger (in absolute value), in line with the findings of Barber and Odean (2008). The *account* fixed effects account for individual differences, such as risk preferences and investor sophistication. And the *stock* fixed effects control for differences among stocks, such as the preferences induced by the familiarity effect. The coefficient of 1.508 (-0.798) for $return^{+}$ ($return^{-}$) indicates that a 1 percentage point increase (decrease) in positive (negative) daily return is associated with a 1.508 (0.798) percentage point increase in the fraction of stocks sold.

Column 2 includes interactions between $I(extremeness)_{i,j,t-1}$ and $return_{i,j,t-1}$. The interactions are both significant at the 0.5% level. The interaction between $I(extremeness)_{i,j,t-1} \times return^{+}_{j,t-1}$ is positive, showing that investors are more likely to sell stocks with high positive returns, if these returns are extreme relative to the returns they have seen before. Similarly, the interaction $I(extremeness)_{i,j,t-1} \times return^{-}_{j,t-1}$ is negative, showing that investors are more likely to sell stocks after large price drops, if these drops are extreme. The economic magnitude of the context effects is substantial, as the coefficient on $return^{-}_{j,t-1}$ increases by more than a factor of five from -0.369 to -1.957 for extreme returns, and the coefficient on $return^{+}_{j,t-1}$ increases by a factor of almost two, from 1.242 to 2.217. The inclusion of *holding day decile* fixed effects (Column 3) does not change these results. These findings suggest that context effects influence investors' perception of stock returns, and that these context effects are stronger for negative returns.

In the remaining columns we add controls and additional fixed effects sequentially, with the full model shown in Column (7). The coefficients of interest drop slightly in magnitude, but remain statistically significant at the 0.5% level throughout. In terms of economic significance, the estimates in Column (7) imply that the coefficient on $return^-_{j,t-1}$ ($return^+_{j,t-1}$) reduces (increases) by a factor of 5.5 (2) when the return is classed as extreme, based on the investors prior experiences.

In terms of controls variables, we find that a stock with a positive return since purchase is 4.1 percentage more likely to be sold than a stock with a negative return since purchase, in line with the disposition effect. The coefficients on $I(highestRSP)_{i,j,t-1}$ and $I(lowestRSP)_{i,j,t-1}$ are positive and significant, in line with the rank-effect, identified by Hartzmark (2015). $Variance_{i,j,t-1}$ also has a positive coefficient, indicating that investors are more likely to sell volatile stocks. $RSP^-_{i,j,t-1}$ 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 stock returns.

2.2 Robustness Checks

2.2.1 Different definitions for extremeness

In our baseline analysis our extremeness dummy $I(extremeness)_{i,j,t-1}$ marks top quartile $extremeness_{i,j,t-1}$. To demonstrate that the results are not 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 3. 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 expected signs and are statistically significant at 0.5% level.

2.2.2 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, to make sure that information on higher frequencies is not affecting our results in Table 4, we replace the *stock* $\times$ *year-month* fixed effect with a *stock* $\times$ *year-week* fixed effect and a *stock* $\times$ *date* fixed effect. The full models are shown in Columns (2) and (4). The findings are in line with those in Table 2. All coefficients of variables of interest show expected signs and are statistically significant at 0.5% level.

2.2.3 Non-linear responses to 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, in Table 5, we estimate our baseline model whilst including a $return_{t-1}$ decile fixed effect in Column (1), and including $return^{2}_{j,t-1}$s in Column (2). The results are in line with those in Table 2, with the $return \times I(extremeness)$ interaction coefficients of similar value and remaining statistically significant at 0.5% level.

2.2.4 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 interpretations 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 Table 6, and are in line with our baseline findings from Table 2.

2.2.5 Placebo test

In earlier analysis, the $extremeness_{i,j,t-1}$ is calculated by subtracting personal experience of extreme returns from the return in day $t-1$. However, it is posible that the return in day $t-1$ dominates in the equation, such that the extreme return subtracted does not matter. If that is the case, the effect would not be from personal experiences. To address this concern, a placebo test using others' experienced extreme returns is carried out. In the placebo test, the maximum and minimum returns experienced in a portfolio is replaced by extreme returns from a random portfolio, in which there are no stocks in common. The $extremeness_{i,j,t-1}$ and $I(extremeness_{i,j,t-1})$ are then constructed by using the extreme returns from the randomly matched portfolio instead of personal experienced extreme returns.

The random match is carried out for 100 times. Related $extremeness_{i,j,t-1}$ and $I(extremeness_{i,j,t-1})$ are calculated and Equation (1) is estimated for each random match. The distributions of coefficients of key variables ($I(extremeness)_{i,j,t-1} \times return^{-}_{j,t-1}$ and $I(extremeness)_{i,j,t-1} \times return^{+}_{j,t-1}$) from 100 regressions are shown in Figure 3. For 100 coefficients of $I(extremeness)_{i,j,t-1} \times return^{-}_{j,t-1}$, 88% of them are either positive or negative insignificant ($p > 0.05$). The coefficent from the baseline model (-1.675) is 15.4 times standard deviation of coefficients (0.102) away from the mean of coefficients (-0.096). For 100 coefficients of $I(extremeness)_{i,j,t-1} \times return^{+}_{j,t-1}$, 79% of them are either negative or positive insignificant ($p > 0.05$). The coefficent from the baseline model (0.864) is 7.5 times standard deviation of coefficients (0.100) away from the mean of coefficients (0.108). Thus, it is safe to claim that the effect does not hold when maximum and minimum returns are drawn from random portflios.

Overall, the placebo test confirms the context effects demonstrated come from an investor's own past experiences.

2.3 Additional tests

2.3.1 Different comparison sets

Until now we have calculated $extremeness_{i,j,t-1}$ using return history of stocks currently held. However, returns generated by stocks that were held but fully liquidated can also exert effects according to the context effects hypothesis. To exmaine this, we re-define our extremeness measure, drawing the minimum and maximum returns for a given investor from all stocks, including those currently held and liquidated, and respective holding periods. The dummy $I(extremeness)_{i,j,t-1}$ is constructed in a similar manner, using 75%tile as a cutoff point. The results, shown in Column (1) Table 7, show that the coefficients of interest are of similar magnitude and statistical significance, as in our baseline results. Thus, our conclusions are robust to this alternative definition of the comparison set.

Next, we restrict the comparison set to returns from the holding periods of stocks that have been liquidated (ex-holding). Redefined maximum return, minimum return, $extremeness_{i,j,t-1}$ and $I(extremeness)_{i,j,t-1}$ are constructed in a similar way. Results are presented in Column (2) Table 7. Variables of interest show expected signs significantly. It means that although some stocks are liquidated, the experienced extreme returns would not be erased and continue to affect selling decisions. Further, we compare the effects from currently holding and ex-holding stocks. Two sets of $extremeness_{i,j,t-1}$ and $I(extremeness)_{i,j,t-1}$ are constructed based on comparison sets with returns from ex-holding stocks and currently holdings stocks separately. Column (3) Table 7 reports the results containing two definitions of $I(extremeness)_{i,j,t-1}$ and their interactions with $return^{-}_{j,t-1}$ and $return^{+}_{j,t-1}$. Results suggest that past extreme returns from both currently holding and ex-holding stocks play important roles in selling decisions. But, the extreme returns generated by currently holding stocks have stronger effects than those generated by ex-holding stocks when returns are negative (p=.008).

In additional, we consider limited attention of investors. In all tests above, maximum and minimum returns are drawn from all 1-day returns history over holding periods. However, investors may not be aware of all 1-day returns if they are not paying attention to their portfolio. Implicitly, this assumes that investors remember the maximum and minimum returns they have seen from all days. To examine the sensitivity of our results to this assumption, we draw the minimum and maximum returns for a given investor from the distributions of the 1-day returns of the stocks in their portfolio, only on days when the investor has logged in their portfolio (about 30% of all trading days). The dummy $I(extremeness)_{i,j,t-1}$ is constructed in a similar manner, using 75%tile as a cutoff point. The results, shown in Column (4) Table 7, show that the coefficients of interest are of similar magnitude and statistical significance, as in our baseline results. Thus, our conclusions are robust to this alternative limited-attention definition of the comparison set.

2.3.2 Different measures of returns

In the baseline model, we use positive and negative 1-day returns as explanatory variables following Barber and Odean (2008). However, it is not clear the return over which horizon is most memorable and has strongest impact on investors. In this section, variables measuring returns in longer periods are introduced: 3-day return, 1-week return, 2-week return, 3-week return and 1-month return. Maximum and minimum experienced returns in terms of aforementioned horizons are picked out for each portfolio similarly to the baseline model. $Extremeness_{i,j,t-1}$ is calculated in a similar manner by subtracting the minimum (maximum) experienced return from a negative (positive) return. The dummy $I(extremeness)_{i,j,t-1}$ is also constructed in a similar manner, using 75%tile as a cutoff point. Equation (1) is estimated using each one of the return variables instead of 1-day return and the probability of selling predicted by each model is shown in Figure 4.

From Figure 4, it can be seen that the "V" shape is always steeper when the *extremeness* is in the fourth quartile, compared to the one when the *extremeness* is in the first three quartiles, in all measures of the return. It suggests that the context effect holds no matter which horizon is chosen to measure the return. At the same time, it is evident that the "V" shapes of both fourth quartile and first three quartiles get flatter and flatter when the horizon gets longer and longer. It suggests that investors react more towards returns over a shorter period.

2.3.3 Recency effect and longer period effect

Several studies in finance have shown evidence of a recency effect on portfolio selection (Malmendier and Nagel, 2011; Bucciol and Zarri, 2015; Knüpfer, Rantapuska, and Sarvimäki, 2017). In this section we first examine whether the recency effect interacts with the context effect. A plausible hypothesis, is that maximum or minimum returns experienced more recently, are more vividly recalled by investors, and thus lead to a stronger context effect.

To test this hypothesis, we calculate the number of days between day $t-1$ and the day when the investor experienced the highest or lowest return. We construct a dummy variable, $I(G)$, equal to 1 if the length is equal or greater than the median and 0 otherwise.[9] We then estimate the model in Equation (1), whilst including interactions between this dummy and the main variables of interest. The results, presented in Columns (1) Table 8, show no interaction between recency and context effects. In Column (2) - (3) Table 8, the cutoff points used to construct $I(G)$ are changed to 75th percentile and 90th percentile respectively. The interactions between the dummy and context effects also show no effects. This finding suggests that time does not alleviate the memory of extreme return experiences. This is consistent with the peak-end effect, where the largest magnitude in a sequence is particularly prominent (Kahneman, Fredrickson, Schreiber, and Redelmeier, 1993).

Next we examine whether the context effects vary by the length since accounts opened. Since the experienced maximum or minimum returns would change more frequently in the beginning period since accounts opened than the later period, one might expect that the effect is stronger in the beginning period. On the other hand, the same objective return is less likely to be regarded extreme when the time goes on for an investor. As a result, the probability of selling would be higher for an extreme return, and thus the effect is stronger in the later period.

To test this, we find out the median trading day for each investor and construct a dummy variable, $I(G)$, equal to 1 if the trading day is after the median trading day and 0 otherwise. We then estimate the model in Equation (1), whilst including interactions between this dummy and the main variables of interest. The results are presented in Columns (4) Table 8. The coefficient of $I(G) \times return^{-}_{i,j,t-1} \times I(extremeness)_{i,j,t-1}$ is negative and statistically significant at the 5%

[9]The 25th, 50th, 75th and 90th percentiles of this length are 26 days, 74 days 175 days and 327 days respectively.

level, which implies that context effects is stronger in the later period. In Column (5) - (6) Table 8, the cutoff points used to construct $I(G)$ are changed to 75th percentile and 90th percentile trading day respectively. The coefficients of $I(G) \times return^{-}_{i,j,t-1} \times I(extremeness)_{i,j,t-1}$ are always negative and statistically significant, showing stronger context effects in the later period and supporting the second expectation discussed above.

2.3.4 Context effects and investor characteristics

In this section, we examine whether context effects are larger for certain types of investors. We consider nine features that may be related to portfolio outcomes: investor age, portfolio return volatility and investor sophistication, which we capture with variables such as the average house price in the postcode of the investor, the average weekly income of people in that area,[10] the initial value of the investors portfolio, the median portfolio value and median winning stock proportion. To examine whether investors who engage with their portfolio more exhibit different context effects, we use trading frequency and login frequency.

To conduct the tests, for each variable we define a dummy variable, $I(G)$, which takes the value of 1 if the specific investor is above median in the sample, and 0 otherwise.[11] We then estimate the model in Equation (1), whilst interacting $I(G)$ with the variables of interest ($return^{-}_{i,j,t-1}$, $return^{+}_{i,j,t-1}$, $I(extremeness)_{i,j,t-1}$, $I(extremeness)_{i,j,t-1} \times return^{-}_{i,j,t-1}$, $I(extremeness)_{i,j,t-1} \times return^{+}_{i,j,t-1}$). The results are reported on Table 10 Columns (1) - (9).

In terms of age, we find that the coefficient of $I(G) \times return^{-}_{i,j,t-1} \times I(extremeness)_{i,j,t-1}$ is negative and statistically significant at the 5% level, which implies that older people exhibit stronger context effects for negative returns. This is consistent with the finding that older investors hold inferior portfolios (Korniotis and Kumar, 2013).

Columns 2 and 3 show no effects related to the area investors reside in. Columns 4 and

[10] Related data in 2011 are acquired from Office for National Statistics.

[11] Note, $I(G)$ is a dummy for investors above the median age for (1); a dummy for investors living in the area with the median house price above the median among sample investors in (2); a dummy for investors living in the area with the median weekly income above the median among sample investors in (3); a dummy for investors having initial portfolio values above the median among sample investors in (4); a dummy for investors having median portfolio values above the median among sample investors in (5); a dummy for investors having the median winning stock proportion in the portfolio across the sample period above the median among sample investors in (6); a dummy for investors whose portfolio returns' standard deviation higher than median across the investors in (7); a dummy for investors trading more frequently than median across the holdings in (8); a dummy for investors logging in more frequently than median across the holdings in (9).

5 also show no effects related to investing size, measured either by the initial value and or the median value of the investor's portfolio. Next, we turn to portfolio performance, using the median winning stock proportion in an investor's portfolios as a proxy. The coefficient of $I(G) \times return^{-}_{j,t-1} \times I(extremeness)_{i,j,t-1}$ is statistically significant at the 0.5% level and it is about twice as large as the coefficient of $return^{-}_{j,t-1} \times I(extremeness)_{i,j,t-1}$. It implies that, investors with more winning stocks in their portfolio, exhibit stronger context effects. Next, we look into portfolio return volatility. If the experienced portfolio returns are less volatile, an extreme return would be more salient. We hypothesize that investors with less volatile portfolio returns would react more to extreme returns. The coefficient of $I(G) \times return^{-}_{j,t-1} \times I(extremeness)_{i,j,t-1}$ is positively significant at 0.5% level, consistent with the hypothesis.

Next we consider trading frequency, a variable analyzed by many studies in household finance (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 coefficients of main variables of interest, $I(G) \times return^{-}_{j,t-1} \times I(extremeness)_{i,j,t-1}$ and $I(G) \times return^{+}_{j,t-1} \times I(extremeness)_{i,j,t-1}$, are statistically significant at the 0.5% level and 5% level respectively. These findings show that investors who trade less frequently exhibit stronger context effects.

The last variable we consider is login frequency, a proxy for attention to the portfolio. Recent work has shown that investors who log in their account more often exhibit a weaker disposition effect (Dierick, Heyman, Inghelbrecht, and Stieperaere, 2019). We calculate the login frequency for each investor as the monthly average number of login days. There is no evidence showing login frequency has an impact on context effects, as the coefficients of key variables of interest are not statistically different from zero.

Overall, we find that context effects are exhibited by all the types of investors, with some evidence that people who are older, with more wining stocks in their portfolio, with lower portfolio returns' volatility and trade less often exhibit stronger context effects.

2.3.5 Topping up decisions

We focus our analysis on selling decisions, as these can be modelled accurately. However, context effects should also be affecting returns-based buying decisions. In this section we examine whether context effects influence the probability investors top 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. This is likely to be a simplification, however, as investors can be also considering other publicly listed companies, which they do not own.

The analysis here is the same as that presented in Table 2, except that the sell dependent variable is replaced with a topup dependent variable that equals to 1 if investor i tops up stock j in day t, and 0 otherwise. The results are presented in Table 9. 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. 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.

2.3.6 Managers' decisions on investment

It has been shown that managers can learn from information revealed by their own firms' stock prices when making investment decisions (Bakke and Whited, 2010; Chen, Goldstein, and Jiang, 2007; Foucault and Fresard, 2014). In this section we try to explore whether context effects play a role in managers' perception of stock prices. The hypothesis is that when Tobin's q is extremely high compared to past Tobin's q generated by the firm, it is perceived higher and leads to much higher investment. To test this hypothesis, a yearly panel is contructed with investment, firm characteristics and CEO information from Execucomp and Compustat.

The dependent variable is capital expenditure (CAPX) or the sum of CAPX and research and development (CAPX & R&D). To capture the effect of stock prices on investment and examine the context effects, the model includes Tobin's q ($Q_{i,t-1}$), $I(extremeness)$ and $Q_{i,t-1} \times I(extremeness)$. $Extremeness$ 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 (or Tobin's q decile fixed effects), 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, except CF, are lagged.

Results are shown in Table 11. The coefficient of $Q_{i,t-1} \times I(extremeness)$, is positive and significant across all model specifications, in line with the context effects hypothesis. It suggests that managers would perceive the same stock price higher if it is extremely high in the price history experienced. Overall, context effects does not affect only in the individual investors' perception, but also in managers' perception.

3 Discussion

We find that investors are more likely to sell stocks with extreme returns (as shown in Figure 1), consistent with attention grabbing hypothesis from Barber and Odean (2008). Our key finding is that the probability of selling increases when the same return is extreme in comparison to an investor's personal return experience (as shown in Figure 2). The coefficient on negative returns decreases by a factor of 5.5 and the coefficient on positive returns increases by a factor of 2. This result implies that investors perceive the magnitudes of returns relative to historical returns from their own portfolios. This is in line with large literature in neuroscience studies and psychology studies, showing that perception is affected by past exposures (e.g. Wallis and Kennerley, 2011; Laming, 1997; Stewart, Brown, and Chater, 2005). The context effect is robust after controlling for the disposition effect (e.g. Odean, 1998; Ben-David and Hirshleifer, 2012), the rank effect (Hartzmark, 2015), public information and different experiences on the same stock.

Although it has been widely recorded that investors trade using stock returns as signals (e.g. Barber and Odean, 2008; Kaniel, Saar, and Titman, 2008), there is an implicit assumption that all individual investors perceive a given return in the same the way. Our results suggest that investors' perceptions are highly affected by past returns from stocks in their own portfolios. Investors would take a given return as extreme if their experienced returns are mundane while others would take it as normal if their own personal history of experienced returns is volatile.

This finding also lends itself to reinforcement learning in the stock market (e.g. Strahilevitz, Odean, and Barber, 2011; Antoniou and Mitali, 2020), where different returns generated from the same stock over different periods lead to different reinvestment decisions. The context effect suggests that even the exactly same returns of a stock could be perceived and interpreted in different ways due to different trading experiences.

Subsample analysis reveals that, although the context effect exists for all types of investors, those with higher age, with smaller portfolio return volatility, with more winning stocks in the portfolio and trade less show a stronger context effect. These are consistent with the findings that older investors hold interior portfolios (Korniotis and Kumar, 2013) and that frequent trading is negatively correlated with portfolio returns (Barber and Odean, 2000; Grinblatt and Keloharju, 2009).

More sophisticated investors, such as firm managers, also display context effects. Managers react more to the Tobin's q when it is extreme compared to past experience. An extreme Tobin's q is associated with a substantially 10% increase in the investment.

4 Conclusion

The way investors treat returns has been regarded as investors using objective and common-knowledge return information as a signal of a firm's fundamental value. Here we show that the very same return elicits dramatically different selling behaviour for 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. Objective returns are interpreted subjectively.

References

An, Li, Joseph Engelberg, Matthew Henriksson, Baolian Wang, and Jared Williams, 2019, The portfolio-driven disposition effect, *Available at SSRN 3126997*.

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, *The 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.

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.

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.

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.

Brown, Gordon DA, Jonathan Gardner, Andrew J Oswald, and Jing Qian, 2008, Does wage rank affect employees' well-being?, *Industrial Relations: A Journal of Economy and Society* 47, 355–389.

Bucciol, Alessandro and Luca Zarri, 2015, The shadow of the past: Financial risk taking and negative life events, *Journal of Economic Psychology* 48, 1–16.

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.

Card, David, Alexandre Mas, Enrico Moretti, and Emmanuel Saez, 2012, Inequality at work: The effect of peer salaries on job satisfaction, *American Economic Review* 102, 2981–3003.

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, *The 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.

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, 2019, Efficient coding and risky choice, *Available at SSRN 3270773*.

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*.

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, 2000, The investment behavior and performance of various investor types: a study of Finland's unique data set, *Journal of Financial Economics* 55, 43–67.

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 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.

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.

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.

Knüpfer, Samuli, Elias Rantapuska, and Matti Sarvimäki, 2017, Formative experiences and portfolio choice: Evidence from the Finnish great depression, *Journal of Finance* 72, 133–166.

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.

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.

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.

Sias, Richard W, 2007, Reconcilable differences: Momentum trading by institutions, *Financial Review* 42, 1–22.

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.

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.

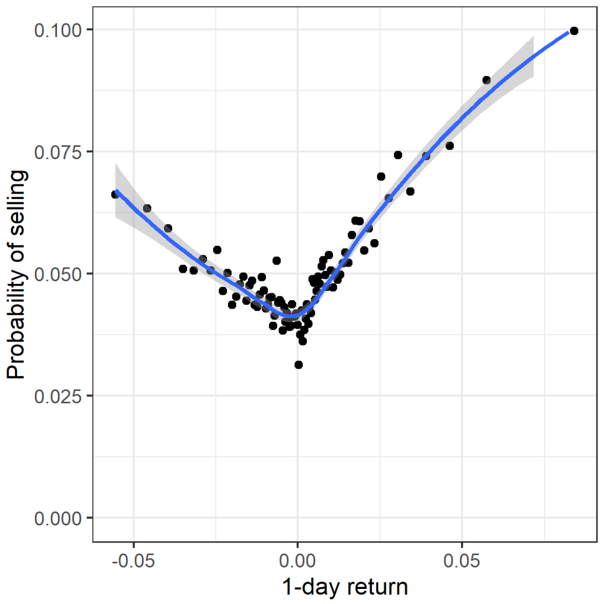

Figure 1. Probability of selling on each percentile of 1-day return
This figure shows the probability of selling on each percentile of 1-day return. Each point represents a percentile of 1-day return. The smoothed conditional means (the dark blue line) and the 95% confidence interval (grey area) are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

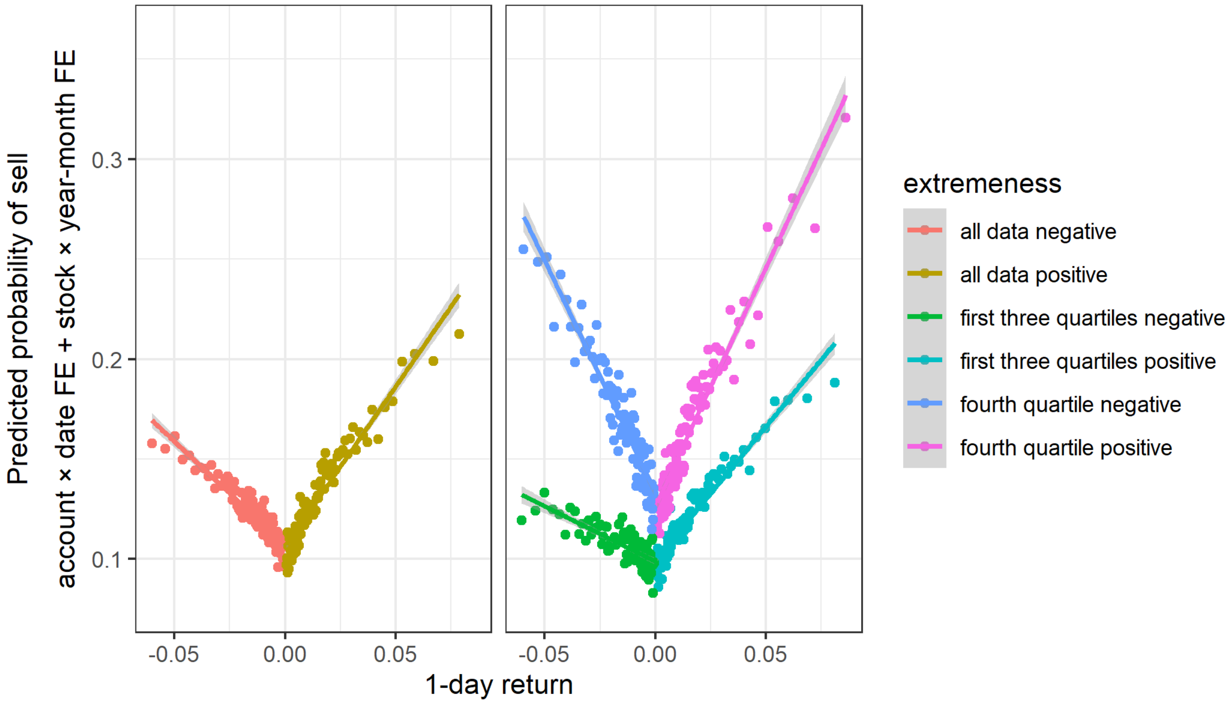

Figure 2. Predicted probability of selling on each percentile of 1-day return, adjusted by *account* $\times$ *date* FE and *stock* $\times$ *year-month* FE

The figure shows the probability of selling predicted by a linear model with *account* $\times$ *date* fixed effect and *stock* $\times$ *year-month* fixed effect. In the left panel, the prediction is broken into two branches: positive 1-day returns and negative 1-day returns. Each branch contains 100 points representing the predicted probability of each percentile. In the right panel, it is further broken by the first three quartiles and the fourth quartile of *extremeness* on top of the signs of 1-day returns. Fitted lines and confidence intervals are generated by linear models. The predicting model is identical as column (7) in Table 2, 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.

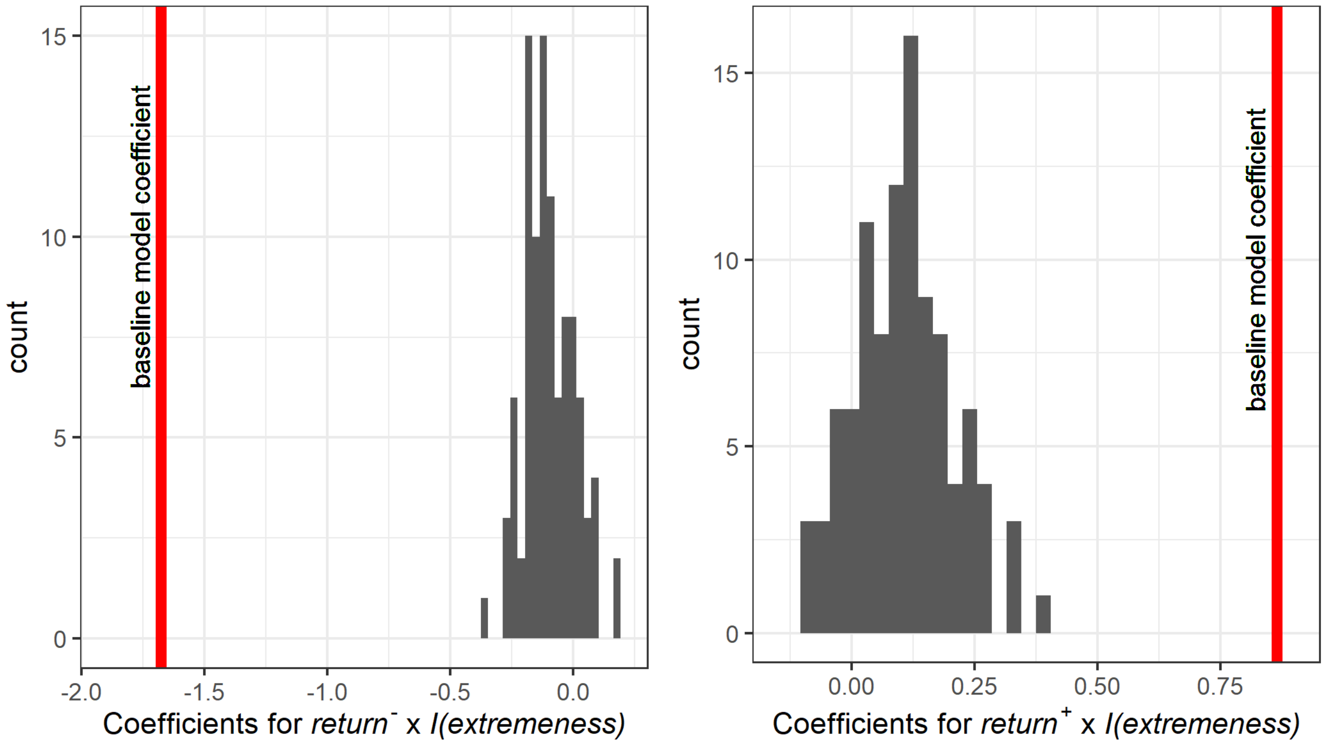

Figure 3. Results from the placebo test

The figure shows the distribution of key varaibles of interest ($return^{-}\times I(extremeness)$ and $return^{+}\times I(extremeness)$) 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 100 times and Model (1) was estimated based on each random match. The distributions of $return^{-}\times I(extremeness)$ and $return^{+}\times I(extremeness)$ 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.

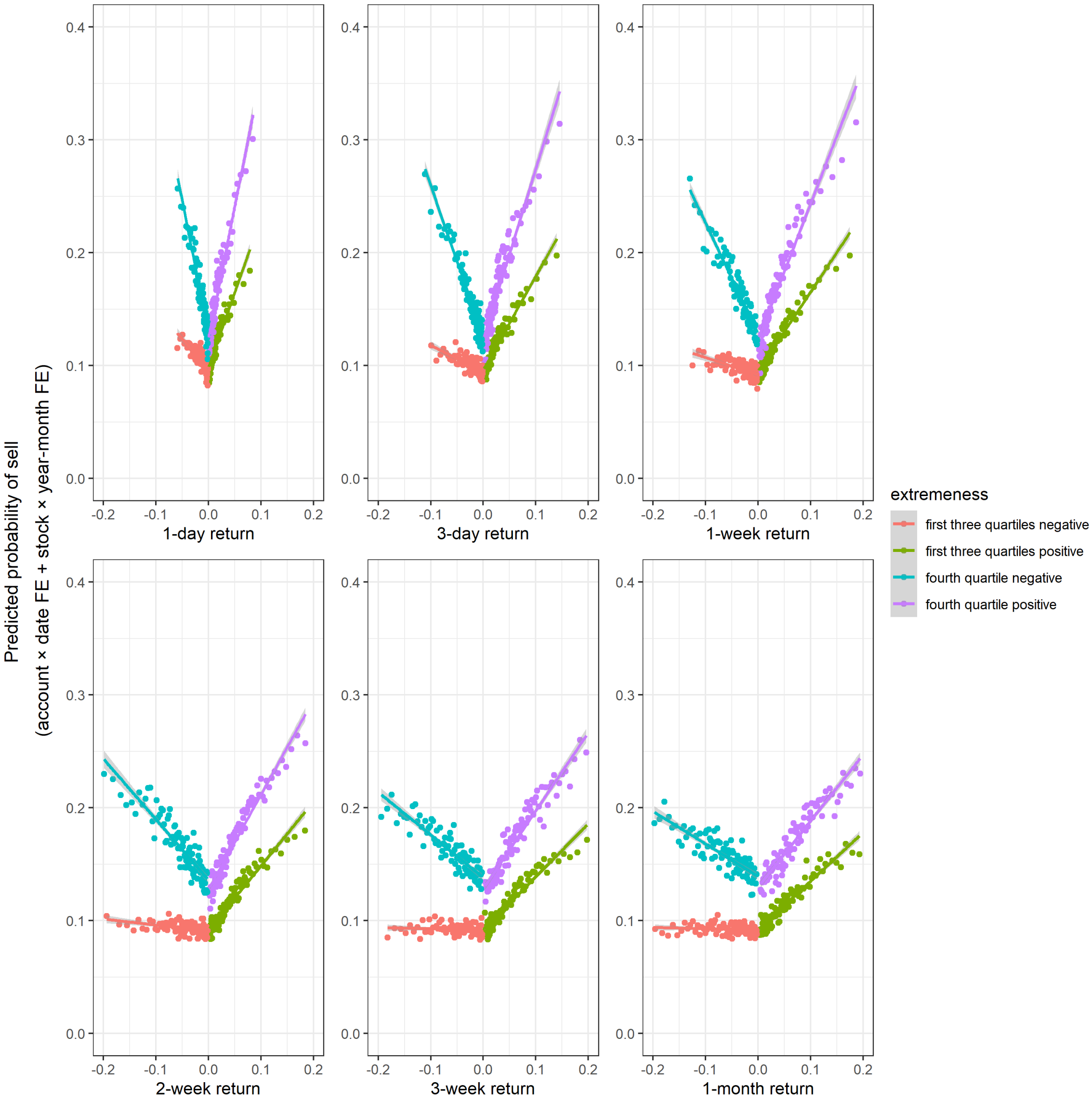

Figure 4. Predicted probability of selling on different measures of the return, adjusted by *account* $\times$ *date* FE and *stock* $\times$ *year-month* FE

The figure shows the probability of selling predicted by a linear model with *account* $\times$ *date* fixed effect and *stock* $\times$ *year-month* fixed effect 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. Fitted lines are generated by linear models. The predicting model is identical as column (7) in Table 2 (except different measures of the return), 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.

Table 1. Summary statistics

Panel A: Summary statistics at the holding level

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
return	456,187	0.0004	0.023	−0.075	−0.009	0.000	0.009	0.089
negative return	198,992	−0.016	0.016	−0.075	−0.021	−0.011	−0.005	−0.00000
positive return	202,388	0.017	0.019	0.00000	0.005	0.011	0.021	0.089
return since purchase	456,187	−0.021	0.226	−0.740	−0.108	−0.010	0.070	0.774
$\sqrt{holding\ days}$	456,187	10.785	5.767	2.236	6.083	9.849	14.697	25.768
variance	456,187	0.001	0.025	0.000	0.0002	0.0003	0.001	9.835
number of holdings	456,187	16.412	14.022	5	8	12	19	128
extremeness	456,187	−0.235	0.253	−1.646	−0.276	−0.156	−0.090	−0.019
extremeness (negative 1-day return)	206,762	−0.193	0.149	−0.999	−0.273	−0.148	−0.083	−0.017
extremeness (positive 1-day return)	198,992	−0.195	0.150	−0.999	−0.274	−0.150	−0.084	−0.019
sell	456,187	0.123	0.328					

Panel B: Summary statistics at the account level

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
age	6,309	47.678	15.205	12.000	32.000	52.000	62.000	112.000
selling.rate	6,312	0.201	0.144	0.000	0.125	0.171	0.200	1.000
% female	5525	17.5						

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)
$\sqrt{holding\ days}$				0.0004	−0.0001	−0.0001	−0.001
				(0.0003)	(0.001)	(0.001)	(0.001)
$\text{RSP}^{-}\times\sqrt{holding\ days}$				-0.003^{*}	−0.002	-0.006^{***}	-0.007^{***}
				(0.001)	(0.001)	(0.001)	(0.002)
$\text{RSP}^{+}\times\sqrt{holding\ days}$				-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)×variance				1.133	0.227	3.979^{*}	4.329^{**}
				(2.338)	(2.768)	(1.861)	(1.621)
I(gain)×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 × 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	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 treat the same 1-day returns differently if returns are extreme for an investor. 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* $\times$*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 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. Robustness check using different extremeness dummy cutoff points and the continuous extremeness variable

	Dependent variable:		
	Sell		
Extremeness variants	50%tile as dummy cutoff point	90%tile as dummy cutoff point	original continuous variable
	(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 75%tile as a cutoff point when constructing $I(extremeness)_{i,j,t-1}$, the 50%tile is used in Column (1); the 90%tile is used in Column (2); and the original continuous $extremeness_{i,j,t-1}$ is used 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 4. Robustness check 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-month* refers to a fixed effect for each pair of sedol and year-month. *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 5. Robustness tests 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)
return^- × I(extremeness)	-1.646^{***}	-1.639^{***}
	(0.155)	(0.155)
return^+ × I(extremeness)	0.841^{***}	0.837^{***}
	(0.140)	(0.141)
Controls	Yes	Yes
Account × date FE	Yes	Yes
Stock × 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 a control. 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 $RSP^-_{i,j,t-1}$, $RSP^+_{i,j,t-1}$, $I(gain)_{i,j,t-1}$, $\sqrt{holding\ days}_{ijt}$, $RSP^-_{i,j,t-1} \times \sqrt{holding\ days}_{ijt}$, $RSP^+_{i,j,t-1} \times \sqrt{holding\ days}_{ijt}$, $variance_{i,j,t-1}$, $I(loss)_{i,j,t-1} \times variance_{i,j,t-1}$, $I(gain)_{i,j,t-1} \times variance_{i,j,t-1}$, $I(highestRSP)_{i,j,t-1}$ 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* 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 6. Robustness check using extremeness (dummy) calculated by the highest/lowest 1-day return except itself

	Dependent variable:	
	Sell	
	(1)	(2)
return^{-}	-0.336^{***}	-1.379^{***}
	(0.072)	(0.112)
return^{+}	0.800^{***}	1.225^{***}
	(0.066)	(0.082)
I(extremeness)	-0.006^{*}	
	(0.003)	
extremeness		0.005
		(0.006)
$\text{return}^{-}\times$I(extremeness)	-1.522^{***}	
	(0.142)	
$\text{return}^{+}\times$I(extremeness)	0.774^{***}	
	(0.123)	
$\text{return}^{-}\times$extremeness		-3.000^{***}
		(0.402)
$\text{return}^{+}\times$extremeness		0.653^{***}
		(0.133)
Controls	Yes	Yes
Account × date FE	Yes	Yes
Stock × year-month FE	Yes	Yes
Holding day decile FE	Yes	Yes
Observations	456,187	456,187
R^2	0.293	0.292

This table presents the results from linear regressionss testing wether the results come from different priors. To test this, $extremeness_{i,j,t-1}$ is recalculted by comparing a 1-day return to the highest/lowest 1-day returns from stocks other than the holding stock, different from the set consisting all stocks in the portfolio. 75%tile is used as the dummy cutoff point again when constructing $I(extremeness)_{i,j,t-1}$. The regression using $I(extremeness)_{i,j,t-1}$ is presented in Column (1) while the one using $extremeness_{i,j,t-1}$ is shown in Column (2). 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. Calculating extremeness (dummy) calculated by different comparison sets

Comparison set for extremeness.1	all stocks	ex-holding	holding	login days
Comparison set for extremeness.2	-	-	ex-holding	-
	Dependent variable:			
	sell			
	(1)	(2)	(3)	(4)
return^-	-0.622^{***}	-1.125^{***}	-1.673^{***}	-0.328^{***}
	(0.102)	(0.127)	(0.175)	(0.072)
return^+	0.874^{***}	1.220^{***}	1.363^{***}	0.773^{***}
	(0.067)	(0.094)	(0.114)	(0.066)
I(extremeness.1)	-0.007^{***}	-0.001	-0.0004	-0.005
	(0.003)	(0.007)	(0.006)	(0.003)
$\text{return}^-\times$I(extremeness.1)	-0.342^{***}	-1.881^{***}	-2.924^{***}	-1.475^{***}
	(0.121)	(0.522)	(0.466)	(0.133)
$\text{return}^+\times$I(extremeness.1)	0.712^{***}	0.653^{***}	0.658^{***}	0.811^{***}
	(0.146)	(0.216)	(0.165)	(0.135)
I(extremeness.2)			0.002	
			(0.007)	
$\text{return}^-\times$I(extremeness.2)			-1.649^{***}	
			(0.500)	
$\text{return}^+\times$I(extremeness.2)			0.513^{*}	
			(0.207)	
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	356,101	356,101	456,187
R^2	0.292	0.281	0.282	0.293

This table presents robustness check by constructing *extremeness* based on different comparison sets. In Column (1), the comparison set includes returns from all stocks and related holding periods ever held by investors. In Column (2), the comparison set is restricted to all past holdings (ruling out stocks that are currently held) and respective holding periods. In Column (3), two (*extremeness*)es are calculated: the first one is the same as in baseline model, with all stocks currently in the portfolio; the second one is the same as in Column (2), with ex-holdings. In Column (4), the comparison set is contrained from all holding days to login days of holdings stocks. 75%tile is used as the dummy cutoff point again when constructing $I(extremeness)_{i,j,t-1}$. $Return^+_{j,t-1}$ 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 5 than 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 and longer period effect

G =	Recency			Longer period		
I(G) cutoff point	50%tile	75%tile	90%tile	50%tile	75%tile	90%tile
	Dependent variable:					
	Sell					
	(1)	(2)	(3)	(4)	(5)	(6)
return$^-$	−0.345***	−0.388***	−0.407***	−0.448***	−0.436***	−0.397***
	(0.092)	(0.078)	(0.072)	(0.097)	(0.080)	(0.078)
return$^+$	0.746***	0.809***	0.850***	0.875***	0.841***	0.840***
	(0.091)	(0.076)	(0.069)	(0.093)	(0.081)	(0.074)
I(extremeness)	−0.007	−0.008*	−0.009**	−0.006	−0.007	−0.007
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
return$^-$×I(extremeness)	−1.710***	−1.658***	−1.648***	−1.377***	−1.405***	−1.532***
	(0.196)	(0.167)	(0.159)	(0.203)	(0.175)	(0.169)
return$^+$×I(extremeness)	0.826***	0.911***	0.851***	0.747***	0.834***	0.855***
	(0.161)	(0.154)	(0.144)	(0.183)	(0.163)	(0.154)
I(G)	−0.001	−0.001	−0.004			
	(0.003)	(0.003)	(0.004)			
I(G)×return$^-$	−0.045	0.083	0.377*	0.125	0.182	0.150
	(0.122)	(0.134)	(0.179)	(0.108)	(0.114)	(0.155)
I(G)×return$^+$	0.135	0.037	−0.263	−0.088	−0.058	−0.108
	(0.113)	(0.122)	(0.149)	(0.110)	(0.112)	(0.133)
I(G)×I(extremeness)	−0.005	0.001	0.012	−0.006	−0.007	−0.010
	(0.006)	(0.008)	(0.014)	(0.007)	(0.008)	(0.010)
I(G)×return$^-$×I(extremeness)	0.076	−0.057	−0.155	−0.579*	−0.913***	−0.856*
	(0.281)	(0.374)	(0.603)	(0.278)	(0.292)	(0.418)
I(G)×return$^+$×I(extremeness)	0.180	−0.284	−0.091	0.221	0.100	0.049
	(0.241)	(0.333)	(0.461)	(0.249)	(0.287)	(0.348)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Account × date FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock × year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Holding day decile FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	456,187	456,187	456,187	456,187	456,187	456,187
R^2	0.293	0.293	0.293	0.293	0.293	0.293

This table presents the results from linear regressions exploring the recency effect and the longer period effect. For the recency effect, the length between current day and the day one experienced corresponding max/min 1-day return is calculated and 25th, 50th, 75th, 90th percentiles are 26 days, 74 days, 175 days and 327 days respectively. In Coumn (1)-(3), $I(G)$ equals to 1 when the length is greater or equal to 74 days, 125 days, 327 days respectively, 0 otherwise. For the longer period effect, median, 75%tile and 90%tile trading dates are picked out for each individuals. In Coumn (4)-(6), $I(G)$ equals to 1 when the trading dates are later than the median, 75%tile and 90%tile trading date 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. Linear regressions on testing perceived 1-day returns: 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)
$\text{return}^- \times$ 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)
$\text{return}^+ \times$ 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 × 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	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 contrast effect influences topping up decisions. The dependent variable is a dummy equal to 1 if the 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 viewed as being 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* × *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 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 10. Subsample analysis: extremeness defined by using the highest 1-day return in portfolio

	Dependent variable:								
	Sell								
G =	Age	House price	Weekly income	Initial value	Median value	Winning stock proportion	Portfolio return standard deviation	Trading frequency	Login frequency
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
return$^-$	−0.174	−0.469***	−0.446***	−0.466***	−0.603***	0.007	−2.331***	−0.559***	−0.423***
	(0.113)	(0.105)	(0.099)	(0.090)	(0.126)	(0.077)	(0.193)	(0.107)	(0.106)
return$^+$	0.815***	0.769***	0.854***	0.909***	0.961***	0.950***	1.379***	0.851***	0.911***
	(0.096)	(0.101)	(0.094)	(0.098)	(0.108)	(0.073)	(0.123)	(0.092)	(0.100)
I(extremeness)	−0.010	−0.006	−0.005	−0.009	−0.011	−0.005	−0.011	−0.017***	−0.012**
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.009)	(0.004)	(0.005)
return$^-$×I(extremeness)	−1.264***	−1.465***	−1.461***	−1.803***	−1.290***	−0.649***	−4.881***	−2.254***	−1.669***
	(0.245)	(0.235)	(0.218)	(0.238)	(0.277)	(0.213)	(0.576)	(0.235)	(0.214)
return$^+$×I(extremeness)	0.953***	0.961***	0.836***	0.909***	0.637**	1.141***	0.949***	1.131***	0.739***
	(0.230)	(0.210)	(0.196)	(0.224)	(0.246)	(0.181)	(0.233)	(0.183)	(0.193)
I(G)×return$^-$	−0.295*	0.210	0.185	0.200	0.333*	−1.280***	1.809***	0.315*	0.103
	(0.136)	(0.141)	(0.135)	(0.132)	(0.152)	(0.174)	(0.249)	(0.135)	(0.140)
I(G)×return$^+$	0.007	0.046	−0.088	−0.171	−0.204	−0.454***	−0.216	−0.054	−0.174
	(0.133)	(0.139)	(0.130)	(0.130)	(0.138)	(0.141)	(0.162)	(0.131)	(0.130)
I(G)×I(extremeness)	0.002	−0.004	−0.008	0.001	0.003	−0.008	0.019	0.019**	0.008
	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.011)	(0.007)	(0.007)
I(G)×return$^-$×I(extremeness)	−0.643*	−0.269	−0.413	0.166	−0.560	−1.284***	3.815***	1.354***	−0.001
	(0.316)	(0.319)	(0.326)	(0.322)	(0.328)	(0.311)	(0.849)	(0.327)	(0.326)
I(G)×return$^+$×I(extremeness)	−0.124	−0.144	0.087	−0.058	0.329	−0.361	−0.341	−0.586*	0.245
	(0.269)	(0.277)	(0.270)	(0.257)	(0.275)	(0.270)	(0.275)	(0.274)	(0.264)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Account × date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock × year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holding day decile FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	454,698	420,278	443,936	453,702	456,187	456,187	456,187	456,187	456,187
R^2	0.293	0.299	0.295	0.293	0.293	0.293	0.293	0.293	0.293
I(G)×return$^-$×I(extremeness)+ return$^-$×I(extremeness)	−1.907***	−1.734***	−1.874***	−1.637***	−1.850***	−1.933***	−1.066	−0.900**	−1.670***
I(G)×return$^+$×I(extremeness)+ return$^+$×I(extremeness)	0.829***	0.817***	0.923***	0.851***	0.966***	0.780***	0.608***	0.545***	0.984***

This table presents the results from linear regressions testing whether the contrast effect varies in different groups of investors. $I(G)$ is a dummy indicating whether it is in a higher group. For Columns (1) - (7), $I(G)$ equals to 1 if the account characteristics are above the median at the account level. For Columns (8) and (9), I(G) equals to 1 if the characteristics are above the median at the holding level. 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 ($return^-_{j,t-1}$,$return^+_{j,t-1}$, $I(extremeness)_{i,j,t-1}$, $I(extremeness)_{i,j,t-1} \times return^-_{j,t-1}$, $I(extremeness)_{i,j,t-1} \times return^+_{j,t-1}$). 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 $I(lowest\ RSP)_{i,j,t-1}$. The dependent variable is a dummy equal to 1 if the stock is sold on day t. *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 11. Context effects in managers' decisions on investment

	Dependent variable:			
	Capital expenditure (CAPX)		CAPX & R&D	
	(1)	(2)	(3)	(4)
$Q_{i,t-1}$	0.021***	0.003***	0.037***	0.011***
	(0.002)	(0.001)	(0.003)	(0.003)
$Q_{i,t-1}\times$ I(extremeness)	0.002***	0.002***	0.003**	0.003***
	(0.001)	(0.000)	(0.001)	(0.001)
I(extremeness)	−0.001	−0.003*	−0.004	−0.005**
	(0.001)	(0.001)	(0.002)	(0.002)
$CF_{i,t-1}$	0.064***	0.061***	0.019	0.015
	(0.007)	(0.007)	(0.012)	(0.012)
$Q^2_{i,t-1}$	−0.002***		−0.002***	
	(0.000)		(0.000)	
$LEV_{i,t-1}$	−0.035***	−0.036***	−0.044***	−0.045***
	(0.003)	(0.003)	(0.006)	(0.006)
$ROA_{i,t-1}$	0.010*	0.008	−0.045***	−0.048***
	(0.005)	(0.005)	(0.013)	(0.013)
$CASH_{i,t-1}$	−0.007	−0.007	0.015	0.014
	(0.005)	(0.005)	(0.008)	(0.008)
$\Delta Sales_{i,t-1}$	0.011***	0.010***	0.011***	0.010***
	(0.002)	(0.002)	(0.003)	(0.003)
$InvAssets_{i,t-1}$	0.665***	0.660***	2.051***	2.045***
	(0.109)	(0.109)	(0.228)	(0.228)
$Experience_{i,t-1}$	0.002	0.001	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
$Experience_{i,t-1}\times Q_{i,t-1}$	−0.000	−0.000	−0.001*	−0.001*
	(0.000)	(0.000)	(0.001)	(0.001)
Tobin's Q decile FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	32,354	32,354	32,354	32,354
R^2	0.666	0.668	0.725	0.726

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 company 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. In all columns we include firm and year fixed effects, whereas in Columns (2) and (4) we additionally include Tobin's Q decile fixed effects. 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 $t-1$
$I(lowest\ RSP)_{i,j,t-1}$	A dummy, equal to 1 when return since purchase of j is lowest in the portfolio held by i at the end of day $t-1$

Table A2. Logit regression and marginal effects

	Logit Regression	Marginal Effects
	Dependent variable:	
	sell	
	(1)	(2)
return$^-$	-9.573^{***}	-0.945^{***}
	(0.423)	(0.001)
return$^+$	11.804^{***}	1.166^{***}
	(0.328)	(0.032)
I(extremeness)	0.154^{***}	0.016^{***}
	(0.014)	(0.001)
return$^-$×I(extremeness)	-7.973^{***}	-0.787^{***}
	(0.704)	(0.070)
return$^+$×I(extremeness)	2.103^{***}	0.208^{***}
	(0.613)	(0.061)
RSP$^-$	2.140^{***}	0.211^{***}
	(0.114)	(0.011)
RSP$^+$	0.150	0.015
	(0.089)	(0.009)
I(gain)	0.294^{***}	0.029^{***}
	(0.013)	(0.001)
$\sqrt{holding\ days}$	-0.012^{***}	-0.001^{***}
	(0.001)	(0.000)
RSP$^-$×$\sqrt{holding\ days}$	-0.048^{***}	-0.005^{***}
	(0.007)	(0.001)
RSP$^+$×$\sqrt{holding\ days}$	-0.035^{***}	-0.004^{***}
	(0.005)	(0.001)
variance	-6.981	-0.689
	(16.877)	(1.667)
I(loss)×variance	6.846	0.676
	(16.878)	(1.667)
I(gain)×variance	6.362	0.628
	(16.885)	(1.667)
I(highest RSP)	1.112^{***}	0.154^{***}
	(0.014)	(0.003)
I(lowest RSP)	0.785^{***}	0.099^{***}
	(0.018)	(0.003)
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. 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. 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 A3. Regressions using market adjusted returns and portfolio adjusted returns

	Dependent variable:	
	sell	
	(1)	(2)
return^{-}	-0.463^{***}	
	(0.075)	
return^{+}	0.846^{***}	
	(0.068)	
$\text{market.ad.return}^{-}$		-0.419^{***}
		(0.070)
$\text{market.ad.return}^{+}$		0.869^{***}
		(0.071)
I(extremeness.portfolio.ad)	-0.007^{*}	
	(0.003)	
I(extremeness.market.ad)		-0.006^{*}
		(0.003)
$\text{return}^{-}\times$I(extremeness.portfolio.ad)	-1.404^{***}	
	(0.163)	
$\text{return}^{+}\times$I(extremeness.portfolio.ad)	0.785^{***}	
	(0.142)	
$\text{return}^{-}\times$I(market.ad)		-1.618^{***}
		(0.164)
$\text{return}^{+}\times$I(market.ad)		0.808^{***}
		(0.143)
Observations	456,187	454,009
R^2	0.292	0.293

This table presents regressions using market adjusted returns and portfolio adjusted returns. 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. 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. 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* $\times$ *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 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.