Waiting for the gain to come:

How variance and skewness shape retail investors' selling behavior

Sabine Bernard*, Martin Weber†, and Benjamin Loos‡

Abstract

We document a new stylized fact about how assets' higher moments of return affect private investors' selling behavior: Investors are more (less) likely to sell high-variance-high-skewness stocks trading at a gain (loss) relative to low-variance-low-skewness stocks trading at a gain (loss). This translates into a high disposition effect for high-variance-high-skewness and an almost insignificant disposition effect for low-variance-low-skewness stocks. The effect holds *within* the asset class of stocks, as well as *across* asset classes (i.e., fund investments), thereby offering a more holistic explanation of selling behavior than theories tailored to specific assumptions. We show that the effect is not driven by rank or attention effects but can be linked to realization utility.

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

JEL Classification: D14, D81, D9, G11

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* Sabine Bernard (bernard@safe-frankfurt.de) is affiliated with the Leibniz Institute for Financial Research SAFE (Theodor-W.-Adorno-Platz 3, 60323, Frankfurt am Main, Germany).

† Martin Weber (weber@bank.bwl.uni-mannheim.de) is affiliated with the University of Mannheim (L9, 1-2, 68131 Mannheim, Germany) and CEPR, London.

‡ Benjamin Loos (benjamin.loos@tum.de) is affiliated with the Technical University of Munich (Arcisstr. 21, 80290 Munich, Germany).

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1. Introduction

There is abundant research examining how investors arrive at the decision of when to part with their assets. Perhaps one of the most prominent patterns is the disposition effect, i.e., investors' tendency to sell assets that increased in value more readily than assets that decreased in value since purchase (e.g., Shefrin and Statman, 1985; Odean, 1998; Weber and Camerer, 1998). While researchers agree on the effect of positive and negative returns on retail investors' selling behavior, we are the first to examine the effect of variance and skewness.

Consider for a moment the role of variance and skewness. Think of two assets, A and B, whose return distributions have the same expected value but differ in variance and skewness. Asset A's return distribution shows a high variance and a high positive skewness, whereas Asset B's return distribution shows a low variance and a low (even negative) skewness. Figure 1 depicts the return distributions of Asset A (solid line) and Asset B (dashed line). At first glance, one notices that the solid and dashed line depict two fundamentally different assets. Kumar (2009) labeled assets with a high variance and high skewness (Asset A) as *speculative* and assets with a low variance and low skewness (Asset B) as *non-speculative*.[1] This categorization into speculative and non-speculative assets neatly summarizes the assets' characteristics and what the asset offers to investors. Having most of the probability mass located above zero, a non-speculative asset with a positive expected value steadily increases in value.[2] On the contrary, a speculative asset offers the investor the chance of a large upside potential. However, such extreme return realizations are rare. Once a rare, outsized positive return occurs, the investor — knowing the rarity of such an event — will cash-in her gain thereby receiving a vast burst of positive realization utility. On the other hand, an investor experiencing a moderate return event (positive or negative) will hold on to the speculative asset since the positively skewed return distribution and the overweighting of small probability events (i.e., probability weighting) makes her wait for an extreme gain sometime in the future (Barberis, 2012). This example suggests that investors holding high-

[1] The term high-variance-high skewness asset and speculative asset, as well as the term low-variance-low-skewness asset and non-speculative asset are used interchangeably throughout the paper.

[2] Theoretically, assets with a negative skewness have a small chance of a large downturn. In Section 6.1, we further show that using an alternative definition of non-speculative assets (i.e., assets with a low variance and low but non-negative skewness) does not alter our findings.

variance-high-skewness assets might follow an ex ante strategy about when to part with their assets: They should stay in the market in the moderate gain/loss region and cash-in extreme gains. We hypothesize that this strategy drives a wedge between the proportion of gains realized (PGR) and the proportion of losses realized (PLR), thereby increasing the disposition effect for high-variance-high-skewness assets relative to low-variance-low-skewness assets.

[Insert Figure 1 here]

In this paper, we investigate the effect of variance and skewness on investors' selling behavior. By sorting assets on their higher moments of return, we get a better understanding of the fundamental characteristics of the asset that is to be sold. This allows us to better understand investors' selling behavior than sorting purely on positive and negative returns. Using a retail investor trading data set of more than 22,000 individuals at a German bank, we find that the extent of the disposition effect and in particular the realization of gains (PGR) and losses (PLR) varies significantly across assets with different types of return distributions. In order to assess whether an asset is a high-variance-high-skewness asset or a low-variance-low-skewness asset, we use a rolling month window approach. We calculate an asset's variance and skewness over the past year using daily returns. Following Kumar (2009), we classify speculative assets as stocks falling into the 10th variance and 10th skewness decile (i.e., highly positively skewed) in month *t*, whereas non-speculative assets are stocks falling into the 1st variance and 1st skewness decile in month *t*. We then analyze investors' trading behavior over the next month.

Figure 2 illustrates the main finding of our paper: Investors show different selling behaviors in high-variance-high-skewness (HVHS) stocks compared to low-variance-low-skewness (LVLS) stocks. HVHS stocks trading at a gain are more frequently sold than LVLS stocks trading at a gain. In contrast, HVHS stocks trading at a loss are less frequently sold than LVLS stocks trading at a loss. Figure 2 shows that investors are 41% more likely to sell a HVHS stock trading at a gain than to sell a LVLS stock trading at a gain. While investors generally do not like to realize assets trading at a loss (e.g., Odean, 1998), they are about 54% less likely to sell a HVHS stock trading at a loss compared to selling a LVLS stock trading at a loss. Ultimately, these changes in gain and loss realization lead to different degrees of the disposition effect in HVHS and LVLS stocks: Investors show a disposition effect that is highly statistically significant at the 1% level and equals 13.60%

in HVHS assets, whereas the disposition effect in LVLS assets is only marginally significant at the 10% level and equals 1.9%. To ensure that our results are not driven by time-varying variance and skewness preferences, we account for systematic differences in investor's variance and skewness *preferences* and for *changes in these preferences* over time by introducing individual and time fixed effects and the interaction of both to the regression framework. Following Ben-David and Hirshleifer (2012), we also account for control variables that are known to affect investors' selling behavior (i.e., holding period, weighted-average purchase price, returns (positive and negative) since purchase, and the interaction between holding periods). We find that the difference in investors' selling behavior between speculative and non-speculative stocks remains highly statistically significant. Interestingly, once we account for control variables as suggested by Ben-David and Hirshleifer (2012), we find that the difference in investors' selling behavior is exclusively driven by changes in PGR and no longer by changes in PLR. Finally, we show that our results cannot be explained by either variance or skewness being high. We observe significant differences in investors' selling behavior only if both variance and skewness are high.

[Insert Figure 2 here]

While focusing on assets with extreme higher moments of return in our main analysis (HVHS vs. LVLS), we show in a complementary analysis that PGR (PLR) gradually increases (decreases) as assets' variance and skewness increase (decrease): The correlation between PGR and variance and skewness deciles is positive (0.93), whereas the correlation between PLR and variance and skewness deciles is negative (-0.79). The difference in PGR and PLR (i.e., the disposition effect) is smallest (highest) if the level of variance and skewness is smallest (highest). Hence, our main result is not driven by comparing assets at the corner of the variance-skewness distribution. Instead, there seems to be a persistent relationship between an asset's level of variance and skewness and investors' gain and loss realization. In several subsample splits, we further investigate how demographics, – which researchers find to affect the disposition effect, – interfere with the size of our effect. In line with previous studies (e.g., Shapira and Venezia 2000; Barber and Odean, 2001; Goyal 2004), we find that factors such as level of sophistication, gender, and age decrease the level of the disposition effect in both asset groups (i.e., HVHS and LVLS), however, they do not diminish the differences in the disposition effect across these groups.

There is empirical evidence showing that investors' selling behavior differs across asset classes (e.g., Chang et al., 2016). To get a more nuanced understanding of investors' selling behavior it is interesting to examine whether our effect only holds within the asset class of stocks or if it also translates into other asset classes frequently held by retail investors, such as passive equity and equity mutual funds. We find that the effect of variance and skewness on investors' selling behavior in fund investments is in line with findings from our stock analysis: Investors have a higher disposition effect in speculative than in non-speculative funds and this difference is statistically significant at the 1%-level. In line with findings from our stock sample analysis, this difference in selling behavior in funds is driven by changes in PGR, and not by changes in PLR as the changes in PLR are insignificant. More precisely, we find that investors' PGR in speculative passive equity funds is between 5.56 and 9.74 percentage points higher than in non-speculative passive equity funds. Investors' PGR in speculative mutual fund is between 2.13 and 3.48 percentage points higher than in non-speculative mutual funds.[3] Thus, across asset classes, the effect of variance and skewness is highest in stocks, followed by passive equity and equity mutual funds.

Our findings can be linked to the concept of realization utility (Barberis and Xiong, 2012) in combination with rolling mental accounts (Frydman, Hartzmark, and Solomon, 2018). According to realization utility theory, investors selling an asset at a gain (loss) get an extra burst of positive (negative) realization utility at the moment of the sale since a positive (negative) investment episode is created. Frydman et al. (2018) add to this by pointing 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. Therefore, 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 investor does not roll her mental account). If investors crave realization utility and therefore demonstrate the observed trading behavior, we should observe lower reinvestment rates after the sale of a HVHS stock trading at a gain than after the sale of a LVLS stock trading at a gain. Analyzing investors' reinvestment decision in our sample, we find that

[3] Note, that within the asset class of stocks, speculative stocks' PGR is between 4.82 and 9.30 percentage points higher than non-speculative stocks' PGR.

investors’ likelihood of reinvesting decreases by between 5.5 and 8.4 percentage points after realizing a gain in a HVHS stock compared to realizing a gain in a LVLS stock. Expanding our analysis to assets in less extreme variance and skewness deciles, we find the likelihood of reinvestment to be negatively correlated (-0.8) 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 level of variance and skewness. To further investigate the realization utility channel, we run a placebo test. In the realization utility model by Barberis and Xiong (2012) selling a losing stock is triggered by a liquidity shock and thus should not be followed by reinvestment. Therefore, we should find no difference in reinvestment behavior after losses. We find that in three out of four model specifications there is no evidence for differences in investors’ selling behavior after realizing losses in speculative and non-speculative stocks.

Our findings might further interfere with other effects that drive individual investors’ selling behavior. By construction, assets that have both a high variance and a high skewness have extreme returns from time to time. Thus, effects such as attention grabbing (e.g., Barber and Odean, 2008) or portfolio rank (Hartzmark, 2015) could affect our results. We therefore analyze how HVHS assets interact with attention grabbing and portfolio rank mechanisms. We find that both effects are not sufficient to explain the differences in investors’ selling behavior for HVHS and LVLS stocks. Investigating investors’ selling behavior across asset classes, our results could also be affected by the concept of cognitive dissonance (Chang et al., 2016). According to cognitive dissonance, the extent of the disposition effect varies across asset classes due to the asset class’s degree of delegation, i.e., is highest for stock investments (non-delegated investment), diminished in index funds, and lowest in mutual funds (fully delegated investment). In contrast to Chang et al. (2016), we do not find evidence for significant differences in the selling behavior of active and passive fund investors. This casts doubt on the concept of delegation being the driver of our result.

Our paper contributes to the literature that examines stock-level attributes associated with retail investors’ selling behavior. While other studies examine how positive returns (e.g., Shefrin and Statman 1985, Odean, 1998), demographics (e.g., Dhar and Zu, 2006), geographic proximity (Coval and Moskowitz, 1999), or the choice of the asset class (Chang et al., 2016) shape investors' selling behavior, our study demonstrates that an investor's selling behavior is significantly affected by an asset's variance and skewness. Our results illustrate that investors' selling behavior *within* and *across* asset classes is strongly affected by the asset's fundamental characteristics (i.e., speculative vs. non-speculative). Thereby, our analyses offer a more holistic understanding of investors' selling behavior than existing studies. Linking our results to the concept of realization, 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). By separating assets along their variance and skewness dimension, we further draw a connection from the gambling literature (e.g., Kumar, 2009) to investors' selling behavior. Researchers show that gambling characteristics such as variance and skewness play an important role in investors' entry decisions (e.g., Friedman and Savage, 1948; Markowitz, 1952; Barberis and Huang, 2008). We add to these findings by demonstrating that not only buying patterns but also selling patterns are strongly affected by higher moments of return.

2. Data and Methodology

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.[4] 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 on a monthly basis. 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,

[4] 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.

income, wealth, and ZIP code. We complement the bank data with market data downloaded 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. After filtering our data, we construct an investor's portfolio on a monthly basis. In line with previous studies (e.g., Odean, 1998; Chang, Solomon, and Westerfield, 2016), we analyze investors' selling behavior in sale months only. To be able to compare investors' selling behavior across 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/his trading history (Chang et al., 2016).

Panel A of Table 1 provides information about our stock sample composition. 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-monthlevel. The medium portfolio value in out sample equals 26,220 Euros. On average investors trade three times a month. As can be expected, the majority of assets in a private investor's portfolio is attributed to stock investments. The average fraction of stock investments in an investor's portfolio is equal to 48.1%. The remaining 51.9% are allotted to active and 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 to be equal to 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. Even though gender is not equally distributed, the gender distribution is comparable to previous studies on private investors' trading behavior (e.g., Dorn and Strobl, 2009; Ben-David and Hirshleifer, 2012). Approximately 8% of our sample can be labeled as highly educated and the average income is equal to 57,000 Euros.

[Insert Table 1 here]

Since we investigate how higher moments of return shape investors' selling behavior, we need to identify HVHS and LVLS assets using market data. Following Kumar (2009), we use a rolling month window approach and calculate an asset's variance and skewness over the past year using daily return data. We calculate variance and skewness for the universe of assets traded in our data set. 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 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 LVLS patterns over the past year. Assets that are not part of the speculative or non-speculative sample are categorized as others (Kumar, 2009). 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. However, as the heatmap in Appendix A shows, 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 located 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. We find that if an asset is classified as an HVHS (LVLS) asset in month t, then this asset is a HVHS (LVLS) asset with a probability of 91% (77%) in the subsequent month.[5] Panel B in Table 1 captures information and characteristics of stocks being categorized as HVHS assets or LVLS assets. Our data captures 2,474 (1,451) asset-month observations of HVHS (LVLS) assets. By construction, HVHS assets show higher variance and skewness than LVLS assets. The differences in variance and skewness are statistically significant. We find the average return on realized gains (losses) in HVHS assets to be six (five) times as high (low) as in LVLS assets. We also find that speculative assets are held

[5] For more details of how assets move along categories, see Appendix B.

significantly longer when trading at a loss compared to non-speculative asset trading at a loss. Interestingly, this picture reverses when analyzing holding periods given the asset is 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 the names of the speculative/non-speculative assets frequently held by private investors in our sample.

Combining the private investor and the market data set, we can now analyze how private investors' selling behavior is affected by higher moments of return. We follow Chang et al. (2016) to analyze investors' selling behavior:

$$Sale_{ijt} = \beta_0 + \beta_1 Gain_{ijt} + \beta_2 Speculative_{jt-1} + \beta_3 Gain_{ijt} \times Speculative_{jt-1} + \beta' X + \epsilon_{ijt}, \quad (1)$$

where observations are at the individual(*i*)-stock(*j*)-month(*t)* level. The variable that is unique to our analysis is the *Speculative* dummy variable. The variable is equals one (zero) if the asset is categorized as HVHS (LVLS) stock 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, weighted-average purchase price, returns (positive and negative), and the interaction between holding periods and return. 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 return is the return since purchase if it is positive or negative, respectively. The dependent variable *Sale* is a dummy variable that equals one whenever a sale takes place. Based on regression equation (1), we are able to 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. According to our hypothesis, investors should 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 across asset groups is given by β_3 and should be positive.

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.

3. The Effect of Variance and Skewness on Investors' Selling Behavior

3.1 Main analysis: Stock sample

To investigate the effect of variance and skewness on investors' selling behavior, we estimate equation (1). The results are in Table 2. Figure 2 (based on Table 2, column (2)) graphically depicts the main results of our paper. Investors' realization of gains and losses is asymmetrically affected by variance and skewness: While an increase in variance and skewness triggers an increase in investors' propensity to sell stocks trading at a gain, it triggers a decrease in investors propensity to sell stocks trading at a loss. This opposing response in investors gain and loss realization to an increase in variance and skewness ultimately leads to a strong disposition effect in HVHS assets and a weak disposition effect in LVLS assets. On average, investors are 42% more likely to sell a speculative asset trading at a gain than to sell a non-speculative asset trading at a gain. In contrast, investors are 54% less willing to realize a speculative asset trading at a loss compared to realizing a non-speculative asset trading at a loss. These differences in PGR (PLR) between HVHS and LVLS 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 HVHS equals 13.6, which is 7 times higher than the disposition effect in LVLS assets, which equals 1.9. Further, the disposition effect in HVHS stocks is highly statistically significant at the 1% level, whereas the disposition effect in LVLS stocks is close to be statistically insignificant.

[Insert Table 2 here]

Our results could be caused by systematic differences in investor's variance and 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. Even in an within individual investor comparison approach, we find investors' selling behavior to be strongly affected by past year skewness and variance. Investors are 4.82 percentage points more likely to sell a HVHS stock trading at a gain than to sell LVLS stock trading a gain, whereas they are 3.25 less likely to sell a HVHS stock trading at a loss than to sell a LVLS stock trading at a loss. The difference in the disposition effect between the two asset groups 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 HVHS stock (10.7%), whereas she suffers from a small disposition effect in a LVLS stock (2.64%) in the same month. This clearly indicates, that an asset's higher moments of return rather than investors' characteristics are strong drivers of investors' selling decisions. We also introduce commonly used control variable from the disposition effect literature (Ben-David and Hirshleifer, 2012) into our regression framework. Investors are still more likely to realize a gain in a speculative asset than in a non-speculative asset but now the difference in PLR across HVHS and LVLS assets (the speculative coefficient estimate) becomes insignificant. The disposition effect in HVHS assets is still more than twice as high as in LVLS assets and differences in the disposition effect are still highly statistically significant. In our most conservative estimation (column (5)), we use investor-month fixed effects to ensure that our results are not driven by different types of investors being active in different months during our sample period. We find HVHS assets' PGR to be more than three times higher than LVLS asstes' PGR.

Comparing HVHS assets to LVLS 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 Appendix A, each asset in our dataset can be located in a two-dimensional space according to its level of variance and skewness. To investigate how PGR and PLR change once an asset's variance and skewness gradually increases, we run a modified version of equation (1):

$$Sale_{ijt} = \beta_0 + \beta_1 Gain_{ijt} + \sum_{u=2}^{10} \beta_u Decile_u + \sum_{v=2}^{10} \beta_V \, Decile_v \times Gain_{ijt} + e_{ijt}, \tag{2}$$

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. 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 the diagonal of the two-dimensional variance-skewness space.

[Insert Figure 3 here]

In Figure 3, we plot PGR and PLR against variance and skewness deciles based on results from equation (2).[6] 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, we find evidence that PGR (PLR) gradually increases (decreases) as variance and skewness increases (decreases). The correlation between PGR and the variance and skewness decile is positive (0.93), whereas the correlation between PLR and the variance and skewness decile is (-0.79). The difference in PGR and PLR is smallest (largest) for assets sorted in variance and skewness decile 1 (decile 10). Therefore, the disposition effect is smallest for LVLS assets and highest for HVHS assets. The differences in PGR and PLR are always statistically significant within a decile. Our findings remain significant after introducing individual and month fixed effects (see Appendix C, column (2)). 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.

[6] Detailed regression results are in Appendix C.

While previous studies show that investors react to the combination of variance and skewness (e.g., Kumar, 2009), it could be that our results are driven by investors reacting to one particular moment, rather than to the combination of both. To further understand the mechanisms behind our findings and to ensure that both variance and skewness are important drivers for the observed effect, we run a modified version of equation (2). Instead of investigating the change in PGR and PLR along the diagonal of the two-dimensional variance-skewness space, we now examine the change in PGR and PLR on the mirrored diagonal. The results are in Appendix D. *Sale* and *Gain* are defined as for equation (2). The *decileX,Y* is a dummy variable that is equal to one if the asset falls into the variance decile X and the variance skewness Y. For example, *decile2,9* contains all assets that are part of variance decile 2 and skewness decile 9. To ensure the comparability of our results, we use the same cluster and fixed effects as in Appendix C (i.e., when investigating changes in PGR and PLR along the diagonal of the two-dimensional variance-skewness space). Due to multicollinearity, we subsume *decile1,10* in the constant. When analyzing changes in PGR and PLR on the mirrored diagonal, we start in the upper left corner (*decile1,10*) of the variance-skewness space and move to the lower right corner (*decile10,1*). Hence, by moving along the mirrored diagonal, we gradually increase variance and decrease skewness. Comparing the regression results from Appendix D (mirrored diagonal) and Appendix C (diagonal), we find that the coefficient estimates become mostly insignificant. Moving along the mirrored diagonal, we find that PGR (PLR) increases (decreases) in terms of magnitude; however, these changes are not significant. There is one exception to this rule: assets that are part of variance decile 9 and skewness decile 2 show a significantly higher PGR than assets located in the variance decile 1 and skewness decile 10. However, this difference turns statistically insignificant once we control for individual and month fixed effects. The fact that investors' PGR and PLR do not change when moving along the mirrored diagonal illustrates that the combination of both variance and skewness rather than one single moment drives our main result.

Since we are the first to test how higher moments of return affect the investors' selling behavior and are using a proprietary dataset, we need to ensure that our results are representative. In column (1) of Table 2 we use the standard disposition effect regression (e.g., Chang et al., 2016) to verify our data. We find that investors' have a disposition effect of 4.3% and the PGR and PLR ratio equals 1.39. Our figures are slightly lower than those found by Odean (1998), who observes a disposition effect of 5% and a PGR and PLR ratio of 1.5. The fact that in our data the average investor shows a lower disposition effect than the average Odean (1998) investor might be due to several reasons. We include investors who at some point in time hold stocks, equity mutual funds, and passive equity funds. Passive funds are often considered to be investment vehicles used by more sophisticated or better financially educated investors. Previous studies show that these investors suffer less from behavioral trading biases (e.g., Shapira and Venezia, 2000; Grinblatt and Keloharju, 2001; Feng and Seasholes, 2005). Moreover, our data contains German rather than U.S. investors and we analyze investors' selling behavior in a more recent time period (e.g., 2010-2015).

3.2 Subsample analysis: Stock investments

3.2.1 Level of sophistication and higher moments of return

Researchers find that investors level of sophistication affects their trading behavior (e.g., Shapira and Venezia, 2000; Grinblatt and Keloharju, 2001; Feng and Seasholes, 2005). These studies typically show that trading biases are less pronounced for highly sophisticated investors. We next investigate whether more sophisticated investors' selling behavior is less sensitive to higher moments of return than less sophisticated investors' selling behavior. To avoid a time-varying measure of sophistication, we use investors' academic title to split the sample among sophisticated and less sophisticated investors. As shown in Table 1, about 8% of our investors hold a Ph.D. or a professorship and thus can be categorized as highly sophisticated. Table 3 contains results from equation (1) using the sample of sophisticated (column (1)) and less sophisticated (column (2)) investors.

[Insert Table 3 here]

Focusing on the two channels of the disposition effect, PGR and PLR, we find that more sophisticated investors' selling behavior is less sensitive to higher moments of return. Sophisticated investors still show a higher propensity to realize gains in HVHS stocks than in LVLS stocks; however, the difference is no longer statistically significant. Turning to sophisticated investors' loss realization, we find that they show a lower propensity to sell HVHS stocks compared to LVLS stocks (i.e., β_2 is negative). While the size of the drop in PLR is comparable to our full sample result (see β_2 in Table 2, column (3)), the drop is only marginally significant. Overall, in the sample of more sophisticated investors, we find no evidence of a disposition effect in non-speculative assets but there is still a disposition effect of 8.66% in speculative assets that is significant at the 5% level.

Turning to the less sophisticated investor sample (column (2)), we find that their selling behavior is strongly affected by higher moments of return. Less sophisticated investors are 4.7 (3.2) percentage points more (less) likely to realize a HVHS asset trading at a gain (loss) than realizing a LVLS asset trading at a gain (loss). These differences are highly statistically significant at the 1% level. We also find the disposition effect to be highly statistically significant for HVHS and LVLS assets: Less sophisticated investors suffer from a disposition effect equal to 10.8% (2.9%) in HVHS (LVLS) assets.

Overall, we find that investors with a higher level of sophistication are less sensitive to higher moments of return. This translates into smaller levels of the disposition effect for speculative and non-speculative assets. These findings are in line with literature which finds that a higher level of investor sophistication diminishes trading biases (e.g., Shapira and Venezia, 2000; Grinblatt and Keloharju, 2001; Feng and Seasholes, 2005).

3.2.2 Gender and higher moments of return

Studies in psychology and behavioral finance document gender differences in investment behavior. For example, Barber and Odean (2001) find that men trade more than women and that excessive trading reduces men's returns. However, in the same year, 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 that are included in a regression, the less important gender becomes.

To investigate how male and female investors react to higher moments of return, we split our sample by gender. Results for male and female investors are summarized in Table 4.

[Insert Table 4 here]

We find that both male and female investors exhibit a disposition effect in speculative and non-speculative assets. The disposition effect is significantly higher for HVHS stocks than for LVLS stocks. This finding fits Grinblatt and Keloharju (2001) and Feng and Seasholes (2005), who find that gender does not crucially affect investor's selling behavior. Looking at changes in PGR in more detail, we find that an increase in skewness and variance more strongly affects male investors' PGR than female investors' PGR. Male investors are three times as likely to sell a HVHS asset trading at a gain relative to a LVLS asset trading at gain, whereas women's PGR only doubles. In line with previous results, both investor groups decrease their PLR when skewness and variance increase. Again, male investors' reaction is more pronounced than female investors whose decrease in PLR scratches the 10% significant level.

We also find that males are more likely to hold speculative assets than females: The average male (female) in the sample holds 2.7 (2.4) speculative assets over the sample period. This fits previous studies claiming that males are more likely to participate in gambling activities (e.g., Clotfelter and Cook, 1990; Kumar, 2009)

3.2.3 Age and higher moments of return

Some studies find age to affect investors' trading behavior (e.g., Goyal, 2004; Ang and Maddaloni, 2005). Feng and Seasholes (2005) argue that sophistication and experience increases with age and therefore reduces trading biases such as the disposition effect. Thus, we should find senior investors to be less sensitive to higher moments of return. To investigate the effect of age on investors' selling behavior, we follow Goyal (2004) and split our dataset into three age cohorts: (i) young (ages 25 to 44), (ii) middle-aged (ages 45 to 64), and (iii) senior > 65. Results are reported in Table 5.

[Insert Table 5 here]

Splitting our dataset by age, we find in Table 5 that the disposition effect in speculative assets is significant at the 1% percent level for all age cohorts: 17.2% for young investors, 9.6% for middle-aged investors, and 10.25% for senior investors. Interestingly, the disposition effect in non-speculative assets decreases in magnitude and significance when age increases. While young investors show a quite pronounced disposition effect in non-speculative assets (5.25%), senior investors do not show a disposition effect in non-speculative assets. We do not see any convergence in PGR (PLR) for HVHS and LVLS assets, i.e., differences in PGR (PLR) for speculative and non-speculative assets are always highly statistically significant at the 1% level in each age group.

3.3 Across asset classes analysis: Fund investments

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 variance and skewness on investors' selling behavior also holds across asset classes.

To comprehensively investigate the effect of higher moments of return 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.[7] We focus on the equity market since comparing selling behavior across different asset classes using several markets would be imprecise. To make results comparable across asset classes, we use the same cluster and fixed effects as in the 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. All variables are defined as for regression (1). Regression results are in Table 6: Panel A shows results using the passive equity fund sample and Panel B shows results using the equity mutual fund sample.

[Insert Table 6 here]

The results provide further evidence showing differences in investors' selling behavior between speculative and non-speculative funds. Analyzing changes in PGR and PLR between speculative and non-speculative funds, we find that PGR is always significantly higher in speculative funds than in non-speculative funds, irrespectively of whether this fund is an active or passive fund. In terms of magnitude, the change in PGR is higher in the passive equity fund sample than in the mutual fund sample. Within the passive fund sample, speculative funds' PGR is between 6.21 (column (3)) and 9.74 (column (2)) percentage points higher than non-speculative funds' PGR. For

[7] Detailed summary statistics of the fund sample are in in Appendix E.

the active fund, the difference in PGR between speculative and non-speculative assets ranges from 2.71 (column (4)) to 3.48 (column (2)) percentage points. Note, that within the asset class of stocks, speculative stocks' PGR is between 4.82 (column (5) in Table 3) and 9.30 (column (5) in Table 2) percentage points higher than non-speculative stocks' PGR (Table 2). Thus, in terms of magnitude, the effect of higher moments of return on investors' selling behavior in passive equity funds are comparable to results in the stock analysis.

Interestingly, the strong differences in PGR between speculative and non-speculative passive funds leads to a significant positive 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.[8] 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. This is illustrated in Table 6 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 findings from our main analysis. They demonstrate that higher moments of return not only affect investors' stock selling behavior but also their funs selling behavior. Thus, our findings hold within but also across asset classes, thereby offering a more holistic understanding of investors' selling behavior.

4. Craving realization utility

4.1 Reinvesting after gains

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. Frydman et al. (2018) show that an investor's investment episode does not necessarily end with the sale of

[8] We will further explore this finding in Section 5.3 when discussing the channel of cognitive dissonance as a potential alternative explanation for our findings.

the asset, as reinvestment can preserve the previous mental account. If craving realization utility drives the higher PGR in speculative assets than in non-speculative assets, we should detect a lower reinvestment activity after investors realize a gain in a speculative asset than in a non-speculative asset. Only if the investor does not reinvest, will she receive a burst of positive realization utility. To test for this prediction, we analyze investors' reinvestment decisions after realizing a gain by running the following regression:

$$Reinvestment_{ijt} = \beta_0 + \beta_1 Speculative_{j,t-1} + e_{ijt} \qquad (3)$$

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 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 7); (ii) the sale is followed 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 7); (iii) the sale is followed by exactly one purchases on the same date (column (3) in Table 7); 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 assets by ± 15% (column (4) in Table 7). The speculative dummy variable is defined as for regression (1). Note, the identification of a reinvestment event requires daily trading data. Hence, throughout the analyses, observations are recorded at the individual-stock-date level.[9] 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 are able to 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

[9] 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.

should be negative. Results are shown in Table 7. To ensure comparability among regressions, we employ the same clusters and fixed effects as before.

[Insert Table 7 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 focused on differences in investors' reinvestment activity between speculative and non-speculative assets. We find that there is a persistent positive relationship between the level of variance and skewness 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 variance and skewness 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 F. Figure 4 graphically depicts our findings.

[Insert Figure 4 here]

Accounting for investor fixed effects and applying reinvestment definition (i), we find that investors' reinvestment activity decreases if variance and skewness increases.[10] We find the correlation between the likelihood to reinvest and the variance and skewness deciles to equal -0.8. This result shows that investor desire to experience a burst of realization utility increases with an asset's level of variance and skewness. 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 4), investors' PGR increases along variance and skewness deciles (see

[10] In an unreported test, we find that this result is not driven by the choice of the reinvestment definition.

Figure 3). This illustrates that the realization of gains, PGR, can be linked to the concept of realization utility.

4.2 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 the realization utility model by 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 for equation (3). We also employ the same fixed effects as in Section 4.1. We confine the sample to the sales of assets trading at a loss. Results are shown in table 8.

[Insert Table 8 here]

We find that for the majority of 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).

5. Interfering effects

5.1 Rank effect

We find that investors' selling behavior is strongly affected by variance and skewness. 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 9 here]

To ensure that our results are not driven by the rank effect, we rerun our baseline regression and exclude observations that are twofold. Twofold observations are observations where the asset is classified as HVHS asset and ranks worst or best in the investor's portfolio. Excluding twofold observations from our sample, we find in Table 9 that the difference in the disposition effect across speculative and non-speculative assets is statistically significant. Investors in HVHS assets have a disposition effect of 7.60%, whereas investors in LVLS 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 HVHS and LVLS assets. The difference in PGR is statistically significant at the 1% level. Investors are 4.4 percentage points more likely to sell a HVHS asset trading at a gain than to sell a LVLS 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 (3)). Moreover, differences in PLR become insignificant once we introduce individual and month fixed effects. Again, this is in line with findings from Table 2.

5.2 Attention effect

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 10 here]

In Table 10, we find that investors show a significantly higher disposition effect in HVHS stocks than in LVLS 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.

5.3 Cognitive Dissonance

In addition to the rank and attention effects, there is a third concept that might interfere with our effect: cognitive dissonance. Cognitive dissonance is a psychological concept developed by Festinger (1957) that has been applied to investors' financial decision making by Chang et al. (2016). In their study, the authors use the concept of cognitive dissonance to explain the differences in investors' disposition effects across asset classes. They argue that investors should show smaller disposition effects in delegated asset classes than in non-delegated asset classes. Their reasoning works as follows: An investor who holds an asset trading at a loss faces cognitive dissonance since her initial investment decision does not result in a positive outcome. By blaming someone else, the investor is able to overcome her cognitive dissonance. Whenever blaming is possible, an investor is more likely to cut a loss, thereby increasing her propensity to realize a loss (PLR), which translates into a lower disposition effect. Thus, assets classes that offer a blaming mechanism, which are delegated, should display smaller disposition effects. Generally speaking, the higher the degree of delegation of an asset class, the more easily it becomes to blame someone else (e.g., the mutual fund manager) and the smaller should be the disposition effect.

In their analyses, Chang et al. (2016) investigate investors' disposition effect across three asset classes: stocks, passive equity funds, and equity mutual funds. The authors consider fund investments to be more delegated than stock investments. Within fund investments, they assume equity mutual funds as fully delegated. Passive equity funds are considered to have a lower degree of delegation than equity mutual funds but a higher degree of delegation than pure stock investments. The authors predict a highly significant disposition effect for stocks, a less positive disposition effect for passive equity funds, and a reverse disposition effect for equity mutual funds. They find the disposition effect to be positive in stock investments, positive but smaller (relative to stock investments) in passive equity funds, and negative in active equity funds.

To test whether cognitive dissonance interferes with our findings, we pool the equity mutual fund and passive equity fund data and modify equation (1). We replace the speculative dummy variable with the mutual fund dummy variable. Then, we can test whether there is a difference in investors' selling behavior across asset classes and whether this difference is statistically significant. The mutual fund dummy variable equals one if the asset is an equity mutual fund. *Sale* and *Gain* for equation (1).

[Insert Table 11 here]

Table 11 shows that both fund classes experience a highly statistically significant reverse disposition effect. The average disposition effect of passive (active) funds is -3.35% (-3.1%). As indicated by the insignificant coefficient of the interaction term (*Gain*$\times$*Mutual Fund*), we do not find a difference in investors' disposition effects across the asset class of equity mutual funds or passive equity funds. We also find that investors' PLR in equity mutual funds is significantly lower than in investors' PLR in passive equity funds. This is indicated by the negative and significant coefficient estimate of the mutual fund dummy variable. The results are robust and hold after introducing investor as well as time fixed effects. Our findings cannot be reconciled with the concept of cognitive dissonance being the underlying driver of investors' selling behavior in our sample.

6. Robustness test

6.1 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 volatility and the lowest but positive skewness among all stocks in our sample.

Appendix 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 volatility but are no longer solely negatively skewed. Approximately 20% of the assets located in box 1/2 are assets with the lowest volatility 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 12.

[Insert Table 12 here]

The results for the alternative specification of non-speculative assets in Table 12 are comparable to the results in our main analysis in Section 3.1. Across all model specifications the interaction term *Gain*$\times$*Speculative* remains highly statistically significant and positive. In line with previous results (Table 2), we find the effect of higher moments of return 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.

6.2 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 13 depicts our results.

[Insert Table 13 here]

In our robustness test results in Table 13, 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.

7. Conclusion

We demonstrate that investors' selling behavior is strongly affected by variance and skewness. Comparing investors' selling behavior across high-variance-high-skewness (HVHS) and low-variance-low-skewness assets (LVLS), we find gain and loss realization to be opposed: HVHS stocks trading at a gain are more frequently realized than LVLS stocks trading at a gain. By contrast, HVHS assets trading at a loss are less frequently realized than LVLS assets trading at a loss. Moreover, we find PGR (PLR) to be positively (negatively) correlated with an asset's variance and skewness. This effect of higher moments of return on investors' selling behavior translates into a high disposition effect for HVHS assets and a close to insignificant disposition effect for LVLS assets.

We find evidence for the concept of realization utility driving the differences in investors' gain realizations across speculative and non-speculative assets. Our results hold across several subsample splits (e.g., sophistication, gender, and age) and across asset classes (e.g., stocks, and active equity fund and passive equity fund investments). Alternative concepts known to affect investors' selling behavior (e.g. rank effect, attention effect, and cognitive dissonance) are not sufficient to explain our findings.

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- Tables -

Table 1: Summary statistics

This table depicts summary statistics for the filtered data used throughout this study. *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 # of trades*, and *asset allocation* of an investor's portfolio are reported monthly. The HHI is calculated following Dorn et al. (2008). We report *Age, Gender, Education,* and *Income* on the account level. *Income* is a self-reported variable. Using daily returns, we calculate annualized *Variance* and *Skewness.* Variance and skewness are winsorized at the 1st and 99th percentiles. *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 investors

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 # of trades (monthly)	3.25 (2.43)
Asset allocation (%)	48.1
Demographics	
Age (Year)	51 (50)
Gender (%)	
Male	85
Female	15
Education (%)	
No title	91.75
Ph.D. or Professor	8.25
Income (€)	56,991 (50,000)

Panel B: Asset characteristics

	High-variance-high-skewness assets	**Low-variance-low-skewness assets**
Stock Investments		
Number of asset-month obs.	2,474	1,451
Variance	85 (56)	0.2 (0.02)
Skewness	98 (81)	-17 (-13)
Holding periods		
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
	Boulder Steel	SAP SE
	TUI AG	Nestlé

Table 2: Higher moments of return and investors' selling behavior

This table provides the variation in investors' selling behavior across high-variance-high-skewness and low-variance-low-skewness 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: Level of sophistication and higher moments of return

This table provides the variation in investors' selling behavior across high-variance-high-skewness and low-variance-low-skewness assets for a sample of sophisticated (column 1) and less sophisticated (column 2) investors. Investors with a PhD or a professorship are classified as sophisticated. 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*. 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) FE Model 1 Sophisticated	(2) FE Model 1 Less sophisticated
Gain	0.00389	0.0286***
	(0.0135)	(0.00904)
Speculative	-0.0366*	-0.0319***
	(0.0185)	(0.00822)
Gain × Speculative	0.0827**	0.0797***
	(0.0398)	(0.0141)
Constant		
Observations	9,734	108,328
R-squared	0.193	0.183
Cluster individual-month	YES	YES
Month FE	YES	YES
Individual FE	YES	YES

Table 4: Gender and higher moments of return

This table provides the variation in investors' selling behavior across high-variance-high-skewness and low-variance-low-skewness assets for male (column (1)) and female (column (2)) investors. 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 10th variance and 10th skewness decile within month t. 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	FE Model 1 - Male	FE Model 1 - Female
Gain	0.0250***	0.0352***
	(0.00934)	(0.0129)
Speculative	-0.0359***	-0.0270*
	(0.00822)	(0.0150)
Gain × Speculative	0.0867***	0.0685**
	(0.0141)	(0.0293)
Constant		
Observations	102,695	13,397
R-squared	0.183	0.192
Cluster individual-month	YES	YES
Month FE	YES	YES
Individual FE	YES	YES

Table 5: Age and higher moments of return

This table depicts the variation in investors' selling behavior across high-variance-high-skewness and low-variance-low-skewness assets for different age cohorts. Following to Goyal (2004), we split our investor sample into the following age cohorts: (i) young (ages 25 - 44), (ii) middle-aged (ages 45 - 64), and (iii) senior > age 65. 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. 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) FE Model 1 Young	(2) FE Model 1 Middle-aged	(3) FE Model 1 Senior
Gain	0.0525***	0.0274***	0.0106
	(0.0127)	(0.0100)	(0.00960)
Speculative	-0.0392***	-0.0336***	-0.0353***
	(0.0139)	(0.00976)	(0.00904)
Gain × Speculative	0.119***	0.0685***	0.0919***
	(0.0299)	(0.0143)	(0.0198)
Constant			
Observations	20,085	61,164	34,599
R-squared	0.223	0.187	0.158
Cluster individual-month	YES	YES	YES
Month FE	YES	YES	YES
Individual FE	YES	YES	YES

Table 6: The effect of variance and skewness: Fund investments

This table depicts the variation in investors' selling behavior across high-variance-high-skewness and low-variance-low-skewness assets in the asset class of funds. Panel A and Panel B contain the sample of passive equity funds and 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

Dependent Variable: Sale	(1) Equity ETFs	(2) Equity ETFs	(3) FE Model1	(4) 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

Dependent Variable: Sale	(1) Only MFs	(2) Only MFs	(3) FE Model1	(4) 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 7: Realization utility and reinvestment behavior after selling a gain asset

This table shows the reinvestment behavior across high-variance-high-skewness and low-variance-low-skewness 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 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 assets 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 HVHS and LVLS 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.

Dependent Variable: Reinvestment	(1)	(2)	(3)	(4)
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 8: Placebo test: Reinvestment after losses

This table shows the reinvestment behavior across high-variance-high-skewness and low-variance-low-skewness 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 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 assets by ± 15%. *Speculative* is a dummy variable that equals one if the asset is part of the 10th variance and 10th skewness decile within month *t*. The sample is limited to sales of HVHS and LVLS 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.

	(1)	(2)	(3)	(4)
Dependent Variable: Reinvestment				
HVHS	-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
Account FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES

Table 9: The rank effect

This table shows the variation in investors' selling behavior across high-variance-high-skewness and low-variance-low-skewness 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 asset is classified as high-variance-high-skewness asset and ranks worst or best in the investor's portfolio. 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 10th variance and 10th skewness decile within month *t*. 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 10: The attention effect

This table provides the variation in investors' selling behavior across high-variance-high-skewness and low-variance-low-skewness assets in the presence of attention/inattention. To identify attention grabbing events we follow Barber and Odean (2008). 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 10th variance and 10th skewness decile within month *t*. 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) Attention	(2) Attention	(3) No Attention	(4) 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 × 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 11: Cognitive Dissonance

This table provides the variation in investors' selling behavior between active and passive fund investments. The polled sample consists of Panel A and Panel B of Table 6. 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. *Mutual Fund* is equal to one if the asset at hand is a mutual fund. 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	MF & EFTF	MF & EFTF
Gain	-0.0335***	-0.0132**
	(0.00489)	(0.00529)
Mutual Fund	-0.0220***	-0.0145***
	(0.00417)	(0.00333)
Gain × Mutual Fund	0.00483	-0.00103
	(0.00415)	(0.00395)
Constant	0.166***	
	(0.00510)	
Observations	1,005,115	1,003,378
R-squared	0.003	0.162
Cluster account-individual	YES	YES
Individual FE	YES	YES
Month FE	YES	YES

Table 12: Robustness: Specification on non-speculative assets

In this table, we replicate Table 2 using an alternative specification of non-speculative assets. Non-speculative assets are defined as assets 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.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Sale	Stocks	Stocks	FE Model 1	FE Model 2	Fe Model 3
Gain	0.0438***	0.0307	0.0172	0.0213	0.0465
	(0.00447)	(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	0.114***	0.0977***			
	(0.00352)	(0.00997)			
Observations	2,921,495	33,861	32,575	32,575	14,189
R-squared	0.004	0.029	0.242	0.247	0.491
Cluster individual-month	YES		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 13: Robustness: Identification of speculative (non-speculative) assets using quartiles

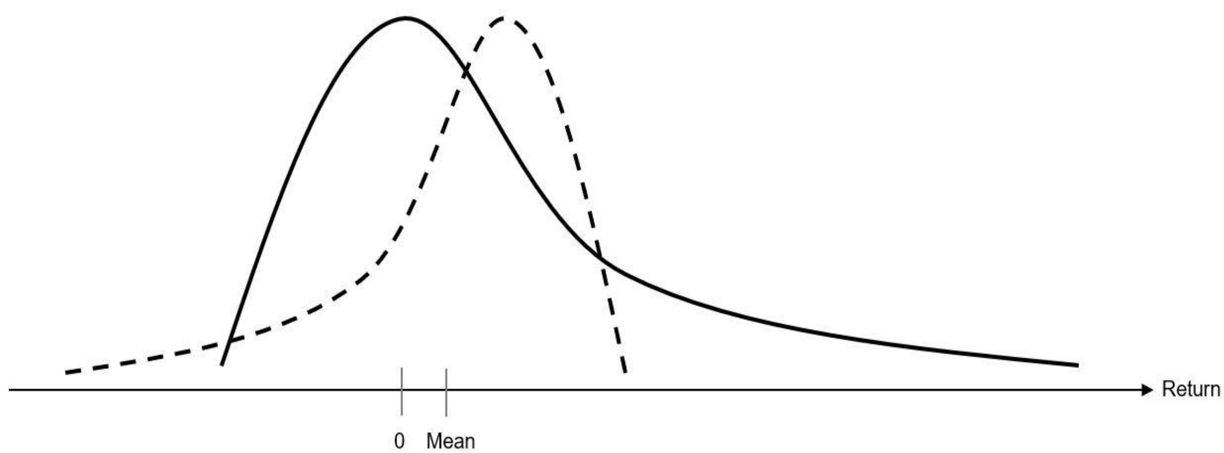
This table provides the variation in investors' selling behavior across high-variance-high-skewness and low-variance-low-skewness assets using an alternative identification strategy. Assets are categorized as speculative or non-speculative if they falling into the 4th variance and 4th skewness quartile in month *t*. 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 10th variance and 10th skewness decile within month *t*. 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

- Figures -

Figure 1: Return distribution of assets that differ in variance and skewness

This figure depicts the return distribution of two assets whose return distributions have the same expected value but differ in variance and skewness. The high-variance-high-skewness (i.e., speculative) Asset A is depicted by the solid line, whereas the low-variance-low-skewness (i.e., non-speculative) Asset B is depicted by the dashed line. Illustrative only.



—— Asset A (high-variance-high-skewness asset)
- - - - Asset B (low-variance-low-skewness asset)

Figure 2: The effect of variance and skewness on investors' PGR and PLR

This figure depicts investors' differences in selling behavior (i.e., PGR and PLR) for high-variance-high-skewness assets and low-variance-low-skewness assets. The figure is based on data from column (2) in Table 2.

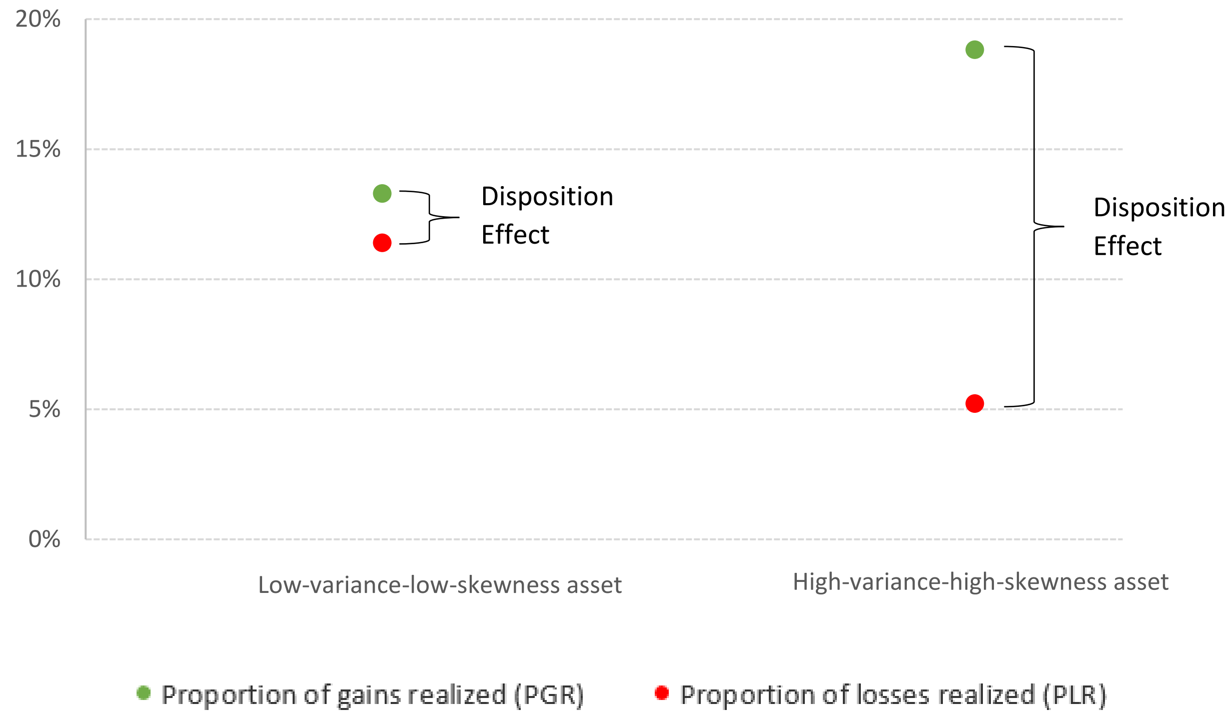


Figure 3: The change in PGR and PLR over variance and skewness deciles

The figure depicts the change in PGR and PLR along variance and skewness deciles. Assets falling into variance and skewness decile 1 (10) are categorized as non-speculative (speculative) assets. The figure is based on equation (2) which can be found in Appendix C.

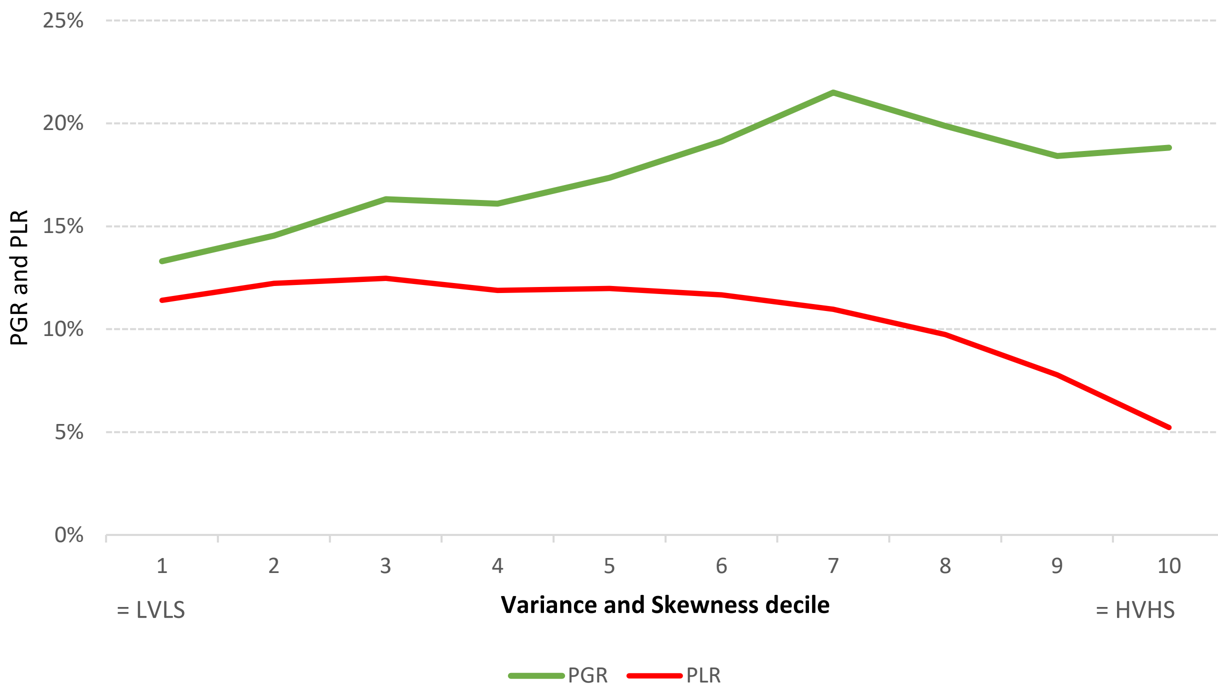
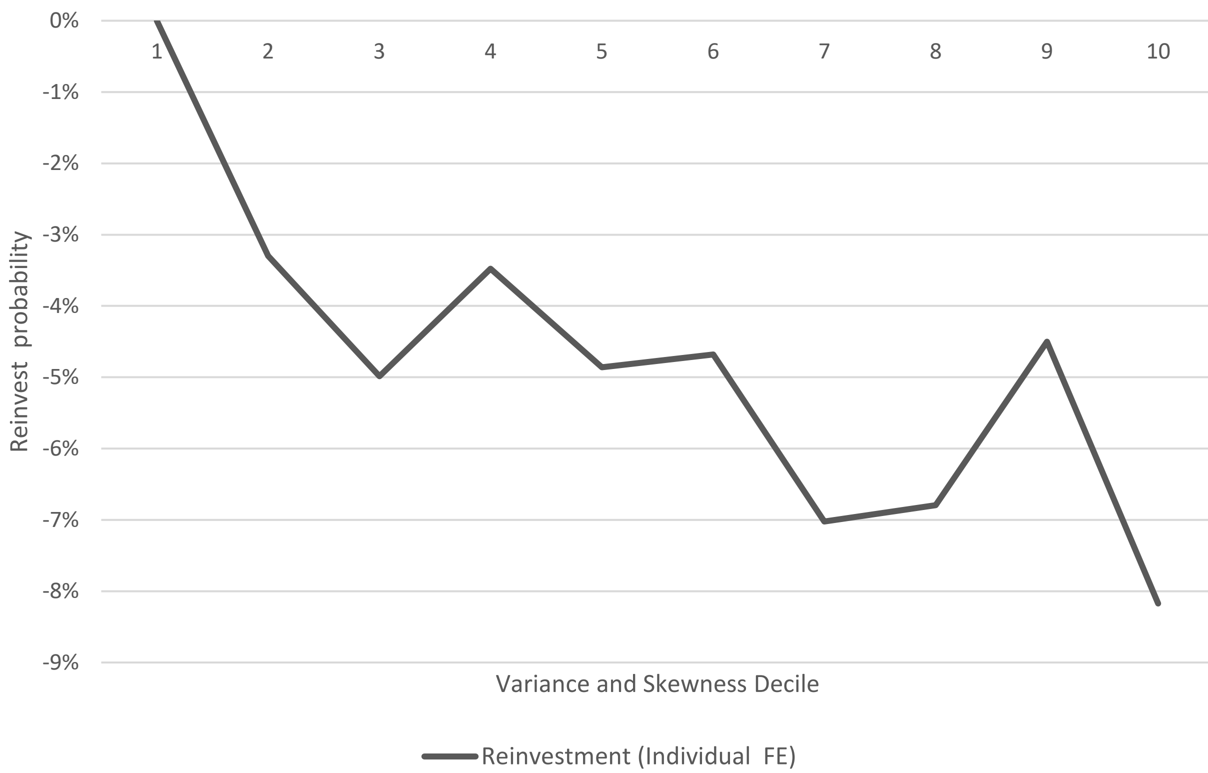


Figure 4: Reinvestment behavior along variance and skewness deciles

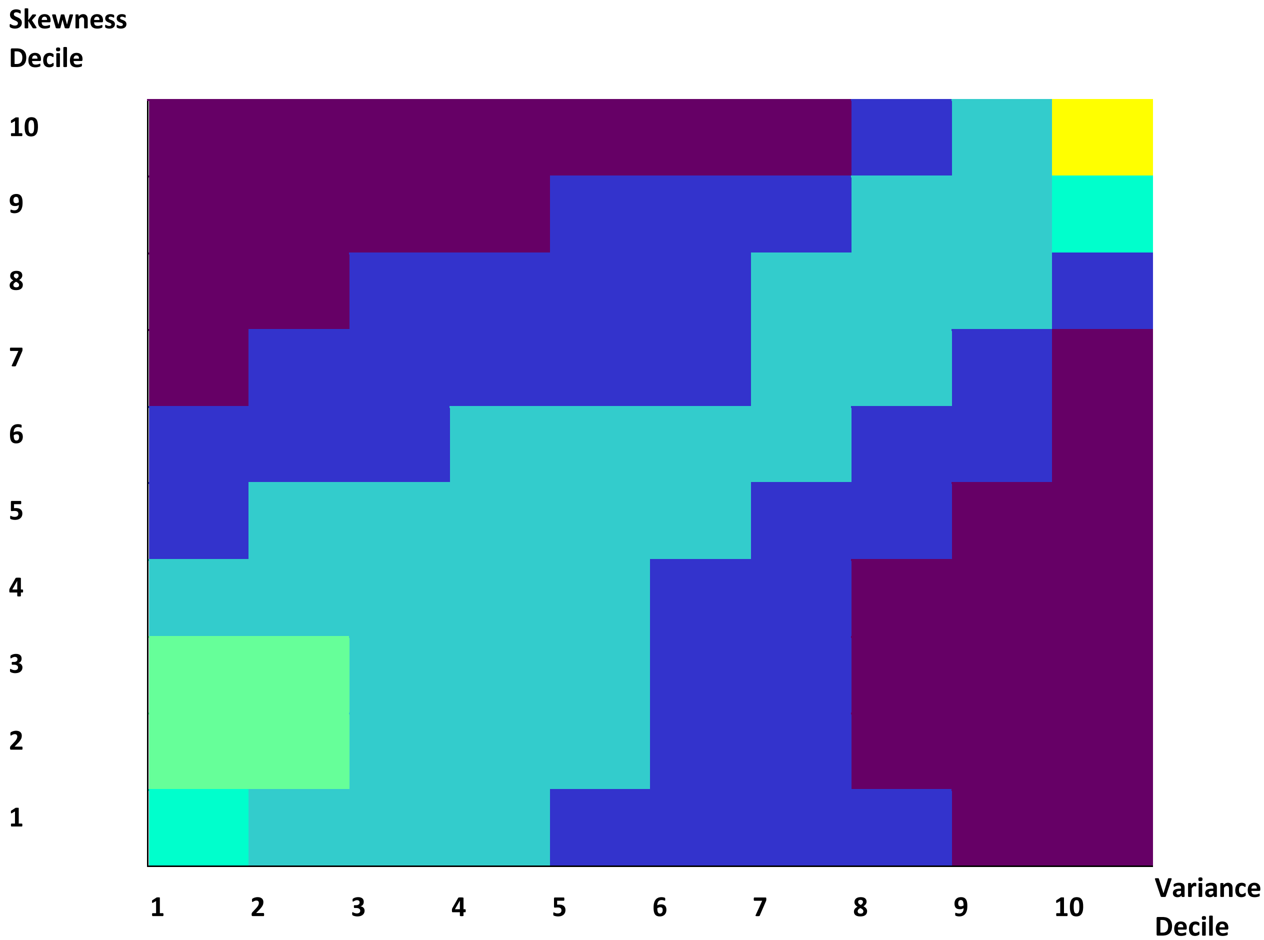
This figure depicts investors' reinvestment behavior along variance and skewness deciles. The x-axis depicts the variance and skewness deciles. For example, decile 2 comprises assets that are part of the 2^{nd} variance and 2^{nd} skewness decile within month *t*. The y-axis depicts investors' reinvestment probability relative to investors' reinvestment probability of assets being part of decile 1. Numbers are taken from running equation (3) for each decile separately. Regression results are in Appendix F.



Appendix

Appendix A: Asset distribution along variance and skewness dimension

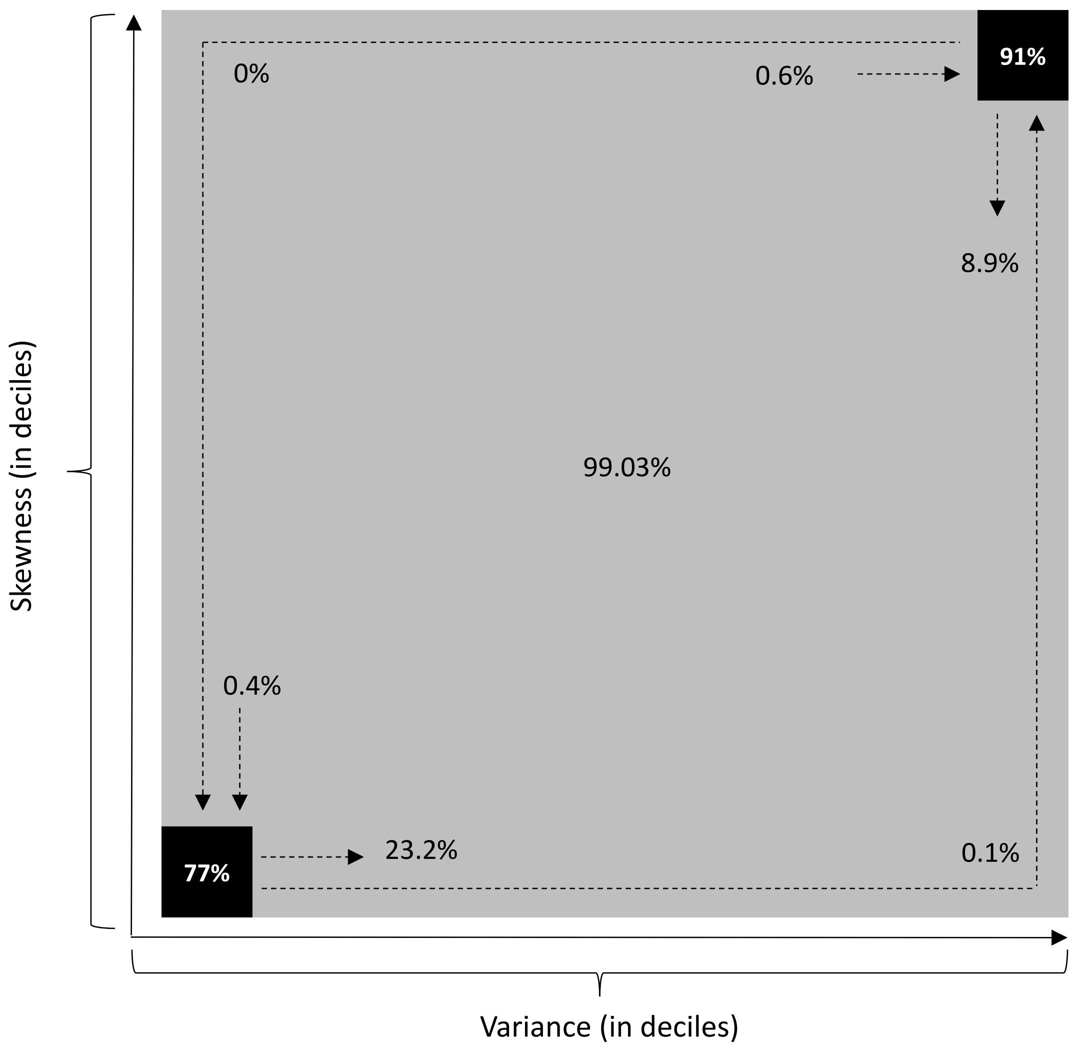
This heatmap depicts the number of assets (average, min, max) along the variance and skewness deciles. The heatmap consists of 100 boxes (i.e., 10x10). The brighter (darker) the color of a box the more (less) assets are located in the specific box.



Color coding	Average	Min	Max
	251	220	380
	167	114	244
	143	64	280
	116	58	178
	75	30	129
	25	1	67

Appendix B: Stock Transition Matrix

This figure shows the transition of stocks among the three categorizations speculative (upper black box), non-speculative (lower black box), and others (grey shaded area). The x-axis depicts the variance deciles 1 to 10, whereas the y-axis depicts the skewness deciles 1 to 10. The dashed arrows illustrate how assets switch among categories. Bolted numbers depict the probability an asset will remain in the same category for the next month. For example, an asset that is categorized as a speculative asset in month *t* will be categorized as speculative in month *t*+1 with 91% probability.



Appendix C: 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 asset 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
Gain	0.0190*	0.0276***
	(0.0105)	(0.00947)
Decile2	0.00820	0.00724
	(0.00895)	(0.00691)
Gain × Decile2	0.00422	0.00514
	(0.00885)	(0.00763)
Decile3	0.0107	0.0133*
	(0.00814)	(0.00710)
Gain × Decile3	0.0194**	0.0173**
	(0.00836)	(0.00777)
Decile4	0.00483	0.0126
	(0.00970)	(0.00781)
Gain × Decile4	0.0231**	0.0186*
	(0.0110)	(0.00955)
Decile5	0.00571	0.0127
	(0.00959)	(0.00774)
Gain × Decile5	0.0349***	0.0283***
	(0.00953)	(0.00850)
Decile6	0.00272	0.0110
	(0.00996)	(0.00802)
Gain × Decile6	0.0555***	0.0394***
	(0.0141)	(0.0128)
Decile7	-0.00442	0.0108
	(0.00967)	(0.00828)
Gain × Decile7	0.0864***	0.0643***
	(0.0157)	(0.0134)
Decile8	-0.0166*	0.00604
	(0.00954)	(0.00832)
Gain × Decile8	0.0823***	0.0567***
	(0.0123)	(0.0109)
Decile9	-0.0362***	-0.0120
	(0.0103)	(0.00861)
Gain × Decile9	0.0873***	0.0717***
	(0.0145)	(0.0125)
Decile10	-0.0618***	-0.0309***
	(0.0107)	(0.00907)
Gain × Decile10	0.117***	0.0915***
	(0.0157)	(0.0137)
Constant	0.114***	
	(0.0102)	
Observations	566,601	564,056
R-squared	0.009	0.126
Cluster individual-month	YES	YES
Individual FE		YES
Month FE		YES

Appendix D: Moving along the mirrored diagonal: PGR and PLR

The table depicts examines the variation in investors' selling behavior along the mirrored diagonal. *Gain* and *Sale* are defined as for equation (1). *DecileX,Y* is a dummy variable that equals one if the asset falls into the variance decile X and the skewness decile Y. For example, Decile2,9 contains all assets that are part of variance decile 2 and skewness decile 9 within month *t*. The same logic applies to the rest of the decile dummy variables. Observations record 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
Gain	0.0170	0.00288
	(0.0435)	(0.0351)
Decile2,9	-0.0485	-0.0452
	(0.0414)	(0.0306)
Gain × Decile2,9	0.0150	0.0254
	(0.0434)	(0.0361)
Decile3,8	-0.0466	-0.0451
	(0.0395)	(0.0307)
Gain × Decile3,8	0.0133	0.0240
	(0.0438)	(0.0349)
Decile4,7	-0.0420	-0.0372
	(0.0424)	(0.0320)
Gain × Decile4,7	0.0275	0.0339
	(0.0442)	(0.0355)
Decile5,6	-0.0263	-0.0328
	(0.0421)	(0.0319)
Gain × Decile5,6	0.0371	0.0430
	(0.0431)	(0.0355)
Decile6,5	-0.0305	-0.0383
	(0.0416)	(0.0315)
Gain × Decile6,5	0.0532	0.0514
	(0.0450)	(0.0368)
Decile7,4	-0.0321	-0.0371
	(0.0416)	(0.0310)
Gain × Decile7,4	0.0537	0.0572
	(0.0454)	(0.0362)
Decile8,3	-0.0594	-0.0497
	(0.0421)	(0.0310)
Gain × Decile8,3	0.0855*	0.0752**
	(0.0462)	(0.0370)
Decile9,2	-0.0599	-0.0422
	(0.0433)	(0.0329)
Gain × Decile9,2	0.172***	0.117**
	(0.0627)	(0.0513)
Decile10,1	-0.0317	-0.0239
	(0.0448)	(0.0329)
Gain × Decile10,1	0.127	-0.0244
	(0.145)	(0.134)
Constant	0.151***	
	(0.0418)	
Observations	153,599	150,450
R-squared	0.009	0.159
Cluster account-month	YES	YES
Individual FE		YES
Month FE		YES

Appendix E: 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. Panel B comprises summary statistics at the asset level (here: equity mutual funds and passive equity funds). On the portfolio level the a*verage # of trades* and *asset allocation* of an investor's portfolio are reported monthly. High-variance-high-skewness assets are assets which are part of the 10th variance and 10th skewness decile in month *t*. Low-variance-low-skewness assets are assets which are part of the 1st variance and 1st skewness decile in month *t*. Numbers in bracket report the median. *Variance* and *Skewness* are annualized and winsorized at the 1st and 99th percentile. *Holding periods* are measured in months. Numbers in bracket report the median.

Panel A: Retail investor		
Sample	**Mutual funds**	**Passive funds**
Portfolio		
Average # of trades (monthly)	2.07 (1.56)	1.78 (1.34)
Asset allocation (%)	31.1	20.8
Panel B: Asset characteristics		
	High-variance-high-skewness assets	**Low-variance-low-skewness assets**
Equity mutual funds		
Number of asset-month observations	574	668
Variance	1.3 (1.1)	0.05 (0.05)
Skewness	17 (12)	-15 (14)
Holding period		
Gain	27 (21)	28 (25)
Loss	32 (31)	27 (25)
Exemplary assets by name	Falcon Gold Equity Fund	DWS Top Dividende
	BNP Paribas Funds Russia Equity	Templeton Frontier Markets Fund
	BlackRock Latin American Opportunities	Invesco Global Dynamik Fonds
Passive equity funds		
Number of asset-month observations	130	111
Variance	1.1	0.1 (0.1)
Skewness	15 (11)	-11 (-10)
Holding period		
Gain	24 (18)	28 (24)
Loss	23 (19)	22 (16)
Exemplary assets by name	Lyxor Euro Stoxx 50 Daily (2x) Leveraged UCITS ETF	iShares Dow Jones Industrial Average
	L&G Gold Mining UCITS ETF	Lyxor STOXX Europe Select Dividend 30
	LYXOR DAILY LEVDAX UCITS ETF	Amundi ETF MSCI World ex Europe

Appendix F: Reinvestment behavior along variance and skewness deciles

The table depicts the change in reinvestment behavior over variance and skewness deciles and serves as basis for Figure 4. *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 7). *Decile2* is a dummy variable that equals one if the asset 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