How speculative asset characteristics shape retail investors' selling behavior

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Abstract

Using German and US brokerage data we find that investors are more likely to sell speculative stocks trading at a gain. Investors' gain realizations are monotonically increasing in a stock's speculativeness. This translates into a high disposition effect for speculative and a much lower disposition effect for non-speculative stocks. Our findings hold across asset classes (stocks, passive, and active funds) and explain cross-sectional differences in investor selling behavior which previous literature attributed primarily to investor demographics. Our results are robust to rank or attention effects and can be linked to realization utility and rolling mental account.

Keywords: Selling Behavior, Disposition Effect, Retail Investor, Speculation, Higher Moments of Return, Realization Utility

JEL Classification: D14, D81, D9, G11

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1. Introduction

A large body of literature investigates how investors choose which assets to sell from numerous possible assets in their portfolio. There can be rational reasons for selecting sales candidates, such as tax optimization, portfolio rebalancing or the arrival of fundamental news that may alter the risk-return profile of an individual asset.

There is also abundant literature showing that investors' selling behavior may be less rationally grounded. The most prominent finding is that investors on average tend to sell assets that increased in value since purchase more frequently than assets that decreased in value since purchase. This selling pattern is known as the disposition effect (Shefrin and Statman, 1985) and is one of the most explored trading behaviors in finance. Hence, the focus in the literature has primarily been on an asset's paper gains and losses, as determinants of investor's selling behavior.

Subsequent research has uncovered the limitations of this focus on gains and losses in explaining selling behavior. The notion of "average selling behavior" can be problematic since it masks considerable variation across investors (Odean, 2000). Dhar and Zu (2006) find that while investors on average are prone to the disposition effect about 20 percent of the investors in their sample show a *reverse* disposition effect. Research has spent considerable energy studying how investor characteristics influence selling behavior within stock investments to explain such cross-section variation.[4] The focus on investor demographics, however, has also reached its limits. This approach has difficulties explaining the finding that the same investor can exhibit different selling behaviors across financial asset classes (e.g., Calvet, Campbell, and Sodini, 2009; Chang, Westerfield, and Solomon, 2016).

Surprisingly, how the characteristics of an asset influence investors' selling decision is underexplored so far. The attempt to explain selling behavior primarily by looking at paper gains and losses and subsequently testing this hypothesis both within and across different asset classes rests on the assumption that knowing an asset's paper gain or loss alone suffices to make predictions about the likelihood of it being sold – irrespective of its risk-return profile.

[4] Scholars document a negative relationship between the level of the disposition effect and investor characteristics such as income and wealth (e.g., Dhar and Zu, 2006; Calvet, Campbell, and Sodini, 2009), age (e.g., Dhar and Zu, 2006), as well as sophistication and experience (e.g., Feng and Seasholes, 2005; Seru, Shumway, and Stoffman, 2010).

In this paper, we hypothesize that an asset's selling propensity depends crucially on its risk-return profile, which we consider its degree of speculation. In fact, the disposition effect is much larger for speculative assets and much lower for non-speculative assets. The cross-sectional variation in selling behavior that prior studies attribute to investor demographics (e.g., wealth, investment experience, age) disappears once we control for an asset's degree of speculation. In other words, it matters less 'who' is selling an asset but rather 'what kind of' asset is sold.

We analyze German and US retail investor trading data to investigate the effect of speculation on private investors' selling behavior. We classify speculative assets as stocks falling into the 10^{th} variance and 10^{th} skewness decile (i.e., highly positively skewed) in month *t*, whereas non-speculative assets are stocks falling into the 1^{st} variance and 1^{st} skewness decile in month *t* (Kumar, 2009). We then analyze investors' selling behavior in month *t+1* in the cross-section.

We find that German investors show significantly different selling behaviors in speculative stocks compared to non-speculative stocks. Analyzing selling behavior across investors, we find that investors' average propensity to realize gains (PGR) is 41% higher for speculative stocks than for non-speculative stocks. While investors generally do not like to realize assets trading at a loss (e.g., Odean, 1998), we find that this tendency is much stronger for speculative assets trading at a loss: Investors are about 54% less likely to sell a speculative stock trading at a loss compared to selling a non-speculative stock trading at a loss. Ultimately, these changes in gain and loss realizations lead to different degrees of the disposition effect[5]: On average, investors exhibit a highly statistically significant disposition effect of 13.60% in speculative stock stocks, whereas the disposition effect in non-speculative stocks is 1.9% and only marginally significant. As results derived at the aggregate level might mask heterogenous selling behavior across investors, we introduce investor, month, and investor×month fixed effects to our regression framework.[6] We find that on the individual investor level differences in selling behavior between speculative and non-speculative assets remain highly statistically significant. Hence, the same investor in the same month adopts different selling patterns dependent on the speculative nature of the stock.

[5] Formally, the disposition effect is defined as the propensity to sell a stock at a gain (PGR) minus the propensity to sell a stock at a loss (PLR).

[6] We thereby account for systematic differences in investor's variance and skewness preferences and for changes in these preferences over time.

Introducing further control variables such as holding period, purchase price, returns since purchase, and interactions between holding periods and returns, we find that the differences in investors' selling behavior are exclusively driven by changes in PGR. Thus, speculation primarily affects investors' selling behavior in the gain domain.

So far, we compare selling behaviors on the two ends of a continuum. If speculation is an important determinant of investors' selling behavior, then we should find a persistent relationship between investors' selling behavior and an asset's speculative nature. Indeed, we find that PGR gradually increases as an assets' degree of speculation increases: The correlation between PGR and variance and skewness deciles is strongly positive (0.90) and highly statistically significant. In contrast, the correlation between PLR and variance and skewness deciles is negative (-0.58) but statistically insignificant. In summary, we provide evidence of a monotonic relationship between an asset's level of speculation and investors' gain realizations.

Next, we explore the effect of asset characteristics and investor demographics. We therefore rerun our main analyses while controlling for investor demographics that are known to affect investors' selling behavior - namely income, wealth, experience, age, and gender. We find that the disposition effect in speculative assets is always higher than in non-speculative assets irrespective of investor demographics. Moreover, the magnitude of the disposition effect in speculative assets and non-speculative assets are of equivalent size across investor demographics. Differences in investors' selling behavior seem to be driven by an asset's degree of speculation rather than by investor demographics. This emphasizes the unifying effect of speculation on selling behavior.

There is empirical evidence showing that investors' selling behavior differs across asset classes (e.g., Chang et al., 2016). We find that investors' selling behavior in passive equity and equity mutual fund investments is in line with findings from our stock analysis: Investors have a significantly higher disposition effect in speculative than in non-speculative funds. Again, this difference is driven by changes in PGR and not by changes in PLR. More precisely, we find that investors' PGR in speculative passive equity funds is between 6.21 and 9.74 percentage points higher than in non-speculative passive equity funds. Investors' PGR in speculative mutual funds is between 2.55 and 3.48 percentage points higher than in non-speculative mutual funds.

To ensure the external validity of our results, we run our main analyses using the well-known Barber and Odean (2000) U.S. individual-investor trading data set. We find that the average U.S. investor experiences a disposition effect of approximately 5% in single stock investments. However, after controlling for speculation, the average U.S. investor no longer shows a significant disposition effect in non-speculative stocks (0.4%) but a strong and significant disposition effect in speculative stocks (10.9%). On the individual investor level changes in selling behavior are driven by changes in gain but not loss realizations. The same U.S. investor in the same months adopts different selling behaviors for speculative and non-speculative assets. These findings on the U.S. sample are in line with findings from the German sample.

Next, we investigate possible channels. Speculative assets that have both a high variance and a high skewness are more likely to have extreme returns. Therefore, we analyze four possible channels: attention (e.g., Barber and Odean, 2008), portfolio rank (Hartzmark, 2015), belief in mean reversion (e.g., Luo, Ravina, Sammon, and Viceira, 2020), and realization utility (Barberis and Xiong, 2012) in combination with rolling mental accounts (Frydman, Hartzmark, and Solomon, 2018). The channel that best seems to fit our findings is the realization utility (RU)/rolling mental accounts channel.[7] An investor who sells an asset at a gain should experience a positive burst of realization utility only if the proceeds from the sale are not reinvested (i.e., the mental account is not rolled). Barberis and Xiong (2012) state that realization utility should be stronger if the investment episode is more salient. If the realization utility channel is driving our results, we should observe lower reinvestment rates after the sale of a speculative stock trading at a gain than after the sale of a non-speculative stock trading at a gain. We find that investors' likelihood of reinvesting decreases by between 5.5 and 8.4 percentage points after realizing a gain in a speculative stock compared to realizing a gain in a non-speculative stock. Expanding our analysis to assets in less extreme variance and skewness deciles, we find the likelihood of reinvestment to be negatively correlated (-0.80) with an asset's variance and skewness level. This result is consistent with our main analysis showing that investors' PGR positively correlates with an asset's

[7] According to RU theory, investors selling an asset at a gain (loss) get an extra burst of positive (negative) realization utility at the moment of sale since a positive (negative) investment episode is created. Frydman et al. (2018) point out that an investor's investment episode does not necessarily end with the sale of an asset as reinvestment can preserve the previous mental account. The interaction of speculation and realization utility is suggested by Barberis and Xiong (2012) who state that RU should be stronger if the investment episode is more salient.

level of speculation. In addition, we run a placebo test. In the realization utility model (Barberis and Xiong, 2012) selling a losing stock is triggered by a liquidity shock and thus should not be followed by reinvestment. Thus, we should not find a difference in reinvestment behavior after losses. Indeed, in three out of four model specifications we find no differences in investors' behavior after realizing losses in speculative and non-speculative stocks. Alternative channels such as attention, portfolio rank, and belief in mean reversion are not driving our findings.

Our paper contributes to the literature that examines stock-level attributes associated with retail investors' selling behavior. While other studies examine how demographics (e.g., Dhar and Zu, 2006), geographic proximity (Coval and Moskowitz, 1999), or the choice of the asset class (Chang et al., 2016) influence the disposition effect, our study demonstrates that an asset's degree of speculation is an important determinant of investors selling behavior.[8] Our results extend the literature by illustrating that investors' selling behavior *within* and *across* asset classes is strongly affected by an asset's fundamental risk-return characteristics (i.e., speculative vs. non-speculative) and thereby contribute to literature that analyzes the relation between speculation and investment decisions. In addition, our results suggest that the cross-sectional variation in selling behavior is driven by the asset characteristic rather than by investor demographics (e.g., Feng and Seasholes, 2005; Dhar and Zu, 2006). While several studies document that gambling behavior influences investments[9], our paper directly links an assets' degree of speculation to individual investors' selling behavior. Moreover, we add to the research suggesting that realization utility is a key driver of the investors' selling behavior (e.g., Frydman, Barberis, Camerer, Bossaerts, and Rangel, 2014; Frydman and Wang, 2020).

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[8] Ben-David and Hirshleifer (2012) find that the probability of selling is a V-shaped function over investors' profits. The authors argue that this selling pattern is a consequence of investors' speculative trading motive and overconfidence. The study differs along ours in two important dimensions. First, Ben-David and Hirshleifer (2012) proxy speculative trading by investor- and transaction-specific characteristics; namely gender, trading frequency, and stock position amount. In contrast, we identify speculation on the asset level by looking at the asset's speculative nature. This allows us to investigate the effect of asset specific characteristics on investors' selling behavior. Second, the authors find that the V-shaped selling pattern is strongest for short holding periods and disappears if the holding period exceeds 250 days. In contrast, we find that asset specific characteristics affect investors' selling behavior beyond one year holding periods. As such our effect prevails in the long run.

[9] Besides theoretical work highlighting the importance of variance and skewness on investors' entry decisions (e.g., Friedman and Savage, 1948; Markowitz, 1952; Barberis and Huang, 2008), researchers find strong empirical evidence that private investors have preferences for speculative assets (e.g., Kumar, 2009; Liu, Wang, Yu, and Zhao, 2020).

2. Data and Methodology

2.1 Data

We use proprietary trading and portfolio holding data of randomly drawn investors from a German online bank. Trades and holdings are reported from January 2010 to December 2015.[10] The trading dataset includes trades on a daily frequency. During the sample period, we observe 2,937,584 stock trades out of which 45% are sales. Each record provides the date of the purchase/sale, the purchase/selling price, the volume traded, and the respective fees. The portfolio holding file reports portfolio holdings on the investor-security level every month. Each of the approximately 11 million records provides information about the account number, security number, year, month, the position's market value, and the position's quantity. We do not exclude or replace accounts that are closed during the sample period. In addition to investors' trading and holding data, we also have information on their demographics, such as age, gender, income, wealth, and ZIP code. We complement the bank data with market data from Datastream. Market data comprises daily data of all securities held or traded by the individual investors during the sample period. We confine our analysis to non-advised investors.

In line with Ben-David and Hirshleifer (2012), we apply the following filters to our raw data. We confine our analyses to common shares that can be identified via Thomson Reuter Datastream. Further, we exclude day trading by netting trades that take place at the same date, in the same security, and in the same account. If an investor sells a position entirely and later repurchases the same security, the average purchase price is set to zero upon the total sale. If the purchase price of the security is unknown, the asset is excluded from the analyses. We then construct an investor's monthly portfolio and analyze investor selling behavior in sale months (e.g., Odean, 1998; Chang et al., 2016). To be able to compare investors' selling behavior across

[10] The dataset has been used in other studies (e.g., Schmittmann, Pirschel, Meyer, and Hackethal, 2015; Bernard, Loos, and Weber, 2020; Laudenbach, Loos, Pirschel, and Wohlfahrt, 2021). We make two adjustments to facilitate the analyses and comparisons across asset classes. Firstly, we focus on investors' trading in the most recent years of the dataset to account for the fact that passive equity funds are rather new financial investment vehicles relative to stocks and equity mutual funds. Secondly, we require investors in our sample to hold stocks, equity mutual funds, and passive equity funds at some point in time. As demonstrated in Appendix A our main results also holds if we remove both restrictions.

asset classes, we require each investor in our sample to hold a stock, an equity mutual fund, and a passive equity fund at some point in time during her trading history (Chang et al., 2016).

Table 1 Panel A provides information about our investor sample. During our sample period, we track 407,100 trades of 22,334 individual investors. In total, the private investor dataset has approximately three million observations on the individual-stock-month level. The median portfolio value in our sample equals 26,220 Euros. On average investors trade three times a month. As expected, the majority of assets in a private investor's portfolio are single stocks. Focusing on asset classes of interest for this study, 48% of investors' portfolio holdings are single stocks, 31% are equity mutual fund investments, and about 21% are passive equity fund investments. The Herfindahl-Hirschman Index (HHI) of the average investor's portfolio is 42.5% which corresponds to an equally weighted portfolio of 2.4 stocks. This fits findings by Ivković, Sialm, and Weisbenner (2008), who find the HHI of U.S. retail investors to equal 43% for portfolios greater than $25,000. The average investor in our sample is 51 years old and male; female investors comprise 15% of our sample similar to gender distributions in previous studies on investor trading behavior (e.g., Dorn and Strobl, 2009; Ben-David and Hirshleifer, 2012). The average income is equal to 57,000 Euros.

[Insert Table 1 here]

Since we investigate how an asset's degree of speculation shapes investors' selling behavior, we need to identify speculative and non-speculative assets in our data set using market data. We follow Kumar (2009) and label assets with a high variance and high skewness as speculative (non-speculative). At the end of month *t*, we compute both historical variance and historical skewness measures using daily return data over the previous 12 months. On the last trading day of each month, we sort stocks into skewness and variance deciles. Stocks that are sorted into the highest variance and highest skewness decile (i.e., decile 10) are categorized as speculative since they show high-variance-high-skewness (HVHS) patterns over the past year. Stocks sorted into the lowest variance and lowest skewness decile (i.e., decile 1) are categorized as non-speculative assets since they demonstrate low-variance-low-skewness (LVLS) patterns over the past year. Assets that are not part of the speculative or non-speculative sample are categorized as others. Note, that we will use the term high-variance-high skewness (HVHS) asset and speculative asset, as well as the term low-variance-low-skewness (LVLS) asset and non-speculative asset interchangeably throughout the paper.[11]

Our main analysis is confined to speculative and non-speculative assets. Hence, if assets are equally distributed along the variance and skewness deciles, we would focus on only 2% of the data. Figure 1 Panel A is a heatmap that consists of 100 boxes and depicts the categorization of assets in our sample along two dimensions: variance and skewness. The darker (brighter) the color of a box the more (less) stocks are in the specific box. The heatmap shows that we find that most assets in our sample are located along the diagonal of the two-dimensional variance-skewness space. Hence, assets are not equally distributed along variance and skewness deciles. Indeed, most of the assets in our sample are in the upper right (high variance and high skewness) or lower left corner (low variance and low skewness) of the heatmap. There are only a few assets that show a high variance (skewness) while showing a low skewness (variance) at the same point in time. Due to the rolling window approach, an asset's classification can change every month. We therefore calculate transition matrixes and check how stable classifications are over time. The transition matrix reveals that if an asset is classified as a speculative (non-speculative) asset in month *t*, then this asset is a speculative (non-speculative) asset with a probability of 91.1% (76.7%) in the subsequent month.[12]

[Insert Figure 1 here]

Panel B in Table 1 captures information on characteristics of stocks being categorized as speculative assets or non-speculative assets. Our data captures 2,474 (1,451) speculative (non-

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[11] Note that we deviate from the definition used in Kumar (2009) in two dimensions, but in robustness tests we also use the Kumar (2009) definition and our results remain robust (see Appendix B). First, Kumar (2009) defines volatility, skewness, and price a defining characteristic of speculative stocks. He argues that high volatility and high skewness assets attract investors because of repeated extreme returns while low prices suggest a cheap bet. We refrain from the price characteristic as our paper focuses on investors' selling behavior. As such, the price of entering the gamble can be considered as sunk costs. Second, in his main analysis, Kumar (2009) uses idiosyncratic volatility and idiosyncratic skewness. Since we are analyzing retail investor trading data, we prefer using historical variance and skewness measures as we do not believe that individual investors run regression models and these metrics are not displayed on the trading front end. In addition, Kumar (2009) finds that results using idiosyncratic volatility and skewness are very similar to results using total volatility and skewness.

[12] For more details of how assets move along categories, see Figure 1 Panel B.

speculative) assets. By construction, speculative assets show higher variance and skewness than non-speculative assets. The differences in volatility and skewness are statistically significant and absolute magnitudes are comparable with findings by Oehler and Schneider (2022). We find the average return on realized gains (losses) in speculative assets to be six (five) times as high (low) as in non-speculative assets. We also find that speculative assets are held significantly longer when trading at a loss compared to non-speculative asset trading at a loss. Interestingly, this picture reverses when analyzing holding periods for asset trading at a gain. Speculative assets trading at a gain have a significantly shorter holding period than non-speculative assets. To check the plausibility of the identification of speculative and non-speculative assets, we also provide exemplary names of the speculative/non-speculative assets frequently held by private investors in our sample. For example, Zurich Insurance is categorized as a non-speculative stock whereas the travel and tourism company TUI is categorized as speculative.

2.2 Empirical Framework

To analyze how individual investors' selling behavior is affected by an asset's speculative nature, we add the *Speculative* dummy variable to the classical disposition effect regression used by Chang et al. (2016). We use the following specifications as our base model:

$$\begin{aligned} Sale_{i,j,t} = \beta_0 + \ & \beta_1 Gain_{i,j,t} + \beta_2 Speculative_{j,t-1} + \beta_3 Gain_{i,j,t} \times Speculative_{j,t-1} \\ & + \beta' X + v_t + v_i + v_{t,i} + \epsilon_{i,j,t}, \end{aligned} \tag{1}$$

where observations are at the individual(*i*)-stock(*j*)-month(*t*) level. The *Speculative* dummy variable equals one (zero) if the stock is categorized as speculative (non-speculative) in the previous month t. *Gain* is a dummy variable that equals one if stock *j* in investor *i*'s account is trading at a gain in month t. An asset is trading at a gain if its value-weighted average purchase price is below its current market price. X is a vector of control variables known to affect investors' selling propensities (Ben-David and Hirshleifer, 2012). These control variables comprise the holding period, purchase price, returns (positive and negative), and the interaction between holding periods and return as well as holding periods and the gain dummy variable. Holding period is the square root of the number of months since the purchase of the position; the weighted-average purchase price is the natural logarithm of the weighted-average purchase price; and the return since purchase if the return since purchase is negative (positive), zero otherwise. The dependent variable *Sale* is a dummy variable that equals one whenever a sale takes place. Finally, v_t are month, v_i are individual, and v_{ti} are individual×month fixed effect. Since investors' selling decisions are most likely correlated within investor and month, we cluster standard errors at the individual and month level in all regressions to overcome intraclass correlation. We also use individual and month fixed effects to account for differences in variance and skewness preferences across investors and over time.

Based on regression equation (1), we can determine the proportion of gains realized (PGR) and proportion of losses realized (PLR), as well as the disposition effect for speculative and non-speculative assets. PGR (PLR) is defined as the total number of realized gains (losses) over the sum of paper and realized gains (losses) in month *t* (Odean, 1998). Thus, speculative assets' PGR is the sum of all coefficients ($\beta_0 + \beta_1 + \beta_2 + \beta_3$), whereas speculative assets' PLR is given by the sum of β_0 and β_2. Correspondingly, non-speculative assets' PGR is given by the sum of β_0 and β_1, whereas non-speculative assets' PLR is given by β_0. The difference between PGR and PLR yields the disposition effect for the respective asset classification. The coefficients of interest in our analyses are $\beta_2 + \beta_3$ and β_2. These terms test whether investors' selling behavior in gains (PGR) and losses (PLR) varies across speculative and non-speculative assets, respectively. We expect investors to be more willing to realize their gains in speculative assets than in non-speculative assets. Thus, we expect $\beta_2 + \beta_3$ to be positive and statistically significant. We also expect β_2 to be negative since investors should be less willing to realize speculative assets trading at a loss than non-speculative assets. Ultimately, this behavior translates into a higher disposition effect in speculative than in non-speculative assets. This difference in the disposition effect between speculative and non-speculative stocks is given by β_3 and should be positive.

3. The effect of speculation on investors' selling behavior

3.1 Single stock sample

To investigate the effect of speculation on investors' selling behavior, we estimate equation (1). The results are in Table 2.[13] We follow the literature and first analyze selling behavior across investors (column (2)) in a first step. Figure 2 graphically depicts the effect of speculation on investor selling behavior. On average, investors' realization of gains and losses is asymmetrically affected by an asset's degree of speculation: Speculative stocks show a higher gain realization but lower loss realization relative to non-speculative stocks. This opposing response in investors gain and loss realization to speculation ultimately leads to a strong disposition effect in speculative stocks and a weak disposition effect in non-speculative stocks. On average, investors are 42% more likely to sell a speculative stock trading at a gain than to sell a non-speculative stock trading at a gain. In contrast, investors are 54% less willing to realize a speculative stock trading at a loss compared to realizing a non-speculative stock trading at a loss. These differences in PGR and PLR between speculative and non-speculative stocks are statistically significant at the 1% level and translate into strong differences in the disposition effect across these two groups. The disposition effect in speculative stocks equals 13.6, which is 7 times higher than the disposition effect in non-speculative stocks, which equals 1.9. Further, the disposition effect in speculative stocks is highly statistically significant at the 1% level, whereas the disposition effect in non-speculative stocks is marginally significant at the 10% level.

[Insert Table 2 here]

As results across investors might mask considerable differences in selling behavior (Odean, 2000), it is crucial to investigate the effect of speculation on selling behavior on the individual level. Results in column (2) could be caused by systematic differences in investor's variance and

[13] In a first step we use the full sample to calculate German investors' average disposition effect by running the standard disposition effect regression: Investors' selling behavior is determined by the asset trading at a gain or loss and not by its speculative nature. We find that investors have a disposition effect of 4.3% and the PGR and PLR ratio equals 1.39 (see Table 2 column (1)). These figures are comparable to existing studies. Note, that in column (1) we use the full sample to investigate selling behavior, whereas, in column (2) to column (5) we limit the sample to speculative and non-speculative assets.

skewness preferences. Additionally, investor's variance and skewness preferences could be dynamic (i.e., they could vary over time). To ensure that our results are not driven by these differences, we introduce individual and month fixed effects to our model (see Table 2, column (3)). We find that this does not alter our results. Investors are 4.82 percentage points more likely to sell a speculative stock trading at a gain than to sell non-speculative stock trading a gain, whereas they are 3.25 pecentage points less likely to sell a speculative stock trading at a loss than to sell a non-speculative stock trading at a loss. The difference in the disposition effect between speculative and non-speculative stocks is given by the coefficient of the speculative-gain interaction and equals 8.07 percentage points. Thus, an investor can suffer from a high disposition effect in a speculative stock (10.7%), whereas she suffers from a small disposition effect in a non-speculative stock (2.64%) in the same month. This clearly indicates, that an asset's degree of speculation rather than investors' characteristics are strong drivers of investors' selling decisions. So far our analyses lack control variables that previous literature has found to affect individual investor selling behavior. Thus, in column (4) we introduce commonly used control variables such as holding period, purchase price, returns since purchase, and interactions between holding periods and returns into our regression framework. We find that the disposition effect in speculative stocks (10.33%) is still more than twice as high as in non-speculative stocks (4.90%) and that this difference is highly statistically significant. However, we find that the coefficient estimate on the speculative dummy variable in column (4) turns insignificant. Hence the difference in the disposition effect bewteen speculative and non-speculative assets is purely driven by changes in gain realizations and no longer by changes in PLR. In our most conservative estimation (column (5)), we use investor-month fixed effects. We essentially exploit variation only from those investors who sell a speculative and non-speculative stock within the same month. Using investor-by-time fixed effects we are more stringent in terms of identification. The downside is a loss in generalizability as we are now only considering decisions made by investors who trade a speculative and non-speculative stock within the same month. We find that differences in selling behavior for speculative and non-speculative stocks remain highly statistically significant. In line with findings from coulmn (4) the coefficient of the speuclative dummy variable remains insignificant indicating that changes in loss realizations do not drive differences in the disposition effect between speculative and non-speculative stocks. Meanwhile, PGR in speculative assets is more than three times as high as in non-speculative.[14]

Comparing speculative assets to non-speculative assets, we find differences in the extremes; however, it is unclear how skewness and variance affect PGR and PLR in-between the extreme cases. As depicted in Figure 1 Panel A, each asset in our dataset can be placed in a two-dimensional space according to its level of variance and skewness. To investigate how PGR and PLR change once an asset's degree of speculation gradually increases, we run a modified version of equation (1):

$$Sale_{i,j,t} = \beta_0 + \beta_1 Gain_{i,j,t} + \sum_{u=2}^{10} \beta_u Decile_u + \sum_{u=2}^{10} \beta_V \, Decile_v \times Gain_{i,j,t} + v_t + v_i + e_{i,j,t}, \qquad (2)$$

Instead of regressing investors' selling decision on gains, decile 10 (i.e., speculative), and the interaction term of both, we now regress investors' selling decisions on deciles 2 to 10 and interact each decile with the gain dummy variable. Deciles are formed as outlines in section 2. *Sale* and *Gain* are defined as before. v_t and v_i are month and individual fixed effects. Due to multicollinearity, we subsume decile 1 (i.e., non-speculative) in the constant. Equation (2) allows us to investigate the change in PGR and PLR along an asset's degree of speculation.

[Insert Figure 3 here]

In Figure 3, we plot PGR and PLR against variance and skewness deciles based on results from equation (2).[15] For example, a stock sorted into the fifth variance and fifth skewness decile has a PGR of 17.4% and a PLR of 12%. The figure shows that while moving along variance and skewness deciles, the wedge between PGR and PLR becomes bigger. Hence, on average we find evidence that PGR (PLR) gradually increases (decreases) as an asset's degree of speculation increases (decreases). The difference in PGR and PLR is smallest (largest) for assets sorted in variance and skewness decile 1 (decile 10). Thus, the disposition effect is smallest for non-speculative assets and highest for speculative assets. The differences in PGR and PLR are always statistically

[14] We report the coefficient estimates of the control variables in Appendix C. We do not report these coefficient estimates in our main tables.

[15] Detailed regression results are in Appendix D.

significant within a decile. In line with previous results, we find that on the individual investor level (see Appendix D column (2)) the effect of speculation on selling behavior affects the gain but not the loss realization. The correlation between PGR and the variance and skewness decile is positive (0.90) and highly statistically significant. In contrast the correlation between PLR and variance and skewness deciles is negative (-0.58) and statistically insignificant. Results remain significant after introducing various control variables (Appendix D column (3)). This analysis illustrates that our main result holds along the diagonal of the two-dimensional variance-skewness space and is not driven by comparing assets in the lower left corner to the upper right corner.

3.2 Investor demographics versus asset characteristics

We find that the same investor adopts different selling behaviors dependent on the asset's characteristics that is about to be sold. Prior literature attributes differences in investors' selling behavior primarily to their demographics. For example, scholars document a negative relationship between the level of the disposition effect and investor characteristics such as income and wealth (e.g., Dhar and Zu, 2006; Calvet, Campbell, and Sodini, 2009), sophistication and experience (e.g., Feng and Seasholes, 2005; Seru, Shumway, and Stoffman, 2010) as well as age (e.g., Dhar and Zu, 2006).[16] If demographics are the main driver of investor selling behavior, then we should not find significant differences within investor's selling behavior since demographics are fixed. Thus, the question at hand is to what extent selling behavior can be explained by asset characteristics and/or investor demographics. To answer this question, we run regression equation (1) while controlling for investor demographics, namely income, wealth, age, sophistication, experience, and gender. Regression results can be found in Appendix E. Figure 4 graphically depicts our findings.

[Insert Figure 4 here]

[16] There is mixed evidence on the effect of gender on trading behavior. Barber and Odean (2001) find that men trade more than women and that excessive trading reduces men's returns. However, Grinblatt and Keloharju (2001) find gender to be unrelated to investors' propensity to sell. Adding to this discussion, Feng and Seasholes (2005) state that the more control variables are included in a regression, the less important gender becomes.

There are two facts that are evident when looking at Figure 4. First, the disposition effect in speculative assets (black bars) is always higher than in non-speculative assets (grey bars) irrespective of investor demographics. For example, when controlling for age, we find that the disposition effect for above median aged investors is 8.73% in speculative and 3.63% in non-speculative. For below median aged investors, we find the disposition effect in speculative stocks to equal 7.83% and in non-speculative stocks to equal 2.47%. These differences in investors' selling behavior across speculative and non-speculative assets are always highly statistically significant. Second, the magnitude of the disposition effect in speculative assets (black bars) and the magnitude of the disposition effect in non-speculative assets (grey bars) are of equivalent size across all investor demographics. In 9 out of 10 cases, the disposition effect in speculative assets ranges between 7.3% (minimum value black bars) and 9.8% (maximum value black bars). The disposition effect in non-speculative assets always ranges between 1.4% (minimum value grey bars) and 3.6% (maximum value black bars). Third, differences in magnitude across demographics but within a degree of speculation are statistically insignificant. For instance, high-income individuals have a disposition effect of 8.34% in speculative assets, whereas low-income individuals show a slightly higher disposition effect of 9.85% in speculative assets. However, the difference of 1.51 percentage points is statistically insignificant. The same holds when we compare the disposition effect for high-income and low-income individuals in non-speculative assets. The difference of -0.48 percentage points (=2.18-2.66) is statistically insignificant.

3.3 Across asset class analysis

Studies show that investors' selling behavior differs across asset classes (e.g., Chang et al., 2016). Thus, it is crucial to examine whether the effect of speculation on investors' selling behavior also holds across asset classes.

To comprehensively investigate the effect of an asset's degree of speculation on investors' selling, we rerun equation (1) analyzing retail investors' trading behavior in equity mutual funds and passive equity funds. We confine our analyses to equity mutual funds and passive equity funds that are identified via Lipper.[17] To make results comparable across asset classes, we use the

[17] Detailed summary statistics of the fund sample are in in Appendix F.

same cluster and fixed effects as in the single stock sample analysis (see Section 3.1). In addition, we account for the fee structures of the funds by introducing a control variable for fees in our fund analyses. Regression results are shown in Table 3: Panel A shows results using the passive equity fund sample and Panel B shows results using the equity mutual fund sample.

[Insert Table 3 here]

The results provide further evidence for differences in investors' selling behavior between speculative and non-speculative funds. Analyzing changes in PGR (i.e., $\beta_2 + \beta_3$) and PLR (β_2) between speculative and non-speculative funds, we find that PGR is always significantly higher in speculative funds than in non-speculative funds – irrespective of whether this fund is an active or passive fund. In terms of magnitude, the change in PGR is higher in the passive equity funds sample than in the active mutual funds sample. Within the passive funds sample, speculative funds' PGR is between 6.21 (0.0468 + 0.0153 in column (3)) and 9.74 (0.108 - 0.0106 in column (2)) percentage points higher than non-speculative funds' PGR. For active funds, the difference in PGR between speculative and non-speculative assets ranges from 2.55 (0.0121 + 0.0134 in column (3)) to 3.48 (0.0549 - 0.0201 in column (2)) percentage points. Remember, that we found speculative stocks' PGR to be between 4.82 (column (3) in Table 2) and 9.30 (column (5) in Table 2) percentage points higher than non-speculative stocks' PGR. Thus, in terms of magnitude, the effect of an asset's degree of speculation on investors' selling behavior in passive equity funds are comparable to results in the single stock sample.

Interestingly, the strong differences in PGR between speculative and non-speculative passive funds lead to a significant disposition effect in speculative passive funds, while we find evidence for a significant reverse disposition effect in non-speculative passive funds. Hence, within one asset class (i.e., here the asset class of passive funds), investors can simultaneously suffer from a standard and a reverse disposition effect. While active fund investors' PGR is significantly higher for speculative than for non-speculative assets, the change in PGR is not large enough to translate into a difference in the disposition effect across speculative and non-speculative active funds after controlling for individual and month fixed effects. This is illustrated in Table 3 by the insignificant coefficient estimate of the gain-speculative interaction term in Panel B in columns (3) and (4). Lastly, we find that there is no difference in PLR between speculative and non-speculative funds, i.e., the speculative coefficient estimate is always insignificant (Panels A and B).

Our findings on the fund sample are in line with the findings from our main analysis based on stock investments. They demonstrate that speculation not only affects investors' stock selling behavior but also their funds selling behavior. Thus, our findings hold within but also across asset classes, thereby offering a more holistic understanding of investors' selling behavior.

4. External Validity

Since we are the first to test the effect of speculation on investors' selling behavior and are using a proprietary dataset, we need to ensure that our results are externally valid. To do so, we replicate our results using the well-known Barber and Odean (2000) individual-investor trading data. This U.S. data set has been frequently used to investigate individual investor trading behavior (e.g., Barber and Odean, 2008; Chang et al., 2016; Frydman et al. (2018)) and differs from our data set in two dimensions: (i) it contains trading and portfolio data od U.S. investors fand and (ii) it covers an earlier time period. We restrict the Barber and Odean (2000) sample to common stocks and process the investors trading data set as described in Chang et al. (2016). The U.S. market data comes from CRSP. To determine if an asset falls into the speculative or non-speculative group, we apply the same methodology as outlined in Section 2. We then run our main regression (1) using the U.S. sample. For comparability of results to our main findings we employ the same fixed effects and control variables as in Table 2.

[Insert Table 4 here]

We find that the average U.S. investor has a disposition effect of approximately 5% (see Table 4 column (1)). However, the disposition effect completely vanishes after controlling for stocks' speculative nature (see Table 4 column (2)). Investors no longer show a disposition effect in non-speculative stocks (-0.11%) but a strong and significant disposition effect in speculative assets (7.83%). Indeed, across all model specifications, U.S. investors disposition effect in non-speculative stocks is always insignificant (i.e., the gain coefficient estimate is always insignificant). On the individual investor level (column (3)), we find that differences in selling behavior between speculative and non-speculative stocks are entirely driven by the increased PGR in speculative stocks (relative to non-speculative stocks). Differences in PLR between speculative and non-speculative stocks are insignificant. This result remains robust after introducing additional control variables (column (4)). Results from the U.S. sample are largely in line with results from the German. The only difference between Table 2 and Table 4 emerges in column (5). After introducing individual×month fixed effects, we neither find evidence for differences in selling behavior of speculative and non-speculative stocks nor evidence for a disposition effect. However, these insignificant results might be caused by the very low number of observations. Less than 800 investors are considered in column (5).

5. Craving realization utility

5.1 Reinvesting after gains

Previous literature has found evidence for realization utility being an important driver of investor selling behavior (e.g., Barberis and Xiong, 2012; Ingersoll and Jin, 2013; Frydman et al., 2014). Realization utility (Barberis and Xiong, 2012) postulates that, at the moment of sale at a gain or a loss, investors get an extra burst of positive or negative realization utility, respectively. Adding to this, Frydman et al. (2018) show that an investor's investment episode does not necessarily end with the sale of the asset, as reinvestment can preserve the previous mental account. An investor who sells an asset at a gain should experience a positive burst of realization utility only if the proceeds from the sale are not reinvested (i.e., the mental account is not rolled). If the realization utility channel is driving our results, we should observe lower reinvestment rates after the sale of a speculative stock trading at a gain than after the sale of a non-speculative stock trading at a gain. [18] To test for this prediction, we analyze investors' reinvestment decisions after realizing a gain by running the following regression:

$$Reinvestment_{i,j,t} = \beta_0 + \beta_1 Speculative_{j,t-1} + e_{i,j,t} \tag{3}$$

Following Frydman et al. (2018), a reinvestment event takes place whenever exactly one sale occurs in an investor's portfolio and this sale is followed by a purchase on the same day. We use several modifications of the reinvestment definition to ensure that our findings are not driven by

[18] The interaction of speculation and realization utility is suggested by Barberis and Xiong (2012) who state that realization utility should be stronger if the investment episode is more salient.

a narrow definition of a reinvestment event. The reinvestment dummy equals one if (i) the sale is followed by several purchases on the same date (column (1) in Table 5); (ii) the sale is followed by several purchases on the same date and the proceeds of the sale match the amount invested in the new assets by ± 15% (column (2) in Table 5); (iii) the sale is followed by exactly one purchase on the same date (column (3) in Table 5); and (iv) the sale is followed by exactly one purchase on the same date and the proceeds of the sale match the amount invested in the new asset by ± 15% (column (4) in Table 5). Note, the identification of a reinvestment event requires daily trading data. Hence, throughout all following analyses, observations are recorded at the individual-stock-day level.[19] Since we explore investors' reinvestment behavior after gain realizations, the sample is limited to the sales of assets trading at a gain.

Based on equation (3), we can test whether investors' reinvestment activity after realizing a speculative (HVHS) stock trading at a gain differs from their reinvestment activity after realizing non-speculative (LVLS) stock trading at a gain. If investors high PGR in speculative assets is consistent with the concept of realization utility, then we should find higher reinvestment rates for non-speculative stocks than for speculative stocks since investors only experience a burst of realization utility if they do not reinvest. Therefore, the coefficient of the speculative dummy should be negative. Results are shown in Table 5. To ensure comparability among regressions, we employ the same clusters and fixed effects as before.

[Insert Table 5 here]

We find that the coefficient of the speculative dummy is negative and statistically significant for all four reinvestment event definitions: Investors are 5.5 to 8.4 percentage points less likely to reinvest after realizing a gain in a speculative asset than after realizing a gain in a non-speculative asset. This finding is in line with our hypothesis that investors' high PGR in speculative assets is driven by their desire for a burst of realization utility.

Thus far, we have focused on differences in investors' reinvestment activity between speculative and non-speculative assets. We find that there is a persistent positive relationship

[19] In our main analyses we use individual-stock-month triples since an investor's position data is only available at the monthly level. However, position data is not required in analyses and thus we use more granular data here.

between the level of speculation and PGR: The higher the level of variance and skewness, the higher investors' PGR (e.g., Figure 3 in Section 3.1). If realization utility is an underlying driver of this trading behavior, we should find that investors' reinvestment activity decreases if the level of speculation gradually increases. To explore how investors' reinvestment behavior changes when moving along variance and skewness deciles, we estimate equation (3) separately for each variance-skewness decile using decile 1 as the base category. Regression results are reported in Appendix G. Figure 5 graphically depicts our findings.

[Insert Figure 5 here]

Accounting for investor fixed effects and applying reinvestment definition (i), we find that investors' reinvestment activity decreases if the degree of speculation increases.[20] We find the correlation between the likelihood to reinvest and the variance and skewness deciles to equal -0.8. This result indicates that investors' desire to experience a burst of realization utility increases with an asset's level of speculation. Moreover, this result is consistent with findings from our main analysis in Section 3.1: While reinvestment activity decreases along variance and skewness deciles (see Figure 5), investors' PGR increases along variance and skewness deciles (see Figure 3). Thus, the most likely channel behind our main results is realization utility.

5.2 Placebo test: Reinvesting after losses

In their realization utility model, Barberis and Xiong (2012) show that investors sell losing stocks only if they are forced to do so by a liquidity shock. Thus, analyzing investors reinvestment activity after losses can be used as a placebo test. According to Barberis and Xiong (2012), selling a losing stock is triggered by a liquidity shock and thus should not be followed by reinvestment. To test this hypothesis, we rerun equation (3). The speculative and reinvestment dummy variables are defined as in equation (3). We also employ the same fixed effects as in Section 5.1. We confine the sample to the sales of assets trading at a loss. Results are shown in Table 6.

[Insert Table 6 here]

[20] In an unreported test, we find that this result is not driven by the choice of the reinvestment definition. Adding month fixed effects does also not alter our results. Unfortunately, we cannot include investor-month fixed effects, as the sample of investors for this analysis is too small.

We find that for most reinvestment definitions, the speculative dummy variable turns insignificant. The only exception is column (2), in which the coefficient is marginally significant at the 10% level. Our results show that there is no difference in reinvestment activity after losses between speculative and non-speculative assets. This is in line with predictions by the realization utility framework of Barberis and Xiong (2012).

6. Alternative channels

6.1 Rank effect

One effect that might interfere with our effect is the rank effect (Hartzmark, 2015). The rank effect describes retail investors' tendency to trade extreme positions in their portfolio, (i.e., they trade the worst, the best, and ignore the rest). Since high variance and high skewness are likely to yield extreme returns, one could attribute our findings to the rank effect.

[Insert Table 7 here]

We rerun our baseline regression and exclude observations where the stock is classified as speculative and ranks worst or best in the investor's portfolio. We still find that the difference in the disposition effect across speculative and non-speculative stocks is statistically significant (Table 7). Investors in speculative assets have a disposition effect of 7.60%, whereas investors in non-speculative assets show no disposition effect (column (1)). Accounting for individual and month fixed effects (column (2)), we find that investors suffer from a statistically significant disposition effect in speculative and non-speculative assets. The difference in PGR is statistically significant at the 1% level. Investors are 4.4 percentage points more likely to sell a speculative asset trading at a gain than to sell a non-speculative asset at a gain. This change in PGR is in line with our results from the main analyses where we find the change in PGR to be 4.8 (see Table 2, column (2)). Moreover, differences in PLR become insignificant once we introduce individual and month fixed effects. Again, this is in line with findings from Table 2.

6.2 Attention

Another effect that might interfere with our results is the attention effect (e.g., Barber and Odean, 2008; Da, Engelberg, and Gao, 2011; Focke, Ruenzi, and Ungeheuer, 2020). Barber and Odean

(2008) state that stocks with extreme one-day returns grab investors' attention. This effect is closely related to the rank effect mentioned above. The difference between both effects is the level on which salience is generated: In the rank effect case, returns become salient on an individual investor's portfolio level, whereas in the attention effect case returns become salient on the market level.

Following Barber and Odean (2008), we use extreme one-day returns as a proxy for attention-grabbing events. Using market data, we sort stock returns into deciles on a daily basis. Decile 1 contains stocks with the lowest daily returns, whereas decile 10 contains stocks with the highest daily returns. Assets falling into decile 1 or decile 10 are classified as attention-grabbing assets. We then split the sample by assets that either grab (decile 1 and decile 10) or do not grab (decile 2 to decile 9) investors' attention and rerun equation (1) for each sample.

[Insert Table 8 here]

In Table 8, we find that investors show a significantly higher disposition effect in speculative stocks than in non-speculative stocks in both samples. In the attention sample (column (2)), we find investors' disposition effect is 10.68% (3.85%) for speculative (non-speculative assets). In the non-attention sample (column (4)), we find investors' disposition effect is 9.63% (1.61%) for speculative (non-speculative assets). These differences in the disposition effect are always highly statistically significant at the 1% level. Our results show that attention affects the level of the disposition effect: The disposition effect of speculative and non-speculative assets is highest (lowest) if attention is high (low). However, the attention argument cannot explain why we find strong differences in the disposition effect while holding the level of attention constant within each sample.

6.3 Belief in mean reversion

There is literature showing that retail investors behave as contrarians (e.g., Luo et al., 2020; Kaniel, Liu, Saar, and Titman, 2012). That means, investors sell stocks that experience price increases and buy stocks that experienced price declines over the past because they expect the stock returns to revert back to the mean. Generally, such beliefs in mean reversion imply a tendency of investors to trade in opposition to stock price movements. While this could explain that investors are more prone to sell gains than losses, it cannot explain why the same investor in the same month is 9.3 percentage points more likely to sell a gain in a speculative asset than in a non-speculative asset (see Table 2 column (5)) – regardless of the size of the gain.[21] In addition, belief in mean reversion is inconsistent with the evidence of longer holding periods in speculative than non-speculative assets (see Table 1). Finally, experimental studies proof belief in mean-reversion to be unrelated to the disposition effect (e.g., Weber and Camerer, 1998).

7. Robustness test

7.1 Alternative specification of non-speculative assets

Kumar (2009) defines non-speculative stocks as stocks with the lowest (i.e., negative) variance and skewness. However, assets with a strong negative skewness carry a small risk of a large downturn. Therefore, retail investors might not perceive negative skewed stocks as low-risk assets. To ensure that our results are not driven by a misspecification of non-speculative assets, we rerun our main analysis using an alternative definition for non-speculative assets. We define non-speculative assets as assets with the lowest variance and the lowest but positive skewness among all stocks in our sample.

Figure 1 Panel A consists of 100 boxes and depicts the categorization of assets in our sample along two dimensions: variance and skewness. Assets categorized into the lowest variance and lowest skewness decile are in the lower left corner. All stocks in the 1/1 box have a low volatile and negatively skewed return distribution. Moving upward along the skewness dimension, assets in box 1/2 have a low variance but are no longer solely negatively skewed. Approximately 20% of the assets located in box 1/2 are assets with the lowest variance and a low but positive skewness. We therefore classify these stocks as non-speculative assets and rerun our main analyses (i.e., Table 2). Note that this change in the definition of non-speculative assets does not affect our categorization of speculative assets. The differences in investors' trading behavior among speculative (10/10) and non-speculative stocks (2/1) are reported in Table 9.

[21] Note, that in Table 2 column (5) we also control for the size of the gain as they are part of the vector of control variables (i.e., BDH (2012) control variables).

[Insert Table 9 here]

The results for the alternative specification of non-speculative assets in Table 9 are comparable to the results in our main analysis in Section 3.1. Across all model specifications the interaction term *Gain×Speculative* remains highly statistically significant and positive. In line with previous results (Table 2), we find the effect of an asset's degree of speculation on investors' selling behavior to be more prevalent over the gain rather than the loss domain. Interestingly we no longer find the coefficient of the *Gain* dummy variable to be significant. Thus, using alternative specifications, investors do no longer have a significant disposition effect within non-speculative stocks.

7.2 Identification of speculative (non-speculative) assets using quartiles

In our main analyses we follow Kumar (2009) and identify assets that belong to the top (bottom) variance and skewness deciles as HVHS (LVLS) assets. To confirm that our results are not solely driven by this quite restrictive classification, we rerun our analysis using quartiles instead of deciles. We classify HVHS assets as assets falling into the 4th variance and 4th skewness quartile in month *t*, whereas we classify LVLS assets as assets falling into the 1st variance and 1st skewness quartile in month *t*. Table 10 depicts our results.

[Insert Table 10 here]

In our robustness test results in Table 10, we observe the same patterns as in our main analyses: Investors' realization of gains and losses is asymmetrically affected by variance and skewness. Indeed, for the change in PGR, not only the sign but also the magnitude matches the results from our main analyses. Using deciles, we find PGR for HVHS stocks to be 4.82 percentage points higher than for LVLS stock, while using quartiles we find the change in PGR to be 4.87 (see FE Model 1 in Tables 2 and Table). Overall, we find the difference in the disposition effect for speculative and non-speculative stocks to be equal to 7.62 percentage points and to be significant at the 1% level. These results are in line with our results depicted in Figure 2 and emphasize that our main result (i.e., using the top and bottom decile to identify non-speculative and speculative stocks) is not driven by a restrictive classification.

8. Conclusion

We demonstrate that investors' selling behavior is strongly affected by an asset's degree of speculation. Comparing investors' selling behavior across speculative and non-speculative assets, we find gain and loss realization to be opposed: Speculative stocks trading at a gain are more likely realized than non-speculative stocks trading at a gain. By contrast, speculative assets trading at a loss are less likely realized than non-speculative assets trading at a loss. Moreover, we find PGR (PLR) to be positively (negatively) correlated with assets' degree of speculation. This effect translates into a high disposition effect for speculative assets and a close to insignificant disposition effect for non-speculative assets. These findings *hold* within and *across* asset classes (stocks, passive and active funds). Moreover, we show that the cross-sectional variation in selling behavior that prior studies attribute to investor demographics disappears once we control for an asset's degree of speculation. In other words, it matters less 'who' is selling an asset but rather 'what kind of' asset is sold.

We find evidence for the concept of realization utility driving the differences in investors' gain realizations across speculative and non-speculative assets. Alternative concepts known to affect investors' selling behavior (e.g. rank effect, attention effect, and belief in mean reversion) are not sufficient to explain our findings.

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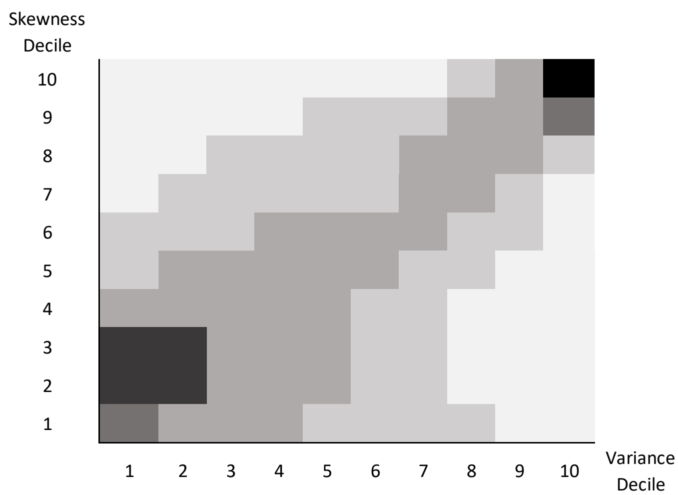
Figure 1: Stock data classification – Heatmap and transition matrix

Panel A: Distribution of stocks along variance and skewness dimension - Heatmap

This heatmap depicts the number of stocks (average, min, max) along the variance and skewness deciles. The heatmap consists of 100 boxes (i.e., 10x10). The darker (brighter) the color of a box the more (less) stocks are in the specific box. Speculative stocks are in the upper right corner (10/10 box) whereas non-speculative assets are in the lower left corner (1/1).



Color	Average	Min	Max
	251	220	380
	171	114	244
	143	64	280
	116	58	178
	75	30	129
	25	1	67

Panel B: Fluctuation of stocks among categorizations - Transition Matrix

This figure shows the transition of stocks among the three categorizations speculative (10/10 box), non-speculative (1/1 box), and others (grey shaded area). Bolted numbers depict the probability that an asset will remain in the same category for the next month. For example, a stock that is categorized as a speculative stock in month *t* will be categorized as speculative in month *t*+1 with 91.1% probability.

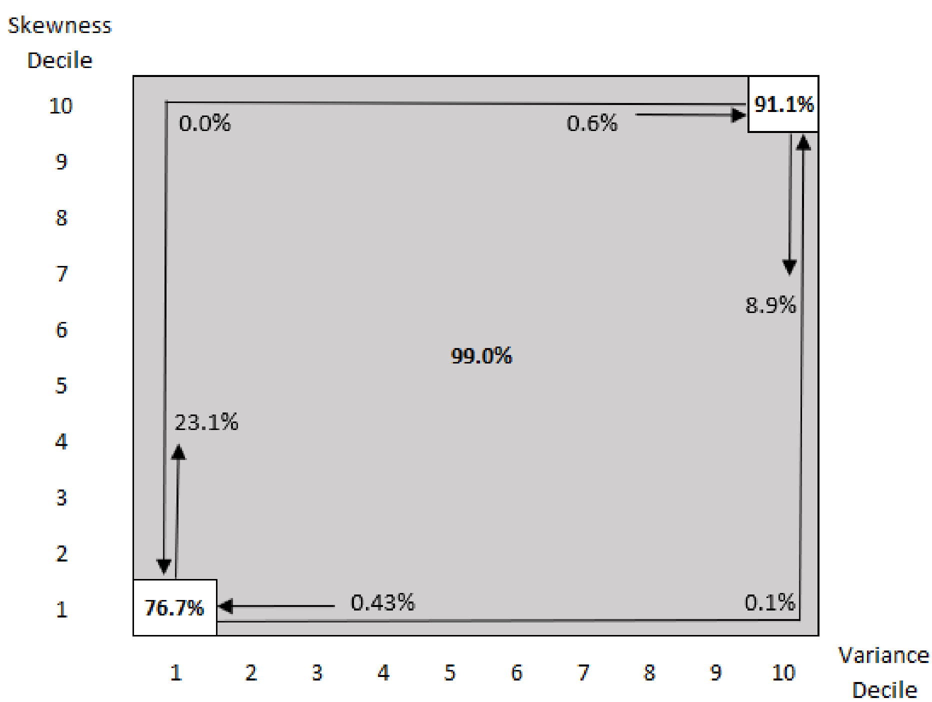


Figure 2: The effect of speculation on investors' selling behavior

This figure depicts investors' differences in selling behavior for speculative and non-speculative stocks. The disposition effect is defined as the difference in the propensity to realize gains (PGR) and the propensity to realize losses (PLR). PGR is defined as the number of absolute gains realized over the number of total gains in the investor's portfolio. PLR is defined vice versa. The figure is based on results from column (2) in Table 2. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

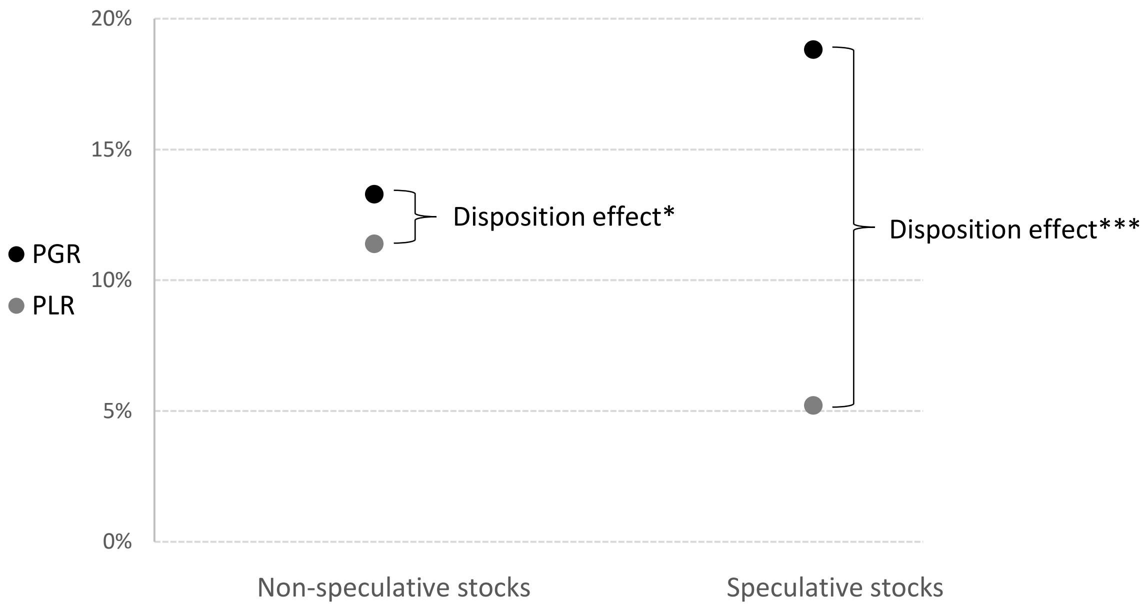


Figure 3: The change in PGR and PLR and stocks' degree of speculation

The figure depicts the change in PGR and PLR along variance and skewness deciles. Stocks falling into variance and skewness decile 1 (10) are categorized as non-speculative (speculative) assets. The figure is based on equation (2). Full regression results are displayed in Appendix D.

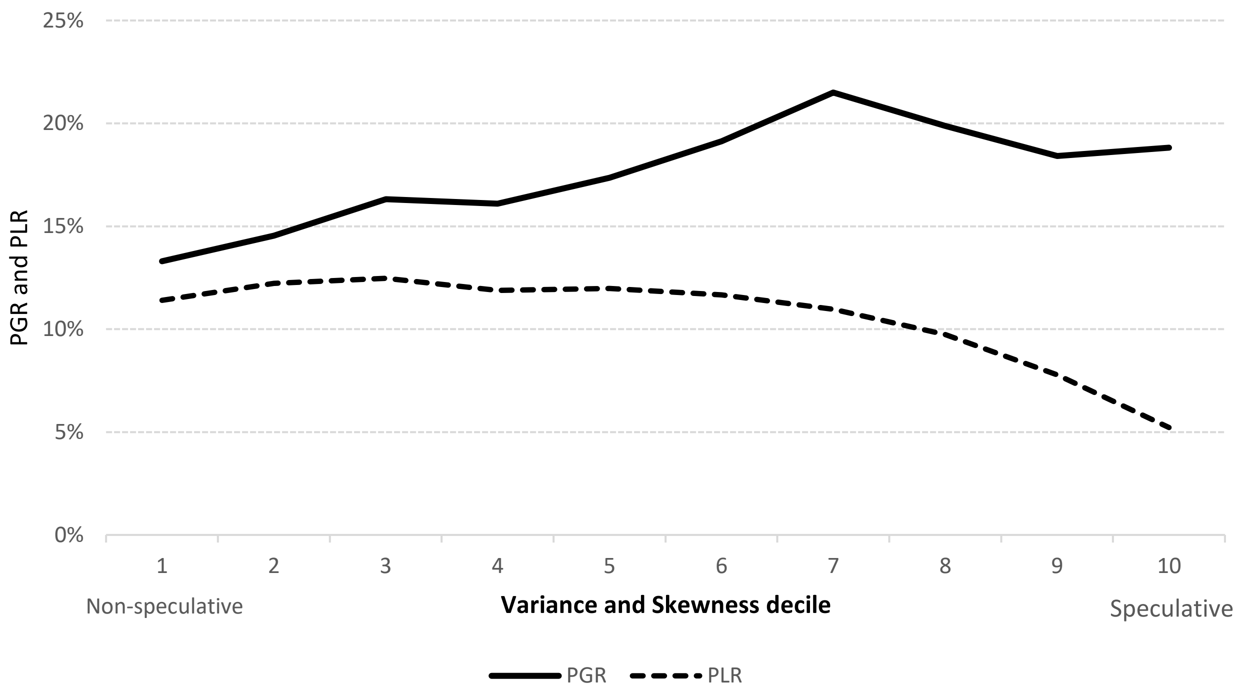


Figure 4: Asset characteristics versus investor demographics

This figure depicts investors' disposition effect for speculative and non-speculative stocks conditional on investors' demographics. The figure is based on regression results reported in Appendix E. Investor demographics comprise income, wealth, experience, age, and gender. Income and wealth are self-reported. Investors are part of the high income (wealth) group if their income falls into the top income (wealth) quartile. Investors are part of the low income (wealth) group if their income falls into the bottom income (wealth) quartile. Following Seru et al. (2010), we measure experience by the cumulative number of trades that an investor has placed. Investors are experienced (experience high = 1) if cumulative number of trades is part of the top trading quartile. Investors are inexperienced (experience low = 1) if cumulative number of trades is part of the bottom trading quartile. Age is measured in years. Gender is equal to 1 (0) if the investor is a male (female).

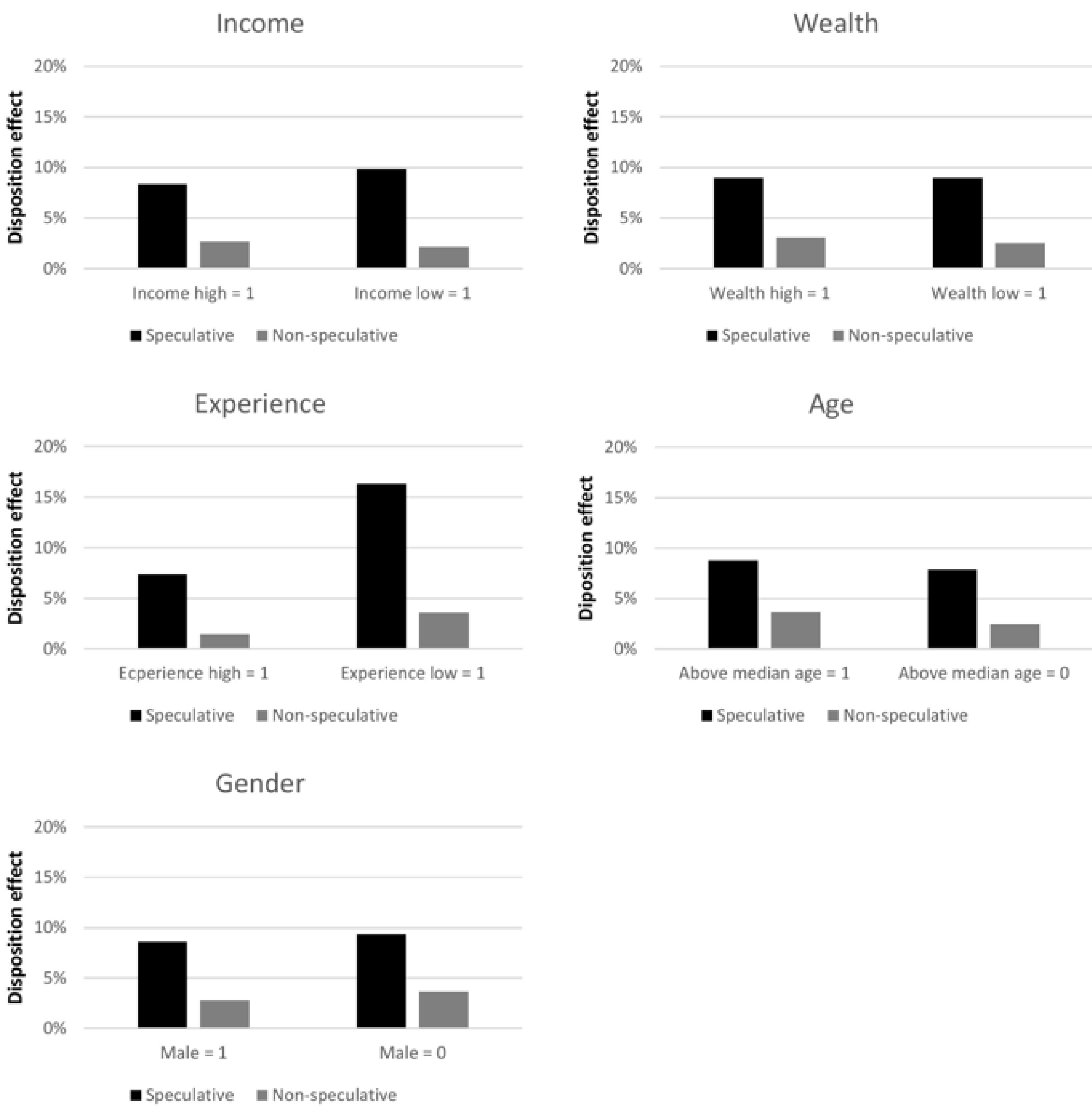


Figure 5: Reinvestment behavior and stocks' degree of speculation

This figure depicts investors' reinvestment behavior along variance and skewness deciles. The x-axis depicts the variance and skewness deciles. For example, decile 2 comprises assets that are part of the 2nd variance and 2nd skewness decile within month *t*. The y-axis depicts investors' reinvestment probability relative to investors' reinvestment probability of stocks being part of decile 1. The figure is based on regression results depicted in Appendix G.

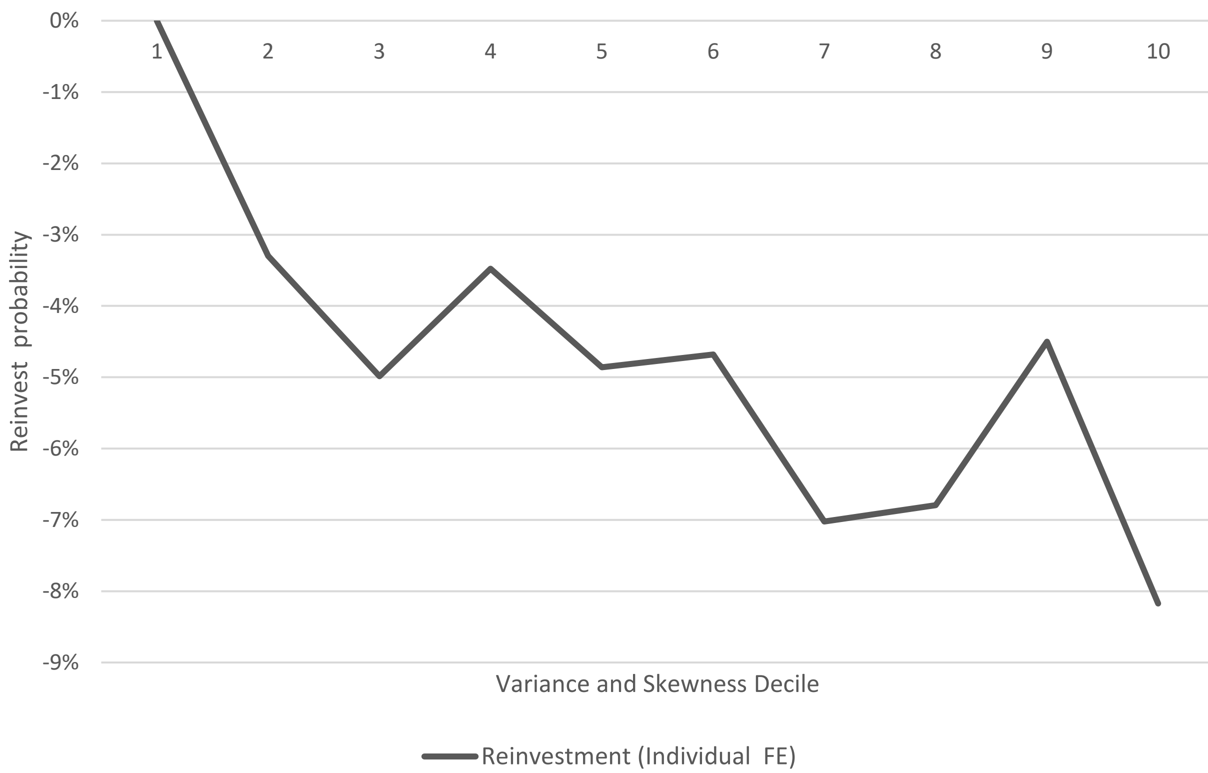


Table 1: Summary statistics

This table depicts summary statistics for the filtered data used throughout this study. Panel A reports information on the individual investor level. *Individuals* is the number of distinct accounts that were active during our sample period (2010-2015). *Number of observations* is the Individual-stock-month triples. On the portfolio level, the *average portfolio value*, *the Herfindahl-Hirschman index (HHI)*, a*verage number of trades*, and *asset allocation* of an investor's portfolio are reported monthly. The HHI is calculated following Dorn et al. (2008). *Asset allocation* is the fraction of the investor's portfolio dedicated to the respective asset class (here stocks). We report *Age, Gender,* and *Income* on the account level. *Income* is a self-reported variable. Panel B reports information on stocks categorized as speculative or non-speculative. *Number of assets* is the distinct number of stocks that were categorized as speculative or non-speculative during the sample period. *Volatility* and *Skewness* are the mean monthly values for total volatility (i.e., standard deviation of returns) and skewness during the months in which the stock is being categorized as speculative/non-speculative. *Holding periods* are measured in months. *Realized return* is the return upon sale for an asset trading at a gain/loss. Numbers in parentheses are medians.

Panel A: Retail investor level

Sample	**Stock Investments**
Individuals	22,334
Number of observations	3,009,585
Portfolio	
Portfolio value	68,100 (26,220)
Herfindahl-Hirschman index (HHI)	42.5 (32.9)
Average number of trades (monthly)	3.2 (2.4)
Asset allocation (%)	48.1
Demographics	
Age (Year)	51 (50)
Gender (%)	
Male	85
Female	15
Income (€)	56,991 (50,000)

Panel B: Asset level

	Speculative	**Non-speculative**
Stock Investments		
Number of assets	2,474	1,451
Volatility (monthly, %)	21.6	1.1
Skewness	0.7	-0.2
Holding periods (in months)		
Gain	14 (7)	16 (9)
Loss	24 (19)	12 (9)
Realized return gain (%)	92 (20)	15 (8)
Realized return loss (%)	-57 (-60)	-11 (-19)
Exemplary assets by name	Santhera Pharmaceuticals AG	Zurich Insurance
	TUI AG	Nestlé

Table 2: Speculation and investors' selling behavior

This table provides the variation in investors' selling behavior across speculative and non-speculative assets. Observations are reported as individual-stock-month triples. The dependent variable *Sale* is a dummy variable equal to one if the investor sells an asset within a particular month t. *Gain* is a dummy variable equal to one if an asset's market price is above the reference point defined as the value-weighted average purchase price. *Speculative* is a dummy variable that equals one if the asset is part of the 10^{th} variance and 10^{th} skewness decile within month *t*. Control variables are defined as in Ben-David and Hirshleifer (2012) (here BDH (2012)) and comprise the holding period, weighted-average purchase price, returns (positive and negative), and the interaction between holding periods and return. Standard errors (in parentheses) are two-way clustered by individual and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Sale	Stocks	Stocks	FE Model 1	FE Model 2	FE Model 3
Gain	0.0430***	0.0190*	0.0264***	0.0490***	0.0427**
	(0.00449)	(0.0105)	(0.00906)	(0.0151)	(0.0183)
Speculative		-0.0618***	-0.0325***	0.0121	0.0123
		(0.0107)	(0.00811)	(0.00913)	(0.0105)
Gain × Speculative		0.117***	0.0807***	0.0543***	0.0807***
		(0.0157)	(0.0139)	(0.0149)	(0.0190)
Constant	0.114***	0.114***			
	(0.00357)	(0.0102)			
Observations	3,009,585	120,629	118,062	118,062	68,856
R-squared	0.004	0.012	0.184	0.186	0.505
Cluster individual-month	YES	YES	YES	YES	YES
Month FE			YES	YES	YES
Individual FE			YES	YES	YES
Controls as in BDH (2012)				YES	YES
Individual-Month FE					YES

Table 3: The effect of speculation on selling: Fund investments

This table depicts the variation in investors' selling behavior across speculative and non-speculative assets in funds. Panel A and Panel B contain the sample of passive equity funds (i.e., index funds / ETFs) and active equity mutual funds, respectively. *Gain*, *Speculative*, and *Sale* are defined as before. Standard errors (in parentheses) are two-way clustered by individual and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Passive equity funds				
	(1)	(2)	(3)	(4)
Dependent Variable: Sale	Equity ETFs	Equity ETFs	FE Model1	FE Model3
Gain	-0.0335***	-0.0713***	-0.0261	-0.0289
	(0.00489)	(0.0192)	(0.0225)	(0.0246)
Speculative		-0.0106	0.0153	0.0249
		(0.0195)	(0.0243)	(0.0289)
Gain × Speculative		0.108***	0.0468*	0.0550**
		(0.0226)	(0.0252)	(0.0276)
Constant	0.166***	0.147***		
	(0.00510)	(0.0192)		
Observations	328,939	14,738	13,504	11,501
R-squared	0.002	0.009	0.297	0.286
Cluster individual-month	YES	YES	YES	YES
Month FE			YES	YES
Individual FE			YES	YES
Fees				YES

Panel B: Equity mutual funds				
	(1)	(2)	(3)	(4)
Dependent Variable: Sale	Only MFs	Only MFs	FE Model1	FE Model3
Gain	-0.0287***	-0.0627***	-0.0160	-0.0166
	(0.00360)	(0.0115)	(0.0124)	(0.0134)
Speculative		-0.0201	0.0134	0.0197
		(0.0139)	(0.0187)	(0.0219)
Gain × Speculative		0.0549***	0.0121	0.00743
		(0.0147)	(0.0153)	(0.0171)
Constant	0.144***	0.158***		
	(0.00382)	(0.0110)		
Observations	676,176	36,879	34,781	28,282
R-squared	0.002	0.005	0.252	0.245
Cluster individual-month	YES	YES	YES	YES
Month FE			YES	YES
Individual FE			YES	YES
Fees				YES

Table 4: External validity

This table depicts individual investors' average disposition effect and the effect of speculation using U.S. data. The average disposition effect is calculated for U.S. investor (column (1)) using the Barber and Odean (2000). The effect of speculation on investors' selling behavior in stocks is reported in column (2) using regression (1). Observations are reported as individual-stock-month triples. The variables *Sale, Gain,* and *Speculative* are defined as before. Standard errors (in parentheses) are two-way clustered by individual and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Sale	U.S. sample	U.S. sample	FE Model 1	FE Model 2	FE Model 3
Gain	0.0536***	-0.00108	-0.00446	0.0114	0.0627
	(0.000978)	(0.0111)	(0.0161)	(0.0290)	(0.0621)
Speculative		0.0333***	-0.0135	0.0231	0.0755
		(0.00887)	(0.0254)	(0.0395)	(0.0725)
Gain x Speculative		0.0794***	0.0937***	0.0609***	0.0429
		(0.0144)	(0.0213)	(0.0214)	(0.0503)
Constant	0.324***	0.299***			
	(0.000953)	(0.00765)			
Observations	1,542,973	22,543	17,908	17,908	4,186
R-squared	0.003	0.006	0.431	0.436	0.656
Cluster individual-month	YES	YES	YES	YES	YES
Individual FE			YES	YES	YES
Month FE			YES	YES	Yes
Controls BDH (2012)				YES	YES
Individual-Month FE					YES

Table 5: Realization utility and reinvestment behavior after selling a gain asset

This table shows the reinvestment behavior across speculative and non-speculative stocks. The dependent variable *Reinvestment* is a dummy variable that equals one if a reinvestment event occurs. Each column corresponds to a different definition of a reinvestment event: (1) a sale is followed by several purchases on the same date; (2) a sale is followed by several purchases on the same date and the proceeds of the sale match the amount invested in the new assets by ± 15%; (3) a sale is followed by exactly one purchases on the same date; and (4) a sale is followed by exactly one purchase on the same date and the proceeds of the sale match the amount invested in the new asset by ± 15%. *Speculative* is defined as before. The sample is limited to sales of speculative and non-speculative assets that trade at a gain. Observations record individual-stock-day triples. Standard errors (in parentheses) are two-way clustered by individual and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable: Reinvestment				
Speculative	-0.0802*	-0.0671**	-0.0843**	-0.0550*
	(0.0458)	(0.0331)	(0.0404)	(0.0279)
Observations	3,388	2,607	3,074	2,560
R-squared	0.485	0.472	0.456	0.472
Cluster individual-month	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES

Table 6: Placebo test: Reinvestment after losses

This table shows the reinvestment behavior across speculative and non-speculative stocks. The dependent variable *Reinvestment* is a dummy variable that equals one if a reinvestment event occurs. Each column corresponds to a different definition of a reinvestment event: (1) a sale is followed by several purchases on the same date; (2) a sale is followed by several purchases on the same date and the proceeds of the sale match the amount invested in the new assets by ± 15%; (3) a sale is followed by exactly one purchase on the same date; and (4) a sale is followed by exactly one purchase on the same date and the proceeds of the sale match the amount invested in the new asset by ± 15%. *Speculative* is a dummy variable that equals one if the asset is part of the 10^{th} variance and 10^{th} skewness decile within month *t*. The sample is limited to sales of speculative and non-speculative assets that trade at a loss. Observations record individual-stock-day triples. Standard errors (in parentheses) are two-way clustered by individual and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable: Reinvestment	(1)	(2)	(3)	(4)
Speculative	-0.0432	-0.0423*	-0.0199	-0.0227
	(0.0343)	(0.0220)	(0.0338)	(0.0199)
Observations	3,357	2,411	2,945	2,369
R-squared	0.486	0.487	0.457	0.488
Cluster account-month	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES

Table 7: The rank effect

This table shows the variation in investors' selling behavior across speculative and non-speculative stocks in the absence of the rank effect. To test for the rank effect, we exclude twofold observations from our analyses. An observation is twofold if the stock is classified as speculative stock and ranks worst or best in the investor's portfolio. *Sale, Gain,* and *Speculative* are defined as before. Standard errors (in parentheses) are two-way clustered by individual and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Dependent Variable: Sale	Stocks	FE Model 1
Gain	0.0138	0.0233**
	(0.0115)	(0.00995)
Speculative	-0.0644***	-0.0108
	(0.0132)	(0.0103)
Gain × Speculative	0.0622**	0.0548**
	(0.0288)	(0.0265)
Constant	0.0961***	
	(0.0110)	
Observations	56,431	56,158
R-squared	0.005	0.195
Cluster individual-month	YES	YES
Individual FE		YES
Month FE		YES

Table 8: The attention effect

This table provides the variation in investors' selling behavior across speculative and non-speculative stocks in the presence of attention/inattention. To identify attention grabbing events we follow Barber and Odean (2008). Accordingly, we then split our main sample into two samples, i.e., *Attention* sample (column (1) and (2)) and *No attention* (column (3) and (4)). *Sale, Gain,* and *Speculative* are defined as before. Standard errors (in parentheses) are two-way clustered by individual and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable: Sale	Attention	Attention	No Attention	No Attention
Gain	0.0388***	0.0385***	-0.00236	0.0161
	(0.00836)	(0.00823)	(0.0187)	(0.0131)
Speculative	-0.0573***	-0.0265***	-0.0791***	-0.0385***
	(0.00749)	(0.00693)	(0.0186)	(0.0105)
Gain $\times$ Speculative	0.0994***	0.0683***	0.109***	0.0802**
	(0.0168)	(0.0146)	(0.0329)	(0.0301)
Constant	0.112***		0.116***	
	(0.00673)		(0.0183)	
Observations	74,021	71,087	46,608	43,938
R-squared	0.019	0.218	0.006	0.247
Cluster individual-month	YES	YES	YES	YES
Individual FE		YES		YES
Month FE		YES		YES

Table 9: Robustness: Specification of non-speculative stocks

In this table, we replicate Table 2 using an alternative specification of non-speculative stocks. Non-speculative stocks are defined as stocks with a low variance (variance decile 1) and a low but positive skewness (skewness decile 2). *Speculative*, *Gain*, and *Sale* are defined as before. Observations are reported as individual-stock-month triples. Control variables are defined as in Ben-David and Hirshleifer (2012) (here BDH (2012)) and comprise the holding period, weighted-average purchase price, returns (positive and negative), and the interaction between holding periods and return. Standard errors (in parentheses) are two-way clustered by individual and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(2)	(3)	(4)	(5)
Dependent Variable: Sale	Stocks	FE Model 1	FE Model 2	Fe Model 3
Gain	0.0307	0.0172	0.0213	0.0465
	(0.0217)	(0.0231)	(0.0266)	(0.0385)
Speculative	-0.0455***	0.00704	0.0205	-0.00466
	(0.0101)	(0.0140)	(0.0172)	(0.0180)
Gain × Speculative	0.105***	0.0767***	0.0554*	0.119***
	(0.0253)	(0.0257)	(0.0281)	(0.0395)
Constant	0.0977***			
	(0.00997)			
Observations	33,861	32,575	32,575	14,189
R-squared	0.029	0.242	0.247	0.491
Cluster individual-month		YES	YES	YES
Individual FE		YES	YES	YES
Month FE		YES	YES	Yes
Controls as in BDH (2012)			YES	YES
Account×Month FE				YES

Table 10: Robustness: Identification of speculative (non-speculative) stocks using quartiles

This table provides the variation in investors' selling behavior across speculative and non-speculative stocks using an alternative identification strategy. *Speculative* is a dummy variable that equals one if the stock is part of the 4^{th} variance and 4^{th} skewness quartile in month *t*. *Sale* and *Gain* are defined as before. Standard errors (in parentheses) are two-way clustered by individual and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Dependent Variable: Sale	Stocks	Stocks FE Model 1	Stocks FE Model 2
Gain	0.0173***	0.0299***	0.0246***
	(0.00531)	(0.00498)	(0.00478)
Speculative	-0.0486***	-0.0275***	-0.0197***
	(0.00423)	(0.00384)	(0.00354)
Gain × Speculative	0.107***	0.0762***	0.0563***
	(0.00773)	(0.00677)	(0.00625)
Constant	0.117***		
	(0.00431)		
Observations	713,608	711,441	711,441
R-squared	0.006	0.121	0.145
Cluster individual-month	YES	YES	YES
Individual FE		YES	YES
Month FE		YES	YES
Holding			YES

Appendix

Appendix A: Speculation and investors' selling behavior – No sample restrictions

This table provides the variation in investors' selling behavior across speculative and non-speculative stocks without any sample restrictions. That means (i) investors are not required to hold a stock, equity mutual fund, or passive equity fund at some point in time and (ii) the sample spans from 2001 – 2015. Observations are reported as individual-stock-month triples. The dependent variable *Sale* is a dummy variable equal to one if the investor sells an asset within a particular month t. *Gain* is a dummy variable equal to one if an asset's market price is above the reference point defined as the value-weighted average purchase price. *Speculative* is a dummy variable that equals one if the asset is part of the 10^{th} variance and 10^{th} skewness decile within month *t*. Control variables are defined as in Ben-David and Hirshleifer (2012) (here BDH (2012)) and comprise the holding period, weighted-average purchase price, returns (positive and negative), and the interaction between holding periods and return. Standard errors (in parentheses) are two-way clustered by individual and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent Variable: Sale	Stocks	FE Model 1	FE Model 2	FE Model 3
Gain	0.0331***	0.0460***	0.0637***	0.0331**
	(0.00849)	(0.00636)	(0.00966)	(0.0137)
Speculative	-0.0482***	-0.0382***	0.0109*	0.00318
	(0.00613)	(0.00516)	(0.00591)	(0.00853)
Gain x Speculative	0.130***	0.0733***	0.0447***	0.0589***
	(0.0106)	(0.00872)	(0.00858)	(0.0121)
Constant	0.132***			
	(0.00595)			
Observations	200,661	192,256	192,256	81,613
R-squared	0.028	0.230	0.234	0.480
Cluster account-month	YES	YES	YES	YES
Individual FE		YES	YES	YES
Month FE		YES	YES	YES
Controls BDH (2012)			YES	YES

Appendix B: Kumar (2009) identification

This table provides the variation in investors' selling behavior across speculative and non-speculative stocks using the Kumar (2009) identification. Assets are categorized as speculative if they fall into the 10th idiosyncratic variance, 10th idiosyncratic skewness, and 1st price decile in month *t*. Assets are categorized as speculative or non-speculative if they fall into the 1st idiosyncratic variance, 1st idiosyncratic skewness, and 10th price decile in month *t*. The variables *Sale* and *Gain* are defined as before. Standard errors (in parentheses) are two-way clustered by individual and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Dependent Variable: Sale	Kumar (2009)	Kumar (2009)
Gain	0.0278***	0.0513***
	(0.00987)	(0.00938)
Speculative	-0.0927***	-0.0477***
	(0.00747)	(0.00831)
Gain x Speculative	0.177***	0.102***
	(0.0275)	(0.0277)
Constant	0.124***	
	(0.00720)	
Observations	54,874	52,373
R-squared	0.031	0.252
Cluster account-month	YES	YES
Individual FE		YES
Month FE		YES

Appendix C: Table 2 including BDH (2012) coefficients

This appendix mirrors Table 2 but includes the coefficient estimates of the BDH (2012) control variables. Observations are reported as individual-stock-month triples. The variables *Sale, Gain,* and *Speculative* are defined as before. Control variables are defined as in Ben-David and Hirshleifer (2012) (here BDH (2012)) and comprise the *Holding period*, *Purchase price*, *Return* (positive and negative), and the interaction between *Holding period* and *Return* as well as *holding period* and *Gain*. *Holding period* is the square root of the number of months since the purchase of the position; *Purchase price* is the natural logarithm of the weighted-average purchase price; *Return (+)* is an indicator for whether the return since purchase is positive; and *Return (-)* is an indicator for whether the return since purchase is negative. Standard errors (in parentheses) are two-way clustered by individual and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Sale	Stocks	Stocks	FE Model 1	FE Model 2	FE Model 3
Gain	0.0430***	0.0190*	0.0264***	0.0490***	0.0427**
	(0.00449)	(0.0105)	(0.00906)	(0.0151)	(0.0183)
Speculative		-0.0618***	-0.0325***	0.0121	0.0123
		(0.0107)	(0.00811)	(0.00913)	(0.0105)
Gain × Speculative		0.117***	0.0807***	0.0543***	0.0807***
		(0.0157)	(0.0139)	(0.0149)	(0.0190)
Sqrt(holding period)				0.0188***	0.0101***
				(0.00254)	(0.00251)
Log(purchase price)				0.00501***	0.00562***
				(0.00126)	(0.00151)
Gain × sqrt(holding period)				-0.0105***	-0.0118***
				(0.00272)	(0.00322)
Return (+)				0.0279**	0.0219
				(0.0115)	(0.0133)
Return (-)				-0.0236*	-0.0001
				(0.0135)	(0.0166)
Return (+) x sqrt (holding period)				-0.00591***	-0.00425
				(0.00216)	(0.00267)
Return (-) x sqrt (holding period)				0.0217***	0.0147***
				(0.00306)	(0.00338)
Constant	0.114***	0.114***			
	(0.00357)	(0.0102)			
Observations	3,009,585	120,629	118,062	118,062	68,856
R-squared	0.004	0.012	0.184	0.186	0.505
Cluster account-month	YES	YES	YES	YES	YES
Month FE			YES	YES	YES
Investor FE			YES	YES	YES
Controls as in BDH (2012)				YES	YES
Investor-Month FE					YES

Appendix D: Moving along the diagonal: PGR and PLR across variance and skewness deciles

The table depicts results from regression equation (2). The results in column (1) serve as basis for Figure 3. *Gain* is defined as for regression equation (1). *Decile2* is a dummy variable that equals one if the stock is part of the 2nd variance and 2nd skewness decile within month *t*. The same logic applies to the rest of the decile dummy variables. Observations are investor-stock-month triples. Standard errors (in parentheses) are two-way clustered by individual and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable: Sale	(1) Stock Sample	(2) FE Model 1	(5) FE Model 2
Gain	0.0190*	0.0276***	0.0385***
	(0.0105)	(0.00947)	(0.0139)
Decile2	0.00820	0.00724	0.00712
	(0.00895)	(0.00691)	(0.00672)
Gain × Decile2	0.00422	0.00514	0.00594
	(0.00885)	(0.00763)	(0.00733)
Decile3	0.0107	0.0133*	0.0149**
	(0.00814)	(0.00710)	(0.00689)
Gain × Decile3	0.0194**	0.0173**	0.0181**
	(0.00836)	(0.00777)	(0.00765)
Decile4	0.00483	0.0126	0.0163**
	(0.00970)	(0.00781)	(0.00783)
Gain × Decile4	0.0231**	0.0186*	0.0187*
	(0.0110)	(0.00955)	(0.00951)
Decile5	0.00571	0.0127	0.0198**
	(0.00959)	(0.00774)	(0.00799)
Gain × Decile5	0.0349***	0.0283***	0.0277***
	(0.00953)	(0.00850)	(0.00849)
Decile6	0.00272	0.0110	0.0239***
	(0.00996)	(0.00802)	(0.00828)
Gain × Decile6	0.0555***	0.0394***	0.0355***
	(0.0141)	(0.0128)	(0.0129)
Decile7	-0.00442	0.0108	0.0285***
	(0.00967)	(0.00828)	(0.00858)
Gain × Decile7	0.0864***	0.0643***	0.0594***
	(0.0157)	(0.0134)	(0.0135)
Decile8	-0.0166*	0.00604	0.0294***
	(0.00954)	(0.00832)	(0.00876)
Gain × Decile8	0.0823***	0.0567***	0.0473***
	(0.0123)	(0.0109)	(0.0110)
Decile9	-0.0362***	-0.0120	0.0184**
	(0.0103)	(0.00861)	(0.00919)
Gain × Decile9	0.0873***	0.0717***	0.0602***
	(0.0145)	(0.0125)	(0.0128)
Decile10	-0.0618***	-0.0309***	0.00858
	(0.0107)	(0.00907)	(0.00935)
Gain × Decile10	0.117***	0.0915***	0.0677***
	(0.0157)	(0.0137)	(0.0140)
Constant	0.114***		
	(0.0102)		
Observations	566,601	564,056	564,056
R-squared	0.009	0.126	0.127
Cluster individual-month	YES	YES	YES
Individual FE		YES	YES
Month FE		YES	YES
Controls BDH 2012			YES

Appendix E: Asset characteristics versus investor demographics

This table shows the variation in investors' selling behavior across speculative and non-speculative stocks while controlling for investor demographics. *Gain*, *Speculative*, and *Sale* are defined as before. Investors demographics comprise income, wealth, experience, age, and gender. Income and wealth are self-reported. Investors are part of the high income (wealth) group if their income falls into the top income (wealth) quartile. Investors are part of the low income (wealth) group if their income falls into the bottom income (wealth) quartile. Following Seru et al. (2010), we measure experience by the cumulative number of trades that an investor has placed. Investors are experienced (experience high = 1) if cumulative number of trades is part of the top trading quartile. Investors are inexperienced (experience low = 1) if cumulative number of trades is part of the bottom trading quartile. Age is measured in years. Gender is equal to 1 (0) if the investor is a male (female). Standard errors (in parentheses) are two-way clustered by individual and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable: Sale	(1) Income	(2) Wealth	(3) Experience	(4) Age	(5) Gender
Gain	0.0218	0.0253	0.0352	0.0247	0.0363**
	(0.0180)	(0.0190)	(0.0259)	(0.0170)	(0.0178)
Speculative	0.0178	0.00865	0.0260	0.0166	0.0216
	(0.0136)	(0.0143)	(0.0261)	(0.0118)	(0.0148)
Demographic	-0.00523	-0.0193**	-0.0508***	0.00451	0.0111*
	(0.00695)	(0.00789)	(0.0146)	(0.00549)	(0.00627)
Gain x Lottery	0.0767***	0.0644***	0.128**	0.0536***	0.0568*
	(0.0240)	(0.0206)	(0.0607)	(0.0171)	(0.0296)
Gain x Demographic	0.00480	0.00544	-0.0209	0.0116	-0.00836
	(0.00870)	(0.00984)	(0.0169)	(0.00711)	(0.00901)
Speculative x Demographic	0.00445	0.0193**	-0.00659	0.00277	-0.00630
	(0.00863)	(0.00958)	(0.0213)	(0.00698)	(0.00921)
Gain x Demographic x Speculative	-0.0199	-0.00521	-0.0687	-0.00260	0.00152
	(0.0251)	(0.0266)	(0.0608)	(0.0184)	(0.0266)
Constant	0.124***	0.128***	0.174***	0.115***	0.108***
	(0.0196)	(0.0206)	(0.0272)	(0.0174)	(0.0189)
Observations	63,853	61,946	59,587	120,629	118,655
R-squared	0.020	0.021	0.026	0.019	0.018
Cluster account-month	YES	YES	YES	YES	YES
Controls as in BDH (2012)	YES	YES	YES	YES	YES

Appendix F: Descriptive active and passive fund sample

This table depicts summary statistics for the asset class of funds. Panel A contains information at the investor level. The a*verage number of trades* and *asset allocation* are reported monthly. *Asset allocation* is the fraction of the investor's portfolio dedicated to the respective asset class (here: equity mutual funds or passive equity funds). Panel B reports information on stocks categorized as speculative or non-speculative. Speculative assets are assets which are part of the 10^{th} variance and 10^{th} skewness decile in month *t*. Non-speculative assets are assets which are part of the 1^{st} variance and 1^{st} skewness decile in month *t*. *Number of assets* is the distinct number of funds that were categorized as speculative or non-speculative during the sample period. *Volatility* and *Skewness* are the mean monthly values for total volatility (i.e., standard deviation of return) skewness during the months in which the fund is being categorized as speculative/non-speculative. *Holding periods* are measured in months. *Realized return* is the return upon sale for an asset trading at a gain/loss. Numbers in parentheses are medians.

	Panel A: Retail investor	
Sample	**Equity mutual funds**	**Passive equity funds**
Portfolio		
Average number of trades	2.07 (1.56)	1.78 (1.34)
Asset allocation (%)	31.1	20.8
	Panel B: Asset characteristics	
	Speculative	**Non-speculative**
Equity mutual funds		
Number of asset observations	574	668
Volatility (monthly, %)	4.1	0.4
Skewness	0.07	-0.2
Holding period (in months)		
Gain	27 (21)	28 (25)
Loss	32 (31)	27 (25)
Exemplary assets by name	BNP Paribas Funds Russia Equity BlackRock Latin American Opportunities	DWS Top Dividende Invesco Global Dynamik Fonds
Passive equity funds		
Number of asset observations	130	111
Volatility (monthly, %)	3.5	0.6
Skewness	0.16	-0.2
Holding period (in months)		
Gain	24 (18)	28 (24)
Loss	23 (19)	22 (16)
Exemplary assets by name	Lyxor Euro Stoxx 50 Daily (2x) Leveraged UCITS ETF LYXOR DAILY LEVDAX UCITS ETF	iShares DJ Industrial Average ETF MSCI World ex Europe

Appendix G: Reinvestment behavior and stocks degree of speculation

The table depicts the change in reinvestment behavior over variance and skewness deciles and serves as basis for Figure 5. *Reinvestment* is a dummy variable that equals one if a sale is followed by several purchases on the same date (see reinvestment definition (1) from Table 5). *Decile2* is a dummy variable that equals one if the stock is part of the 2nd variance and 2nd skewness decile within month *t*. The same logic applies to the rest of the decile dummy variables. Reinvestment behavior across decile 2-10 is compared against reinvestment behavior in Decile 1. The sample is limited to sales of stocks that trade at a gain. Observations record individual-stock-day triples. Standard errors (in parentheses) are two-way clustered by individual and month. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Y=Reinvestment	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Decile2	-0.0330***								
	(0.0115)								
Decile3		-0.0499***							
		(0.0126)							
Decile4			-0.0348**						
			(0.0137)						
Decile5				-0.0486**					
				(0.0197)					
Decile6					-0.0468**				
					(0.0215)				
Decile7						-0.0702***			
						(0.0229)			
Decile8							-0.0679**		
							(0.0278)		
Decile9								-0.0450	
								(0.0410)	
Decile10									-0.0817*
									(0.0435)
Observations	9,384	8,118	6,395	5,103	5,046	4,593	3,989	3,287	3,388
R-squared	0.410	0.415	0.437	0.446	0.448	0.456	0.457	0.482	0.463
Cluster individual-month	YES	YES	YES	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES	YES