Daily Winners and Losers[a]

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Abstract

The arguably most salient feature of the cross-section of stocks is being a daily winner or loser: these stocks are ranked in many newspapers and on popular webpages, making them subject to spikes in attention. In line with the literature on attention-grabbing stocks, we find that retail investor buying pressure surges when stocks are ranked. After the ranking, stocks underperform unranked stocks by 1.60% (15%-20%) during the subsequent month (three years). For unranked stocks, the idiosyncratic volatility puzzle and related anomalies (maximum daily returns, expected idiosyncratic skewness) disappear. Hence, attention-driven overpricing of daily winners and losers provides a simple explanation for several puzzling patterns in empirical asset pricing.

Keywords: Investor Attention, Stock Rankings, Retail Investors, Idiosyncratic Volatility Puzzle.

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1 Introduction

What information about the cross-section of stock returns is most easily obtainable for retail investors? In this paper, we argue that the most salient return-based information is a stock's status as daily winner or loser. Newspapers, webpages, and TV business channels rank stocks by daily returns and list the winners and losers, i.e., the top and bottom stocks:

[Insert Figure 1 about here]

As a result, daily winners and losers are stocks that receive extreme return-related shocks in investor attention. These spikes in investor attention for daily winners and losers are likely to affect trading and prices. Investor attention is limited (Kahneman, 1973) and attention spikes can lead to trading, and—due to short sale constraints—to increases in buy-sell imbalances. Retail investors in particular are constrained in short-selling and the level of attention they can pay to stocks. In line with this reasoning, Barber and Odean (2008) find that retail buy-sell imbalances surge for attention-grabbing stocks. They mention that the associated buying pressure might push up prices and lead to subsequent underperformance of stocks. Indeed, Da, Engelberg, and Gao (2011) provide evidence in favor of attention-induced overpricing of stocks by showing that stocks that investors search for intensively on the internet underperform subsequently.

Combining the stylized fact that daily winners and losers experience large spikes in investor attention and the insight that attention induces buying pressure and overpricing, two conjectures directly follow: Daily winners and losers should (i) experience retail buying pressure and (ii) overpricing reflected by underperformance after being ranked. Despite being an obviously attention-catching event, the impact of a stock being ranked in daily winner and loser lists on subsequent returns has caught surprisingly little attention in the literature.

Furthermore, since daily winners and losers are stocks with extreme daily returns, they tend to be stocks with high idiosyncratic volatility, high maximum daily returns, as well as high idiosyncratic skewness. Incidentally, these stock characteristics—in spite of being associated with risk—have all been linked to subsequent underperformance of stocks (Ang, Hodrick, Xing, and Zhang, 2006, 2009; Bali, Cakici, and Whitelaw, 2011; Boyer, Mitton, and Vorkink, 2010). Hence, attention-induced overpricing of daily winners and losers could potentially explain puzzling patterns in empirical asset pricing.

In our paper, we analyze the trading and pricing of daily winners and losers. For asset pricing tests, we focus on the commonly used 1963-2015 period and stocks listed on NYSE, AMEX, or NASDAQ. To measure retail and institutional trading of daily winners and losers, we use data from a large discount brokerage (provided by Barber and Odean (2008), 1991-1996) and by ANcerno (used by e.g. Goldstein, Irvine, Kandel, and Wiener (2009) and Puckett and Yan (2011), 1997-2010), respectively.

First, to test whether daily winners and losers are overpriced, we estimate their performance after the ranking. We make sure our findings are not explained by fundamental risk or other factors related to extreme returns. Our identification strategy relies on a comparison of results based on the commonly used close-to-close rankings to rankings based on unconventional return period definitions (typically not used to compute the published return rankings) like two-day returns or open-to-close returns. These alternative rankings also measure return extremeness and capture similar statistical properties of the stocks, but are not strongly related to published rankings. We then analyze whether our findings can be explained by—or can themselves explain—the idiosyncratic volatility puzzle, as well as the pricing of stocks with high maximum daily returns and high expected idiosyncratic skewness (Ang, Hodrick, Xing, and Zhang, 2006; Bali, Cakici, and Whitelaw, 2011; Boyer, Mitton, and Vorkink, 2010).

Second, to test whether daily winners and losers experience retail buying pressure and institutional liquidity provision, we estimate buy-sell-imbalances of retail and institutional investors, as well as short interest for ranked stocks. To complement our asset pricing findings, we analyze the variation of effects across firms with varying limits to arbitrage (liquidity, short sale constraints) and in times when we expect particularly large retail buying-pressure (high sentiment, high saliency of daily winner and loser returns).

We find robust evidence for attention-induced overpricing of daily winners and losers: Stocks that were both daily winners and daily losers in a given month underperform stocks that were neither daily winners nor losers by 1.72% in the subsequent month, by around 10% over the following year, and by more than 15% over the next three years. An equal-weighted (value-weighted) 'Never-minus-Both' (NMB) investment strategy going long in stocks that never made it into the ranking in the previous month and short in stocks that appeared in both, at least one daily top- and one daily bottom-ranking, attains an annualized Sharpe-Ratio of 1.32 (0.77) from 1963 to 2015 (Momentum: 0.58). The effect is not driven by daily winners alone. Rather, the contribution of winners and losers to the NMB strategy return is of roughly equal importance.

Recently, Harvey (2017) raises concerns that many asset pricing patterns might be due to 'p-hacking'. He suggests to define prior odds for a hypothesis based on the economic plausibility of the suspected effect. While the economic plausibility of the effect we analyze is in the eye of the beholder—Eugene Fama might consider a prior of 99:1 that no ranking-induced return effect exists as plausible, while Robert Shiller, Brad Barber or Terrance Odean might apply a less conservative prior of 4:1 or even 1:1—applying the method suggested in Harvey (2017) we find that our main result continues to be statistically significant even if we assume a prior of 99:1 against a return effect.

To identify daily winner and loser rankings as the drivers of our main finding, we rank stocks by uncommon return periods, e.g. two-day returns or open-to-close returns, instead of close-to-close returns. We find that the underperformance of daily winners and losers disappears for these uncommon return rankings. This shows that fundamental risk or other factors related to extremeness of returns do not drive our results. As an illustration, firms with exciting lottery-like projects and thus extreme cash flows and stock returns are attractive to investors with lottery preferences. This might lead to higher prices and lower returns. However, such lottery-firms' low returns cannot explain the underperformance of daily winners and losers, because their extreme returns are equally well measured via open-to-close or two-day return rankings, which we show not to be priced.

Furthermore, the underperformance of daily winners and losers cannot be explained by a large set of factor models. Our results also obtain based on Fama and MacBeth (1973) regressions controlling for a long list of firm characteristics. And we document in detail that controlling for idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang, 2006) and closely related return features like last month's maximum daily return (Bali, Cakici, and Whitelaw, 2011) or expected idiosyncratic skewness (Boyer, Mitton, and Vorkink, 2010) does not explain our results.

However, our results help to explain the idiosyncratic volatility puzzle and related anomalies: Stocks that were neither daily winners nor daily losers last month do *not* exhibit the significantly negative idiosyncratic volatility-return relation documented in Ang, Hodrick, Xing, and Zhang (2006). These stocks represent 93% of the NYSE/AMEX/NASDAQ overall market capitalization! When we add factor returns of our NMB investment strategy to the Carhart (1997) 4-factor model, the alpha of a strategy that buys high idiosyncratic volatility stocks and sells low idiosyncratic volatility stocks switches signs and increases from a highly significant negative value of -0.84% to a positive and insignificant value of 0.18% per month. In contrast, adding the idiosyncratic volatility factor to the Carhart (1997) 4-factor model only reduces the alpha of our NMB strategy from 1.76% to 0.97% per month, which is still economically very large and highly statistically significant. Furthermore, according to Hou and Loh (2016)'s decomposition method, the status as daily winner or loser explains a larger fraction of the idiosyncratic volatility puzzle than any other variable suggested in the literature as a potential explanation for the puzzle.[1] Hence, our findings suggest that daily winners and losers are the main drivers behind the idiosyncratic volatility puzzle.

Similar results hold for the low returns of stocks with high max returns (Bali, Cakici, and Whitelaw, 2011) and high expected idiosyncratic skewness (Boyer, Mitton, and Vorkink, 2010): Here, we also document that the effects documented in the literature are only found in the small subset of stocks that were past daily winners and losers, but not among the majority of all other stocks, suggesting that attention effects might also explain them.

We next investigate who buys and sells daily winners and losers: We analyze retail and institutional trading activity in these stocks, as well as changes in short interest. Extreme daily returns have been related to increased buying by retail investors (e.g., Barber and Odean, 2008). We can confirm that retail buy-sell imbalances of daily winners and losers increase, while institutional buy-sell imbalances decrease and short interest increases. These results holds after controlling for other determinants of trading such as monthly returns. In line with retail buying pressure and institutional liquidity provision, we find that the underperformance of daily winners and losers during the month after the ranking is driven by intraday returns, which are dominated by institutional traders (Lou, Polk, and Skouras,

[1]The exception is Bali, Cakici, and Whitelaw (2011)'s max return, which is so highly correlated with idiosyncratic volatility that Hou and Loh (2016) exclude it for most of their analysis, arguing that it is just another way to measure idiosyncratic volatility. This is not the case for our variable that is positively but much more weakly correlated with idiosyncratic volatility.

2017). Thus, daily winners and losers tend to be bought by retail investors after being ranked (and before they underperform significantly), while institutional investors and short-sellers provide liquidity and trade in the opposite direction.

However, the liquidity provision by institutional investors does not seem to be sufficient to offset the price-pressure induced by retail buying of daily winners and losers. A potential reason for this could be limits to arbitrage. We indeed find some evidence that limits to arbitrage seem to play a significant role in the persistent underperformance of daily winners and losers: On the one hand, our NMB strategy returns are significantly larger for stocks with above-median residual retail ownership and with below-median firm size, suggesting that limits to arbitrage in the form of short-sale constraints and higher valuation uncertainty for small firms might prevent arbitrageurs from pushing down prices quickly for daily winners and losers. On the other hand, even among stocks with low retail ownership and large market capitalization, the NMB strategy returns still amount to 1.70% and 1.50% per month, respectively, and are highly significant in both cases. Furthermore, we find at best a weak impact of liquidity on our results: Firms with above and below median values of the Amihud (2002) illiquidity ratio perform virtually the same, while the firms with an above-median value with respect to the Corwin and Schultz (2012) spread proxy have slightly higher NMB strategy returns. However, the Carhart (1997) four factor alpha of the difference in NMB strategy returns between liquid and illiquid stocks is not statistically significant.

The time variation of the returns to selling daily winners and losers suggests that saliency of daily winners and losers, as well as investor sentiment play a role in creating demand for these stocks. We argue that daily winners and losers are more salient, when the underlying daily returns of ranked stocks are particularly extreme as compared to other stocks. Using the cross-sectional average of daily stock return standard deviation and return kurtosis in a given month as time-varying salience proxies, we find that the returns of our investment strategy are particularly high when salience of ranked stocks is particularly high. Furthermore, consistent with the results in Stambaugh, Yu, and Yuan (2012) that anomalies are often stronger after periods of high sentiment, we also find that the NMB investment strategy does particularly well after high levels of the Baker and Wurgler (2006) sentiment index, consistent with investor sentiment increasing the buying-pressure of investors who buy daily winners and losers.

Our study contributes to two main strands of the empirical asset pricing literature. First, our analysis provides novel evidence on the impact of attention-induced effects and salience on stock prices. Thus it is closely related to the the papers by Barber and Odean (2008) and Da, Engelberg, and Gao (2011) discussed above, as well as to Bali, Cakici, and Whitelaw (2011) who document a negative impact of the maximum daily return of a stock on returns in the next month, consistent with attention towards these stocks leading to temporarily inflated prices and subsequently lower returns.[2] Chen, Hou, and Stulz (2015) find that stocks from industries with more salient outcomes (as measured by industry-level dispersion in profitability) have higher valuations and lower realized returns than firms from other, 'boring' industries. Fang and Peress (2009) find that newspaper coverage of firms is associated with lower stock returns for a subsample of US stocks between 1993 and 2002. They argue that visibility in the media increases investor recognition, which lowers expected returns (Merton, 1987).[3]

[2]The theoretical motivation behind attention-induced overpricing goes back to Lintner (1969), Miller (1977), and Mayshar (1983), who analyze the effects of heterogenous beliefs combined with short-sale constraints on asset prices. Barber and Odean (2008) add that individual investors' search problem is greater for buying than selling decisions, so that attention leads to buying pressure even for investors who already own a stock.

[3]In contrast, Hillert and Ungeheuer (2017) use 1924-2013 newspaper coverage to show that firms with persistently higher visibility outperform less visible stocks. They find that visibility also predicts improvements in corporate governance, as well as higher sales and profitability growth. This is consistent with

Furthermore, there are two closely related papers contemporaneous to ours that also examine the impact of return rankings: Peng, Rao, and Wang (2016) and Wang (2017) both analyze the effect of rankings on Chinese stock exchanges (Shanghai and Shenzen, respectively). In line with our findings, they both find evidence consistent with attention-induced overpricing of ranked winner stocks on Chinese markets. Our paper differs and goes beyond these papers in several aspects: (i) While our paper focuses on the US market, which is by far the largest stock market in the world, they analyze the Shanghai and Shenzen Stock Exchanges. (ii) More importantly, we are the first to examine whether ranking effects can explain related asset pricing anomalies like the idiosyncratic volatility puzzle. (iii) We are the first to document that ranked loser stocks (and not only ranked winner stocks) also become overpriced and subsequently underperform. This finding is important to test the Bordalo, Gennaioli, and Shleifer (2013) model discussed below. (iv) Our paper uses a different identification strategy. While they identify ranking effects based on maximum price change hitting events, a strategy going back to Seasholes and Wu (2007), we focus on differences in results based on alternative return ranking definitions as described above. Our approach has the advantage that our results are not driven by specific cases where stocks hit the maximum daily price change allowed on the Chinese stock exchanges of typically +10% (which is a large price change in absolute terms), but by purely relative ranking effects, even in the absence of large absolute price changes. In other words, our results are not only valid locally around a 10% price increase of daily winners. (v) Moreover, we go beyond their analysis by examining the roles of limits to arbitrage and sentiment for the underperformance of daily winners and losers.

Another paper on daily return ranks is Ungeheuer (2017). He analyzes the effect of daily stock returns on the cross-section of investor attention and finds that daily winners and losers

visibility creating value through monitoring and advertising, while stock markets inadequately price the positive effects of visibility.

experience large attention spikes—measured by Wikipedia firm page views and Google search volume—whereas stocks that have extreme returns but do not make it into the winner- and loser-rankings do not exhibit significant increases in investor attention. This insight supports our claim that the status as daily winner and loser is arguably the most salient return-based feature of the cross-section of stocks.

The impact of rank effects on investor behavior is also analyzed in a recent paper by Hartzmark (2014). He finds that investors are most likely to sell the relatively most extreme winners and losers of their portfolios, highlighting the importance of top- and bottom-ranks for retail investor decisions. However, while he studies relative ranks according to invest-specific holding period returns within the portfolios investors already hold, we focus on market-wide rankings and eventual attention-induced buying (rather than selling) of investors. Furthermore, we can document a strong influence of ranking appearances on subsequent returns.

Our work is also related to a recent theoretical model of Bordalo, Gennaioli, and Shleifer (2013) in which they argue that salient information is overweighted by investors. A stock appearing in a ranking is certainly a very salient event. However, while our result on the negative abnormal returns of salient ranked winner stocks is consistent with the theoretical predictions of Bordalo, Gennaioli, and Shleifer (2013), their model would also predict lower prices and subsequently positive abnormal returns of salient ranked loser stocks. We are the first to identify the performance of ranked losers and we find exactly the opposite of salience-induced overperformance: Daily losers strongly underperform non-ranked stocks.

Second, we contribute to the literature on the idiosyncratic volatility puzzle by showing that ranking-induced overpricing can explain the negative return premium of high idiosyncratic volatility stocks documented in Ang, Hodrick, Xing, and Zhang (2006). Many subsequent papers have confirmed this pattern and suggest different explanations. For example, Boyer, Mitton, and Vorkink (2010) suggest expected idiosyncratic skewness, Bali, Cakici, and Whitelaw (2011) the max effect, Han and Lesmond (2011) illiquidity, and Han and Kumar (2013) the retail trading proportion as drivers of the puzzle. Hou and Loh (2016) provide a comprehensive overview of the most important candidate explanations and also introduce a testing procedure to determine which variables can explain how much of the puzzle. They find that lagged returns have the highest explanatory power, explaining nearly 34% of the idiosyncratic volatility puzzle. We contribute to this line of research by suggesting ranking effects as the main driver of the idiosyncratic volatility puzzle and find that a simple dummy indicating that a stock was a daily winner or loser last month can explain more than 64% of the idiosyncratic volatility puzzle-and thus nearly twice as much as the next best candidate variable. With a more refined proxy for rank salience—taking into account how close to the top and how often a stock was ranked—the unexplained fraction of the puzzle reduces to below 4% and is statistically insignificantly different from zero.

In summary, our evidence is fully consistent with attention-driven retail buying pressure leading daily winners and losers to be significantly overpriced after having been ranked. We find that they are heavily bought by retail investors during the month when they are ranked. Subsequently, ranked stocks strongly underperform stocks that were neither daily winners nor daily losers in the following month and over up to three years. Additionally, the underperformance of daily winners and losers after the ranking provides a simple explanation for the idiosyncratic volatility puzzle and related anomalies (maximum daily returns, expected idiosyncratic skewness), but it is itself not explained by these well-known return effects.

In Section 2 we describe the datasets used and our methodology to identify daily winners and losers. In Section 3 we report the main finding, the underperformance of daily winners and losers. Section 4 deals with the relation between our findings and the idiosyncratic volatility puzzle. In Section 5 we analyze the trading activity of retail and institutional investors in daily winners and losers. We then analyze which firms and which periods drive the return effect in Section 6. Finally, we conclude in Section 7.

2 Data and Methodology

Our primary data source is the CRSP stock database. We include all common shares traded on the NYSE, the AMEX, and NASDAQ. Our sample spans from July 1963 through December 2015. We drop all stock-month observations for which the stock price is below 5 USD at the end of the previous month. However, our later robustness tests will show that our results do not depend on the price filter, the inclusion of NASDAQ stocks, or the inclusion of small firms below the 1^{st} NYSE-decile (see Section 3.5).

Our main variable of interest is a stock's status as daily winner or daily loser. In choosing the number of stocks from the CRSP universe that we classify as daily winners and losers, respectively, we face a tradeoff: On the one hand, picking a very high number, like the day's top and bottom 200 stocks from the CRSP universe, makes it less likely that the respective stocks are really seen as winners or losers and that all of them are visible for investors via rankings in newspapers or on webpages. On the other hand, picking a very low number, like the day's top and bottom 40 stocks, leads to the misclassification of many stocks actually listed in winner or loser rankings as stocks that did not make the rankings. Although newspapers and financial web pages typically publish a ranking of only the top and bottom 10 or 20 stocks, due to different conventions, these rankings often barely overlap. Differences can be due to different stock universes (based on exchanges, indices, price and volume requirements), or to different source of close-to-close returns.[4] As an illustration,

[4]E.g., the Wall Street Journal excludes stocks with prices below 2 USD and volumes below 2,000 shares

in Figure 1 we provide the winner and loser rankings of the New York Times and the Wall Street Journal for the same day (April 5$^{\text{th}}$, 2016). While the Wall Street Journal gives a Top-/Bottom-15 ranking, the New York Times provides a Top-/Bottom-20 ranking. More importantly, the overlap in the respective lists across newspapers is far from perfect. Only 10 (6) stocks that belong to the Top-15 (Bottom-15) ranking of the Wall Street Journal also appear among the top (bottom) 20 stocks from the New York Times list for the same day. Whereas the Wall Street Journal's print ranking is currently based on the Composite stock universe, the Wall Street Journal's web ranking (see bottom of Figure 1) is available for the NYSE, NASDAQ, and ARCA stock universes as well.

[Insert Figure 2 about here]

To find a reasonable threshold rank in the CRSP universe for the classification of daily winners and losers, we compute the CRSP ranks for stocks in the four Wall Street Journal (WSJ) universes' top and bottom 15 ranks, which are—in contrast to other historical rankings—available for the last five years of our sample period. These CRSP ranks are displayed in Figure 2. WSJ-ranked stocks regularly rank between rank 50 and 70 in the full CRSP universe. CRSP ranks above 80 for WSJ-ranked stocks, however, are very infrequent.[5] Thus, we pick a relatively high and conservative threshold of 80 stocks to define daily winners and losers based on our comprehensive sample of stocks. While this will regularly lead to some stocks being classified as daily winners or losers although they did not actually appear in any daily ranking, this should work against us finding ranking-induced effects. Furthermore, it has the advantage that the portfolios that we will later analyze contain a sufficient number of

on the previous day from the stock universe used to select daily winners and losers. This heterogeneity, opacity, and time-varying nature of rankings makes it impossible to replicate all historical rankings well.

[5]Figure 1 is truncated at rank 100. The fraction of WSJ-ranked stocks with a CRSP rank above 100 is below 10%.

stocks in each month and that we always have populated portfolios when conducting sample splits in our later analysis. In robustness tests, we find that our main results generally hold for various alternative levels of the thresholds. Results are economically stronger for lower thresholds, which is in line with a higher likelihood of stocks to be ranked and more salience for stocks ranked closer to the top. It additionally illustrates that the threshold of 80 is not a delicate choice (see Section 3.5).

Consistent with the bulk of the empirical asset pricing literature, we conduct our main asset pricing tests on the monthly frequency. We define $\mathrm{I_{WL}}$, a monthly indicator variable that is one when a stock was both, a daily winner *and* a daily loser at least once in the previous month. Similarly, we define a dummy variable $\mathrm{I_W}$ ($\mathrm{I_L}$) that takes on the value one, if a stock was a daily winner (loser), but *not* a daily loser (winner), at least once during the previous month.[6] Summary statistics on our ranking indicators and other key variables are shown in Panel A of Table 1.

[Insert Table 1 about here]

The mean for $\mathrm{I_{WL}}$ is 0.0495, meaning that 4.95% of all stocks were on at least one day among the daily winners and on at least one day among the daily losers in the previous month. The respective numbers for $\mathrm{I_L}$ and $\mathrm{I_W}$ are 5.74% and 7.98%, respectively. The probability of being a past winner is higher than the probability of being a past loser due to our procedure of dropping stocks with a price of less than 5 USD at the beginning of the month which affects more of the daily losers.

[6] A more precise measure for salience due to rankings would not just measure whether a stock was ranked as a daily winner and loser last month, but also whether the stock was ranked closer to the top and how often it was ranked. We show results for such a refined measure of rank salience in Section 4. In our main results we aim to keep the ranking measure simple and based on the least possible number of assumption, which leaves us with the three ranking indicator variables.

We also show other key return characteristics of the stocks in our sample. In some of our later analysis we will analyze the relation between the returns of ranked stocks and the Ang, Hodrick, Xing, and Zhang (2006) idiosyncratic volatility puzzle in detail. Thus, we calculate the idiosyncratic volatility of each stock as the standard-deviation of the residuals from the Fama and French (1992) 3-factor model, estimated with last month's daily returns and show related variables like idiosyncratic and systematic skewness, expected idiosyncratic skewness (as in Boyer, Mitton, and Vorkink (2010)), the lottery index LIDX (as in Chen, Kumar, and Zhang (2015)), and the maximum (minimum) daily return over the previous month, Max (Min) (as in Bali, Cakici, and Whitelaw (2011)). Note, that the latter variables are defined based on the time-series of a stock's individual returns within a month, while our main variable of interest, $\mathrm{I_{WL}}$, is defined based on the relative daily ranking within the cross-section of all stocks. All variables used in our analysis are defined in detail in Appendix A.

The correlations between our main variables are shown in Panel B of Table 1. The strongest cross-correlation between any of the variables is observed between idiosyncratic volatility and Max and amounts to 0.86. This strong correlation confirms findings of Hou and Loh (2016) who suggest that Max is essentially just another way to measure idiosyncratic volatility. The correlations between $\mathrm{I_{WL}}$, $\mathrm{I_L}$, and $\mathrm{I_W}$, respectively, and other variables are all clearly below 0.5, so that we face no problems of multi-collinearity if we use them jointly in later regressions. The strongest correlation between $\mathrm{I_{WL}}$ and any of the variables is with idiosyncratic volatility and amounts to 0.34, showing that our variable—unlike Max—is not just another way to measure idiosyncratic volatility. The relationship between $\mathrm{I_{WL}}$ and idiosyncratic volatility will be analyzed in more depth in Section 4.

Other data sources we use include firm characteristics from Compustat's annual financial statement dataset, monthly averages of transaction-weighted daily bid-ask spreads from the transactions-and-quotes (TAQ) database (1996-2010), quarterly institutional ownership according to firms' 13F filings from the SEC's EDGAR system (3/1980-3/2015) as well as monthly short-interest from Compustat (2003-2015), and various factor return time series provided by the authors of the respective papers. To measure daily retail trading we use data from a large discount brokerage (provided by Barber and Odean (2008), 1991-1996) and to measure daily institutional trading we use data provided by ANcerno (used by e.g. Goldstein, Irvine, Kandel, and Wiener (2009) and Puckett and Yan (2011), 1997-2010).

3 Performance of Daily Winners and Losers

3.1 Univariate Portfolio Sorts

At the beginning of each month, we sort stocks into portfolios based on whether they appeared in a daily top- or bottom ranking in the previous month. We construct four portfolios: The 'Never' portfolio contains all stocks that never appeared in the top- or bottom ranking in the previous month. The 'Loser' ('Winner') portfolio contains all stocks that appeared at least once in the bottom (top) daily return ranking, but never in the top (bottom) daily return ranking in the previous month. Finally, the 'Both' portfolio contains all stocks that at least once appeared in the top daily return ranking *and* at least once appeared in the bottom daily return ranking in the previous month. The vast majority of stocks (on average 78% of them) is sorted into the 'Never' portfolio. As larger stocks are less likely to be daily winners or losers, the 'Never' portfolio makes up more than 93% of overall market capitalization in an average month, while the stocks in the 'Both' portfolio on average represent 1.13% of overall market capitalization.

In Panel A of Table 2 we show the equal- and value-weighted returns of the four portfolios over the period July 1963 through December 2015.

[Insert Table 2 about here]

The 'Never' portfolio delivers the highest average value-weighted (equal-weighted) monthly return of 0.53% (0.82%), while the loser and the winner portfolios' value-weighted (equal-weighted) returns amount to -0.17% and 0.39% (0.38% and 0.20%), respectively. In stark contrast, the stocks in the 'Both' portfolio deliver a very large negative value-weighted (equal-weighted) average return of -1.07% (-0.90%) per month. Consequently, a trading strategy going long in the stocks from the 'Never' portfolio and short in the stocks from the 'Both' portfolio delivers a monthly value-weighted (equal-weighted) return of 1.60% (1.72%), with a t-statistic of 5.46 (9.08). The Sharpe-Ratio of this value-weighted (equal-weighted) 'Never' minus 'Both' (NMB) strategy amounts to 0.77 (1.32). To put this into context, the Sharpe Ratio of the momentum strategy amounts to 0.56 over the same period. Hence, stocks that were both daily winners and losers last month significantly underperform stocks that never made the rankings.

Stocks that were daily winners, but not losers, last month also clearly underperform the 'Never' stocks in the equal-weighted portfolio by 0.62% per month, whereas their underperformance in the value-weighted portfolio drops to a statistically insignificant 0.14% per month. The underperformance of winner stocks is also consistent with salience theory as recently suggested in Bordalo, Gennaioli, and Shleifer (2013) according to which investors put too much weight on very salient information, where salient information is understood as outcomes that are very different from the average. Being ranked as a winner is thus very salient in this sense and investors might put too much weight on this positive information which can then lead to an overvaluation and subsequent underperformance. However, stocks that were daily losers, but not winners, last month also clearly underperform the 'Never' stocks in the value-weighted portfolio by 0.70% per month, whereas their underperformance in the equal-weighted portfolio is weaker at 0.44% per month but still statistically significant at the 1%-level. The general underperformance of 'Loser' stocks is inconsistent with the salience theory of Bordalo, Gennaioli, and Shleifer (2013), that would predict that daily losers will be undervalued and eventually outperform. The underperformance of 'Loser' stocks also suggests that our results are not just driven by Bali, Cakici, and Whitelaw (2011)'s finding that stocks with high maximum daily returns last month underperform or by Fu (2009)'s finding that the low returns of high idiosyncratic volatility stocks are due to return reversal. Furthermore, microstructure issues that are sometimes blamed for causing short-term reversal effects, e.g., Ball, Kothari, and Shanken (1995) and Avramov, Chordia, and Goyal (2006), also do not explain our overall findings: Results remain significant when we leave a 1-month gap between the ranking and portfolio formation (see Table B1 in Appendix B).

3.2 Evidence from Factor Models

Panel B of Table 2 presents the alphas and exposures from CAPM 1-factor (1F), Fama and French (1993) 3-factor (3F), and Carhart (1997) 4-factor (4F) regressions of our equal-weighed and value-weighted NMB strategy returns with monthly rebalancing. NMB loads significantly negative on the market and the size factor, and significantly positive on the value factor. There is also a small but insignificant positive exposure to the momentum factor. The alpha ranges from 1.75% per month (21.03% p.a.) for the value weighted strategy in the 4-factor model up to 1.92% per month (23.03% p.a.) for the value weighted strategy in the simple market model. The effects are economically large and statistically significant at all conventional levels in each case, with t-statistics based on Newey and West (1987) standard errors (one lag) ranging from 7.20 to 12.86. Thus, they also easily cross the conservative hurdle of 3.00 recently suggested in Harvey, Liu, and Zhu (2016) and we can reject the null hypothesis of 'zero outperformance' even if we view the hypothesis of attention-induced overpricing of daily winners and losers as a long-shot with 1:99 odds (Harvey, 2017).

We also control for a battery of alternative factors that can have an impact on the cross-section of stocks and that are discussed in the literature. Monthly alphas from all these regressions are shown in Panel C of Table 2. In the first line, we repeat the results from the benchmark 4-factor model from Panel B for easy comparison. In subsequent lines, in addition to the four factors from the Carhart (1997) model, we include (i) the short- and long-term reversal factors from Kenneth French's data library (ST and LT), (ii) the Hirshleifer and Jiang (2010) undervalued-minus-overvalued (UMO) factor, (iii) the Frazzini and Pedersen (2014) betting-against-beta (BAB) factor, (iv) the Asness, Frazzini, Israel, Moskowitz, and Pedersen (2017) quality-minus-junk (QMJ) factor, (v) the Kelly and Jiang (2014) tail risk factor, (vi) the Chabi-Yo, Ruenzi, and Weigert (2017) crash-sensitivity factor (CRW), (vii) the Pástor and Stambaugh (2003) (PS) and (viii) the Sadka (2006) (fixed-transitory and variable-permanent) systematic liquidity factors, (ix) the Novy-Marx (2013) profitability factor (PMU), (x) and the Stambaugh and Yuan (2017) mispricing factors (SY). Additionally, we run the Fama and French (2015) five factor (5F) and the Hou, Yue, and Zhang (2015) four factor model (Q-model) instead of the Carhart (1997) model. Irrespective of the specific factor model, we find uniformly strong evidence of a large positive alpha of our NMB strategy that never falls below 1% per month and can be as high as 2.25% per month. T-statistics range from 4.38 up to 12.15.

To get an impression of the long-term performance and the temporal stability of the NMB strategy returns, we plot the performance of a $1 investment over our sample period from July

1963 to December 2015 for several self-financing trading strategies (ignoring trading costs): the NMB strategy (equal- and value-weighted NMB + risk-free rate), as well as the value-weighted CRSP market index (Mktrf + risk-free rate) and the momentum strategy (from Kenneth French's data library, MOM + risk-free rate) in Figure 3. All strategy returns are (de-)leveraged to have the same volatility as the market return to make them comparably risky. The NMB strategies deliver constantly strong returns with only very few short episodes with negative returns. In spite of their similar performance before the volatility adjustment, the equal-weighted NMB strategy outperforms the value-weighted NMB strategy after the volatility-adjustment. This is because the value-weighted short leg is often dominated by few large firms and thus badly diversified and volatile. Both NMB strategies strongly outperform the momentum strategy as well as the market: The $1 investment from July 1963 into the equal-weighted (value-weighted) NMB strategy turns into $249,999 ($3,081) until December 2015, whereas the momentum strategy returns $663 and the market returns $151.[7] The large volatility-adjusted outperformance of both NMB strategies illustrates the economic significance of the overpricing of daily winners and losers.

[Insert Figure 3 about here]

In Figure 4 we display the average cumulative Carhart (1997) alpha of the value-weighted (equal-weighted) NMB strategy returns from the first month after portfolio formation to month 36 without monthly rebalancing.[8] The figure clearly shows that the underperformance of daily winners and losers is not a short-term effect: Even many months after portfolio formation, the effect is still significant and there is no sign of a reversal. The cumulative alpha

[7]A risk-free $1 investment from July 1963 would have returned $12.30 in 2015.

[8]We zoom in instead of out by looking at daily strategy returns directly after the ranking in Figures C1 and C2 of Appendix C. Short-term price effects are difficult to measure, however, since the extreme returns leading to the rankings themselves and microstructure effects (short-term reversal) confound the price impact and reversal pattern until around 10 days after the ranking day. These results are discussed in Appendix D.

of the NMB strategy after three years amounts to around 17% (15%) for the value-weighted (equal-weighted) strategy. Hence, an investment strategy with overlapping portfolios and infrequent rebalancing could be used to minimize transaction costs which are thus not likely to eat up much of the documented strategy returns. Note that reversal effects over one to three years are commonly found in the literature, e.g. after fund flow induced price pressure in Coval and Stafford (2007) and Lou (2012).

[Insert Figure 4 about here]

3.3 Firm-Level Cross-Sectional Regressions

Overall, the evidence presented thus far clearly shows that last month's daily winners and losers underperform strongly after being ranked. Standard factor models cannot explain this return effect. We now turn to Fama-MacBeth regressions, to check whether firm characteristics can explain the underperformance of daily winners and losers on the stock level. We regress this month's individual stock returns on firm characteristics available at the end of last month, including dummies for 'Both', I_{WL}, 'Loser', I_L, and 'Winner', I_W, status.[9] Results are reported in Table 3.

[Insert Table 3 about here]

In Specification (1) of Panel A, we include I_{WL} (daily winner *and* daily loser last month) and control for a stock's β, the logarithm of its size and its book to market ratio, last year's return (momentum), last month's return (short-term reversal), and the previous two years' returns (long-term reversal).

[9] We separately analyze the relation to the idiosyncratic volatility puzzle in Section 4.

Controlling for all these firm characteristics, the monthly return for stocks that were daily winners *and* daily losers last month is 1.56% lower than the return of otherwise similar stocks. The effect is statistically highly significant with a t-statistic of 12.48. Thus we can easily reject the null hypothesis of 'no return effect', even if our prior gives long-shot odds of 1:99 to the underperformance of daily winners and losers (Harvey, 2017). Furthermore, the coefficients of all control variables are as expected. In particular, small firms, value stocks, last year's winners, last month's losers, and long-term losers exhibit higher returns.

In Specification (2) we additionally include the dummies I_L and I_W. The coefficient estimates on both variables indicate statistically significant underperformance of past 'Loser' and 'Winner' stocks, respectively. Stocks that were daily losers but not daily winners underperform stocks that did not appear in the rankings by 0.76% per month (t-statistic 10.03), while stocks that were daily winners but not daily losers underperform stocks that did not make the rankings by 0.28% per month (t-statistic 4.04). Similar as above, while the latter effect would also be consistent with the salience theory of Bordalo, Gennaioli, and Shleifer (2013), the underperformance of daily losers runs in the opposite direction. It is also inconsistent with an explanation based on 'the return reversal of a subset of small stocks with high idiosyncratic volatilities' (Fu, 2009). The return effect for 'Both' stocks increases slightly relative to Specification (1), which is due to the fact that the three daily winner and loser dummies, I_{WL}, I_L, and I_W, are mechanically negatively correlated: If one of them is 1, the other is zero and vice versa for all pairs.

Motivated by Fama and French (2015) we add operating profitability and asset growth as control variables in Specification (3). As expected profitable firms exhibit higher future returns, while firms with strong asset growth exhibit lower returns. Our main results remain largely unaffected.

Gervais, Kaniel, and Mingelgrin (2001) find that trading activity is related to future stock returns. We later show that daily winners and losers are heavily traded (see Section 5), so that controlling for trading activity might influence our results. Thus, in Specification (4) we add last month's level and change in turnover. As in Gervais, Kaniel, and Mingelgrin (2001), stocks with increasing trading activity exhibit higher future returns (the 'high-volume return premium'), while a high turnover level is related to lower future returns, which is consistent with high turnover stocks being more liquid and delivering lower returns. More importantly, controlling for these effects does not affect our main findings either.

Finally, to make sure results are not driven by the salience of industry-returns or small- vs large-firm returns we add Fama/French-48 industry dummies and NYSE-size-decile dummies in Specification (5). Additionally, there we also include exchange dummies. This does not change our estimates for the underperformance of daily winners and losers either. Hence, our results are robust to controlling for firm-specific characteristics.

3.4 Alternative Definitions of Daily Returns

If the low returns of daily winners and losers are indeed driven by rankings of stocks, the effect should be strongest when returns are measured from close to close (i.e. 4pm to 4pm), as this is the convention used by most newspapers. CRSP provides open prices starting in July 1992, so that we can compare the changes when we re-compute rankings based on less common day-conventions for the 8/1992-12/2015 period. In Panel B of Table 3 we analyze the pricing of ranked stocks based on returns from close-to-close (Specification 1), open-to-open (Specifications 2 and 3), open-to-close (Specifications 4 and 5), close-to-open (Specifications 6 and 7), and based on 2-day close-to-close returns (Specifications 8 and 9). To avoid multi-collinearity issues with multiple highly correlated regressors we use I_{Any}, a dummy that is 1 if a stock was ranked at least once as a a daily winner or a daily loser last month based on the various return conventions, instead of splitting up the effect into I_{WL}, I_L, and I_W.

As expected, we find that the returns of winners and losers are most extreme when stocks are ranked based on close-to-close returns (-0.60% per month, see Specification 1). When ranking stocks by the other, unusual measures (Specifications 2, 4, 6, and 8), the effect decreases by at least 25%. The strongest effect among the alternatives amounts to 0.45% per month for the two-day returns in Specification 8. The most convincing test for the importance of rankings is based on regressions where we jointly include I_{Any} based on close-to-close returns, $I_{Any,C2C}$, as well as based on the less common alternative day-conventions for returns, $I_{Any,Alt}$, in one regression. In these regressions, only the close-to-close rankings significantly predict underperformance of daily winners and losers (see Specifications 3, 5, 7, and 8), while the impact of $I_{Any,Alt}$ is always insignificant irrespective of which alternative day-convention is used. If the fundamental idiosyncratic risk of a stock was the reason for the underperformance of daily winners and losers, we would not expect such systematic differences when unusual day-conventions are used to rank stocks. As an illustration, short sale constraints (Drechsler and Drechsler, 2017; Stambaugh, Yu, and Yuan, 2015), strategic risk shifting in response to bad news (Chen, Strebulaev, Xing, and Zhang, 2017), or the asymmetric effective taxation of capital losses and gains (Boguth and Stein, 2017) have all been brought forward to explain low returns of high idiosyncratic volatility stocks, but they alone cannot explain the finding that extreme close-to-close rankings matter whereas alternative rankings do not. Hence, the importance of ranking by close-to-close, not open-to-open etc., is strong evidence in favor of our interpretation that the strong return patterns we document are really due to the importance of daily rankings.

3.5 Robustness Checks

In Panel A of Table B2 in Appendix B we perform further robustness checks based on Specification (2) of Table 3. We vary the price filter (excluding stocks with prices below 1 and 3 USD, respectively, instead of 5 USD), exclude small (below 1st NYSE-decile) firms, exclude NASDAQ firms, use industry- and DGTW-adjusted returns, and refrain from winsorizing controls. None of these robustness checks qualitatively change our main results.

In Panels B and C of Table B2, we vary the threshold used to define daily winners and losers from the top/bottom 5 to the top/bottom 320 stocks (instead of our default threshold of 80). In Panel B, we present results using our standard price filter of 5 USD. We find that the strength of the impact of I_{WL} is increasing from -1.65% per month to -2.42% per month and -3.02% per month, respectively, if we only use the top/bottom 40 and 20 stocks instead of the top/bottom 80 stocks. For even lower cutoffs coefficient estimates decrease and statistical significance starts to vanish. This effect is probably due to the very small number of stocks for which I_{WL} would be equal to one in these cases. While the fraction of stocks that are both, a daily winner and a daily loser at least once in a given month, is still above 1% for a threshold of 40 stocks, it is only 0.13% (0.05%) for a threshold of 10 (5) stocks. In these cases, the 'Both' portfolio often is not populated.

Thus, in Panel C we use the less strict price filter of 1 USD. Doing so leads to an increase in the percentage of stocks that were both daily winners and losers in a month by a factor of about three for the very low cutoffs. Now, we find a perfectly monotone relationship between the threshold to define top/bottom stocks and the strength of the impact of I_{WL}. When focusing on the Top-/Bottom-5 (10) stocks, we find a NMB strategy return of -3.52% (-2.16%) per month with a t-statistic of -6.05 (-6.07).

The more pronounced effects for lower thresholds can also be confirmed based on portfolio sorts. In Table B3 we repeat the analysis from Table 2 using a threshold of 20 instead of 80 to define top/bottom stocks. The equal-weighted (value-weighted) NMB strategy return nearly doubles from 1.60% (1.72%) per month to 3.04% (2.82%) per month. However, the Sharpe-Ratio of the value-weighted NMB strategy only slightly increases from 0.77 to 0.82 and even decreases from 1.32 to 0.91 for the equal-weighted strategy because of the much higher return variance due to the smaller size of the 'Both' portfolio in this case. Nevertheless, the Carhart (1997) Alpha of the value weighted (equal weighted) NMB strategy still strongly increases to 3.65% (3.01%) per month with a t-statistic of 7.32 (6.65). The generally stronger results for the lower thresholds show that our previous choice to use a relatively large number of stocks to define daily winners and losers was conservative.

Last, we show that our results are robust within different subperiods. In Table B4 of Appendix B we report Fama-MacBeth regressions for the subperiods 1989-2015, 1963/7-1988, and 1928-1963/6. Stocks ranked as winners and losers exhibit significantly lower returns in all three subperiods. Within the pre-1963 subperiod, the average number of stocks per cross-section is at 688 and thus much lower than in the later two subperiods (2124 and 2869). It seems likely that a smaller cross-section of stocks traded on less exchanges will result in more homogenous rankings containing fewer stocks. Hence, we additionally test a threshold for the classification of daily winner or loser of 20 instead of 80, which tripples the effect size for stocks ranked as daily winners and losers.

4 Relation to the Idiosyncratic Volatility Puzzle

To be a daily winner or a daily loser, a stock needs to exhibit an extreme daily return relative to other stocks. Hence, daily winners and losers are likely to exhibit high idiosyncratic volatility. Consistently, the correlation between $\mathrm{I_{WL}}$ and idiosyncratic volatility is positive and substantial at 0.34 (see Panel B of Table 1). It is well known from the literature on the idiosyncratic volatility puzzle, that stocks with high idiosyncratic volatility exhibit low future returns (e.g. Ang, Hodrick, Xing, and Zhang (2006)) which might provide a possible explanation for our findings.

In this section, we show that (i) the known negative volatility-return relation does not explain the underperformance of daily winners and losers, and that (ii) the idiosyncratic volatility puzzle is confined to the small subset of stocks that were daily winners or losers last month, suggesting that daily winners and losers are the main drivers of the idiosyncratic volatility puzzle.

To get a better understanding of the stocks in our strategy portfolios, we first show average characteristics of last month's daily winners and losers for the current month, i.e., the holding period of our investment strategies. In Table 4, we report different measures of idiosyncratic and systematic risk as well as relative spreads for the 'Never', 'Loser', 'Winner', and 'Both' portfolios, respectively.[10]

[Insert Table 4 about here]

As expected, daily winners and losers are also predictably more extreme than other stocks subsequent to being ranked: stocks that were both daily winners and losers in the previous month have nearly twice the idiosyncratic volatility, and nearly twice the maximum and

[10] All variables are defined in detail in Appendix A.

minimum daily returns compared to stocks that were neither daily winners nor daily losers last month. Similarly, idiosyncratic skewness of the daily winners and losers is also much higher than that of the stocks in the 'Never' portfolio. Thus, we now turn to a thorough analysis of the relation between daily winners' and losers' underperformance and the idiosyncratic volatility puzzle based on portfolio sorts (4.1), factor models (4.2), Fama and MacBeth (1973) regressions (4.3), and the Hou and Loh (2016) decomposition method (4.4).

4.1 Portfolio Sorts

In Panel A of Table 5 we report returns of equal- and value-weighted portfolios sorted by idiosyncratic volatility. Idiosyncratic volatility is calculated as in Ang, Hodrick, Xing, and Zhang (2006) as the standard-deviation of residuals from the Fama and French (1993) 3-factor model. To check whether the underperformance of high idiosyncratic volatility stocks is driven by daily winners and losers, we compare portfolio sorts based on the full NYSE/AMEX/NASDAQ universe ('all stocks') to sorts based on the full universe but excluding the stocks that appeared in a ranking in the previous month ('only Never').

[Insert Table 5 about here]

For the full stock universe, we can confirm the results of Ang, Hodrick, Xing, and Zhang (2006) that high idiosyncratic risk stocks underperform low idiosyncratic risk stocks. We find that the stocks in highest idiosyncratic volatility quintile underperform those in the lowest idiosyncratic volatility quintile by -0.66% (-0.55%) per month in equal-weighted (value-weighted) sorts. The return difference is statistically significant at the 1%-level in both cases. However, when we exclude the 22% of stocks (7% of market capitalization) that were daily winners or losers last month, the underperformance of high idiosyncratic risk stocks is strongly reduced to a negligible -0.03% (-0.15%) in the equal-weighted (value-weighted) sorts. The idiosyncratic volatility puzzle becomes statistically insignificant and economically negligible for both, the equal- and the value-weighted portfolio sort, showing that it is completely driven by past daily winner- and loser stocks.

Other papers aiming at a better understanding of the Ang, Hodrick, Xing, and Zhang (2006) idiosyncratic volatility puzzle analyze other related variables, arguing that they provide an explanation for the observed patterns. For example, Bali, Cakici, and Whitelaw (2011) use last month's maximum daily return and finds that this measure at least partially drives the idiosyncratic volatility effect. Thus, we repeat our above analysis for this alternative measure. Results in Panel B show that stocks with high maximum daily returns last month tend to underperform stocks with low maximum daily returns, confirming the results of Bali, Cakici, and Whitelaw (2011). However, the underperformance of maximum daily return stocks also becomes small and insignificant when we exclude daily winners and losers for both, equal- and value-weighted sorts.

Boyer, Mitton, and Vorkink (2010) document that stocks with high expected idiosyncratic skewness underperform stocks with low expected idiosyncratic skewness and argue that this effect might explain the idiosyncratic volatility puzzle. To analyze whether the effect shown in Boyer, Mitton, and Vorkink (2010) is also driven by daily winner and loser stocks we repeat our analysis based on expected idiosyncratic skewness. Due to the data requirements for the estimation of expected idiosyncratic skewness, we follow Boyer, Mitton, and Vorkink (2010) and restrict the analysis to January 1988 through December 2015.[11] Results in Panel C show that we can also replicate the finding that high expected idiosyncratic skewness stocks

[11]This restriction is necessary as one of the input parameters (turnover) to estimate expected idiosyncratic skewness is only reliably available for NASDAQ stocks since 1983 and Boyer, Mitton, and Vorkink (2010) use a 5 year estimation window for their prediction.

underperform by, in our case, 0.57% (0.72%) based on equal-weighted (value-weighted) sorts. However, once we exclude daily winners and losers, the effect is substantially reduced and is insignificant for equal-weighted sorts. It only remains significant at the 10% level in value-weighted sorts.[12]

Hence, excluding the small subset of daily winners and losers from the stock universe strongly reduces all three anomalies that are related to idiosyncratic volatility.

4.2 Factor Models

Factor models provide another method to check how much of the NMB premium can be explained by the idiosyncratic volatility puzzle, and vice versa. In Panel A of Table 6 we report alphas and factor exposures for regressions of the value-weighted NMB strategy's return on the Carhart (1997) 4-factor model alone (Specification (1)) and together with quintile-portfolio based high-low returns of the idiosyncratic volatility strategy (Specification (2)), the maximum daily return strategy (Specification (3)), the expected idiosyncratic skewness strategy (Specification (4)), and all three strategies jointly (Specification (5)).

[Insert Table 6 about here]

As expected, the NMB strategy has a negative and significant exposure to the three factor returns for the idiosyncratic volatility factor (-0.82), the max factor (-0.66), and the expected skewness factor (-0.53) in Specifications (2) to (4). Once we include all three additional factors jointly, the impact of Max loses its significance, probably due to its high correlation with idiosyncratic volatility.

[12]When we include years prior to 1988 (by only focusing on stocks for which turnover data is available), there is actually no statistically significant underperformance of high expected idiosyncratic skewness stocks after excluding daily winners and losers even in the value-weighted case.

However, in either case, these exposures cannot explain the returns to selling daily winners and losers: The Carhart (1997) 4-factor alpha is somewhat reduced, but still always remains above 1.18% per month (with a t-statistic never smaller than 5.43) when we use value-weighted strategy returns. When we use equal-weighted strategy returns for the NMB strategy, as well as the three idiosyncratic risk strategies, the alpha always remains above 0.95% per month (t-statistic always above 6.81). Hence, this analysis also shows that the underperformance of daily winners and losers cannot be explained by the idiosyncratic risk puzzles.

In Panel B of Table 6 we reverse the logic of the regressions from Panel A and report alphas and exposures for regressions of the idiosyncratic volatility, maximum daily return, and expected idiosyncratic skewness high-low strategies on the Carhart (1997) 4-factor model alone (Specifications (1), (3) and (5)) and together with the NMB factor (Specifications (2), (4) and (6)). As expected, the three strategies exhibit a significant negative Carhart (1997) 4-factor alpha in Columns (1), (3), and (5), i.e., we can replicate the idiosyncratic risk puzzles. However, the exposures of the idiosyncratic volatility, maximum daily return, and expected idiosyncratic skewness strategies to the NMB factor (-0.29, -0.25, and -0.14, respectively, and always significant at the 1%-level) turn the alpha of all three strategies insignificant. When we use equal-weighted portfolio returns, controlling for the exposure to daily winners and losers even leads to a significantly *positive* alpha of high idiosyncratic volatility stocks (0.18% per month) and high expected idiosyncratic skewness stocks (0.47% per month). The positive equal-weighted alpha for high idiosyncratic volatility after controlling for the NMB factor is consistent with the positive premium suggested by Merton (1987). In any case, the idiosyncratic risk puzzles can be completely explained by controlling for exposure to daily winner and loser returns.

4.3 Firm-Level Cross-Sectional Regressions

Fama and MacBeth (1973) regressions provide a third method to check how the underperformance of daily winners and losers is linked to the pricing of idiosyncratic volatility and related variables like Max or expected idiosyncratic skewness.

In Table 7 we extend results from Specification (2) of Table 3 (repeated in Specification (1) of Table 7) and include idiosyncratic volatility (Specification (2)), Max (Specification (3)), and expected idiosyncratic skewness (Specification (4)) as well as systematic skewness (Specification (5)). As results in Table 4 show pronounced differences with respect to liquidity and the Chen, Kumar, and Zhang (2015) lottery index LIDX between ranked stocks and stocks from the 'Never' portfolio, we also control for the impact of these variables in Specification (6) and (7), respectively, as well as all for of these variables jointly in Specification (8).[13]

[Insert Table 7 about here]

In each case, the impact of I_{WL} remains significant with t-statistics ranging from -9.67 up to -13.01, showing that none of the additional control variables can (individually or jointly) explain the strong underperformance of daily winners and losers. Coefficient estimates are very similar to those in Table 3, indicating an underperformance of 1.37% to 1.67% per month of stocks that were daily winners and losers in the previous month. Only the underperformance of stocks that were daily winners but not losers last month becomes statistically insignificant in Specifications (2) and (3), but is still significant even in Specification (8) where we jointly include all variables. The variables related to the idiosyncratic volatility puzzle itself remain statistically significant and negative in Specifications (2) through (4). This is consistent with

[13] As idiosyncratic volatility and Max are highly correlated (see Table 1), there are potential multicollinearity problems in the last specification. However, excluding either one of the two variables and repeating the same regression delivers very similar results.

our findings from the portfolio sorts in Table 5: A significant marginal underperformance of high idiosyncratic volatility stocks may be left *within the daily winners and losers*, even if there is no significant underperformance for stocks that did not make the rankings. Thus, we can still expect to find a significant impact of idiosyncratic volatility in Fama and MacBeth (1973) regressions even after controlling for the impact of I_{WL}. Regarding the other new controls, we find no impact of systematic skewness, but a significantly negative (positive) impact of the Chen, Kumar, and Zhang (2015) lottery index and of illiquidity, consistent with the literature.

4.4 Hou and Loh (2016) Decomposition

Hou and Loh (2016) argue that comparing Fama and MacBeth (1973) coefficients of idiosyncratic volatility before and after including a potential explanatory variable for the idiosyncratic volatility puzzle as we do above does not provide a valid estimate of the fraction of the idiosyncratic volatility puzzle explained. They provide a decomposition method for the idiosyncratic volatility's Fama and MacBeth (1973) coefficient, and find that the variables that individually explain the highest fraction of the idiosyncratic volatility puzzle are the retail trading proportion, RTP, at 22.3%, bid/ask spreads at 30.4%, and lagged monthly returns at 33.7%.[14] We run the Hou and Loh (2016) decomposition method and report results in Table 8. Hou and Loh (2016)'s method decomposes the Fama and MacBeth (1973) coefficient of idiosyncratic volatility from a regression of DGTW-returns on idiosyncratic volatility into a part explained by a candidate variable and a part that is left unexplained.

[14] Using the same methodology and Max as an explanatory variable leads to a fraction of the puzzle explained by Max of 112.0% in Hou and Loh (2016) and 109.10% with our data. However, Hou and Loh (2016) exclude last month's maximum daily return from most of their analysis, arguing that—at a correlation of close to 0.9 with idiosyncratic volatility—it is just another measure of idiosyncratic volatility. The correlation of daily winner and loser status with idiosyncratic volatility remains well below 0.5, see Panel B of Table 1, so that such concerns are not relevant with respect to our analysis.

[Insert Table 8 about here]

For a fair comparison to alternative candidate variables from Hou and Loh (2016), we use a 1$ price filter, just like Hou and Loh (2016), and we restrict ourselves to use only one indicator variable for winner/loser-status at first. First, we combine our three indicator variables into one by adding them up: The status as daily winner *or* daily loser last month (I_{Any} in row 1 of the table) can individually explain 65% of idiosyncratic volatility's Fama and MacBeth (1973) coefficient. Using the status as daily winner *and* daily loser (I_{WL}) together with the status as daily loser only (I_L) or daily winner only (I_W), reduces the unexplained fraction of the idiosyncratic volatility coefficient from 35% to 15% (see rows two to four of Table 8 in Panel A). The status as daily winner is more important in explaining the negative price of idiosyncratic volatility than the status as daily loser. In comparison with other explanatory variables from Hou and Loh (2016), the status as daily winner and loser is the most powerful explanatory variable for the idiosyncratic volatility puzzle.

However, our indicator variables for the status of daily winner and loser cannot explain the full Fama and MacBeth (1973) coefficient of idiosyncratic volatility. This is not surprising—even if the salience due to daily winner and loser rankings explains the entire coefficient—since our simple indicator variables do not capture salience of ranked stocks due to higher ranks or due to more frequent rankings last month. Thus, idiosyncratic volatility might still measure the marginal effect of higher salience within stocks ranked last month. To test this hypothesis, we construct a refined rank salience measure. We first compute a daily salience score, which declines linearly from 80 to 0 for stocks ranked at ranks 1 to 81 in CRSP and is zero for other stocks. We then take the average of this daily rank salience proxy over the trading days of last month, separately for winners and losers, to get a monthly rank salience measure. In our regressions we use the log of 1+ this measure to reduce the impact of outliers. In contrast to our simple daily winner and loser indicators, this measure also increases when a stock is ranked multiple times and when it is ranked closer to the top of the ranking.

Results for our refined rank salience measure are reported in Panel B of Table 8. The unexplained fraction of the Fama and MacBeth (1973) idiosyncratic volatility coefficient shrinks to 4% when the sum of salience due to winner and loser rankings is used as a refined measure. This unexplained fraction is insignificantly different from zero. As in Panel A, the salience due to being a daily winner is more important in explaining the negative price of idiosyncratic volatility than the salience of daily losers (see rows two to four in Panel B). Again, we cannot reject the hypothesis that 100% of the idiosyncratic volatility puzzle is explained by salience due to being a daily winner or loser.

In summary, we show (i) that the idiosyncratic volatility puzzle and related anomalies do not explain the underperformance of daily winners and losers and (ii) that the idiosyncratic volatility puzzle and related anomalies are confined to the small subset of stocks that were daily winners or losers last month, i.e., that daily winners and losers are the main drivers of these anomalies.

5 Retail and Institutional Trading Activity

In this section, we explore the trading in daily winner and loser stocks. As trading proxies we analyze institutional and retail buy-sell imbalances, as well as short interest. As short interest is only available to us on the monthly level, we first focus on monthly contemporaneous panel regressions of trading activity measures on daily winner and loser status and control variables. Thus, this analysis is obviously plagued by endogeneity concerns and should be understood as descriptive rather than causal. We then re-run our tests as predictive daily regressions for retail and institutional buy-sell imbalances, which are available to us on the daily level.

We first run panel regression with firm and month fixed effects and double-clustered standard errors, regressing buy-sell-imbalances ($\frac{Buys-Sells}{Buys+Sells}$) and short interest (Short Int.) this month on the contemporaneous status as daily winner and loser, as well as the same control variables as in Specification (2) of Table 3 and the absolute deviation of stock returns from market returns. The latter variable is included to capture the idiosyncratic component of a stock's monthly return. Results are reported as Specifications (1) to (3) in Table 9.

[Insert Table 9 about here]

It is likely that retail investors are particularly prone to attention-grabbing events like stocks making it into one of the daily rankings. Indeed, Barber and Odean (2008) find that retail buy-sell imbalances increase for stocks with extreme returns. We use their data from a large discount broker (available for January 1991 to January 1997) to analyze whether daily winners and daily losers tend to be bought by retail investors. We regress monthly buy-sell imbalances on the status as daily winner and loser. Results are reported in Specification (1) of Table 9. Retail buy-sell imbalances clearly increase for daily winners and losers. Stocks that are both daily winners and daily losers show 8.29% higher buy-sell imbalances, while imbalances for stocks that were daily losers (winners), but not daily winners (losers) increase by 6.25% (10.99%). All coefficients are statistically significant at the 1% level. These results are consistent with daily winners and losers experiencing retail demand spikes.

If institutional investors act as liquidity providers for daily winners and losers that are bought by retail investors, then we should observe analogous negative changes in buy-sell imbalances for institutional investors, as well as increases in short interest (assuming that short-sellers are typically institutional investors). We use ANcerno's institutional trade data (January 1997 to January 2011) and show in Specification (2) of Table 9 that stocks that are daily winners and losers show a decrease in institutional buy-sell imbalances of 4.35%. Stocks that were daily winners, but not daily losers experience a decrease in institutional buy-sell imbalances of 6.22%. These effects are statistically significant at the 1% level. However, there is no significant change in buy-sell imbalances for stocks that were daily losers, but not winners in a given month.

For changes in short interest, which are available from Compustat for the years 2003 to 2015, however, there is a statistically highly significant increase for stocks that were daily losers, but not winners, as well as for stocks that were both winners and losers. In contrast, daily winners that were not losers experience a significant contemporaneous decrease in short interest (Specification (3) of Table 9), but the economic magnitude is only about 15% of that of the status of being a daily winner and loser. Short interest is highly persistent, which is reflected by the high coefficient for lagged short interest of 0.94 and the high R^2 of 96% in Specification (3). To make sure our results are not affected by this persistence, we repeat the regression with differences in short interest. Results are reported in Specification (4) and qualitatively the same as for the regression in levels. Combining monthly institutional buy-sell imbalances and short interest, we find evidence consistent with liquidity provision to daily winner and loser stocks by institutional investors during the month in which they are ranked.

Since our retail and institutional trading data are available at the daily frequency, we can improve upon Specifications (1) and (2) by running predictive daily instead of contemporaneous monthly panel regressions. Specification (5) shows that the status as daily loser (winner) predicts 4.11% (12.65%) higher retail buy-sell imbalances on the subsequent trading day, consistent with our monthly results in Specification (1). Specification (6) is in line with our results on liquidity provision by institutional traders in Specifications (2) to (4), as buy-sell imbalances significantly decrease for both losers (-0.71%) and winners (-3.33%).

Hence, retail investors tend to buy daily winners and losers (Specifications (1) and (5) of Table 9) and institutional investors (and short-sellers) tend to sell them (Specifications (2) to (4) and (6) of Table 9). The overall pattern of our findings is consistent with the view that retail investors are subject to ranking-driven attention effects while institutional investors tend to provide liquidity (or start to trade against the emerging overpricing). Since retail trading activity empirically tends to happen after the markets close, whereas institutional trading happens mostly intraday, it could be that the reversal effect we document in the month subsequent to the ranking is stronger intraday, whereas overnight trading by retail investors might stop or even reverse the reversal (see Lou, Polk, and Skouras, 2017). To test this hypothesis, we recompute our main result from Specification (2) of Table 3 separately for overnight and intraday returns in Table 10. Monthly overnight and intraday returns are calculated assuming that splits and dividends happen after markets close, as in Lou, Polk, and Skouras (2017). We also use their stock universe of NYSE, AMEX, and NASDAQ stocks excluding firms smaller than the NYSE's first size quintile and their time period starting in 1993 (CRSP's open prices become available mid-1992).

[Insert Table 10 about here]

Specification (1) of Table 10 replicates our main result for Lou, Polk, and Skouras (2017)'s restricted stock universe and time period. We again find underperformance for stocks ranked as both daily winners and losers (-0.87%, significant at the 10% level), or as daily losers only (-0.89%, significant at the 1% level) last month. Stocks ranked as daily winners only do not underperform in this sample and time period (0.12%, statistically insignificant).[15] Next, we split up monthly stock returns into their overnight and intraday components in Specifications (2) and (3). In Specification (2), we find highly significant *positive* return effects for ranked stocks, consistent with retail buying pressure after markets close. In Specification (3), we find highly significant negative return effects for ranked stocks, which are strong enough to lead to reversal effects in the full monthly stock returns in Specification (1). Hence, our results are fully consistent with an intraday reversal driven by institutional trading and overnight trading in the opposite direction. Our estimates for control variables are consistent with Lou, Polk, and Skouras (2017). In particular, beta and size are priced positively overnight and negatively intraday. Value accrues intraday and momentum accrues overnight. Additionally, we find that short-term reversal accrues overnight, whereas long-term reversal accrues intraday (Lou, Polk, and Skouras (2017) do not include these last two variables).

In summary, our results on the trading and overnight vs. intraday pricing of daily winners and losers are fully consistent with attention-induced retail buying pressure due to trading after markets close and institutional intraday liquidity provision.

[15]The insignificance of the daily winner coefficient is driven by the time period after 1992, not by the exclusion of small firms: Including small firms during the same time period leads to stronger effects for daily winners and losers (-1.56%, significant at the 1% level), a similar effect for daily losers (-0.86%, significant at the 1% level), and a still insignificant effect for daily winners (-0.08%, statistically insignificant).

6 Which Firms and Periods Drive Results?

6.1 Retail Ownership and Limits to Arbitrage

Possibly, limits to arbitrage prevent a profitable implementation of the NMB strategy in reality. Trading costs as a limit to arbitrage are unlikely to explain our findings, as the effect we document is long-lived and can be taken advantage of using a low turnover trading strategy. However, there might be other impediments. Thus, we now analyze differences in the underperformance of daily winners and losers between firms in the cross-section of stock returns depending on various proxies for limits of arbitrage. In Table 11 we report raw returns of our NMB strategy among firms with high and low retail ownership (as a proxy for short sale constraints), firm size, and the liquidity measures by Amihud (2002) and Corwin and Schultz (2012), respectively. Firms are split according to the cross-sectional median in the ranking month. We also show the difference in strategy returns between above and below median firms as well as the Carhart (1997) 4-factor alpha of this difference.[16]

[Insert Table 11 about here]

Retail ownership (one minus the percentage of shares outstanding owned by institutions according to 13f filings) is highly correlated with firm size and illiquidity. Thus, instead of using it directly, we follow Nagel (2005) and others in using residual retail ownership, which is the residual from cross-sectional regressions of the logit transformation of retail ownership on firm size, the square of firm size, and the Amihud (2002) illiquidity ratio. Due to data availability our analysis of retail ownership only starts in April 1980.

[16] We also repeat our analysis but leave a 1-month gap between ranking and holding period to decrease the effect of short term reversal, which strongly interacts with firm size and illiquidity (Ball, Kothari, and Shanken (1995)). Results remain similar and are reported in Table B5 of Appendix B.

Our results show significantly positive NMB strategy returns for both, high and low residual retail ownership firms. However, the underperformance of daily winners and losers is significantly stronger for stocks with high residual retail ownership: while the NMB strategy return amounts to 0.95% per month among low retail ownership firms, it is by 0.79% per month higher (statistically significant at the 1%-level), amounting to 1.74% among high retail ownership firms. The Carhart alpha of the difference in strategy returns amounts to 0.81% and is significant at the 1%-level. Overall, the stronger results for high retail ownership stocks are consistent with high short sale constraints preventing liquidity provision for these stocks.

When we use size or the Amihud illiquidiy ratio as proxies for limits of arbitrage, we find no significant difference in NMB strategy returns among firms with high and low limits to arbitrage. Only splitting the sample by the Corwin and Schultz (2012) proxy for spreads leads to stronger NMB premiums for illiquid stocks. However, even in this case the NMB strategy return among illiquid stocks still amounts to 1.19% and is significant at the 1%-level.

In summary, while there is some indication that short-sale constraints due to large residual retail ownership and limits of arbitrage due to market illiquidity may be a reason for the high returns to selling daily winners and losers (at least when using the Corwin and Schultz (2012) liquidity proxy), the still highly significant and economically large NMB strategy returns among stocks with supposedly low limits to arbitrage suggest that short-sale constraints and limits to arbitrags cannot fully explain the effects we document.

6.2 Impact of Rank Saliency

Next, we analyze how the returns to selling daily winners and losers vary over time. First, we analyze whether differences in the saliency of ranked winner and loser stocks influence strategy returns. As proxies for saliency, we use the cross-sectional average of daily stock returns' standard-deviations and return kurtosis for each month, arguing that when these measures are taking on a high value daily winners and losers tend to exhibit absolutely extreme, attention-grabbing returns relative to other stocks.

To examine the impact of saliency, we regress the NMB strategy's returns on the Carhart (1997) 4-factor model, as well as the time series of the two saliency proxies. Results are presented in Specification (1) and (2) in Table 12.

[Insert Table 12 about here]

We find a statistically significant positive impact of both proxies on our strategy returns, meaning that after periods of increased salience (as measured by return extremeness), the returns to selling daily winners and losers are higher. All non-return variables in this table are standardized to have a mean of zero and a standard-deviation of one, so that the coefficients can be interpreted as the effects of one standard-deviation more salience on the NMB premium. These effect-sizes are 1.01% (t-statistic 3.26) and 0.35% (t-statistic 2.29) per month for stocks' standard deviations and kurtosis, respectively. Hence, one standard-deviation more salience of winners and losers according to our two proxies significantly increases the NMB strategy return by about 20% to 60% from 1.74% to 2.75% (=1.74%+1.01%) and 2.09% (=1.74%+0.35%), respectively.

6.3 Impact of Sentiment

In the last step of our empirical analysis, we consider the effect of sentiment on our NMB strategy returns. Stambaugh, Yu, and Yuan (2012) show that a large number of anomalies in cross-sectional stock returns are stronger after high levels of sentiment. To analyze whether this is also the case for our strategy, in Specification (3), we add standardized investor sentiment (from Baker and Wurgler (2006), orthogonalized for the impact of macroeconomic conditions) to our regression of value-weighted NMB strategy returns on the Carhart (1997) factors. Sentiment has a positive impact: we find that a one-standard deviation higher level of investor sentiment increases the average monthly NMB strategy return by 0.79% (t-statistic 3.22). This finding is consistent with Stambaugh, Yu, and Yuan (2012) and with additional buying pressure of highly active retail investors during times of 'good sentiment', so that the overpricing and eventual reversal after being ranked become stronger.

7 Conclusion

We find that stocks that make it into daily top and bottom rankings on at least one day in the previous month significantly underperform stocks that do not make it into the rankings in subsequent months. The effect is economically large and statistically highly significant. Results survive a large battery of robustness tests. Our findings on institutional and retail trading activity suggest that retail investors buy ranked stocks, while institutional investors tend to provide liquidity and (short-)sell these stocks. The effect is driven by both, stocks that appear in the winner as well as in the loser rankings. It is driven by close-to-close daily returns which is the return convention used by daily winner and loser rankings, suggesting that ranking-based attention effects are driving our results.

Our findings also provide a potential solution to the idiosyncratic volatility puzzle of Ang, Hodrick, Xing, and Zhang (2006) and related anomalies: we find that the significantly negative return premium of high volatility stocks can only be documented among stocks that appeared in the rankings in the previous month, but not for all other stocks that make up 93% of total market capitalization. These patterns suggest that the idiosyncratic volatility puzzle is driven by a subgroup of stocks that raise a lot of investor attention due to their appearance in daily winner and loser rankings.

The price patterns we document might give rise to incentives for firm executives to opportunistically time SEOs or insider sales after periods in which the firm regularly appeared in the daily rankings. They might even try to manipulate their daily returns to make it more likely for their firm to appear in rankings prior to such events in order to artificially inflate short-term stock prices. For example, a firm could try to spread a (positive or negative) rumor and later officially deny the rumor, which might lead to appearances in both, a daily winner and a daily loser ranking in a short period of time and eventually to temporarily inflated prices. However, whether firms really engage in such kind of activities is pure speculation.

References

Amihud, Y., 2002, “Illiquidity and Stock Returns: Cross-Section and Time-Series Effects,” *Journal of Financial Markets*, 5, 31–56.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang, 2006, “The Cross-Section of Volatility and Expected Returns,” *Journal of Finance*, 61(1), 259–299.

——— , 2009, “High idiosyncratic volatility and low returns: International and further U.S. evidence,” *Journal of Financial Economics*, 91(1), 1–23.

Asness, C. S., A. Frazzini, R. Israel, T. J. Moskowitz, and L. H. Pedersen, 2017, “Size Matters, if You Control Your Junk,” *Journal of Financial Economics, forthcoming.*

Avramov, D., T. Chordia, and A. Goyal, 2006, “Liquidity and Autocorrelations in Individual Stock Returns,” *Journal of Finance*, 61(5), 2365–2394.

Baker, M., and J. Wurgler, 2006, “Investor Sentiment and the Cross-Section of Stock Returns,” *The Journal of Finance*, 61(4), 1645–1680.

Bali, T. G., N. Cakici, and R. F. Whitelaw, 2011, “Maxing out: Stocks as lotteries and the cross-section of expected returns,” *Journal of Financial Economics*, 99(2), 427–446.

Ball, R., S. P. Kothari, and J. Shanken, 1995, “Problems in measuring portfolio performance. An application to contrarian investment strategies,” *Journal of Financial Economics*, 38(1), 79–107.

Barber, B. M., and T. Odean, 2008, “All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors,” *The Review of Financial Studies*, 21(2), 785–818.

Boguth, O., and L. Stein, 2017, "Asymmetric Taxation and the Demand for Idiosyncratic Volatility," Working Paper.

Bordalo, P., N. Gennaioli, and A. Shleifer, 2013, "Salience and Asset Prices," *American Economic Review*, 103(3), 623–628.

Boyer, B., T. Mitton, and K. Vorkink, 2010, "Expected Idiosyncratic Skewness," *Review of Financial Studies*, 23(1), 170–202.

Carhart, M. M., 1997, "On Persistence in Mutual Fund Performance," *The Journal of Finance*, 52(1), 57–82.

Chabi-Yo, F., S. Ruenzi, and F. Weigert, 2017, "Crash Sensitivity and the Cross-Section of Expected Stock Returns," *Journal of Financial and Quantitative Analysis*.

Chen, J., K. Hou, and R. M. Stulz, 2015, "Are Firms in "Boring" Industries Worth Less?," Working Paper.

Chen, Y., A. Kumar, and C. Zhang, 2015, "Searching for Gambles: Investor Attention, Gambling Sentiment, and Stock Market Outcomes," Working Paper.

Chen, Z., I. A. Strebulaev, Y. Xing, and X. Zhang, 2017, "Strategic Risk Shifting and the Idiosyncratic Volatility Puzzle," Working Paper.

Corwin, S. A., and P. Schultz, 2012, "A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices," *The Journal of Finance*, 67(2), 719–759.

Coval, J. D., and E. Stafford, 2007, "Asset fire sales (and purchases) in equity markets," *Journal of Financial Economics*, 86(2), 479–512.

Da, Z., J. E. Engelberg, and P. Gao, 2011, "In Search of Attention," *The Journal of Finance*, 66(5), 1461–1499.

Drechsler, I., and Q. F. Drechsler, 2017, "The Shorting Premium and Asset Pricing Anomalies," Working Paper.

Fama, E. F., and K. R. French, 1992, "The Cross-Section of Expected Stock Returns," *The Journal of Finance*, 47(2), 427–465.

——— , 1993, "Common risk factors in the returns on stocks and bonds," *Journal of Financial Economics*, 33, 3–56.

——— , 2015, "A five-factor asset pricing model," *Journal of Financial Economics*, 116(1), 1–22.

Fama, E. F., and J. D. MacBeth, 1973, "Risk, Return and Equilibrium: Empirical Tests," *Journal of Political Economy*, 81(3), 607–636.

Fang, L., and J. Peress, 2009, "Media Coverage and the Cross-section of Stock Returns," *The Journal of Finance*, 64(5), 2023–2052.

Frazzini, A., and L. H. Pedersen, 2014, "Betting Against Beta," *Journal of Financial Economics*, 111(1), 1–25.

Fu, F., 2009, "Idiosyncratic risk and the cross-section of expected stock returns," *Journal of Financial Economics*, 91(1), 24–37.

Gervais, S., R. Kaniel, and D. H. Mingelgrin, 2001, "The High-Volume Return Premium," *Journal of Finance*, 56(3), 877–919.

Goldstein, M. A., P. Irvine, E. Kandel, and Z. Wiener, 2009, "Brokerage Commissions and Institutional Trading Patterns," *Review of Financial Studies*, 22(12), 5175–5212.

Han, B., and A. Kumar, 2013, "Speculative Retail Trading and Asset Prices," *Journal of Financial and Quantitative Analysis*, 48(2), 377–404.

Han, Y., and D. Lesmond, 2011, "Liquidity Biases and the Pricing of Cross-Sectional Idiosyncratic Volatility," *Review of Financial Studies*, 24(5), 1590–1629.

Hartzmark, S. M., 2014, "The Worst, the Best, Ignoring All the Rest: The Rank Effect and Trading Behavior," *Review of Financial Studies*, 28(4), 1024–1059.

Harvey, C. R., 2017, "Presidential Address: The Scientific Outlook in Financial Economics," *The Journal of Finance*, 72(4), 1399–1440.

Harvey, C. R., Y. Liu, and H. Zhu, 2016, "...and the Cross-Section of Expected Returns," *Review of Financial Studies*, 29(1), 5–68, Working Paper.

Hillert, A., and M. Ungeheuer, 2017, "The Value of Visibility," Working Paper.

Hirshleifer, D., and D. Jiang, 2010, "A Financing-Based Misvaluation Factor and the Cross-Section of Expected Returns," *Review of Financial Studies*, 23(9), 3401–3436.

Hou, K., and R. K. Loh, 2016, "Have we solved the idiosyncratic volatility puzzle?," *Journal of Financial Economics*, 121(1), 167–194.

Hou, K., C. Yue, and L. Zhang, 2015, "Digesting Anomalies: An Investment Approach," *Review of Financial Studies*, 28(3), 650–705.

Kahneman, D., 1973, *Attention and Effort*. Prentice-Hall, Englewood Cliffs, NJ.

Kelly, B., and H. Jiang, 2014, "Tail Risk and Asset Prices," *Review of Financial Studies*, 27(10), 2841–2871.

Lintner, J., 1969, "The Aggregation of Investor's Diverse Judgments and Preferences in Purely Competitive Security Markets," *Journal of Financial and Quantitative Analysis*, 4(4), 347–400.

Lou, D., 2012, "A Flow-Based Explanation for Return Predictability," *The Review of Financial Studies*, 25(12), 3457–3489.

Lou, D., C. Polk, and S. Skouras, 2017, "A Tug of War: Overnight Versus Intraday Expected Returns," Working Paper.

Mayshar, J., 1983, "On Divergence of Opinion and Imperfections in Capital Markets," *American Economic Review*, 73(1), 114–128.

Merton, R. C., 1987, "A Simple Model of Capital Market Equilibrium with Incomplete Information," *The Journal of Finance*, 42(3), 483–510.

Miller, E. M., 1977, "Risk, Uncertainty, and Divergence of Opinion," *Journal of Finance*, 32(4), 1151–1168.

Nagel, S., 2005, "Short sales, institutional investors and the cross-section of stock returns," *Journal of Financial Economics*, 78(2), 277–309.

Newey, W. K., and K. D. West, 1987, "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55(3), 703–708.

Novy-Marx, R., 2013, "The other side of value: The gross profitability premium," *Journal of Financial Economics*, 108(1), 1–28.

Pástor, L., and R. F. Stambaugh, 2003, "Risk and Expected Stock Returns," *Journal of Political Economy*, 111(3), 642–685.

Peng, D., Y. Rao, and M. Wang, 2016, "Do Top 10 Lists of Daily Stock Returns Attract Investor Attention? Evidence from a Natural Experiment," *International Review of Finance*, 16(4), 565–593.

Puckett, A., and X. S. Yan, 2011, "The Interim Trading Skills of Institutional Investors," *Journal of Finance*, 66(2), 601–633.

Sadka, R., 2006, "Momentum and Post-Earnings-Announcement Drift Anomalies: The Role of Liquidity Risk," *Journal of Financial Economics*, 80(2), 309–349.

Seasholes, M. S., and G. Wu, 2007, "Predictable Behavior, Profits, and Attention," *Journal of Empirical Finance*, 14(5), 590–610.

Stambaugh, R. F., J. Yu, and Y. Yuan, 2012, "The short of it: Investor sentiment and anomalies," *Journal of Financial Economics*, 104(2), 288–302.

——— , 2015, "Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle," *Journal of Finance*, 70(5), 1903–1948.

Stambaugh, R. F., and Y. Yuan, 2017, "Mispricing Factors," *Review of Financial Studies*, 30(4), 1270–1315.

Ungeheuer, M., 2017, "Stock Returns and the Cross-Section of Investor Attention," Working Paper.

Wang, B., 2017, "Ranking and Salience," Working Paper.

Figure 1: Winners and Losers in the Media

Wall Street Journal, 2016/04/05:

Percentage Gainers...

Company	Symbol	Latest Session Close	Latest Session Net chg	Latest Session % chg	52-Week High	52-Week Low	52-Week % chg
OncoCyte	OCX	6.07	1.85	43.84	10.24	2.45	…
Virgin America	VA	55.11	16.21	41.67	55.47	26.30	88.6
Sky Solar Holdings ADR	SKYS	5.90	1.64	38.50	32.00	1.12	-50.3
Ruckus Wireless	RKUS	13.24	3.24	32.40	13.50	7.25	5.3
Transcontinental Realty	TCI	12.03	2.12	21.39	14.75	8.05	18.3
USMD Holdings	USMD	12.16	1.81	17.49	13.59	6.50	24.7
Unico American	UNAM	11.00	1.61	17.20	13.76	8.15	…
Edwards Lifesciences	EW	105.08	15.16	16.86	107.90	61.38	50.3
Flexion Therapeutics	FLXN	10.95	1.53	16.24	29.09	7.56	-52.2
Sorrento Therapeutics	SRNE	6.30	0.85	15.60	26.80	4.25	-46.8
Genocea Biosciences	GNCA	6.83	0.88	14.79	16.10	2.56	-39.2
MediciNova	MNOV	9.00	1.10	13.92	9.37	2.62	164.7
NantKwest	NK	9.72	1.09	12.63	38.40	6.10	…
Global Blood Therapeutics	GBT	18.14	2.01	12.46	57.00	12.24	…
SteadyMed	STDY	2.89	0.32	12.45	11.14	2.00	-66.3

Percentage Losers

Company	Symbol	Latest Session Close	Latest Session Net chg	Latest Session % chg	52-Week High	52-Week Low	52-Week % chg
Vericel	VCEL	3.77	-2.11	-35.31	6.69	1.69	1.9
Great Basin Scientific	GBSN	4.46	-2.05	-31.49	12810.00	3.69	-99.9
Staffing 360 Solutions	STAF	[illegible]	-0.54	-20.64	10.29	1.80	33.7
iRadimed	IRMD	15.51	-3.85	-19.89	33.25	14.54	0.3
Natus Medical	BABY	31.84	-7.80	-19.68	51.05	29.34	-19.7
Smith Wesson Hldg	SWHC	22.78	-4.98	-17.94	30.44	12.72	76.2
Direxion Brazil Bull 3X	BRZU	70.90	-11.88	-14.35	339.06	26.40	-71.5
ConforMIS	CFMS	10.28	-1.71	-14.26	26.93	7.56	…
ARC Group Worldwide	ARCW	2.17	-0.36	-14.23	3.44	1.35	-44.7
Brocade Comm Systems	BRCD	9.19	-1.45	-13.63	12.88	7.40	-22.8
GeoPark	GPRK	2.55	-0.35	-12.07	5.73	2.45	-39.6
Clovis Oncology	CLVS	17.26	-2.11	-10.89	116.75	16.70	-74.9
Naked Brand Group	NAKD	2.00	-0.23	-10.31	6.74	1.79	-52.4
Cartesian Inc	CRTN	2.00	-0.23	-10.31	4.40	1.31	-44.8
ProShs Ultra MSCI Brazil	UBR	36.05	-4.38	-10.17	87.00	37.61	-48.9

New York Times, 2016/04/05:

Stock (TICKER)	Close	Chg	% Chg	Volume (100)
20 TOP GAINERS				
Virgin America (VA)	55.11	+16.21	+41.7	156951
Ruckus Wirel (RKUS)	13.24	+3.24	+32.4	376342
USMD Holding (USMD)	12.16	+1.81	+17.5	136
Unico Americ (UNAM)	11.00	+1.61	+17.2	221
Edwards Lifesc (EW)	105.08	+15.16	+16.9	90782
Flexion (FLXN)	10.95	+1.53	+16.2	5822
Sorrento (SRNE)	6.30	+0.85	+15.6	5759
Genocea (GNCA)	6.83	+0.88	+14.8	48553
MediciNova I (MNOV)	9.00	+1.10	+13.9	8255
NantKwest (NK)	9.72	+1.09	+12.6	6110
GBT (GBT)	18.14	+2.01	+12.5	5310
Nuvectra (NVTR)	6.96	+0.75	+12.1	4707
AGTC (AGTC)	16.24	+1.69	+11.6	1878
Aqua Metals (AQMS)	7.93	+0.78	+10.9	1942
Esperion The (ESPR)	19.36	+1.86	+10.6	7674
Odyssey Mari (OMEX)	9.05	+0.81	+9.8	1598
AveXis (AVXS)	28.17	+2.41	+9.4	938
Eiger (EIGR)	20.00	+1.68	+9.2	215
Swestn Energy (SWN)	8.51	+0.70	+9.0	234006
Stratasy (SSYS)	27.65	+2.25	+8.9	19743

Stock (TICKER)	Close	Chg	% Chg	Volume (100)
20 TOP LOSERS				
iRadimed (IRMD)	15.51	−3.85	−19.9	4629
Natus Medica (BABY)	31.84	−7.80	−19.7	27199
Smith & Wess (SWHC)	22.78	−4.98	−17.9	142074
ConforMIS (CFMS)	10.28	−1.71	−14.3	9896
Brocade Comm (BRCD)	9.19	−1.45	−13.6	339469
Clovis Oncol (CLVS)	17.26	−2.11	−10.9	26528
Sturm Ruger & (RGR)	65.24	−6.38	−8.9	11520
TerraForm Po (TERP)	9.07	−0.76	−7.7	52502
Blue Buffalo (BUFF)	23.64	−1.93	−7.5	17595
Alamos Gold (AGI)	5.20	−0.41	−7.3	17909
Allegheny Tec (ATI)	15.19	−1.19	−7.3	25508
NV5 Global (NVEE)	25.64	−1.98	−7.2	904
Valeant (VRX)	26.11	−1.99	−7.1	259345
LivaNova (LIVN)	49.62	−3.74	−7.0	10279
AmTrust Fin (AFSI)	24.91	−1.84	−6.9	35270
Vista Outdoo (VSTO)	49.16	−3.53	−6.7	5744
Titan Intl (TWI)	5.04	−0.36	−6.7	3137
PulteGroup (PHM)	17.21	−1.21	−6.6	224934
Amaya INC (AYA)	12.90	−0.88	−6.4	1628
BorgWarner (BWA)	35.28	−2.40	−6.4	35434

Wall Street Journal Website, 2016/11/03:

Gainers (Roll over for charts and headlines) 5:02 pm EDT 11/03/16
NYSE | Nasdaq | Arca | **Composite**

Issue	Price	Chg	% Chg	Volume
Inteliquent (IQNT)	22.58	5.84	34.89	5,639,533
MetaldynePerform (MPG)	19.20	4.90	34.27	4,287,811
TechnicalComms (TCCO)	2.95	0.65	28.26	1,842,305
EnviroStar (EVI)	10.40	1.85	21.64	108,862
EnerNOC (ENOC)	5.80	0.95	19.59	297,150

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Decliners (Roll over for charts and headlines) 5:02 pm EDT 11/03/16
NYSE | Nasdaq | Arca | **Composite**

Issue	Price	Chg	% Chg	Volume
TrilliumTherap (TRIL)	6.85	-7.75	-53.08	2,552,000
AACHoldings (AAC)	7.80	-8.09	-50.91	3,734,902
DiplomatPharmacy (DPLO)	12.95	-9.43	-42.14	16,961,196
SequentialBrands (SQBG)	4.80	-2.43	-33.61	2,570,952
Fitbit (FIT)	8.51	-4.30	-33.57	72,700,405

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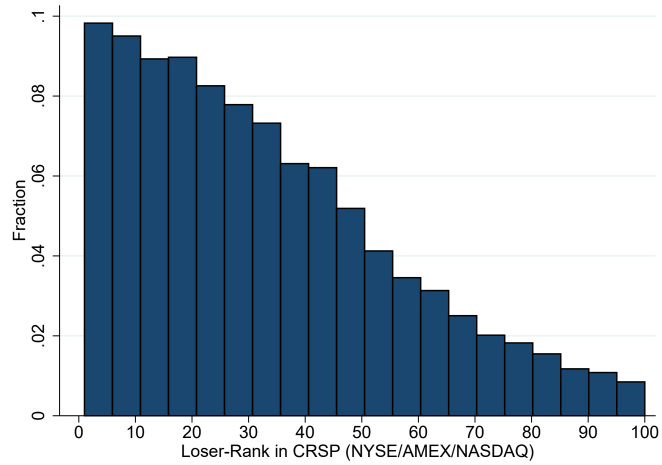
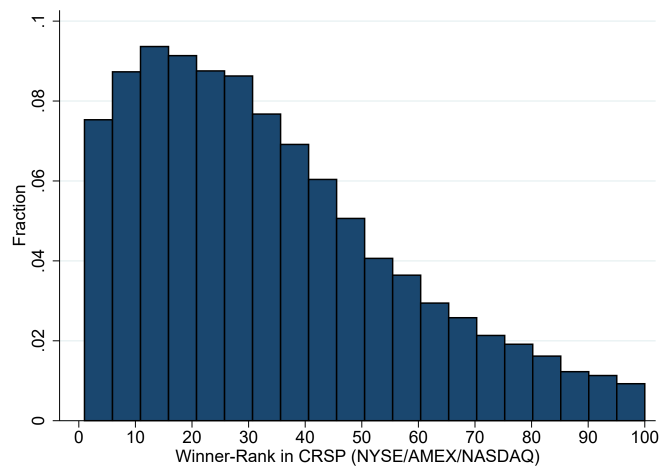
Figure 2: CRSP-Ranks of WSJ-Ranked Stocks

Panel A: CRSP Loser-Rank of WSJ-Losers
(Composite, NYSE, NASDAQ)

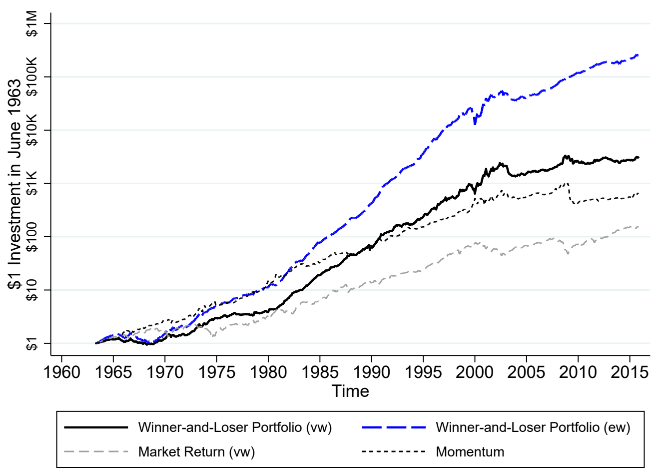


Panel B: CRSP Winner-Rank of WSJ-Winners
(Composite, NYSE, NASDAQ)



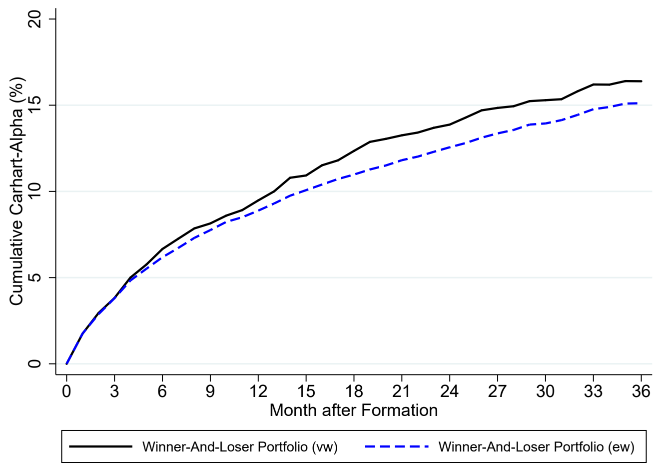
In this figure, we display the distribution of ranks in CRSP, sorting by daily stock returns of common stocks traded on NYSE/AMEX/NASDAQ, for the gainers and losers in the Wall Street Journal's Composite, NYSE, and NASDAQ rankings 5/2010-2015 (15 gainers and 15 losers each, but with overlap between Composite and the other two rankings). We exclude stocks that are ranked in Wall Street Journal rankings but are not part of the CRSP NYSE/AMEX/NASDAQ common stock universe, or not in CRSP's top/bottom 100 (less than 10% of WSJ-ranked stocks).

Figure 3: Performance of 1$ investment in 1963



In this figure, we display the performance of investments of 1$ in 7/1963 into different self-financing trading strategies (ignoring trading costs): the Never-Both strategy (equal- and value-weighted NMB + risk-free rate), the CRSP value-weighted market index (Mktrf + risk-free rate), and the momentum strategy (from Kenneth French's data library, MOM + risk-free rate). All strategy returns are (de-)leveraged to have the volatility of the market index to adjust for risk. The Never-Both strategy consists of selling stocks that were both daily winner *and* daily loser last month, and buying stocks that were neither daily winner nor daily loser last month. Daily winners (losers) are defined as the day's 80 top (bottom) performers. The sample covers all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ from 7/1963 to 12/2015.

Figure 4: Selling Daily Winners/Losers: Performance after Formation



In this figure, we display the average cumulative Carhart-Alpha for NMB strategy from the first month after portfolio formation to month 36 after formation. The NMB strategy consists of selling stocks that were both daily winner *and* daily loser last month, and buying stocks that were neither daily winner nor daily loser last month. Daily winners (losers) are defined as the day's 80 top (bottom) performers. Carhart-Alphas adjust the simple Never-Both return by market, size, value and momentum factor returns. We report value-weighted (vw) and equal-weighted (ew) results. The underlying sample covers all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ from 7/1963 to 12/2015.

Table 1: Summary Statistics

	Panel A: Univarate Distributions					
Variable	Mean	Median	Std. Dev.	p10	p90	N
I_L	0.0574	0.0000	0.2327	0.0000	0.0000	2,108,953
I_W	0.0798	0.0000	0.2710	0.0000	0.0000	2,108,953
I_{WL}	0.0495	0.0000	0.2169	0.0000	0.0000	2,108,953
Idio. Vola.	0.0214	0.0180	0.0081	0.0081	0.0390	2,108,953
LIDX	0.4347	0.4236	0.1825	0.1869	0.6906	2,108,953
E(Idio.Skew.)	0.5010	0.4489	0.3241	0.1082	0.9490	2,108,953
Syst. Skew.	-5.8008	-2.5726	97.3011	-123.1244	106.8211	2,108,953
Max	0.0568	0.0451	0.0413	0.0180	0.1109	2,108,953
Min	0.0473	0.0391	0.0314	0.0165	0.0878	2,108,953
Beta	0.8991	0.8431	0.1302	0.0724	1.7934	2,108,953
ln(size)	19.0268	18.8507	1.9734	16.6004	21.6856	2,108,934
ln(B/M)	-0.6439	-0.5730	0.8331	-1.8834	0.3869	1,643,838
$\text{Return}_{\text{t-12,t-2}}$	0.1704	0.1150	0.4014	-0.3009	0.7686	2,078,274
$\text{Return}_{\text{t-1,t-1}}$	0.0150	0.0079	0.1067	-0.1152	0.1597	2,108,934
$\text{Return}_{\text{t-36,t-13}}$	0.3640	0.2378	0.6603	-0.3811	1.3804	1,861,547

Panel B: Correlations

	I_L	I_W	I_{WL}	Idio. Vola.	LIDX	E(Idio. Skew.)	Syst. Skew.	Max	Min	Beta	ln(size)	ln(B/M)	$Ret_{t-12,t-2}$	$Ret_{t-1,t-1}$	$Ret_{t-36,t-13}$
I_L	1.0000														
I_W	-0.0726	1.0000													
I_{WL}	-0.0526	-0.0628	1.0000												
Idio. Vola.	0.1938	0.3096	0.3417	1.0000											
LIDX	0.0908	0.2387	0.2557	0.4974	1.0000										
E(Idio.Skew.)	0.0497	0.1177	0.1650	0.2355	0.4919	1.0000									
Syst. Skew.	0.0048	-0.0277	-0.0178	-0.0467	-0.0365	-0.0250	1.0000								
Max	0.0084	0.4571	0.3213	0.8566	0.4509	0.1972	-0.0252	1.0000							
Min	0.3999	0.0329	0.3004	0.7578	0.3337	0.1273	-0.0352	0.5304	1.0000						
Beta	0.0877	0.0800	0.0979	0.1410	0.1155	-0.1064	-0.0014	0.1785	0.1961	1.0000					
ln(size)	-0.0697	-0.1110	-0.1704	-0.2827	-0.5472	-0.6262	0.0309	-0.1951	-0.1644	0.1928	1.0000				
ln(B/M)	-0.0059	-0.0308	-0.0076	-0.1046	0.0229	0.1397	0.0124	-0.1150	-0.0821	-0.2401	-0.3293	1.0000			
$Return_{t-12,t-2}$	0.0171	0.0054	0.0158	-0.0265	0.1150	-0.0373	-0.0232	-0.0313	-0.0121	0.0437	0.0228	-0.2981	1.0000		
$Return_{t-1,t-1}$	-0.2207	0.2667	0.0261	0.1190	0.0463	0.0363	-0.0238	0.3362	-0.2789	-0.0123	0.0079	-0.0816	-0.0086	1.0000	
$Return_{t-36,t-13}$	0.0142	-0.0174	-0.0153	-0.0127	-0.1139	0.0800	-0.0026	-0.0154	0.0128	0.1566	0.0664	-0.3055	-0.1109	-0.0315	1.0000

In this table, we report summary statistics for our main variables. For variable definitions, see Appendix A. The statistics are based on pooled observations of all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ from 7/1963 to 12/2015.

Table 2: Univariate Sorts and Factor Models

Panel A: Univariate Sorts

Portfolio	Value-Weighted	Equal-Weighted	% of Stocks	% of Market Cap.
Never	0.53%	0.82%	77.88%	93.14%
Loser	-0.17%	0.38%	6.54%	2.62%
Winner	0.39%	0.20%	8.90%	3.11%
Both	-1.07%	-0.90%	6.67%	1.13%
Never-Loser	0.70%***	0.44%***		
(NML)	(3.74)	(3.30)		
Never-Winner	0.14%	0.62%***		
(NMW)	(0.85)	(5.15)		
Never-Both	1.60%***	1.72%***		
(NMB)	(5.46)	(9.08)		
Sharpe-Ratio	0.77	1.32		
T (Months)	630	630		

Panel B: Factor Models

	Value-Weighted Never-Both (NMB)			Equal-Weighted Never-Both (NMB)		
	(1F)	(3F)	(4F)	(1F)	(3F)	(4F)
Rm-Rf	-0.6457***	-0.3293***	-0.3029***	-0.3549***	-0.1165***	-0.1091***
	(-8.58)	(-4.79)	(-4.82)	(-7.09)	(-2.81)	(-2.78)
SMB		-1.1245***	-1.1257***		-0.7256***	-0.7259***
		(-13.02)	(-12.42)		(-9.79)	(-9.53)
HML		0.4089***	0.4557***		0.4428***	0.4559***
		(3.38)	(3.75)		(5.49)	(5.43)
MOM			0.1416*			0.0395
			(1.72)			(0.70)
Alpha	1.92%***	1.88%***	1.75%***	1.90%***	1.80%***	1.76%***
	(7.31)	(8.80)	(7.20)	(10.55)	(12.86)	(11.71)
Alpha p.a.	23.03%***	22.57%***	21.03%***	22.78%***	21.56%***	21.13%***
T (Months)	630	630	630	630	630	630

Panel C: Other Factor Models				
	Value-Weighted Never-Both (NMB)	Equal-Weighted Never-Both (NMB)	T (Months)	Years
4F	1.75%***	1.76%***	630	7/1963-
	(7.20)	(11.71)		12/2015
4F + ST + LT	1.79%***	1.74%***	630	7/1963-
	(6.80)	(10.27)		12/2015
4F + UMO	1.73%***	1.74%***	510	7/1962-
	(5.29)	(9.75)		12/2014
4F + BAB	1.61%***	1.60%***	630	7/1963-
	(5.93)	(10.44)		12/2015
4F + QMJ	1.00%***	1.20%***	630	7/1963-
	(4.38)	(9.33)		12/2015
4F + Kelly	2.12%***	2.00%***	480	1/1973-
	(6.97)	(10.89)		12/2012
4F + CRW	1.91%***	1.90%***	594	7/1963-
	(7.50)	(12.15)		12/2012
4F + PS	1.86%***	1.85%***	576	1/1968-
	(6.84)	(11.04)		12/2015
4F + Sadka	2.25%***	2.11%***	357	4/1983-
	(6.04)	(9.20)		12/2012
4F + PMU	1.38%***	1.51%***	594	7/1963-
	(4.96)	(8.85)		12/2012
4F + SY	1.17%***	1.43%***	630	7/1963-
	(4.58)	(9.92)		12/2015
FF-5F	1.45%***	1.45%***	630	7/1963-
	(6.73)	(11.66)		12/2015
Q-Model	1.70%***	1.57%***	503	7/1972-
	(5.72)	(8.36)		12/2013

In this table, we report univariate sorts by winner/loser status (Panel A), alphas and exposures from our main factor models (Panel B), and alphas from other factor models (Panel C). Daily winners (losers) are defined as the day's 80 top (bottom) performers. Stocks that were both daily winners *and* daily losers last month are in the 'Both' portfolio. Stocks that were only daily winners (losers) last month, but not daily losers (winners) are in the 'Winner' ('Loser') portfolio. All other stocks are in the 'Never' portfolio. (1F) stands for the 1-factor model with market returns. (3F) stands for the 3-factor model with market, size, and value factor. (4F) stands for the 4-factor model extending (3F) by the momentum factor. For definitions of factors, see Appendix A. All results are reported for value- and equal-weighted portfolios. The sample covers all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ from 7/1963 to 12/2015 (Panels A and B, in Panel C factors are sometimes available only for a subperiod). t-statistics are based on Newey and West (1987) standard errors with one lag and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 3: Fama/MacBeth Regressions

Panel A: Main Specifications					
	(1)	(2)	(3)	(4)	(5)
I_{WL}	-0.0156***	-0.0165***	-0.0147***	-0.0165***	-0.0164***
	(-12.48)	(-12.71)	(-10.86)	(-12.67)	(-13.03)
I_{L}		-0.0076***	-0.0074***	-0.0074***	-0.0080***
		(-10.03)	(-9.23)	(-9.71)	(-10.58)
I_{W}		-0.0028***	-0.0023***	-0.0027***	-0.0026***
		(-4.04)	(-3.57)	(-3.94)	(-4.14)
Beta	0.0001	0.0004	0.0004	0.0010	-0.0002
	(0.06)	(0.28)	(0.35)	(0.85)	(-0.14)
ln(Size)	-0.0006*	-0.0008**	-0.0010***	-0.0008**	-0.0002
	(-1.86)	(-2.39)	(-3.08)	(-2.49)	(-0.51)
ln(B/M)	0.0025***	0.0024***	0.0023***	0.0023***	0.0032***
	(4.34)	(4.20)	(3.84)	(4.28)	(7.19)
$Ret_{t-12,t-2}$	0.0127***	0.0126***	0.0123***	0.0130***	0.0114***
	(9.29)	(9.25)	(9.08)	(9.46)	(9.35)
$Ret_{t-1,t-1}$	-0.0417***	-0.0432***	-0.0429***	-0.0446***	-0.0543***
	(-11.19)	(-11.39)	(-11.12)	(-11.77)	(-15.11)
$Ret_{t-36,t-13}$	-0.0004	-0.0005	-0.0007	-0.0006	-0.0001
	(-0.76)	(-0.86)	(-1.21)	(-1.02)	(-0.31)
Op.Profitability			0.0100***		
			(5.57)		
Asset Growth			-0.0074***		
			(-7.43)		
ln(Turnover)				-0.0010**	
				(-2.49)	
Δln(Turnover)				0.0011***	
				(3.34)	
FF48-FEs	No	No	No	No	Yes
Size-Decile-FEs	No	No	No	No	Yes
Exchange-FEs	No	No	No	No	Yes
T	630	630	630	630	630
Average R^2	6.46%	6.66%	6.95%	7.39%	12.81%
Average N	2507	2507	1821	2369	2454

Panel B: Alternative Day-Convention for Rankings (8/1992-12/2015)

	(1) C2C only	(2) O2O only	(3) C2C & O2O	(4) O2C only	(5) C2C & O2C	(6) C2O only	(7) C2C & C2O	(8) 2D only	(9) C2C & 2D
$I_{Any,C2C}$	-0.0060***		-0.0055***		-0.0053***		-0.0059***		-0.0053***
	(-5.75)		(-6.54)		(-6.13)		(-5.76)		(-6.06)
$I_{Any,Alt}$		-0.0038***	-0.0008	-0.0039***	-0.0010	-0.0023***	-0.0002	-0.0045***	-0.0009
		(-3.52)	(-0.89)	(-3.53)	(-0.95)	(-2.93)	(-0.32)	(-3.76)	(-0.81)
Beta	-0.0002	-0.0004	-0.0002	-0.0003	-0.0002	-0.0006	-0.0002	-0.0003	-0.0002
	(-0.11)	(-0.16)	(-0.09)	(-0.13)	(-0.09)	(-0.27)	(-0.10)	(-0.13)	(-0.10)
ln(Size)	-0.0002	-0.0001	-0.0002	-0.0002	-0.0002	0.0000	-0.0002	-0.0002	-0.0002
	(-0.49)	(-0.32)	(-0.54)	(-0.36)	(-0.55)	(-0.09)	(-0.49)	(-0.37)	(-0.53)
ln(B/M)	0.0017*	0.0017**	0.0017*	0.0017**	0.0017*	0.0018**	0.0017*	0.0017*	0.0016*
	(1.92)	(1.99)	(1.93)	(2.00)	(1.95)	(2.07)	(1.92)	(1.95)	(1.91)
$Ret_{t-12,t-2}$	0.0090***	0.0092***	0.0091***	0.0092***	0.0091***	0.0091***	0.0091***	0.0092***	0.0091***
	(4.33)	(4.39)	(4.35)	(4.42)	(4.36)	(4.37)	(4.33)	(4.39)	(4.35)
$Ret_{t-1,t-1}$	-0.0215***	-0.0217***	-0.0213***	-0.0213***	-0.0213***	-0.0221***	-0.0214***	-0.0214***	-0.0214***
	(-4.03)	(-4.09)	(-4.01)	(-3.98)	(-3.97)	(-4.16)	(-4.01)	(-4.00)	(-3.99)
$Ret_{t-36,t-13}$	-0.0007	-0.0006	-0.0007	-0.0006	-0.0007	-0.0006	-0.0007	-0.0007	-0.0007
	(-0.89)	(-0.80)	(-0.89)	(-0.81)	(-0.88)	(-0.72)	(-0.88)	(-0.86)	(-0.91)
T	281	281	281	281	281	281	281	281	281
Average R^2	5.77%	5.76%	5.85%	5.77%	5.86%	5.69%	5.84%	5.78%	5.85%
Average N	2930	2930	2930	2930	2930	2930	2930	2930	2930

In this table, we report results from Fama and MacBeth (1973) regressions of this month's return on stock characteristics available at the end of last month. I_{WL} is an indicator variable that takes the value 1 if a stock was both a daily winner *and* a daily loser last month. I_W (I_L) indicates that a stock was only a daily winner (loser), but not a daily loser (winner) last month. $I_{Any,C2C}$ ($I_{Any,Alt}$) takes the value 1 if a stock was a daily winner and/or loser last month, where rankings are based on close-to-close returns (alternative day-conventions, i.e. open-to-open, open-to-close, close-to-open, and 2-day returns). For definitions of other variables, see Appendix A. The sample covers all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ from 7/1963 to 12/2015. t-statistics are based on Newey and West (1987) standard errors with one lag and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 4: Portfolio Characteristics

Variable	Never	Loser	Winner	Both	Years
Idio. Vola.	1.87%	2.89%	2.79%	3.72%	7/1963-12/2015
Max	4.98%	7.69%	7.43%	9.78%	7/1963-12/2015
Min	4.21%	6.20%	5.99%	7.72%	7/1963-12/2015
LIDX	0.3952	0.5109	0.5895	0.6515	7/1963-12/2015
Idio. Skew.	0.2066	0.2741	0.2875	0.3249	7/1963-12/2015
Syst. Skew.	-5.0468	-7.3369	-10.4535	-10.8030	7/1963-12/2015
Beta	0.8711	1.0994	1.0639	1.0666	7/1963-12/2015
Rel. Spread	1.89%	2.37%	2.40%	3.76%	1/1996-12/2010

In this table, we report portfolio characteristics (equal-weighted) for our four main portfolios. Stocks that were both daily winners *and* daily losers last month are in the 'Both' portfolio. Stocks that were only daily winners (losers) last month, but not daily losers (winners) are in the 'Winner' ('Loser') portfolio. All other stocks are in the 'Never' portfolio. The sample covers all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ from 7/1963 to 12/2015, if the portfolio characteristic is available that long. For definitions of variables, see Appendix A.

Table 5: Relation to the Idiosyncratic Volatility Puzzle: Excluding Daily Winners and Losers

Portfolio	Low	2	3	4	High	High-Low
			Panel A: Sorting by Idiosyncratic Volatility (7/1963-12/2015)			
all stocks	0.73%	0.90%	0.95%	0.80%	0.07%	-0.66%***
(equal-weighted)						(-3.02)
only Never	0.70%	0.83%	0.96%	0.92%	0.67%	-0.03%
(equal-weighted)						(-0.18)
all stocks	0.51%	0.56%	0.58%	0.52%	-0.04%	-0.55%**
(value-weighted)						(-2.17)
only Never	0.53%	0.53%	0.58%	0.62%	0.38%	-0.15%
(value-weighted)						(-0.69)
			Panel B: Sorting by Max (7/1963-12/2015)			
all stocks	0.82%	0.96%	0.90%	0.68%	0.08%	-0.74%***
(equal-weighted)						(-3.66)
only Never	0.79%	0.95%	0.96%	0.82%	0.58%	-0.22%
(equal-weighted)						(-1.27)
all stocks	0.53%	0.51%	0.62%	0.51%	0.21%	-0.32%
(value-weighted)						(-1.38)
only Never	0.54%	0.54%	0.57%	0.60%	0.48%	-0.06%
(value-weighted)						(-0.30)
			Panel C: Sorting by E(Idio.Skew.) (1/1988-12/2015)			
all stocks	0.91%	0.92%	0.84%	0.73%	0.34%	-0.57%***
(equal-weighted)						(-2.81)
only Never	0.92%	0.97%	0.87%	0.84%	0.66%	-0.26%
(equal-weighted)						(-1.50)
all stocks	0.78%	0.65%	0.57%	0.53%	0.06%	-0.72%**
(value-weighted)						(-2.54)
only Never	0.80%	0.68%	0.58%	0.60%	0.33%	-0.47%*
(value-weighted)						(-1.91)

In this table, we report results of portfolio sorts by idiosyncratic volatility (Panel A), max return (Panel B), and expected idiosyncratic skewness (Panel C). We report the portfolio returns including daily winners and losers from last month ('all stocks') and excluding them ('only Never'). Daily winners (losers) are defined as the day's 80 top (bottom) performers. For definitions of other variables, see Appendix A. Results are reported for equal- and value-weighted portfolios. The sample covers all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ from 7/1963 to 12/2015 (1/1988 to 12/2015) for Panels A and B (Panel C). t-statistics are based on Newey and West (1987) standard errors with one lag and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 6: Relation to the Idiosyncratic Volatility Puzzle: Factor Models

Panel A: Explaining the Return to Daily Winners and Losers (NMB)					
	(1)	(2)	(3)	(4)	(5)
Rm-Rf	-0.3029***	0.0062	-0.0160	-0.2748***	-0.0239
	(-4.82)	(0.13)	(-0.37)	(-4.64)	(-0.51)
SMB	-1.1257***	-0.2027	-0.5326***	-0.6632***	-0.0897
	(-12.42)	(-1.39)	(-3.90)	(-5.10)	(-0.61)
HML	0.4557***	0.0050	0.0802	0.4217***	0.0478
	(3.75)	(0.05)	(0.74)	(4.43)	(0.47)
MOM	0.1416*	0.0073	0.0762	0.0187	-0.0372
	(1.72)	(0.11)	(1.14)	(0.27)	(-0.60)
Idio.Vola.		-0.8180***			-0.7807***
		(-8.76)			(-5.14)
Max			-0.6628***		0.0671
			(-6.55)		(0.44)
E(Idio.Skew.)				-0.5323***	-0.2476***
				(-5.64)	(-2.89)
Alpha (all vw)	1.75%***	1.18%***	1.43%***	1.62%***	1.18%***
	(7.20)	(5.43)	(6.30)	(6.87)	(5.59)
Alpha (all ew)	1.76%***	0.97%***	0.95%***	1.73%***	1.08%***
	(11.71)	(8.74)	(6.81)	(13.82)	(9.10)

Panel B: Explaining the Return to Idio. Vola., Max and E(Idio.Skew.)						
	Idio. Vola.		Max		E(Idio.Skew.)	
	(1)	(2)	(3)	(4)	(5)	(6)
Rm-Rf	0.3778***	0.2892***	0.4325***	0.3573***	0.1531**	0.0873
	(8.35)	(6.99)	(8.91)	(7.61)	(2.02)	(1.26)
SMB	1.1284***	0.7990***	0.8947***	0.6151***	0.7256***	0.5517***
	(17.45)	(12.01)	(12.30)	(8.50)	(9.98)	(5.45)
HML	-0.5509***	-0.4176***	-0.5658***	-0.4526***	-0.3216**	-0.2300**
	(-6.26)	(-6.25)	(-5.80)	(-5.75)	(-2.33)	(-1.98)
MOM	-0.1642**	-0.1228**	-0.0988	-0.0636	-0.3400***	-0.3098***
	(-2.50)	(-2.24)	(-1.43)	(-1.04)	(-4.81)	(-4.58)
NMB		-0.2925***		-0.2484***		-0.1435***
		(-6.94)		(-5.90)		(-3.13)
Alpha (all vw)	-0.70%***	-0.18%	-0.49%***	-0.05%	-0.65%***	-0.35%
	(-4.57)	(-1.22)	(-3.17)	(-0.33)	(-2.81)	(-1.60)
Alpha (all ew)	-0.84%***	0.18%**	-0.92%***	-0.02%	-0.32%*	0.47%***
	(-7.17)	(1.98)	(-7.70)	(-0.23)	(-1.87)	(3.22)

In this table, we report alphas and exposures of factor models. We first regress returns of the Never-Both (NMB) strategy on the market, size, value and momentum factor, as well as factor returns of high-low quintile portfolios based on idiosyncratic volatility, Max and E(Idio.Skew.) (Panel A). We then regress returns of the idiosyncratic volatility, Max and E(Idio.Skew.) strategies on the market, size, value and momentum factor, as well as our Never-Both strategy (Panel B). All results are reported for value-weighted portfolios, alphas also for equal-weighted portfolios. The sample covers all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ from 7/1963 to 12/2015 (except Panel B's E(Idio.Skew.) results, which use data from 1988 onwards, as in Boyer, Mitton, and Vorkink (2010)). t-statistics are based on Newey and West (1987) standard errors with one lag and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 7: Relation to the Idiosyncratic Volatility Puzzle: Fama/MacBeth Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I_{WL}	-0.0165***	-0.0132***	-0.0140***	-0.0176***	-0.0164***	-0.0160***	-0.0167***	-0.0137***
	(-12.71)	(-9.67)	(-10.32)	(-8.22)	(-12.77)	(-13.01)	(-12.80)	(-9.82)
I_L	-0.0076***	-0.0061***	-0.0071***	-0.0100***	-0.0075***	-0.0076***	-0.0077***	-0.0062***
	(-10.03)	(-7.58)	(-9.74)	(-8.57)	(-10.04)	(-10.28)	(-9.87)	(-7.64)
I_W	-0.0028***	-0.0011	-0.0009	-0.0019*	-0.0028***	-0.0023***	-0.0029***	-0.0015*
	(-4.04)	(-1.57)	(-1.11)	(-1.76)	(-4.03)	(-3.77)	(-4.22)	(-1.93)
Beta	0.0004	0.0007	0.0008	0.0005	0.0004	0.0007	0.0007	0.0014
	(0.28)	(0.54)	(0.65)	(0.24)	(0.33)	(0.56)	(0.51)	(1.25)
ln(Size)	-0.0008**	-0.0010***	-0.0009***	-0.0005	-0.0008**	-0.0011***	-0.0002	-0.0003
	(-2.39)	(-3.20)	(-2.85)	(-1.48)	(-2.44)	(-4.37)	(-0.37)	(-0.81)
ln(B/M)	0.0024***	0.0023***	0.0023***	0.0016**	0.0024***	0.0022***	0.0025***	0.0022***
	(4.20)	(4.15)	(4.17)	(2.22)	(4.19)	(4.11)	(4.35)	(4.11)
$Ret_{t-12,t-2}$	0.0126***	0.0127***	0.0126***	0.0097***	0.0126***	0.0128***	0.0123***	0.0121***
	(9.25)	(9.35)	(9.32)	(5.33)	(9.25)	(9.31)	(8.95)	(8.73)
$Ret_{t-1,t-1}$	-0.0432***	-0.0421***	-0.0404***	-0.0268***	-0.0432***	-0.0436***	-0.0442***	-0.0442***
	(-11.39)	(-11.00)	(-9.92)	(-5.39)	(-11.42)	(-11.55)	(-11.77)	(-11.60)
$Ret_{t-36,t-13}$	-0.0005	-0.0006	-0.0005	-0.0006	-0.0005	-0.0007	-0.0004	-0.0007
	(-0.86)	(-1.01)	(-0.96)	(-0.91)	(-0.87)	(-1.42)	(-0.76)	(-1.36)
Idio. Vola.		-0.1299***						-0.1351***
		(-3.76)						(-3.68)
Max			-0.0331***					0.0047
			(-3.35)					(0.47)
E(Idio.Skew.)				-0.0040*				0.0008
				(-1.86)				(0.55)
Syst. Skew.					0.0000			0.0000
					(-1.10)			(-0.86)
LIDX						-0.0049**		-0.0036*
						(-2.10)		(-1.77)
Amihud							0.0006**	0.0007**
							(1.97)	(2.41)
T	630	630	630	336	630	630	630	630
Years	7/1963-12/2015	7/1963-12/2015	7/1963-12/2015	1/1988-12/2015	7/1963-12/2015	7/1963-12/2015	7/1963-12/2015	7/1963-12/2015
Average R^2	6.66%	6.91%	6.87%	6.05%	6.79%	6.96%	7.11%	8.07%
Average N	2507	2506	2506	2826	2506	2507	2374	2351

In this table, we report results from Fama and MacBeth (1973) regressions of this month's return on stock characteristics available at the end of last month. I_{WL} is an indicator variable that takes the value 1 if a stock was both a daily winner *and* a daily loser last month. I_W (I_L) indicates that a stock was only a daily winner (loser), but not a daily loser (winner) last month. For definitions of other variables, see Appendix A. The sample covers all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ from 7/1963 to 12/2015 (except Specification (4), which use data from 1988 onwards, as in Boyer, Mitton, and Vorkink (2010)). t-statistics are based on Newey and West (1987) standard errors with one lag and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 8: Relation to the Idiosyncratic Volatility Puzzle: Hou/Loh Decomposition

	Decomposition of Idio. Vola. (7/1975-12/2012 with DGTW-Returns)						
	Explained		Unexplained		Total		Avg.N
	Panel A: With Simple Ranking Dummies						
I_{Any}	-0.1134	64.61%***	-0.0621	35.39%***	-0.1755	100.00%	3941
		(14.63)		(8.01)			
I_{WL}	-0.1174	66.92%***	-0.0259	14.77%**	-0.1755	100.00%	3941
		(8.04)		(2.05)			
I_L	0.0168	-9.58%**					
		(-2.08)					
I_W	-0.0489	27.89%***					
		(6.31)					
	Panel B: With Refined Rank Salience Proxy						
S_L+S_W	-0.1685	96.02%***	-0.0070	3.98%	-0.1755	100.00%	3941
		(9.22)		(0.38)			
S_L	-0.0409	23.32%***	0.0052	-2.94%	-0.1755	100.00%	3941
		(7.79)		(-0.25)			
S_W	-0.1397	79.62%***					
		(7.29)					

In this table, we report results from the decomposition method by Hou and Loh (2016). We use DGTW-adjusted stock returns as the dependent variable, and each line represents the decomposition of the Idio. Vola. coefficient from a univariate Fama and MacBeth (1973) regression of this month's returns on last month's Idio. Vola. into a fraction that is explained by the respective candidate variable(s), and a fraction that remains unexplained. In Panel A, we report results for our main daily winner and loser indicator variables: I_{Any} is an indicator variable that takes the value 1 if a stock was a daily winner *and/or* a daily loser last month. I_{WL} is an indicator variable that takes the value 1 if a stock was both a daily winner *and* a daily loser last month. I_W (I_L) indicates that a stock was only a daily winner (loser), but not a daily loser (winner) last month. In Panel B, we use a refined proxy for salience due to daily winner and loser rankings: S_L is the log of 1+ the monthly average of a daily loser salience score, where the score declines linearly from 80 to 0 as the CRSP rank increases from 1 to 81 (the score is 0 for all other stocks). S_W is the analogous proxy for salience due to winner rankings. For definitions of other variables, see Appendix A. The sample covers all $\geq$ \$1 U.S. common stocks traded on the NYSE, AMEX and NASDAQ from 7/1975-12/2012, if DGTW-adjustments are available, as in Hou and Loh (2016). t-statistics are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 9: Trading Activity

	Contemporaneous Monthly				Predictive Daily	
	(1)	(2)	(3)	(4)	(5)	(6)
	BS_{Ret}	BS_{Ins}	Short Int.	Δ Short Int.	BS_{Ret}	BS_{Ins}
I_{WL}	0.0829***	-0.0435***	0.0020***	0.0015***		
	(4.78)	(-6.76)	(12.39)	(10.85)		
I_L	0.0625***	0.0050	0.0012***	0.0010***	0.0411***	-0.0071**
	(6.69)	(0.91)	(11.20)	(11.63)	(6.22)	(-2.10)
I_W	0.1099***	-0.0622***	-0.0002**	-0.0002***	0.1265***	-0.0333***
	(10.33)	(-14.80)	(-2.49)	(-3.15)	(16.64)	(-9.80)
Beta	0.0214***	0.0142***	0.0009***	0.0002	0.0015	0.0087***
	(4.73)	(3.91)	(8.33)	(1.59)	(1.57)	(5.97)
ln(Size)	-0.0010	-0.0225***	-0.0002	-0.0001	0.0208***	-0.0098***
	(-0.12)	(-5.69)	(-1.57)	(-1.31)	(8.93)	(-5.63)
ln(B/M)	-0.0203**	-0.0148***	0.0000	-0.0001	-0.0058***	-0.0076***
	(-2.48)	(-3.47)	(-0.04)	(-0.95)	(-3.04)	(-4.44)
$Ret_{t-12,t-2}$	-0.0619***	0.0305***	-0.0004**	0.0000	0.0021	0.0116***
	(-6.86)	(6.17)	(-2.52)	(-0.27)	(1.06)	(6.36)
$Ret_{t-1,t-1}$	-0.4565***	0.4605***	0.0026***	0.0032***	-0.0540***	0.0257***
	(-17.36)	(20.03)	(5.15)	(7.27)	(-14.04)	(6.31)
$Ret_{t-36,t-13}$	0.0122**	-0.0090***	0.0002***	0.0001*	0.0060***	-0.0030***
	(2.55)	(-3.60)	(3.29)	(1.98)	(5.16)	(-2.75)
$\|Ret_{t-1,t-1} - Ret_m\|$	0.4268***	-0.1517***	0.0043***	0.0034***	0.0399***	-0.0072
	(15.14)	(-7.79)	(7.56)	(7.19)	(8.79)	(-1.28)
LDV	0.0595***	0.2278***	0.9382***	0.0536***	0.0806***	0.3217***
	(21.42)	(64.35)	(304.94)	(9.49)	(43.12)	(257.29)
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	185,609	357,785	395,815	394,538	3,901,986	7,661,098
Years	2/1991-1/1997	2/1997-1/2011	2/2003-12/2015	2/1991-1/1997	2/1997-1/2011	
R^2	3.99%	9.86%	95.70%	5.44%	1.76%	12.82%

In this table, we report results from panel regressions of this month's trading activity on stock characteristics available at the end of this month in Specifications (1) to (4), and today's trading activity on yesterday's stock characteristics in Specifications (5) and (6). I_{WL} is an indicator variable that takes the value 1 if a stock was both a daily winner *and* a daily loser last month. I_W (I_L) indicates that a stock was only a daily winner (loser), but not a daily loser (winner) last month (in the first four specifications) or yesterday (in the last two specifications). The monthly regression in Specification (4) is based on differenced short interest, whereas the other regressions in Specifications (1) to (3) and (5) to (6) use levels of buy-sell imbalances and control for persistence by including one lag of the dependent variable (LDV). For definitions of other variables, see Appendix A. The sample covers all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ. t-statistics are based firm- and time-clustered standard errors and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 10: Fama/MacBeth Regressions: Overnight vs. Intraday Returns

	(1) Full	(2) Overnight	(3) Intraday
I_{WL}	-0.0087*	0.0257***	-0.0296***
	(-1.88)	(7.75)	(-7.10)
I_{L}	-0.0089***	0.0132***	-0.0197***
	(-4.82)	(9.21)	(-9.60)
I_{W}	0.0012	0.0119***	-0.0086***
	(0.71)	(8.76)	(-5.40)
Beta	-0.0005	0.0089***	-0.0087***
	(-0.22)	(8.35)	(-3.98)
ln(Size)	-0.0006	0.0010***	-0.0022***
	(-1.17)	(4.31)	(-4.15)
ln(B/M)	0.0011	-0.0004	0.0010
	(1.19)	(-1.09)	(1.16)
$Ret_{t-12,t-2}$	0.0054**	0.0110***	-0.0060**
	(2.12)	(12.84)	(-2.43)
$Ret_{t-1,t-1}$	-0.0219***	-0.0279***	0.0028
	(-3.33)	(-7.10)	(0.47)
$Ret_{t-36,t-13}$	-0.0009	0.0022***	-0.0034***
	(-1.09)	(6.45)	(-4.28)
T	276	276	276
Average R^2	8.50%	5.12%	8.56%
Average N	1676	1676	1676

In this table, we report results from Fama and MacBeth (1973) regressions of this month's full, overnight, and intraday return (as in Lou, Polk, and Skouras, 2017) on stock characteristics available at the end of last month. I_{WL} is an indicator variable that takes the value 1 if a stock was both a daily winner *and* a daily loser last month. I_W (I_L) indicates that a stock was only a daily winner (loser), but not a daily loser (winner) last month. For definitions of other variables, see Appendix A. The sample covers all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ with a market capitalization above NYSE's first size quintile, from 1/1993 to 12/2015. t-statistics are based on Newey and West (1987) standard errors with one lag and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 11: Variation over Firms

Portfolio	Low	High	High-Low	Carhart-Alpha
		Residual Retail Ownership (4/1980-3/2015)		
NMB	1.70%***	2.53%***	0.83%*** (3.26)	0.90%*** (3.64)
		Size (7/1963-12/2015)		
NMB	1.90%***	1.50%***	-0.39% (-1.30)	-0.47%* (-1.68)
		Amihud (2002)-Illiquidity (7/1963-12/2015)		
NMB	1.87%***	1.87%***	-0.00% (-0.01)	0.15% (0.57)
		Corwin and Schultz (2012)-Spread (7/1963-12/2015)		
NMB	1.19%***	1.76%***	0.58%* (1.66)	0.43% (1.33)

In this table, we report independent double sorts for Never-Minus-Loser (NML), Never-Minus-Winner (NMW), and Never-Minus-Both (NMB) strategy returns. We sort by the respective variable of interest into below- ('Low') and above-median ('High') stocks and by winner/loser status. For definitions of variables, see Appendix A. All results are reported for equal-weighted portfolios. In addition to simple High-Low returns, we report Carhart-Alphas, i.e. High-Low returns adjusted for exposure to the market, size, value, and momentum factor returns. The sample covers all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ from 7/1963 to 12/2015. t-statistics are based on Newey and West (1987) standard errors with one lag and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table 12: Variation of NMB Returns over Time

	Saliency of Winners and Losers		Baker/Wurgler Sentiment
Rm-Rf	-0.2987***	-0.2968***	-0.3006***
	(-4.81)	(-4.75)	(-4.71)
SMB	-1.1400***	-1.1465***	-1.1056***
	(-12.99)	(-13.04)	(-12.05)
HML	0.4661***	0.4604***	0.4493***
	(3.97)	(3.90)	(3.74)
MOM	0.1650**	0.1649**	0.1433*
	(2.00)	(1.99)	(1.77)
Avg.Vola.	0.0094***	0.0101***	
(stdized)	(3.02)	(3.26)	
Avg.Kurt.		0.0035**	
(stdized)		(2.29)	
BW-Sentiment			0.0079***
(stdized)			(3.22)
Alpha	1.73%***	1.74%***	1.80%***
	(7.31)	(7.35)	(7.09)
T (Months)	630	630	604
Years	7/1963-12/2015	7/1963-12/2015	7/1965-10/2015

In this table, we report exposures and alphas from factor models. We regress the value-weighted Never-Both (NMB) strategy returns on market, size, value, and momentum factor returns, as well as additional variables. For definitions of these variables, see Appendix A. The sample covers all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ from 7/1963 to 12/2015, if the additional variables are available until back then. t-statistics are based on Newey and West (1987) standard errors with one lag and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

A Appendix: Variable Description

The following table briefly defines the main variables used in our empirical analysis. Abbreviations for the data sources are:

(i) CRSP: CRSP's Stocks Database

(ii) CS: Compustat

(iii) TAQ: Trade-and-Quote database

(vii) 13f: 13f filings (institutional ownership)

(iv) SVI: Google Trends

(v) NYT: New York Times Chronicle database

(vi) OP: From the homepages of or from correspondence with the authors of the respective original papers

EST indicates that the variable is estimated or computed based on original variables from the respective data sources.

Variable Name	Description	Source
I_{WL}	Indicator variable that is one when a stock was both, a daily winner *and* a daily loser last month. A day's top 80 (bottom 80) stocks of CRSP's NYSE/AMEX/NASDAQ universe are defined as daily winner (loser).	CRSP, EST
I_{L}	Indicator variable that is one when a stock was a daily loser, but not a daily winner last month. A day's top 80 (bottom 80) stocks of CRSP's NYSE/AMEX/NASDAQ universe are defined as daily winner (loser).	CRSP, EST
I_{W}	Indicator variable that is one when a stock was a daily winner, but not a daily loser last month. A day's top 80 (bottom 80) stocks of CRSP's NYSE/AMEX/NASDAQ universe are defined as daily winner (loser).	CRSP, EST

Variable Name	Description	Source
I_{Any}	Indicator variable that is one when a stock was a daily winner *or* a daily loser last month. A day's top 80 (bottom 80) stocks of CRSP's NYSE/AMEX/NASDAQ universe are defined as daily winner (loser).	CRSP, EST
Idio. Vola.	The standard-deviation of residuals from the Fama and French (1992)-model, estimated with last month's daily returns ($\geq$ 10 observations required).	CRSP, OP, EST
LIDX	Lottery index, scaled between 0 and 1, as in Chen, Kumar, and Zhang (2015).	CRSP, OP, EST
Idio. Skew.	The skewness of residuals from the Fama and French (1992)-model, estimated with last month's daily returns ($\geq$ 10 observations required).	CRSP, OP, EST
E(Idio.Skew.)	Expected idios. skewness as in Boyer, Mitton, and Vorkink (2010).	CRSP, EST
Syst. Skew.	The coefficient of the square of market returns in a regression last month's daily returns on market returns and squared market returns ($\geq$ 10 observations required).	CRSP, EST
Max	A stock's maximum daily return last month, as in Bali, Cakici, and Whitelaw (2011).	CRSP, EST
Min	A stock's minimum daily return last month, multiplied by -1.	CRSP, EST
Beta	The coefficient of the market return in a regression of last month's daily returns on market returns ($\geq$ 10 observations required).	CRSP, EST
ln(size)	The log of a firm's equity market capitalization.	CRSP, EST
ln(B/M)	The log of a firm's book/market ratio, with ceq from CS as book-equity.	CS, CRSP, EST
$Ret_{t-12,t-2}$	Last year's return, excluding the most recent month.	CRSP, EST
$Ret_{t-1,t-1}$	Last month's return.	CRSP, EST
$Ret_{t-36,t-13}$	The return of the two years prior to last year.	CRSP, EST

Variable Name	Description	Source
Rm-Rf	Value-weighted market return over the one-month Treasury bill rate according to Kenneth French's data library.	OP
SMB	Small minus big factor return according to Kenneth French's data library.	OP
HML	High minus low factor return according to Kenneth French's data library.	OP
MOM	Momentum factor return according to Kenneth French's data library.	OP
MOM	Momentum factor return according to Kenneth French's data library.	OP
ST	Short-term reversal factor return according to Kenneth French's data library.	OP
LT	Long-term reversal factor return according to Kenneth French's data library.	OP
UMO	Hirshleifer and Jiang (2010) (undervalued-minus-overvalued) factor returns.	OP
BAB	Betting-against-beta factor returns according to Frazzini and Pedersen (2014).	OP
QMJ	Asness, Frazzini, Israel, Moskowitz, and Pedersen (2017) quality-minus-junk factor returns.	OP
Kelly	Kelly and Jiang (2014) factor returns.	CRSP, EST
CRW	Chabi-Yo, Ruenzi, and Weigert (2017)'s tail risk factor returns.	OP
PS	Pástor and Stambaugh (2003) liquidity factor returns.	OP
Sadka	Sadka (2006) liquidity factor returns.	OP
PMU	Profitable-Minus-Unprofitable factor from Novy-Marx (2013).	OP
SY	Mispricing factors from Stambaugh and Yuan (2017).	OP
FF-5F	Fama and French (2015) factor returns (2x3) according to Kenneth French's data library.	OP
Q-model	Q-factor returns according to Hou, Yue, and Zhang (2015).	OP
Operating Profitability	The firm's operating profitablilty, as in Fama and French (2015).	CS, EST
Asset Growth	Investments variable from Fama and French (2015).	CS, EST

Variable Name	Description	Source
Rel.Spread	Transaction-weighted relative spread.	TAQ, EST
Amihud	Amihud (2002)'s illiquidity ratio, based on last year's daily returns and dollar-volumes.	CRSP, EST
S_L	The log of the monthly average of a daily loser salience score +1, where the score declines linearly from 80 to 0 as the CRSP rank increases from 1 to 81 (the score is 0 for all other stocks).	CRSP, EST
S_W	Like S_L, but for daily winners.	CRSP, EST
BS_{Ret}	Buy-Sell-Imbalances ($\frac{Buys-Sells}{Buys+Sells}$) for retail investors, based on the number of stocks bought and sold that month or day.	OP, EST
BS_{Ins}	Buy-Sell-Imbalances ($\frac{Buys-Sells}{Buys+Sells}$) for institutional investors, based on the number of stocks bought and sold that month or day.	OP, EST
Short Int.	Number of stocks shorted normalized by shares outstanding, using the most recent date each month between 2003 and 2015.	CS, CRSP, EST
Corwin-Schultz	Corwin and Schultz (2012) spread proxy from Shane Corwin's web-page.	OP
Price	A stock's price.	CRSP, EST
Size	A firm's equity market capitalization.	CRSP, EST
Residual Retail Ownership	As in Nagel (2005), normalized for size, size^2, and Amihud (2002)-illiquidity.	13f, EST
Avg.Vola. (stdized)	Monthly average of firms' return standard-deviations, based on daily returns of that month.	CRSP, EST
Avg.Kurt. (stdized)	Monthly average of firms' return kurtoses, based on daily returns of that month.	CRSP, EST
BW-Sentiment (stdized)	Sentiment (orthogonalized) from Baker and Wurgler (2006).	OP
Δ Gamb.Sent. (stdized)	Gambling sentiment: The log-change in the Google search volume for the term 'lottery', as in Chen, Kumar, and Zhang (2015). In an alternative specification yearly log-changes in the number of New York Times articles containing the term 'lottery' are used.	SVI, NYT, EST

B Appendix: Additional Tables

Table B1: Univariate Sorts and Factor Models: 1-Month Gap

Univariate Sorts with 1-Month Gap				
Portfolio	Value-Weighted		Equal-Weighted	
	Raw Return	Carhart-Alpha	Raw Return	Carhart-Alpha
Never	0.53%	0.04%	0.78%	0.15%
Loser	0.03%	-0.38%	0.12%	-0.47%
Winner	0.36%	-0.19%	0.43%	-0.27%
Both	-0.58%	-1.15%	-0.32%	-0.97%
Never-Loser	0.49%***	0.42%***	0.66%***	0.63%***
(NML)	(2.79)	(3.23)	(5.27)	(7.68)
Never-Winner	0.17%	0.23%	0.36%***	0.43%***
(NMW)	(0.94)	(1.54)	(2.88)	(5.18)
Never-Both	1.11%***	1.20%***	1.11%***	1.12%***
(NMB)	(3.82)	(5.41)	(5.97)	(7.80)
Sharpe-Ratio	0.55		0.88	
T (Months)	630	630	630	630

In this table, we report univariate sorts by winner/loser status with raw returns and alphas of the Carhart 4-factor model. Daily winners (losers) are defined as the day's 80 top (bottom) performers. Stocks that were both daily winners *and* daily losers the month before last month are in the 'Both' portfolio. Stocks that were only daily winners (losers) the month before last month, but not daily losers (winners) are in the 'Winner' ('Loser') portfolio. All other stocks are in the 'Never' portfolio. All results are reported for value- and equal-weighted portfolios. The sample covers all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ from 7/1963 to 12/2015. t-statistics are based on Newey and West (1987) standard errors with one lag and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table B2: Fama/MacBeth Regressions: Robustness

Panel A: Varying the Sample and Adjusting Returns							
	Price ≥ 1	Price ≥ 3	Larger 1^{st} NYSE-Decile	No NASDAQ	Industry-Adjusted Returns	DGTW-Adjusted Returns	Non-Winsorized Controls
I_{WL}	-0.0108***	-0.0163***	-0.0166***	-0.0159***	-0.0164***	-0.0187***	-0.0164***
	(-9.74)	(-14.21)	(-7.85)	(-4.25)	(-12.40)	(-11.11)	(-13.03)
I_L	-0.0027***	-0.0059***	-0.0095***	-0.0068***	-0.0077***	-0.0088***	-0.0078***
	(-3.99)	(-8.82)	(-10.24)	(-6.00)	(-10.18)	(-9.48)	(-10.11)
I_W	-0.0032***	-0.0034***	-0.0020**	-0.0045***	-0.0026***	-0.0028***	-0.0025***
	(-4.55)	(-4.94)	(-2.34)	(-4.67)	(-4.03)	(-3.24)	(-3.59)
T	630	630	630	630	630	450	630
Years	7/1963-12/2015	7/1963-12/2015	7/1963-12/2015	7/1963-12/2015	7/1963-12/2015	7/1975-12/2012	7/1963-12/2015
Average R^2	5.82%	6.28%	8.04%	7.67%	4.53%	3.48%	6.58%
Average N	3186	2815	1787	1487	2455	2720	2507

Panel B: Varying the Threshold for Winner/Loser-Status with ≥ $5 price filter							
	Top/Bottom 5	Top/Bottom 10	Top/Bottom 20	Top/Bottom 40	Top/Bottom 80	Top/Bottom 160	Top/Bottom 320
I_{WL}	-0.0175**	-0.0158**	-0.0302***	-0.0242***	-0.0165***	-0.0103***	-0.0042***
	(-2.01)	(-2.42)	(-6.41)	(-9.99)	(-12.71)	(-12.05)	(-6.20)
I_L	-0.0194***	-0.0177***	-0.0155***	-0.0105***	-0.0076***	-0.0032***	-0.0002
	(-5.86)	(-7.68)	(-10.13)	(-10.22)	(-10.03)	(-5.90)	(-0.51)
I_W	-0.0031	-0.0053**	-0.0045***	-0.0040***	-0.0028***	-0.0005	0.0010**
	(-1.01)	(-2.34)	(-3.10)	(-3.70)	(-4.04)	(-0.80)	(2.14)
T	630	630	630	630	630	630	630
Years	7/1963-12/2015	7/1963-12/2015	7/1963-12/2015	7/1963-12/2015	7/1963-12/2015	7/1963-12/2015	7/1963-12/2015
Average R^2	6.62%	6.65%	6.66%	6.67%	6.66%	6.65%	6.57%
Average N	2507	2507	2507	2507	2507	2507	2507

Panel C: Varying the Threshold for Winner/Loser-Status with ≥ $1 price filter							
	Top/Bottom 5	Top/Bottom 10	Top/Bottom 20	Top/Bottom 40	Top/Bottom 80	Top/Bottom 160	Top/Bottom 320
I_{WL}	-0.0352***	-0.0216***	-0.0166***	-0.0128***	-0.0108***	-0.0068***	-0.0033***
	(-6.05)	(-6.07)	(-7.35)	(-8.66)	(-9.74)	(-7.23)	(-3.88)
I_L	-0.0107***	-0.0074***	-0.0054***	-0.0037***	-0.0027***	-0.0024***	-0.0009*
	(-3.48)	(-4.36)	(-4.34)	(-4.27)	(-3.99)	(-4.25)	(-1.68)
I_W	-0.0069***	-0.0079***	-0.0065***	-0.0051***	-0.0032***	0.1000	0.0019***
	(-2.70)	(-4.60)	(-5.80)	(-5.54)	(-4.55)	(1.19)	(3.74)
T	630	630	630	630	630	630	630
Years	7/1963-12/2015	7/1963-12/2015	7/1963-12/2015	7/1963-12/2015	7/1963-12/2015	7/1963-12/2015	7/1963-12/2015
Average R^2	5.86%	5.85%	5.84%	5.84%	5.82%	5.80%	5.72%
Average N	3186	3186	3186	3186	3186	3186	3186

In this table, we report results from Fama and MacBeth (1973) regressions of this month's return on stock characteristics available at the end of last month. We use control variables from Specification (2) of Table 3, but do not report control variables. The base sample for Panels A and B (C) covers all ≥ $5 (≥ $1) U.S. common stocks traded on the NYSE, AMEX and NASDAQ from 7/1963 to 12/2015. We then adjust this sample to test for robustness (Panel A) and vary the threshold used to define winners and losers from 5 to 320 (Panels B and C). For definitions of variables, see Appendix A. t-statistics are based on Newey and West (1987) standard errors with one lag and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table B3: Univariate Sorts and Factor Models: Threshold 20

Univariate Sorts with Threshold of 20 for Winner/Loser Status				
Portfolio	Value-Weighted		Equal-Weighted	
	Raw Return	Carhart-Alpha	Raw Return	Carhart-Alpha
Never	0.51%	0.02%	0.75%	0.09%
Loser	-0.91%	-1.46%	-0.44%	-1.00%
Winner	-0.04%	-0.71%	-0.43%	-1.12%
Both	-2.60%	-3.63%	-2.14%	-2.94%
Never-Both	3.04%***	3.65%***	2.82%***	3.01%***
(NMB)	(5.71)	(7.32)	(6.48)	(6.65)
Sharpe-Ratio	0.82		0.91	
T (Months)	630	630	630	630

In this table, we report univariate sorts by winner/loser status with raw returns and alphas of the Carhart 4-factor model. Daily winners (losers) are defined as the day's 20 top (bottom) performers. Stocks that were both daily winners *and* daily losers the month before last month are in the 'Both' portfolio. Stocks that were only daily winners (losers) the month before last month, but not daily losers (winners) are in the 'Winner' ('Loser') portfolio. All other stocks are in the 'Never' portfolio. All results are reported for value- and equal-weighted portfolios. The sample covers all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ from 7/1963 to 12/2015. t-statistics are based on Newey and West (1987) standard errors with one lag and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table B4: Fama/MacBeth Regressions: Time Splits

	(1) 1/1989- 12/2015	(2) 7/1963- 12/1988	(3) 1/1928- 6/1963	(4) 1/1928- 6/1963
I_{WL}	-0.0180***	-0.0148***	-0.0020**	-0.0064***
	(-7.89)	(-13.33)	(-2.38)	(-4.78)
I_L	-0.0016	-0.0040***	0.0005	-0.0043***
	(-1.41)	(-5.87)	(0.76)	(-4.56)
I_W	-0.0097***	-0.0054***	-0.0002	-0.0003
	(-8.20)	(-5.97)	(-0.36)	(-0.23)
Beta	0.0001	0.0006	0.0006	0.0007
	(0.06)	(0.39)	(0.24)	(0.28)
ln(Size)	-0.0002	-0.0015***	-0.0009**	-0.0012***
	(-0.38)	(-2.82)	(-2.29)	(-2.94)
ln(B/M)	0.0016**	0.0032***	0.0019**	0.0019**
	(2.03)	(3.93)	(2.23)	(2.16)
$Ret_{t-12,t-2}$	0.0103***	0.0152***	0.0152***	0.0148***
	(5.53)	(7.59)	(6.81)	(6.74)
$Ret_{t-1,t-1}$	-0.0260***	-0.0613***	-0.0874***	-0.0830***
	(-5.19)	(-11.47)	(-13.11)	(-12.61)
$Ret_{t-36,t-13}$	-0.0007	-0.0003	-0.0025*	-0.0027*
	(-0.96)	(-0.33)	(-1.77)	(-1.89)
T	324	306	426	426
Average R^2	5.84%	7.53%	12.14%	12.58%
Average N	2869	2124	688	688
Threshold	80	80	80	20

In this table, we report results from Fama and MacBeth (1973) regressions of this month's return on stock characteristics available at the end of last month. I_{WL} is an indicator variable that takes the value 1 if a stock was both a daily winner *and* a daily loser last month. I_W (I_L) indicates that a stock was only a daily winner (loser), but not a daily loser (winner) last month. The threshold used to classify stocks as daily winners or losers is decreased from 80 to 20 in Specification (4). For definitions of other variables, see Appendix A. The sample covers all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ in different subperiods. t-statistics are based on Newey and West (1987) standard errors with one lag and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

Table B5: Variation over Firms (with 1-Month Gap)

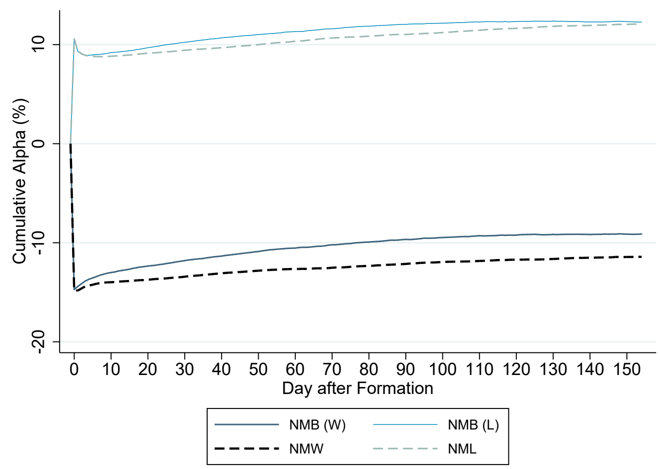
Portfolio	Low	High	High-Low	Carhart-Alpha
		Residual Retail Ownership (4/1980-3/2015)		
NMB	0.95%***	1.74%***	0.79%*** (2.97)	0.81%*** (2.98)
		Size (7/1963-12/2015)		
NMB	1.12%***	1.00%***	-0.12% (-0.42)	-0.14% (-0.47)
		Amihud (2002)-Illiquidity (7/1963-12/2015)		
NMB	1.34%***	1.06%***	-0.27% (-1.02)	-0.13% (-0.49)
		Corwin and Schultz (2012)-Spread (7/1963-12/2015)		
NMB	0.35%	1.10%***	0.75%** (2.52)	0.79%** (2.55)

In this table, we report independent double sorts for Never-Minus-Loser (NML), Never-Minus-Winner (NMW), and Never-Minus-Both (NMB) strategy returns. We sort by the respective variable of interest into below- ('Low') and above-median ('High') stocks and by winner/loser status with a 1-month gap. For definitions of variables, see Appendix A. All results are reported for equal-weighted portfolios. In addition to simple High-Low returns, we report Carhart-Alphas, i.e. High-Low returns adjusted for exposure to the market, size, value, and momentum factor returns. The sample covers all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ from 7/1963 to 12/2015. t-statistics are based on Newey and West (1987) standard errors with one lag and are reported in parentheses. ***, **, and * indicate significance at the one, five, and ten percent level, respectively.

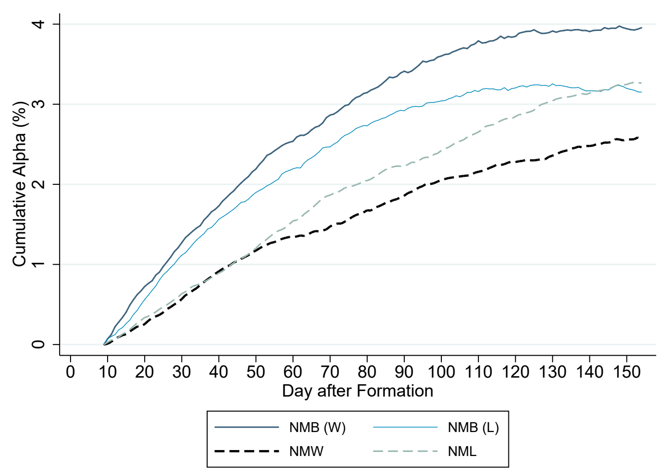
C Appendix: Additional Figures

Figure C1: Returns to Daily Strategy Selling Ranked Stocks: Winners and Losers Separately

Panel A: Including Day of Ranking



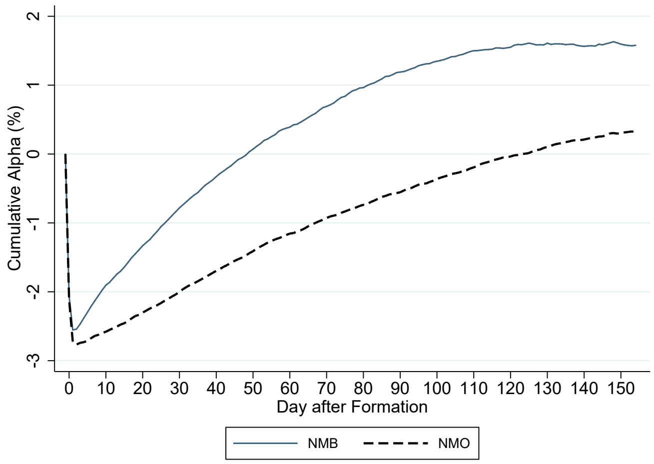
Panel B: Starting on Day 10 After Ranking



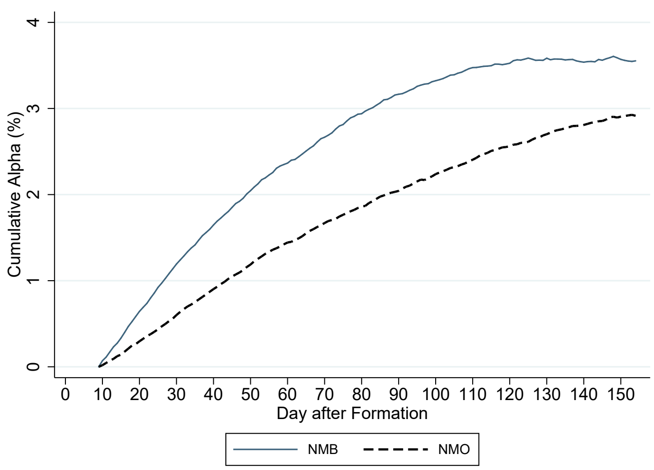
In this figure, we display the cumulative Carhart-alpha of four investment strategies. The strategy NMW (NML) sells stocks ranked as winners (losers) on day 0, but not ranked as losers (winners) during the previous 22 trading days. The strategy NMB (W) (NMB (L)) sells stocks ranked as winners (losers) on day 0, which were also ranked as losers (winners) during the previous 22 trading days. Panel A starts on the day of the ranking (and thus represents a forward-looking, non-investable trading strategy). Panel B starts on day 10 after the trading to skip the effects related to short-term reversal. The sample covers all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ from 7/1963 to 12/2015.

Figure C2: Returns to Daily Strategy Selling Ranked Stocks: Winners and Losers Together

Panel A: Including Day of Ranking



Panel B: Starting on Day 10 After Ranking



In this figure, we display the cumulative Carhart-alpha of two investment strategies. The NMO strategy is an equal-weighted portfolio of the NMW and NML strategies from Figure C1. The NMB strategy is an equal-weighted portfolio of the NMB (W) and NMB (L) strategies from Figure C1. Panel A starts on the day of the ranking (and thus represents a forward-looking, non-investable trading strategy). Panel B starts on day 10 after the trading to skip the effects related to short-term reversal. The sample covers all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ from 7/1963 to 12/2015.

D Appendix: Daily Returns After the Ranking

In Figures C1 and C2 of Appendix C we report cumulative daily Carhart-alphas of investment strategies that sell daily winners and losers from the ranking day zero to 150 trading days after the ranking day. Strategies are equal-weighted, rebalanced daily, and alphas are computed separately for each day. As for our main analysis, the sample covers all $\geq$ \$5 U.S. common stocks traded on the NYSE, AMEX and NASDAQ from 7/1963 to 12/2015.

[Insert Figure C1 about here]

In Figure C1, we display the cumulative Carhart-alpha of four investment strategies. All strategies buy stocks that were never ranked as winners or losers last month. The strategy NMW (NML) sells stocks ranked as winners (losers) on day 0, but not ranked as losers (winners) during the previous 22 trading days. These two strategies are comparable to our monthly strategies NMW and NML, i.e. the strategies selling winners that were never losers last month and vice versa. The strategy NMB (W) (NMB (L)) sells stocks ranked as winners (losers) on day 0, which were also ranked as losers (winners) during the previous 22 trading days. These two strategies are comparable to our monthly NMB strategy, i.e. our main strategy, which sells stocks ranked as winners and losers last month. Panel A starts on the day of the ranking and thus represents a forward-looking, non-implementable trading strategy. We can clearly see the high returns of daily winners and the low returns of daily losers, which lead to downward jumps in the NMW and NMB (W) strategies and upwards jumps in the NML and NMB (L) strategies. Directly after the ranking, we observe short-term reversal effects, which might be caused by microstructure issues like a bid-ask bounce. Note that we cannot directly observe the impact of attention-induced buying, since it is confounded by (i) the extreme returns leading to the ranking itself and (ii) the short-term reversal on the subsequent trading days. After a few days these confounding factors die out and we can observe clear upward trends consistent with an underperformance of daily winners and losers, see Panel B for the performance of strategies after day 10. Effects are stronger for the NMB strategies, consistent with an ongoing reversal due to the earlier ranking in addition to the current ranking on day zero.

[Insert Figure C2 about here]

In Figure C2, we display the cumulative Carhart-alpha of two investment strategies. The NMO strategy is an equal-weighted portfolio of the NMW and NML strategies from Figure C1. The NMB strategy is an equal-weighted portfolio of the NMB (W) and NMB (L) strategies from Figure C1. Similar to the NMB strategy on the monthly level, these strategies have the advantage of combining daily winners and losers, so that confounding effects like the extreme returns on the ranking day and short-term reversal partially cancel out. Again, Panel A starts on the day of the ranking thus represents a forward-looking, non-implementable trading strategy. The average return of winners and losers on the ranking day is clearly positive at 2% to 3%, so that the NMO and NMB strategies experience low returns. This is consistent with attention-induced buying leading to higher returns for both winners and losers, but since we do not know how large the winner and loser returns should have been without attention-induced buying, we cannot interpret these low NMO and NMB returns as ranking-induced price impacts. A few days after the ranking day (see Panel B), we observe a clear upward drift in both NMO and NMB strategy returns, consistent with a reversal after attention-induced overpricing of daily winners and losers. As for the strategies separating winners and losers in Figure C1, effects are stronger for the NMB strategy, consistent with an ongoing reversal due to the earlier ranking in addition to the current ranking on day zero.