Does Underreaction Explain Short-term Return Reversals?

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Abstract

Short-term return reversals are often attributed to investor overreaction or compensation for liquidity provision. We propose an alternative mechanism based on investor *underinference*: it takes time for investors to carry the industry news reflected in some stocks' prices over into the prices of fundamentally linked stocks. Stocks whose recent returns are inconsistent with the direction of their industry are hence likely to lag behind in reflecting the industry news and their returns should reverse subsequently, leading to within-industry return reversals. We find supportive evidence for this prediction: reversals based on stocks that lag behind in pricing industry news are twice as strong compared to the standard within-industry reversal strategy. The performance persists for several weeks and remains robust to documented frictions. Our findings suggest that underinference is a key mechanism driving short-term reversals.

1 Introduction

Empirical asset pricing research has extensively documented a pattern in which stocks that perform well relative to others in one month tend to underperform in the subsequent month, a phenomenon known as short-term return reversal (e.g., Jegadeesh and Titman 1993; Nagel 2012; Dai et al. 2024). Two leading theories have been particularly influential in explaining

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short-term reversals: investor overreaction and liquidity provision. Investor overreaction conjectures that reversals are the result of markets correcting some investors' initial overreaction to news (e.g., Shiller 1984; De Bondt and Thaler 1985; Subrahmanyam 2005; Stambaugh et al. 2012). Although intuitive, this explanation faces challenges, such as explaining why reversals tend to be stronger when stocks are not subject to news events (Chan 2003; Dai et al. 2024). In contrast, liquidity provision attributes short-term reversals to intermediaries who require compensation for providing liquidity (e.g., Nagel 2012; Hameed and Mian 2015). While this explanation also captures key aspects of reversals, it leaves several critical questions unanswered. Why could liquidity effects persist beyond the very short term, extending for several days or weeks (Nagel 2012)? Why do both marketwide illiuqidity and sentiment correlate with short-term reversal profitability (Da et al. 2014b)? Moreover, why are short-term reversals closely intertwined with patterns of industry momentum (Dai et al. 2024)?

To address these puzzles, we propose an alternative mechanism based on investor underinference and provide empirical support for it. In particular, we assume that when industry news is already reflected in the prices of some stocks (which we label *Leaders*), investors don't fully carry that information over to others (which we label *Laggards*). This leads to a systematic underreaction in the prices of the lagging stocks. Our approach is motivated by previous work on gradual diffusion of information (e.g., Hong and Stein 1999), limited investor attention (e.g., Hirshleifer and Teoh 2003; Da et al. 2014a) and limits to arbitrage that prevent sophisticated investors from promptly exploiting cross-asset mispricing (Shleifer and Vishny, 1997). Importantly, unlike previous research investigating lead-lag effects (Lo and MacKinlay, 1990; Brennan et al., 1993; Badrinath et al., 2015; Chordia and Swaminathan, 2000) stocks can dynamically switch between the roles of *Leader* and *Laggard* in our setting.

Our framework suggests that reversal strategies can be profitable even without investor overreaction or illiquidity, offering a new perspective on their documented performance. For example, consider an industry whose outlook is improving. Some stocks' prices immediately reflect this information (*Leaders*), while the prices of others lag behind in adjusting (*Laggards*). The key insight is that due to the positive change in the outlook of the industry, *Laggards* are more likely to be clustered among the loser stocks than among the winner stocks. Hence, loser stocks perform better than winners subsequently, as *Laggards'* prices gradually adjust to the good news. Symmetrically, in case of a *deteriorated* industry outlook, *Leaders* would cluster among industry losers and *Laggards* would cluster among industry winners, contributing to reversals by decreasing the future returns of winners whose prices have yet to reflect the worsened outlook. Recognizing this nuance is crucial, as it highlights that the previously documented performance of return reversals might stem from underinference: investors do not trade aggressively enough when correcting the mispricings of fundamentally linked stocks.

Our model helps reconcile several outstanding puzzles. First, Chan (2003) shows that reversals are stronger for stocks that do not make the headlines – counterintuitive under the overreaction hypothesis but consistent with our model, where *Laggards* are precisely those that receive relatively less investor attention. Second, while liquidity-based theories suggest that reversals should dissipate quickly, our mechanism implies more persistent effects, as underreaction is plausibly shaped by attention frictions and limits to arbitrage. Third, Da et al. (2014b) document that both liquidity constraints and market sentiment affect the long and short legs of short-term reversal strategies asymmetrically. Our model explains these patterns by market frictions and the known underreaction to news contradicting to market sentiment (Antoniou et al., 2013). Finally, our model connects the literature on short-term reversals with short-term industry momentum (Moskowitz and Grinblatt, 1999) by arguing that both arise from differential underreaction to industry-level news.

While to us it is unobservable which stocks are *Leaders* or *Laggards*, our model implies that Laggards are more likely to be found among the losers of outperforming industries and among the winners of underperforming industries – stocks whose returns appear inconsistent with the recent direction of their industry. We use this prediction to construct a proxy for identifying *Laggards* empirically. Using this proxy, we find strong support for the model's predictions. Among *Laggards*, an equal-weighted long-short portfolio – buying the bottom 30% of stocks of top performing industries and selling the top 30% of stocks of industries with the weakest performance yields an average monthly return of 2.79%, with a t-statistic of 10.92. This is nearly twice as large as the return from a standard within-industry reversal strategy, which earns 1.45% per month. For value-weighted portfolios, the gap is similar: 1.36% per month (t=7.87), compared to 0.66% for the traditional within-industry reversals. Importantly, when applying the same construction to *Leaders* – stocks whose performance aligns with their respective industry's, and hence they are less likely to be mispriced through the lens of our model – we observe no reversal effect. These results are difficult to reconcile with theories based on overreaction or liquidity provision, and instead provide empirical support for underinference as a key mechanism behind return reversals.

A potential concern is that our empirical proxy for Laggards might disproportionately capture stocks that are more prone to illiquidity or investor overreaction, which could independently explain the stronger reversals we observe. However, the data suggest the opposite. Leaders experience substantially more extreme returns during the formation month: their average absolute return exceeds 17%, compared to just 10% for Laggards. Under either the liquidity provision or overreaction hypotheses, stronger return signals should lead to more pronounced reversals. Yet we find that Leaders exhibit no meaningful reversals. Importantly, the two groups are otherwise comparable in observable characteristics such as size and book-to-market ratio, suggesting that the difference in reversal strength is not driven by risk or style differences.

We also examine how standard proxies for limits to arbitrage influence return reversals across *Leaders* and *Laggards*. Under the liquidity provision or investor overreaction hypotheses reversal profits should diminish for stocks with lower frictions. Prior work finds that reversals weaken when penny stocks are excluded, when turnover is large, and when focusing on large market capitalization, liquid stocks. Cheng et al. (2017) further show that reversals weaken as institutional investors become more active in trading a stock, which they proxy with prior quarter stock returns. While these frictions could plausibly reduce reversals under existing theories, our framework makes a sharper prediction: limits to arbitrage should matter only for mispriced stocks – that is, *Laggards*. *Leaders*, whose prices already reflect industry information, should not exhibit reversals, regardless of frictions.

Consistent with this, we find that arbitrage constraints have stronger influence on *Laggards*' reversals than on *Leaders*'s reversals. For instance, *Laggards* continue to exhibit strong and significant reversals even among stocks with relatively low frictions – those that are larger, more liquid, have large turnover, or avoided poor performance in the prior quarter. Notably, Medhat and Schmeling (2021) document short-term momentum for stocks with high turnover and while *Laggards*' reversals do weaken with turnover in our tests, they remain large and statistically significant for stocks above median turnover. We also examine time-series variation in market-wide frictions, using measures such as the VIX index and aggregate stock market liquidity. These indicators predict the strength of reversals among *Laggards* but have no explanatory power for reversals among *Leaders*. These findings challenge traditional explanations but align closely with our model: underinference-based mispricing is selective and persistent, and frictions matter only to the extent they delay correction among *Laggards*.

We also conduct a series of robustness checks to rule out alternative explanations. First, we implement a placebo test in which we randomly assign stocks to pseudo-industries and re-estimate our strategy. In this randomized setting, reversals are slightly stronger among placebo Leaders than placebo Laggards—highlighting that our main findings rely on fundamental linkages between firms. Second, we control for a range of standard risk factors and anomalies, including long-term reversal, short-term reversal, short-term momentum (Medhat and Schmeling, 2021), and industry momentum. None of these variables account for the predictive power of our *Laggards*-based reversal strategy. Third, we examine the timing of return patterns. While the profits from a standard short-term reversal strategy become statistically insignificant by the second week, the *Laggards*-based reversal strategy remains significantly profitable for up to six weeks. In contrast, strategies based on *Leaders* exhibit no statistically significant reversals at any horizon. Together, these results further support our interpretation: return reversals are concentrated among Laggards, and are not driven by previously documented effects.

The rest of the paper is organized as follows. Section 2 describes our model and its main implications. Section 3 details the data and variable construction. Section 4 presents the main results, while Section 5 concludes.

2 A lead-lag model

There are two assets, *Lead(er)* and *Lag(gard)* and they pay a final dividend at $t = 2$, D^{Lead} and D^{Lag}, respectively. Dividends follow a factor structure such that $D^{Lead} = I + \epsilon^{Lead}$ and $D^{Lag} = I + \epsilon^{Lag}$, where I is the common (industry) factor. Random variables follow independent Gaussian distributions with $\epsilon^{Lead}, \epsilon^{Lag} \sim N(0, \sigma_\epsilon^2)$ and $I \sim N(0, \sigma_I^2)$. Investors are risk-neutral and at $t = 0$ prices equal the unconditional expectation, $P_0^{Lead} = P_0^{Lag} = 0$.

At $t = 1$ news s^{Lead} and s^{Lag} arrive about final dividends. We label *Leader* the asset whose news reveals its dividend and *Laggard* the asset whose news only reveals the value of the idiosyncratic factor, i.e., $s^{Lead} = D^{Lead}$ and $s^{Lag} = \epsilon^{Lag}$. As investors know which stock is the *Leader* and the *Laggard*, efficient prices of both assets should contain all information revealed by the news. With risk-neutrality and a unit discount factor, efficient prices at $t = 1$ satisfy $P_1^{Lead} = D^{Lead}$ and $P_1^{Lag} = \epsilon_{Lag} + E[I|P_1^{Lead}]$. Payoff distributions imply $E[I|P_1^{Lead}] = \beta P_1^{Lead}$, where $\beta = \frac{\sigma_I^2}{\sigma_I^2+\sigma_\epsilon^2}$ and, therefore, the price or the news of the *Leader* does not contain additional information to predict the *Laggard*'s dividend.

We now introduce the friction in the model, which we label cross-asset underinference. Formally, cross-asset underinference occurs when instead of using β, markets price the *Laggard* with some $\tilde{\beta} = (1 - \rho)\beta$, where $\rho \in [0, 1]$ is the measure of underinference. With $\rho > 0$, *Laggard* is mispriced at $t = 1$ as it underreacts to information about I revealed in *Leader*'s price.

Below we interpret the common factor I as an *industry factor*, which also motivates our empirical tests. The news about a given company could be any information that surfaces about the company, like an analyst report upgrading its earnings forecast. While this clearly has a positive impact on the value of the company, valuation implications for its industry peers are less obvious. I.e., it may take some time for markets to figure out the extent to which the good news is driven by industry developments or only company specific developments.

The literature provides multiple plausible reasons for cross-asset underinference. Fixed costs associated with setting up firm-specific data processing procedures (Merton, 1987) may lead each investor to specialize into a small subset of stocks. Extending the idea of gradual information diffusion (Hong and Stein, 1999) to multiple assets implies that information only spreads gradually across assets. Limited investor attention (Hirshleifer and Teoh, 2003; Da et al., 2014b) may imply that investors specializing in certain stocks tend to overlook news about companies outside their scope. Finally, cross-asset learning (Cespa and Foucault, 2014) can slow down when prices are less informative due to transient shocks.

Cross-asset underinference generates both industry momentum and within-industry reversals as *Laggard*'s price does not instantly reveal the information revealed by *Leader*'s price in case $\rho > 0$. Denoting $R_t^{Lead} = P_t^{Lead} - P_{t-1}^{Lead}$ and $R_t^{Lag} = P_t^{Lag} - P_{t-1}^{Lag}$, and defining industry momentum as the autocovariance of the industry average return $R_t^I = \frac{R_t^{Lead} + R_t^{Lag}}{2}$, while defining within-industry reversals as the strategy that sets portfolio weights proportionally to prior period performance similarly to Lehmann (1990), Nagel (2012) and Hameed and Mian (2015), yields:

$$Industry\ momentum : Cov\left(R_1^I, R_2^I\right) = \frac{1}{4}(1+\tilde{\beta})\sigma_I^2\rho \geq 0 \tag{1}$$

$$Within-industry\ reversals : E\left[\sum_{i \in Lead, Lag}(R_1^i - R_1^I)R_2^i\right] = -\frac{1-\tilde{\beta}}{2}\sigma_I^2\rho \leq 0. \tag{2}$$

Both of the above directly follow from *Laggard*'s underreaction to the industry factor at $t = 1$. Note that the results in (1) -(2) do not hinge on the econometrician knowing which asset was the Leader or the Laggard.[1] In addition to implying the documented patterns of industry momentum (Moskowitz and Grinblatt, 1999) and short-term return reversals (Jegadeesh and Titman, 1993), cross-asset underinference also serves as a microfoundation for price delay (Jegadeesh and Titman, 1995; Hou and Moskowitz, 2005), while remaining agnostic about the process of how stocks switch between the roles of Leader and Laggard.

2.1 Identifying Leaders and Laggards

In order to investigate empirically the extent to which reversals are driven by Laggards, we need to identify who Leaders and Laggards are. Notice that in our model investors know who Leaders and Laggards are, but this is not observable to the econometrician. However, the

[1] It is worth emphasizing that momentum and reversals are both a result of the initial mispricing of Laggards. Unlike models that explain short-run momentum and *long-term* reversals, like Daniel et al. (1998), Hong and Stein (1999) or Luo et al. (2021), among others, reversals and industry momentum occur simultaneously here as the market corrects the mispricing of Laggards.

econometrician can compute the posterior likelihood of being a Leader or a Laggard based on the distribution of stock returns.

From the econometrician's perspective, returns are distributed following a mixture of normally distributed random variables, where each stock $i \in \{1, 2\}$ in each period t could be a Leader or a Laggard. To illustrate this, let $\bar{R}_t$ denote the average return of the two assets in period t (average returns are observable to the econometrician). While the econometrician does not know whether (i) asset 1 is the Leader and asset 2 is the Laggard or (ii) asset 2 is the Leader and asset 1 is the Laggard, we assume that each of these two states occur with 50% probability and the econometrician knows this prior probability.[2] If so, the bivariate distribution of R_1^1 and $\bar{R}_1$ follows a mixture of two normal distributions. If asset 1 is the Leader, then

$$R_1^1 \sim N(0, \sigma_I^2 + \sigma_\epsilon^2) \;\; and \;\; Cov(R_1^1, \bar{R}_1) = \frac{1}{2}(1 + (1-\rho)\beta)(\sigma_I^2 + \sigma_\epsilon^2), \tag{3}$$

whereas if asset 1 is a Laggard, then

$$R_1^1 \sim N(0, (1-\rho)^2\beta\sigma_I^2 + \sigma_\epsilon^2) \;\; and \;\; Cov(R_1^1, \bar{R}_1) = \frac{1}{2}((1-\rho)(1 + (1-\rho)\beta)\sigma_I^2 + \sigma_\epsilon^2), \tag{4}$$

while the variance of the average $\bar{R}_1$ is the same in both of the above cases.

Intuitively, the Leader has larger variance and also larger covariance with the average (even if $\rho = 0$). Building on this allows us to compute the posterior probability of an asset being the Leader. Formally, the bivariate distribution of R_1^1 and $\bar{R}_1$ has a different covariance matrix, either Σ_{Lead} (if asset 1 is the Leader) or Σ_{Lag} (if asset 1 is the Laggard). Denoting the bivariate normal PDF with $\phi(R_1^1, \bar{R}_1, \Sigma)$ (means are suppressed from notation as they are always equal to zero), the posterior probability of asset 1 being the Leader equals to

$$prob[Asset\ i\ is\ Leader | R_1^i, \bar{R}_1] = \frac{\phi(R_1^i, \bar{R}_1, \Sigma_{Lead})}{\phi(R_1^i, \bar{R}_1, \Sigma_{Lead}) + \phi(R_1^i, \bar{R}_1, \Sigma_{Lag})} \tag{5}$$

Solving equation (5) leads to

$$\frac{\phi(R_1^i, \bar{R}_1, \Sigma_{Lead})}{\phi(R_1^i, \bar{R}_1, \Sigma_{Lead}) + \phi(R_1^i, \bar{R}_1, \Sigma_{Lag})} = \frac{1}{1 + e^{-\gamma \bar{R}_1 (R_1^i - \bar{R}_1)}}, \tag{6}$$

[2] In the Appendix we investigate the more general case with $N > 2$ assets and $0 < n < N$ Leaders.

where γ is always non-negative and is equal to

$$\gamma = \frac{2\beta^2}{\sigma_\epsilon^2}\left(2\rho - \rho^2 + \frac{\sigma_\epsilon^2}{\sigma_I^2}\right). \tag{7}$$

The constant γ determines the extent to which the average return and a stock's return are informative about the stock being a Leader or a Laggard. It is increasing in the variance of the common factor, σ_I^2, and also increasing in the extent of underinference, ρ. Note that even in the case of no underinference ($\rho = 0$), $\gamma \geq 0$ as the returns of Leaders and Laggards follow different distributions. The only case when $\gamma = 0$ is when $\sigma_I^2 = 0$, that is, when returns are only driven by idiosyncratic shocks.

Importantly, the posterior probability in (6) is increasing in the product $\bar{R}_1(R_1^i - \bar{R}_1)$. This product tells us that winner stocks of industries with positive average returns ($R_1^i >> \bar{R}_1$ and $\bar{R}_1 > 0$) together with loser stocks of industries with negative average returns ($R_1^i << \bar{R}_1$ and $\bar{R}_1 < 0$) are more likely to be Leaders while the loser stocks of industries with positive average ($R_1^i << \bar{R}_1$ and $\bar{R}_1 > 0$) together with the winner stocks of industries with negative average returns ($R_1^i >> \bar{R}_1$ and $\bar{R}_1 < 0$) are more likely to be Laggards. This motivates our empirical approach for identifying Leaders and Laggards below. In Appendix A we generalize the model to have $N > 2$ assets out of which $0 < n < N$ are Leaders, while $N - n$ assets are Laggards. We show that the posterior of being a Leader is still proportional to $\bar{R}_1(R_1^i - \bar{R}_1)$ as long as $n = N/2$.

3 Data

In this section, we present the description of our data and show how we classify stocks as Leaders, as Laggards (or as Other). We use CRSP and Compustat from July 1962 to March 2022. Following the literature, we select ordinary common shares traded on one of the three largest US exchanges (NYSE, NASDAQ, AMEX). We use the methodology of classifying stocks into the 12 or 49 industries available on Kenneth R. French's website. In addition, we use I/B/E/S to compute analyst coverage and 13F filings to compute institutional ownership. To be included in our sample, we require stocks to have non-missing volume, price and shares outstanding for the given month (so turnover and size can be computed) in addition to 13 months of consecutive returns (so stock momentum can also be computed), from the monthly CRSP files.[3] We filter out stocks for which we cannot compute their respective

[3]We use CIZ Version 2 of CRSP, which adjusts holding returns with information available on delistings. Where returns are not available during our holding period in the monthly CRSP files, we use the daily CRSP

book-to-market ratios (Fama and French, 1992). These criteria leave us with an average of 3394 stocks per month.

3.1 Who are Leaders and Laggards?

Based on the model detailed in Section 2, we categorize stocks as Leaders, Laggards, or Others. Specifically, using the industry classification from Kenneth R. French's website, we first assign each stock to one of 12 industries. Each month, industries are ranked according to their equal-weighted average returns, and we identify the top two and bottom two performing industries. A stock is classified as a Leader if its return is either above the 70th percentile among stocks within the top two industries or below the 30th percentile within the bottom two industries. Conversely, a stock is considered a Laggard if its return is above the 70th percentile within the bottom two industries or below the 30th percentile within the top two industries.

To provide more insights on the characteristics of the stocks in each category, Table 1 reports the time series averages of cross-sectional statistics for Leader, Laggard, and Other stocks and Figure 1 shows how we classify stocks as Leaders and Laggards in a stylized way. First, the average absolute return in the portfolio formation month is significantly higher for Leaders (17.67%) than for Laggards (9.98%) (see Figure 1 for the intuition). This evidence counters the concern that the reversal signal might be stronger for Laggards.

Second, characteristics seem to align with our model. Recall that news arrives both for Leaders and Laggards in the model, and consistent with this, we observe in the data that both Leaders and Laggards are more likely to make earnings announcements compared to Other stocks, with Leaders also submitting slightly more 8-K filings relative to Laggards. Further, compared to Other stocks, both Leaders and Laggards exhibit higher trading activity. Nevertheless, Leaders display significantly higher turnover, greater analyst coverage, higher online search volume, and higher abnormal dollar volume compared to Laggards, indicating that Laggards receive relatively lower investor attention. Notably, turnover has been identified as a potentially relevant characteristic for understanding return reversals. While Avramov et al. (2006) find that reversals are strongest among high-turnover, low-liquidity stocks, Medhat and Schmeling (2021) report short-term momentum, rather than reversal, in high-turnover stocks when sorting by both prior-month return and turnover. More recently, Dai et al. (2024) provide evidence that lower turnover is associated with stronger reversals, which they attribute to the longer inventory duration required for liquidity provision. In our setting, both Laggards and Leaders exhibit slightly higher turnover than Other stocks,

files to find a price close to the end of the holding period and use that to compute a holding period return.

suggesting that our observed reversals are unlikely to be driven purely by turnover-related effects.

There is no significant and/or meaningful difference between Leaders and Laggards in terms of other characteristics like size, book-to-market ratio, momentum, Amihud illiquidity, institutional ownership, and information discreteness suggesting that apart from the characteristics previously highlighted, Leaders and Laggards are broadly similar.

Since Leaders and Laggards are selected exclusively from winner and loser industries, there is a concern that our results may be disproportionately driven by a small number of industries. This concern arises because industries with fewer constituent stocks tend to exhibit greater return volatility, making them more likely to be classified as extreme performers. A priori we would expect that on average, 9.67% of stocks to be classified as Leaders and Laggards each. Empirically, we find that 8.9% of stocks enter these portfolios due to smaller industries making it slightly more frequently to winner and loser status. During our sample period, the industry with the smallest average number of constituents had 65 stocks (Telcm) while the industry with the largest number of average constituents had 515 stocks (Money). The industries most frequently making it to top or bottom two are Utils (450 months), Enrgy (449 months), BusEq (333 months) and Telcm (287 months), while the industries least likely to make it to winner or loser status are NoDur (154 months), Manuf (131 months), Shops (95 months) and, Other (77 months). It is reassuring that "Other" was the least frequent industry among the winners and losers confirming that the stocks in this portfolio are diversified across industries.

Finally, we note that Laggard and Leader status is persistent to some extent as shown in Table 2. I.e., a Laggard is approximately 60% more likely to remain a Laggard compared to the unconditional probability using our benchmark classification and the same holds for Leaders. As suggested by Table 2, this largely follows from the persistence of industry performance (Moskowitz and Grinblatt, 1999): winner industries are twice as likely to remain winners compared to the rest of the industries and the same holds for loser industries.

4 Results

4.1 Laggards' and Leaders' reversals

Table 3 presents our benchmark results. We first report the performance of the within-industry reversal strategy that builds a long-short portfolio using the winners (Top 30% of stocks) and losers (Bottom 30% of stocks) within each industry. Our estimate of -1.45% per month is close to those published in the literature, e.g., Table 2 of Da et al. (2014b) report a raw performance of -1.20% per month for a slightly different specification. Compared to this, implementing the reversal strategy on Laggards generates reversal returns of -2.83% per month with equal-weighted portfolios or -1.36% with value-weighted portfolios. Adjusting for standard risk factors, like a four-factor model, does not lead to noticeable differences. Finally, the reversal strategy based on Leaders generates small and insignificant returns.

The fact that Laggards produce large and significant reversals, while Leaders do not is a striking result. While Leaders and Laggards are similarly (il)liquid during the formation month (see Table 1), Leaders experience more extreme returns as shown on Panel B of Table 3. Therefore, we would expect Leaders to be more prone to price pressure or investor overreaction during the formation month.

To illustrate this point, we repeat the analysis using placebo industries. Specifically, we draw from the annual empirical distribution of industry sizes to randomly assign stocks to 12 placebo industries each year. We then compute placebo industry average returns and use them, along with individual stock returns, to classify stocks as (placebo) Laggards and Leaders, mirroring our main approach. This process is repeated 1000 times, and results are summarized in Table 4. As expected, placebo Leaders tend to show slightly, though often insignificantly, larger reversals than placebo Laggards. Crucially, even the most extreme placebo estimates fall short of those from "true" industries. For instance, the largest placebo Laggard reversal out of a 1000 trials yields an equal-weighted return of -1.28% per month, compared to -2.83% with true industries. Figure 2 shows the distribution of t-statistics from the 1000 placebo trials under the null that reversals of Laggards and Leaders perform equally. While our "true" industry result yields a Newey-West t-statistic of -6.84, the placebo trials have a mean of 2.35 and a standard deviation of 1.00—placing our estimate more than 9 standard deviations from the placebo mean. These results highlight the critical role of industry links in driving the observed reversals.

4.2 Robustness tests and persistence

We carry out a number of robustness tests. First, we drop stocks whose share price was below $5 at the end of the formation month to reduce market microstructure effects. This decreases the average number of stocks per month in our sample from 3394 to 2606 while increasing average market cap from an average of $2.3 billion to $2.9 billion. Second, in order to see the extent to which potential bid-ask bounces drive reversals (Conrad et al., 1997) we skip a day between portfolio formation and the holding period by omitting the first day's return when computing holding month returns. Third, instead of only selecting Leaders and Laggards from the top two and bottom two industries each month, we classify six out of 12 industries as winners and the rest as losers. This implies that the number of stocks classified as Leaders and Laggards more than triple and will not be restricted to industries with extreme performance. Finally, we use the finer, 49 industry classification available on Kenneth French's website and use the top and bottom 10-10 industries to select Leaders and Laggards, while maintaining the 30th and 70th return percentiles within industries as cutoffs.

Table 5 shows that removing penny stocks or skipping a day between the formation month and the holding month does reduce reversals by up to a third but the results still remain economically large and statistically significant. As expected, selecting Laggards and Leaders from a wider set of industries weakens the results which is consistent with the noisier selection of Laggards and Leaders, however, all our conclusions remain the same. Finally, moving to a less coarse industry classification scheme while classifying approximately the same number of stocks as Laggards and Leaders leaves our results virtually unchanged.

Figure 3 tracks the performance of the four alternative specifications presented in Table 5 across time. While it is notable that since the 1990s Laggards' reversal has gradually weakened, it is striking to see that despite their larger return variation during portfolio formation, in *none* of these tests do Leaders show larger reversals than Laggards.

To investigate the return persistence of the various portfolios, we compute Wednesday close to Wednesday close weekly stock returns to track the performance of Laggards' reversal, Leaders' reversal and the conventional short-term return reversal strategy, STREV[4]. Figure 4 illustrates. We use the monthly sorts to classify stocks as Laggards and Leaders as before. But, instead of focusing on the subsequent month as a holding period, we track the performance of the long-short strategies during each of the 11 weeks after portfolio formation. Since our weekly returns always start on a Thursday, we skip 1-7 days between the end of the formation month and the first holding period week depending on the first day of a month.[5]

Unlike STREV that only produces significant returns in the first week after formation, Laggards' reversal yields a significant return up to week 6 after formation.[6] This further

[4]Kenneth French's website provides the following definition for the STREV strategy, which we implement on our sample: "We use six value-weight portfolios formed on size and prior (1-1) returns to construct STRev. The portfolios, which are formed monthly, are the intersections of 2 portfolios formed on size (market equity, ME) and 3 portfolios formed on prior (1-1) return. The monthly size breakpoint is the median NYSE market equity. The monthly prior (1-1) return breakpoints are the 30th and 70th NYSE percentiles. STREV is the average return on the two low prior return portfolios minus the average return on the two high prior return portfolios" We multiply the returns to the long-short strategy by -1 so that consistently with rest of our results, reversals are indicated by negative returns.

[5]E.g., if the first trading day in a month falls on a Monday, we skip that Monday, Tuesday and Wednesday, but if the first trading day is a Thursday, we skip an entire week between portfolio formation and the first holding period week.

[6]We have repeated this by using equal-weighted portfolios in STREV but the differences in results are

supports the notion that Laggards' reversal is driven by these stocks' initial underreaction to industry information. However, Leaders' weekly reversals show no patterns and remain close to zero from the first week of the holding period.

4.3 Influence of trading frictions

Motivated by the literature on limits to arbitrage (Shleifer and Vishny, 1997) and stock mispricing, we explore whether the reversals we observe are concentrated in environments where arbitrage is more constrained and mispricings are more likely to persist. Previous research has shown that smaller and less liquid stocks – typically associated with higher arbitrage risk and greater trading frictions – exhibit stronger return reversals (Nagel, 2012; Hameed and Mian, 2015), while high turnover may instead reflect short-term momentum (Medhat and Schmeling, 2021). To ensure our findings are not merely a byproduct of these known associations, we first compute the median market equity within each industry and month to classify stocks into small-cap and large-cap groups. Within each size group, industry, and month, we then use the 30th and 70th percentiles of the return distribution to identify Laggards and Leaders, respectively. We apply a similar sorting methodology with other measures associated with trading frictions: turnover, Amihud's illiquidity measure, and lagged quarterly returns (as in Cheng et al. (2017)). As expected, Table 6 shows that return reversals are more pronounced among stocks that are smaller, less actively traded, more illiquid, and those that have underperformed in the prior quarter — all characteristics associated with greater mispricing.

However, Table 6 also reveals the surprising result that apart from the prior quarters' return, the three characteristics size, turnover and illiquidity, all have a significantly larger influence on Laggards' reversals than on Leaders' reversals. This is surprising through the lens of the liquidity provision hypothesis, which would not imply these differences between Leaders and Laggards. Through the lens of our model, the results suggest that trading frictions amplify investor underinference.

Time-series tests focusing on adverse market conditions lead to similar conclusions. Table 7 shows that Laggards' reversal increases with implied volatility (measured with the lagged VIX index), though the association is only marginally significant (t=-2.32). The estimate on lagged VIX in column (1) implies that a one standard deviation increase in lagged VIX (7.7 points) increases reversals by 0.77% (the latter amounting to 13% of its respective standard deviation). Greater market uncertainty slows down the diffusion of industry information, which is in line with investors allocating more attention to market news, e.g., an implication

negligible.

of category learning (Peng and Xiong, 2006).

Comparing the results in Tables 7 and 8 reveals that while Laggards' reversal seems to be driven by illiquidity to some extent, this is not the case for Leaders. To measure aggregate illiquidity, we compute Amihud (2002)'s illiquidity measure (Amihud INNOV ILLIQ) every month for each stock using daily data and then we compute their value-weighted average for each month. As there is a significant downward trend in the raw Amihud measure, we compute innovations from it by calculating the percent difference between the month t value and the average value between months $t-1 : t-24$ as in Avramov et al. (2016). In addition, we use the innovations from Pastor and Stambaugh (2003)'s aggregate liquidity series (PS INNOV LIQ) as an additional proxy for liquidity.

The estimate on lag Amihud INNOV ILLIQ in Column (2) of Table 7 implies that a one standard deviation increase in aggregate illiquidity increases reversals by -0.59% or by 12% when measured by Laggards' reversal's standard deviation. This is an economically large estimate and using our other proxy for liquidity, PS INNOV LIQ gives consistent results. However, in untabulated results we also find that the relation between value-weighted Laggards' reversal and liquidity measures become insignificant. Together these suggest that the mispricing of small cap Laggards is amplified during periods of aggregate illiquidity shocks.

Market sentiment also significantly influences various asset pricing anomalies. Stambaugh et al. (2012) find that anomalies are stronger (with more profitable long-short strategies) following periods of high sentiment. Specifically, they highlight that the short legs of strategies become particularly profitable following high sentiment periods and attribute this to the interplay of high sentiment and short-sale constraints. Da et al. (2014b) provides evidence for this argument in the context of short-term return reversals.

To empirically examine the role of sentiment, Table 9 presents separate regressions of the long and short legs of our reversal strategies on indicators of sentiment states. Sentiment states are identified based on the sentiment index developed by Baker and Wurgler (2006), categorizing periods as low (high) sentiment when the index is below (above) its 30th (70th) percentile threshold.

The regression results in column (4) support the findings of Stambaugh et al. (2012) and Da et al. (2014b), indicating that winner Laggards from previously losing industries indeed perform worse during high sentiment periods. In addition, the results from column (1) provide some evidence that loser Laggards from previously winning industries perform better during low sentiment periods. Columns (5)-(7) repeat the analysis for the long and short legs of Leaders' reversal, but none of the coefficients on sentiment state indicators enter the regressions with significance. Through the lens of our model, these results support the notion that investor underinference becomes more pronounced when the sign of an industry shock contradicts the sign of the prevailing market sentiment, a possible implication of cognitive dissonance (Antoniou et al., 2013).

4.4 Relation to short-term reversal and industry momentum

Apart from a few exceptions, including Hameed and Mian (2015), Da et al. (2014b) and Dai et al. (2024), the literature has largely stayed silent on the relation between short-term return reversals and industry momentum (Moskowitz and Grinblatt, 1999), despite the clear intuition that links them: if industries are subject to short-term news-related momentum, this will attenuate the performance of reversal strategies as loser stocks are likely to be selected from loser industries, while winner stocks are more likely to be selected from winner industries. Through the lens of liquidity-driven reversals, industry momentum contaminates the traditional measures of stock-return reversals as these should be corrected by benchmarking returns against those of industry peers. In fact, the correlation coefficient between STREV and an industry momentum strategy (IMOM) is 0.70, which tells us that these strategies are closely related, in line with the findings of Dai et al. (2024).[7,8]

However, as we have seen in Section 2 our trading friction of cross-asset underinference implies both industry momentum and reversals. This link emerges because of stocks' differential underreaction to industry factors. That is, based on our model, removing Laggard stocks from conventional short-term reversal and industry momentum strategies should hinder both of their performance, while removing Leaders should improve their performance, as the latter group of stocks is predicted to suffer less from investor underinference.

Table 10 shows how the performance of conventional short-term reversals (STREV) and that of industry momentum (IMOM) are influenced when these strategies are implemented without Laggard or without Leader stocks. In principle, when dropping a random subset of stocks from a portfolio we would not expect significant changes to its mean return. However, when we drop Laggards, the performance of both of these strategies (measured by average return) deteriorates in the order of 20%. This is despite only dropping about 9% (30%) of constituents stocks in the STREV (IMOM) strategy.

To the contrary, dropping Leaders improves the performance of these portfolios. Moreover, Leaders also do not appear to be contributing by providing added diversification, as

[7] Industry momentum (IMOM) sorts stocks into portfolios based on their respective industry's average monthly return and buys (short-sells) the value-weighted portfolio of stocks from the top (bottom) two industries (using the 12 industry classification available on Kenneth French's website).

[8] The observed positive correlation indicates that, on average, when industry momentum exhibits strong performance (characterized by substantial positive returns), the STREV strategy tends to perform comparatively poorly (i.e., it does not generate correspondingly large negative returns).

dropping them *decreases* the standard deviations of these long-short portfolios.[9] Recall, that Leaders are stocks with extreme returns during the formation month. Hence, it appears that while they are classified as Leaders, they remain prone to modest return continuation as also revealed by Table 3. This modest return continuation significantly hinders the performance of both STREV (because it is a return continuation) and IMOM (because it is only modest). Through the lens of our model, this result is consistent with our proxy for Leader stocks being noisy: due to our approach we will inevitably misclassify some stocks that underreact to industry factors as Leaders.

Next, we perform a series of spanning tests to investigate how Laggards' reversal relates to conventional reversal and industry momentum strategies while controlling for standard risk factors. Table 11 reports the results for both equal-weighted and value-weighted results. First, commonly used factors, such as the five-factor model of Fama and French (2015) and momentum of Carhart (1997) do not explain Laggards' reversal. Second, columns (4) and (8) show that a significant share of the performance of Laggards' reversal can be attributed to the performance of conventional short-term reversals (STREV) and short-term industry momentum (IMOM), but these strategies do not fully span Laggards' reversal returns.[10] Finally, other factors like the long-term reversal factor (LTREV) of De Bondt and Thaler (1985) and the short-term reversal and short-term momentum strategies of Medhat and Schmeling (2021) show little to no partial correlations with Laggards' reversal.[11]

We also perform cross-sectional tests to illustrate that in addition to short-term return reversals, reversals towards industry averages as well as industry momentum effects are strongest among Laggard stocks. Table 12 shows results from estimating Fama and MacBeth (1973) regressions using one month lagged market capitalization as weights in the cross-sectional regressions. First, we establish in column (1) that lagged industry average returns ($\bar{R}_{j(i)}$) predict stock returns (Moskowitz and Grinblatt, 1999). Then, in column (2) we interact $\bar{R}_{j(i)}$ with indicators for "Laggards" and "Other" stocks (as defined in Table 1) to see the extent to which different stocks are subject to industry momentum. The results show that Laggards are the most subject to industry momentum, while for Leaders (our benchmark group) the association is insignificant. Columns (3)-(4) repeat the analysis with within-industry reversals, i.e., the difference between a stock's return and its respective industry's average return ($R_i - \bar{R}_{j(i)}$). Again, the results show that within-industry reversals

[9]In case of STREV the standard deviation drops from 3.08% to 2.60% while for IMOM it decreases from 4.90% to 4.87%.

[10]See STREV's definition in footnote 4. Note that in line with our definition of reversals, we multiply the returns of STREV by -1, so negative returns are associated with reversals.

[11]Medhat and Schmeling (2021) document short-term reversals for low turnover stocks and short-term momentum for high turnover stocks when double sorting stocks on prior month returns and turnover, respectively.

are insignificant for Leaders while robust for Laggards. Finally, in columns (5)-(6) we repeat the analysis for short-term reversals and find that a one standard deviation increase in stock returns during the formation month is associated with a decrease in returns of 0.93% during the subsequent month for Laggards, compared with a 0.03% decrease for Leaders and a 0.46% decrease for all other stocks. These results provide further evidence that underreaction to industry information can manifest as return reversals.

5 Conclusions

We propose an alternative explanation for short-term return reversals that does not rely on investor overreaction or liquidity provision. Instead, we consider a simple model featuring lead-lag dynamics driven by the gradual diffusion of industry-level information across stocks. Motivated by this model, we categorize stocks as Leaders, which appear to reflect industry information early, and Laggards, which adjust their prices only after the information has propagated through the cross-section.

Our findings not only reveal a striking asymmetry in return reversals between Leaders and Laggards but also contribute to a better understanding of several patterns documented in the literature. Short-term reversal strategies are approximately twice as profitable when applied to Laggards compared to standard within-industry strategies, while reversals are entirely absent among Leaders. This contrast is particularly noteworthy given that Leaders exhibit substantially larger absolute returns during the formation month, a feature that would typically predict stronger, not weaker, reversals. These results challenge conventional explanations. Both overreaction based and liquidity provision based theories fail to account for the stronger reversals among stocks with weaker initial return signals, and neither adequately explains the persistence and robustness of reversals among Laggards, which last for up to six weeks. Furthermore, consistent with our model's prediction, the fact that Laggards contribute to both short-term reversals and industry momentum suggests that these anomalies may arise from a shared mechanism: the delayed incorporation of common information. These patterns hold after accounting for standard risk factors, known anomalies, and market frictions, and remain robust across a range of placebo and subsample tests.

Our results highlight that underreaction to industry-level information is a potent and persistent source of mispricing. The delayed adjustment of Laggards not only drives short-term reversals but also amplifies industry momentum, linking two return patterns that have traditionally been attributed to distinct frictions within a unified framework of investor underinference. This insight may help inform future research on how information spreads across fundamentally linked assets and how frictions in that process affect asset price dynamics.

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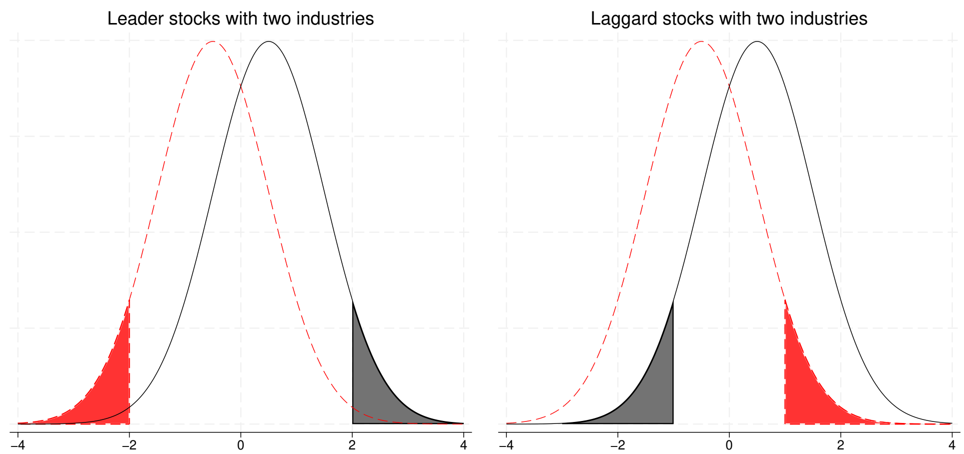

Figure 1: Classifying stocks as Leaders and Laggards. The figure illustrates the distribution of stock returns in the red/dash and black/solid industries. The shaded areas in the left panel show that Leaders are the losers of the loser red/dash industry together with the winners of the winner black/solid industry. Similarly, the right panel shows that Laggards are the losers of the winner black/solid industry together with the winners of the loser red/dash industry.

Table 1: Summary statistics of Leaders and Laggards. The table shows time series averages of cross-sectional statistics. Using the industry classification on Kenneth R. French's website, we first assign stocks to one of 12 industries. Industries are ranked according to their monthly equal-weighted average returns, and we identify the top two and bottom two performing industries. A stock is classified as a Leader if its return is either above the 70th percentile among stocks within the top two industries or below the 30th percentile within the bottom two industries. Conversely, a stock is considered a Laggard if its return is above the 70th percentile within the bottom two industries or below the 30th percentile within the top two industries. Information discreetness is the ID measure of Da et al. (2014a) using past three months of daily data (times 100). TS-SVI is the stock ticker Google search volume index obtained from deHaan et al. (2024). ADV is dollar volume in month t divided by the average dollar volume during months $t-1:t-12$, similarly to Barber and Odean (2008). Number of analysts following a stock (Analyst coverage) is available from 1976m1, while the earnings announcement indicator (EA) is available from 1970m1. The total number of submitted 8-K SEC filings during the month (8-K filings) is available from 1996m1. The share of institutional holdings (IO) is available from 1980q1 from 13F filings. For other variables, the sample period is 1962m7-2022m3. Variable names in bold indicate significant differences between the Means of Leaders and Laggards with $p < 0.05$.

	Leaders		Laggards		Other	
	Mean	SD	Mean	SD	Mean	SD
$\lvert \mathbf{R}_{it} \rvert$	17.67	(16.40)	9.98	(10.01)	9.10	(10.73)
EA	0.351	(0.41)	0.346	(0.42)	0.326	(0.42)
8-K filings	0.92	(1.01)	0.88	(1.00)	0.82	(0.95)
Turnover	0.13	(0.15)	0.10	(0.12)	0.09	(0.11)
Analyst coverage	5.46	(6.60)	5.20	(6.59)	5.43	(6.66)
TS-SVI	10.55	(14.45)	9.81	(13.94)	9.45	(13.97)
ADV	1.37	(1.18)	1.15	(0.92)	1.13	(0.92)
Log Size	4.93	(1.91)	4.99	(1.96)	4.99	(1.96)
Log BM	-0.55	(0.83)	-0.54	(0.81)	-0.50	(0.81)
MOM	0.14	(0.55)	0.14	(0.50)	0.14	(0.48)
Amihud	4.79	(15.14)	4.72	(15.01)	4.27	(14.34)
IO	0.41	(0.25)	0.40	(0.26)	0.43	(0.26)
Info discreetness	1.54	(11.07)	1.26	(10.08)	1.03	(10.17)

Table 2: Monthly transitions of industries and stocks. The left panel shows the transition probabilities of industries between "Loser", "Other" and "Winner" states, where a Loser (Winner) state is defined as the two industries with the lowest (highest) equal-weighted returns during a month and the Other state are the industries with average returns in-between. The right panel shows the transition probabilities of stocks between Leader, Laggard and Other status as defined in the caption of Table 1.

	Transition of industries			Transition of stock status			
	Loser	Other	Winner		Laggards	Other	Leaders
Loser Industries	31.98	53.14	14.87	Laggards	14.07	73.2	12.73
Other Industries	13.23	73.06	13.7	Other	7.87	84.27	7.86
Winner Industries	15.08	54.61	30.31	Leaders	12.76	72.67	14.57
Total	16.67	66.67	16.67		8.85	82.26	8.89

Table 3: Portfolios of Leaders and Laggards. Stocks are sorted as described in Table 1. FF3+MOM α shows the four-factor alpha of the long-short strategy controlling for the Fama-French 3 factors and momentum (Fama and French, 1992; Carhart, 1997). Newey-West t-statistics adjusted with 12 lags are provided in parentheses (Newey and West, 1987).

Stock return group	Equal-weighted All	Laggards	Leaders	Diff	Value-weighted All	Laggards	Leaders	Diff
Panel A: Holding month returns								
Bottom 30	1.65	2.37	0.87		0.97	1.39	0.46	
Middle 40	0.85	.	.		0.67	.	.	
Top 30	0.21	-0.46	1.17		0.31	0.03	0.72	
Top 30	-1.45	-2.83	0.31	-3.14	-0.66	-1.36	0.26	-1.62
- Bottom 30	(-9.53)	(-10.92)	(1.02)	(-6.84)	(-6.08)	(-7.87)	(1.09)	(-4.94)
FF3+MOM	-1.53	-2.79	0.12	-2.91	-0.62	-1.28	0.18	-1.46
α	(-8.04)	(-10.08)	(0.28)	(-4.98)	(-4.75)	(-6.70)	(0.62)	(-3.91)
Panel B: Formation month returns								
Bottom 30	-11.77	-8.28	-14.55		-8.44	-5.39	-11.87	
Middle 40	-0.04	.	.		0.16	.	.	
Top 30	14.85	9.51	19.84		9.43	5.69	13.74	

Table 4: Results with placebo industries. We repeat the analysis presented in Table 3 with placebo industries. Using the respective annual empirical distribution of stocks across the 12 Fama-French industries to randomly assign stocks into 12 placebo industries, and we reassign stocks to placebo industries each year. We then compute placebo industry average returns to rank placebo industries, allowing us to compute the results of Table 3 with placebo industries. We repeat this 1000 times and tabulate the mean, standard deviation, minimum and maximum of the estimates as well as their Newey-West t-statistics.

	Equal Weighted			Value Weighted		
	Laggards	Leaders	Diff	Laggards	Leaders	Diff
Top 30 - Bottom 30 estimates						
Mean	-0.97	-1.34	0.37	-0.39	-0.43	0.03
Standard Deviation	0.10	0.11	0.16	0.11	0.13	0.18
Min	-1.28	-1.66	-0.07	-0.74	-0.85	-0.57
Max	-0.51	-0.91	0.87	0.02	-0.06	0.64
Top 30 - Bottom 30 Newey-West t-statistics						
Mean	-5.75	-6.62	2.35	-2.40	-2.31	0.19
Standard Deviation	0.95	0.76	1.00	0.73	0.72	0.98
Min	-7.77	-8.67	-0.46	-5.22	-4.75	-2.86
Max	-1.49	-2.97	5.96	0.10	-0.29	3.63

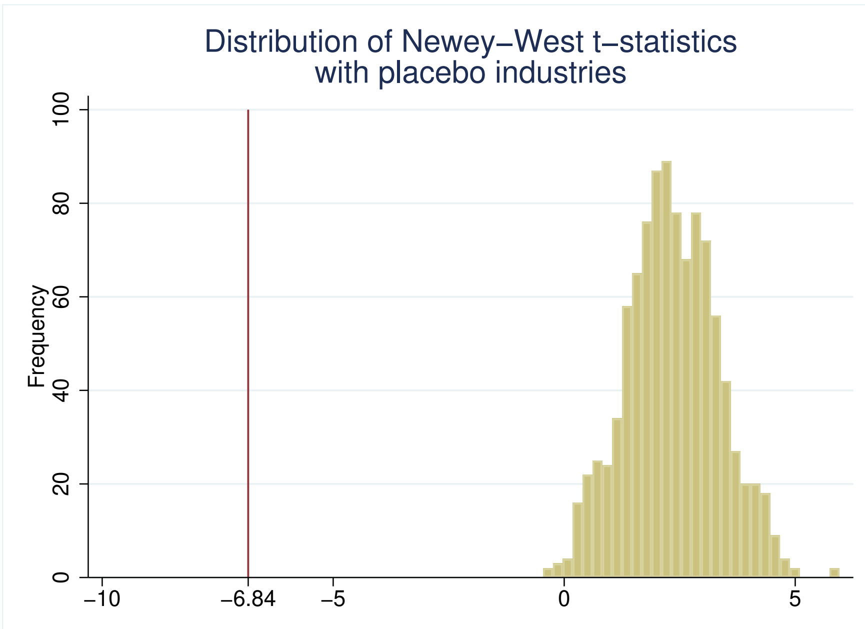

Figure 2: Histogram of t-statistics with sorting stocks into placebo industries. We repeat the analysis presented in Table 3 with placebo industries. Using the respective annual empirical distribution of stocks across the 12 Fama-French industries to randomly assign stocks into 12 placebo industries, we reassign stocks to placebo industries each year. We then compute placebo industry average returns to rank placebo industries, allowing us to compute the results of Table 3 with placebo industries. We repeat this 1000 times and compute the test statistic corresponding to the "Top 30 -Bottom 30" row and equal-weighted "Diff" column of Table 3. The vertical line shows the t-statistic based on actual industries from Table 3 while the bars show the distribution of the 1000 t-statistics based on placebo industries.

Table 5: Results with limiting market microstructure biases and alternative industry classifications. This table repeats the analysis of Table 3 by (i) dropping stocks that have a share price below $5 ("No penny stocks"); (ii) skipping the first day of the holding period when computing holding period returns ("Skipping a day"); (iii) using the top and bottom 6 industries when sorting stocks into Laggards and Leaders ("6/12 industries") and (iv) using the top and bottom 10 industries from the 49 indsutry classification available on Kenneth French's website when sorting stocks into Laggards and Leaders ("10/49 industries"). Newey-West t-statistics adjusted with 12 lags are provided in parentheses (Newey and West, 1987).

	Equal-Weighted			Value-Weighted		
	Laggards	Leaders	Diff	Laggards	Leaders	Diff
Benchmark results						
FF3+MOM α	-2.79	0.12	-2.91	-1.28	0.18	-1.46
	(-10.08)	(0.28)	(-4.98)	(-6.70)	(0.62)	(-3.91)
No penny stocks						
FF3+MOM α	-2.16	0.37	-2.52	-1.23	0.16	-1.39
	(-10.19)	(1.22)	(-5.74)	(-6.51)	(0.56)	(-3.79)
Skipping a day						
FF3+MOM α	-2.11	0.42	-2.53	-0.90	0.15	-1.05
	(-8.45)	(1.14)	(-4.69)	(-4.80)	(0.51)	(-2.61)
6/12 industries						
FF3+MOM α	-2.14	-0.87	-1.27	-0.92	-0.34	-0.59
	(-11.21)	(-3.51)	(-5.15)	(-6.76)	(-1.72)	(-2.70)
10/49 industries						
FF3+MOM α	-2.73	-0.34	-2.40	-1.21	-0.00	-1.21
	(-11.09)	(-0.95)	(-5.15)	(-7.13)	(-0.00)	(-3.58)

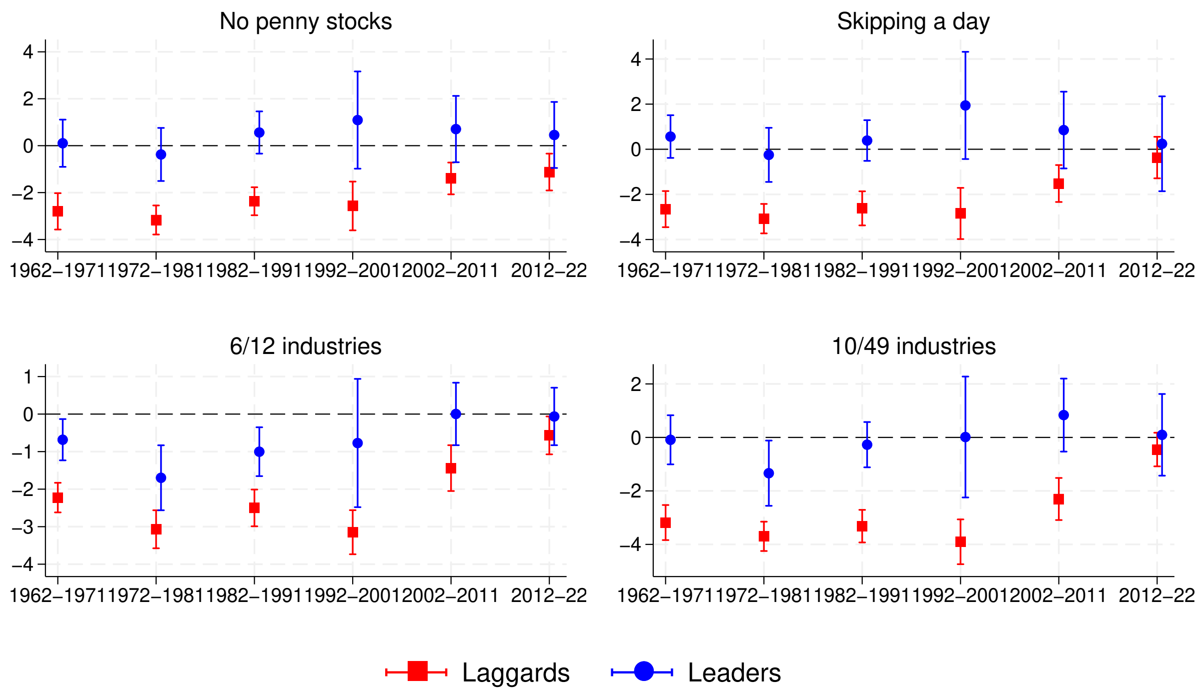

Figure 3: Reversals of Laggards (squares) and Leaders (circles) per decade. The figures show equal-weighted return reversals for the four alternative specifications tabulated in Table 5 for each decade separately in our sample together with their 95% confidence intervals. The four panels correspond to (i) dropping stocks that have a share price below \$5 ("No penny stocks"); (ii) skipping the first day of the holding period when computing holding period returns ("Skipping a day"); (iii) using the top 6 and bottom 6 industries when sorting stocks into Laggards and Leaders ("6/12 industries") and (iv) using the top 10 and bottom 10 industries from the 49 industry classification available on Kenneth French's website when sorting stocks into Laggards and Leaders ("10/49 industries").

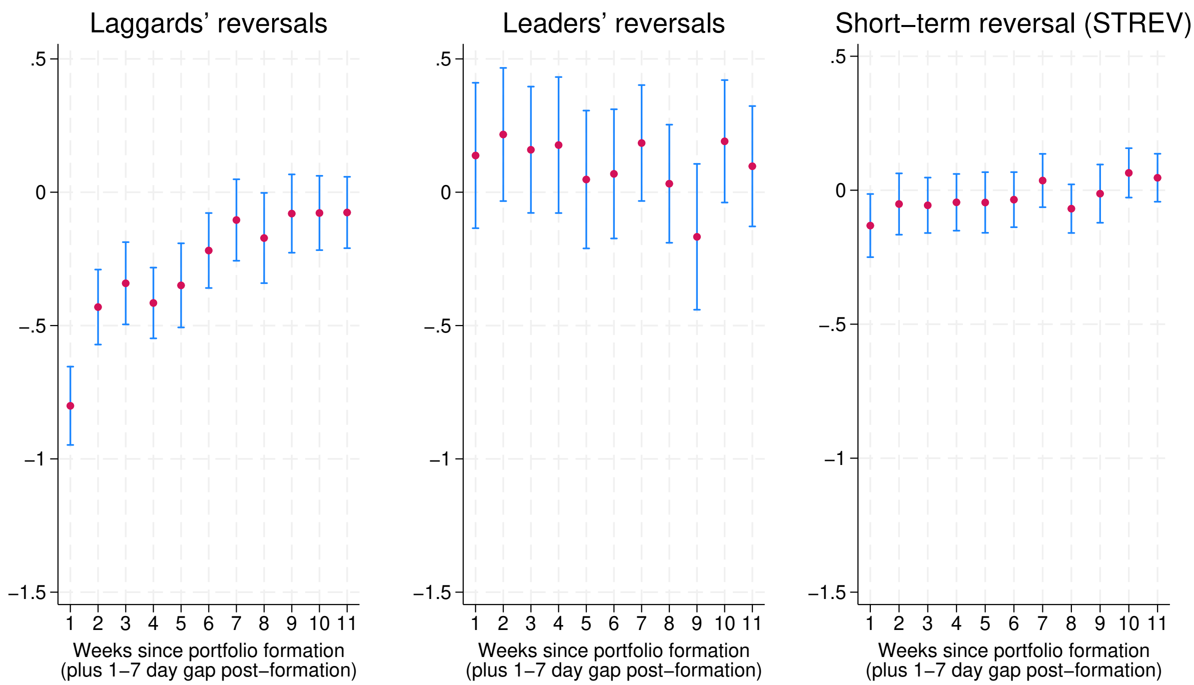

Figure 4: Persistence of reversals. We compute Wednesday close to Wednesday close weekly stock returns and use these to track the performance and their 95% confidence intervals of the various strategies based on monthly sorts. We skip 1-7 day(s) between our monthly portfolio formation and the holding period depending on the first day of the holding period month (i.e., 7 for Thursdays, 6 for Fridays ... and 1 for Wednesdays). Laggards' and Leaders' reversals are based on equal-weighted portfolios. STREV is the conventional short-term reversal strategy (see definition in footnote 4) computed from our sample.

Table 6: Laggards' reversal and stock characteristics. Within each industry and month we find the median value of stock characteristics market capitalization (Size), Turnover, the illiquidity measure of Amihud (2002) and the prior three-month return measure ($R_{t-4:t-1}$) of Cheng et al. (2017), respectively, and use it to split the sample into Small and Large characteristic groups. Then, we look for the 30th and the 70th return percentile within month, industry and Small/Large characteristic stocks and use these to follow the same procedure as discussed in Table 1 to classify stocks into Small and Large Laggards and Leaders, respectively. Finally, we compute the equal-weighted reversal strategies for the different subsamples. We report Carhart (1997) four-factor alphas and Newey-West adjusted t-statistics with 12 lags.

	Size			Turnover		
	Small	Large	Diff	Small	Large	Diff
Laggards	-3.54	-1.74	-1.80	-3.12	-2.04	-1.08
	(-9.73)	(-8.67)	(-6.57)	(-8.65)	(-7.16)	(-3.65)
Leaders	-0.29	0.19	-0.48	-0.02	0.08	-0.10
	(-0.61)	(0.72)	(-1.40)	(-0.07)	(0.20)	(-0.48)
Diff	-3.26	-1.93	-1.32	-3.10	-2.12	-0.98
	(-4.92)	(-4.90)	(-2.90)	(-5.59)	(-3.87)	(-2.60)
	Amihud			$R_{t-4:t-1}$		
	Small	Large	Diff	Small	Large	Diff
Laggards	-1.58	-3.73	2.15	-3.19	-2.28	-0.92
	(-7.28)	(-9.99)	(7.05)	(-9.23)	(-10.43)	(-3.90)
Leaders	0.29	-0.37	0.66	-0.71	0.72	-1.43
	(0.97)	(-0.82)	(2.15)	(-1.58)	(2.55)	(-4.94)
Diff	-1.87	-3.36	1.49	-2.48	-3.00	0.52
	(-4.33)	(-5.25)	(3.50)	(-3.88)	(-7.28)	(1.35)

Table 7: Laggards' reversal and market states. Laggards' reversal is computed as the equal-weighted long-short strategy as in Table 3. VIX is the average daily VIX during the previous month. Amihud INNOV ILLIQ value-weights Amihud (2002)'s stock level illiquidity measure each month and computes the innovations as the percent difference between the value in month t and its average value between months $t-1 : t-24$. PS INNOV LIQ are the innovations from Pastor and Stambaugh (2003)'s aggregate liquidity measure obtained from WRDS. SENT is the sentiment index of Baker and Wurgler (2006) and is downloaded from Jeffrey Wurgler's website. Newey-West adjusted t-statistics with 12 lags are in parentheses.

	Laggards' reversal, equal-weighted				
	(1)	(2)	(3)	(4)	(5)
Mkt-rf	0.07	-0.00	0.00	0.01	0.06
	(0.78)	(-0.09)	(0.03)	(0.13)	(0.64)
SMB	-0.06	-0.12	-0.13	-0.12	-0.05
	(-0.43)	(-1.40)	(-1.44)	(-1.35)	(-0.35)
HML	0.04	0.08	0.10	0.11	0.05
	(0.28)	(0.61)	(0.81)	(0.90)	(0.34)
RMW	0.31	0.27	0.26	0.27	0.35
	(1.73)	(1.74)	(1.73)	(1.66)	(1.82)
CMA	-0.19	-0.21	-0.22	-0.22	-0.18
	(-0.59)	(-0.95)	(-1.06)	(-1.01)	(-0.57)
UMD	-0.03	-0.05	-0.03	-0.02	-0.02
	(-0.27)	(-0.64)	(-0.37)	(-0.29)	(-0.20)
lag VIX	-0.10				-0.07
	(-2.32)				(-1.23)
lag Amihud INNOV ILLIQ		-1.00			-0.49
		(-3.16)			(-0.92)
lag PS INNOV LIQ			5.81		3.37
			(1.83)		(0.67)
lag SENT				-0.10	-0.66
				(-0.43)	(-0.98)
Constant	-0.65	-2.86	-2.85	-2.91	-1.23
	(-0.69)	(-10.45)	(-10.14)	(-9.77)	(-1.07)
Observations	387	705	705	681	387
R-squared	0.04	0.04	0.03	0.03	0.05

Table 8: Leaders' reversal and market states. Leaders' reversal is computed as the equal-weighted long-short strategy as in Table 3. For variable definitions see the caption of Table 7.

	Leaders' reversal, equal-weighted				
	(1)	(2)	(3)	(4)	(5)
Mkt-rf	-0.39	-0.25	-0.25	-0.25	-0.37
	(-1.56)	(-1.68)	(-1.68)	(-1.69)	(-1.43)
SMB	-0.10	-0.13	-0.14	-0.14	-0.08
	(-0.37)	(-0.79)	(-0.81)	(-0.79)	(-0.31)
HML	-0.19	-0.27	-0.26	-0.25	-0.15
	(-0.72)	(-1.19)	(-1.19)	(-1.15)	(-0.50)
RMW	-0.48	-0.23	-0.24	-0.25	-0.43
	(-1.17)	(-0.68)	(-0.68)	(-0.68)	(-0.96)
CMA	0.86	0.62	0.62	0.60	0.92
	(1.79)	(1.73)	(1.74)	(1.58)	(1.78)
UMD	0.54	0.59	0.60	0.60	0.58
	(1.54)	(2.41)	(2.40)	(2.39)	(1.61)
lag VIX	-0.08				-0.11
	(-0.67)				(-0.94)
lag Amihud INNOV ILLIQ		-0.45			0.66
		(-0.54)			(0.67)
lag PS INNOV LIQ			5.02		-4.65
			(0.60)		(-0.40)
lag SENT				0.08	-1.26
				(0.14)	(-0.76)
Constant	2.46	0.11	0.11	0.16	3.28
	(1.08)	(0.23)	(0.24)	(0.31)	(1.44)
Observations	387	705	705	681	387
R-squared	0.14	0.13	0.13	0.13	0.14

Table 9: Sentiment and the different legs of reversals. lag SENT low is an indicator for time periods when SENT is below its 30th percentile value and lag SENT high is an indicator for time periods when SENT is above its 70th percentile value.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Laggards Bottom 30		Laggards Top 30		Leaders Bottom 30		Leaders Top 30	
Mkt-rf	0.99	0.99	1.00	1.00	1.18	1.17	0.93	0.93
	(27.14)	(26.71)	(20.89)	(21.07)	(9.79)	(9.56)	(19.28)	(19.14)
SMB	0.88	0.89	0.76	0.76	0.92	0.93	0.79	0.79
	(12.57)	(12.45)	(10.21)	(10.70)	(8.99)	(9.06)	(8.64)	(8.70)
HML	0.01	0.01	0.13	0.14	0.19	0.18	-0.07	-0.07
	(0.15)	(0.09)	(1.61)	(1.78)	(1.33)	(1.24)	(-0.58)	(-0.58)
RMW	-0.21	-0.23	0.05	0.06	-0.24	-0.25	-0.49	-0.49
	(-2.41)	(-2.54)	(0.50)	(0.67)	(-1.14)	(-1.15)	(-2.56)	(-2.60)
CMA	0.33	0.32	0.10	0.12	-0.28	-0.29	0.32	0.31
	(3.14)	(2.97)	(0.60)	(0.72)	(-1.22)	(-1.20)	(1.78)	(1.75)
UMD	-0.13	-0.13	-0.15	-0.15	-0.58	-0.58	0.02	0.02
	(-2.00)	(-1.96)	(-4.11)	(-4.15)	(-3.63)	(-3.70)	(0.14)	(0.12)
lag SENT low	0.62		0.33		0.56		0.41	
	(1.69)		(1.03)		(1.14)		(0.85)	
lag SENT high		0.33		-0.89		0.25		0.07
		(0.91)		(-2.99)		(0.33)		(0.16)
Constant	1.87	1.98	-0.95	-0.60	0.63	0.74	0.83	0.94
	(6.44)	(7.11)	(-5.39)	(-3.81)	(1.42)	(2.77)	(3.03)	(3.81)
Observations	681	681	681	681	681	681	681	681
R-squared	0.72	0.72	0.74	0.74	0.61	0.61	0.60	0.60

Table 10: Laggards' and Leaders' contribution to short-term reversals and short-term industry momentum. Short-term reversals shown in this table are computed from our sample following the description in footnote 4. Industry momentum (IMOM) sorts stocks into portfolios based on their respective industry's average monthly return and buys (short-sells) the value-weighted portfolio of stocks from the top (bottom) two industries (using the 12 industry classification available on Kenneth French's website). The Dropping Laggards (Leaders) row recalculates the performance of the strategies without Laggards (Leaders). Newey-West adjusted t-statistics with 12 lags are in parentheses.

	Short-term reversals (STREV)	Industry momentum (IMOM)
Using all	-0.56	0.66
stocks	(-5.20)	(4.33)
Dropping	-0.45	0.52
Laggards	(-3.73)	(3.14)
Dropping	-0.70	0.84
Leaders	(-7.10)	(4.56)
Difference	0.25	-0.32
	(5.00)	(-3.63)

Table 11: Laggards' reversal: factor exposures and abnormal returns. This table shows time-series regressions for the equal-weighted and value-weighted Laggards' reversal. The explanatory variables are the factors from Fama and French (2015), the momentum factor (UMD) of Carhart (1997), the long-term reversal factor (LTREV) of De Bondt and Thaler (1985), the conventional short-term reversal factor (STREV), the short-term reversal (MS STRev) of Medhat and Schmeling (2021), value-weighted industry momentum (IMOM) using the 12 industry classification on Kenneth French's website that buys (short-sells) a value-weighted portfolio of the top (bottom) two industries and the short-term momentum (MS STMom) of Medhat and Schmeling (2021). The sample period is 1963m7-2022m3.

	Laggards' reversals, equal-weighted				Laggards' reversals, value-weighted			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mkt-rf	0.00	-0.08	-0.08	-0.04	-0.03	-0.09	-0.09	-0.02
	(0.07)	(-1.45)	(-1.92)	(-0.85)	(-0.45)	(-1.63)	(-2.25)	(-0.53)
SMB	-0.13	-0.16	-0.12	-0.04	-0.06	-0.09	-0.05	0.05
	(-1.43)	(-2.15)	(-1.69)	(-0.59)	(-0.85)	(-1.62)	(-1.04)	(1.16)
HML	0.11	0.06	-0.01	0.03	0.03	-0.01	-0.07	-0.03
	(0.90)	(0.51)	(-0.06)	(0.31)	(0.23)	(-0.04)	(-1.19)	(-0.60)
RMW	0.26	0.25	0.15	0.06	0.22	0.22	0.14	0.04
	(1.68)	(2.10)	(1.58)	(0.62)	(2.24)	(2.57)	(2.31)	(0.74)
CMA	-0.24	-0.13	-0.09	-0.06	-0.11	-0.04	0.02	0.03
	(-1.10)	(-0.71)	(-0.70)	(-0.53)	(-0.62)	(-0.23)	(0.21)	(0.37)
UMD	-0.03	0.06	0.14	0.10	-0.07	0.00	0.07	0.03
	(-0.33)	(0.99)	(3.27)	(2.45)	(-1.37)	(0.02)	(1.13)	(0.66)
LTREV		0.03		0.11		0.02		0.11
		(0.29)		(1.11)		(0.15)		(1.88)
STREV		-0.57		0.46		-0.40		0.75
		(-5.99)		(4.92)		(-3.38)		(15.31)
MS STRev		0.04		0.04		-0.00		-0.00
		(1.79)		(2.15)		(-0.10)		(-0.14)
IMOM			-0.66	-0.86			-0.73	-1.02
			(-19.24)	(-15.05)			(-30.83)	(-36.66)
MS STMom			-0.01	-0.05			0.05	0.01
			(-0.75)	(-2.33)			(3.73)	(0.62)
Constant	-2.86	-3.03	-2.42	-1.95	-1.34	-1.54	-0.93	-0.34
	(-9.92)	(-10.39)	(-10.10)	(-8.53)	(-6.97)	(-6.41)	(-7.00)	(-3.18)
R-squared	0.03	0.12	0.42	0.47	0.02	0.09	0.60	0.71
Observations	705	705	705	705	705	705	705	705

Table 12: Cross-sectional regressions to predict returns one month ahead. This table shows Fama and MacBeth (1973) cross-sectional WLS regressions with $t+1$ monthly stock returns as the dependent variable and month t Amihud's illiquidity measure (Amihud), market capitalisation (Size), cummulative stock returns between $t-12:t-1$ (MOM), log book-to-market ratio, the average return of the stock i's respective industry $\bar{R}_{j(i)}$ (i.e., short-run industry momentum) and the difference between stock i's return and the stock i's respective industry average $R_i - \bar{R}_{j(i)}$ (i.e., industry reversal) as independent variables. Amihud, Size, MOM, log BM are winsorized at 1% and 99% each month. Non-binary independent variables are standardized with their means and standard deviations. Interactions are computed using the standardized variables. Laggard, Leader and Other are defined as in Table 1. Month t winsorized size are used as weights in the cross-sectional regressions. Newey-West adjusted t-statistics with 12 lags are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Amihud	0.04	0.03	0.03	0.03	0.02	0.03
	(0.49)	(0.42)	(0.35)	(0.37)	(0.30)	(0.33)
Size	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(-1.24)	(-1.27)	(-1.20)	(-1.34)	(-1.14)	(-1.34)
MOM	0.30	0.30	0.31	0.30	0.31	0.31
	(4.18)	(4.19)	(3.97)	(4.00)	(4.03)	(3.99)
log BM	0.09	0.09	0.09	0.09	0.09	0.09
	(1.77)	(1.87)	(1.59)	(1.69)	(1.64)	(1.72)
Turnover	-0.01	-0.00	0.05	0.05	0.05	0.05
	(-0.16)	(-0.03)	(0.51)	(0.55)	(0.45)	(0.52)
$\bar{R}_{j(i)}$	0.17	0.05				
	(4.63)	(0.95)				
Other*$\bar{R}_{j(i)}$		0.09				
		(1.81)				
Laggard*$\bar{R}_{j(i)}$		0.30				
		(4.94)				
Laggard		0.11		0.13		0.11
		(1.31)		(1.69)		(1.33)
Other		0.02		0.09		0.07
		(0.24)		(0.96)		(0.78)
$R_i - \bar{R}_{j(i)}$			-0.48	-0.04		
			(-8.12)	(-0.39)		
Other*$(R_i - \bar{R}_{j(i)})$				-0.48		
				(-5.01)		
Laggard*$(R_i - \bar{R}_{j(i)})$				-0.73		
				(-5.18)		
R_i					-0.38	-0.03
					(-5.97)	(-0.32)
Other*R_i						-0.42
						(-5.29)
Laggard*R_i						-0.89
						(-5.42)
Constant	1.06	1.04	1.08	1.00	1.08	1.01
	(5.43)	(4.88)	(5.55)	(4.61)	(5.52)	(4.66)
Observations	2,433,902	2,433,902	2,433,902	2,433,902	2,433,902	2,433,902
Avg. R-squared	0.10	0.11	0.09	0.11	0.10	0.11
# of time periods	717	717	717	717	717	717

Table 13: Variable Definitions

Variable	Definition
Laggards' reversal	Using all stocks with a valid monthly return and SIC we compute equal-weighted industry returns using the 12 industry classification available on Kenneth French's website. Then, within the 2 worst (best) performing industries we buy (short sell) stocks whose returns are above (below) their respective industry's 70th (30th) return percentile.
Leader's reversals	Using all stocks with a valid monthly return and SIC we compute equal-weighted industry returns using the 12 industry classification available on Kenneth French's website. Then, within the 2 best (worst) performing industries we buy (short sell) stocks whose returns are above (below) their respective industry's 70th (30th) return percentile.
STREV	We calculate it using our sample following the definition available on Kenneth French's website: "We use six value-weight portfolios formed on size and prior (1-1) returns to construct STREV. The portfolios, which are formed monthly, are the intersections of 2 portfolios formed on size (market equity, ME) and 3 portfolios formed on prior (1-1) return. The monthly size breakpoint is the median NYSE market equity. The monthly prior (1-1) return breakpoints are the 30th and 70th NYSE percentiles. STREV is the average return on the two low prior return portfolios minus the average return on the two high prior return portfolios" We multiply the results by -1 so that consistently with the rest of our results, reversals are indicated by negative returns.
IMOM	It buys (short-sells) the value-weighted portfolio of stocks from the best (worst) performing two industries (using the 12 industry classification available on Kenneth French's website).
LTREV	Long-term reversal factor from Kenneth French's website.
MS STRev, MS STMom	As in Medhat and Schmeling (2021), we double sort stocks into deciles on prior month returns and turnover to compute value-weighted portfolios. MS STRev (MS STMom) is long in stocks that fall in the lowest (highest) turnover decile within the highest return decile, while short in stocks the fall in the lowest (highest) turnover decile within the lowest return decile of stocks.
Mkt-rf, SMB, HML, RMW, CMA	Fama-French 5 factors from Kenneth French's website available from 1963m7.
UMD	Momentum factor from Kenneth French's website..
Amihud	From the daily CRSP files we divide absolute daily return with the dollar trading volume for each day and then take the average of these daily ratios for each stock and month.

Variable	Definition
Amihud INNOV ILLIQ	Similarly to Avramov et al. (2016)'s INNOV_MKTILLIQ measure, we use the above Amihud measure, winsorize it at the 1st and 99th percentile each month and then compute value-weighted monthly averages. Finally, we compute innovations by taking the month t values and divide them with the average value during months $t-1:t-24$.
PS INNOV LIQ	Innovation in Pastor-Stambaugh aggregate liquidity series downloaded from WRDS.
SENT	Baker and Wurgler (2006) investor sentiment index downloaded from Jeffrey Wurgler's website. Available from 1965m7.
ADV	From the daily CRSP files we first compute daily dollar trading volume and aggregate that to the monthly level. ADV in month t then takes the monthly measure for month t and divides by its average for months $t-1:t-12$ similarly to Barber and Odean (2008).
MOM	For month t it is the cumulative returns from month $t-13$ to $t-2$.
Size (Market Cap)	From CRSP variables: MthPrc*ShrOut/1000.
Analyst Coverage	Number of analysts issuing 1-year ahead EPS forecasts from LSEG IBES. Available from 1976m1.
TS-SVI	Google Search Volume Index for a stock ticker obtained from the Github repository of deHaan et al. (2024). Available from 2004m1.
Info Discreetness	Information discreetness is the ID measure of Da et al. (2014a) using past three months of daily data (times 100): $sgn(R_{t:t-2})[\%\text{neg}_{t:t-2} - \%\text{pos}_{t:t-2}]$, where $R_{t:t-2}$ is the cumulative return during months t, $t-1$ and $t-2$, $sgn()$ is the sign function, and $\%\text{neg}_{t:t-2}$ ($\%\text{pos}_{t:t-2}$) is the percent of days with negative (positive) returns during the three months.

6 Appendix A: Lead-Lag model model with $N > 2$ assets

Suppose there are N assets indexed by $i =\in \{1, 2..., N\}$ and $0 < n < N$ are Leaders while $N - n$ are Laggards. Each asset has a final payoff $D^i = I + \epsilon^i$, where random variables are iid normal with $\epsilon^i \sim N(0, \sigma_\epsilon^2)$ and $I \sim N(0, \sigma_I^2)$. Similarly to the setup in the main text, $P_1^i = D^i$ for Leaders and $P_1^i = \epsilon_i + (1 - \rho)E[I|Q]$ for Laggards, where Q represents the information set of investors and ρ is the underreaction parameter. As investors understand who Leaders are, their information set can be represented with the average price of Leaders (it is a sufficient statistic), i.e., $Q = \sum_L P_1^i/n$, where the sum goes over Leader assets.

Solving for $(1 - \rho)E[I|Q]$ leads to

$$(1 - \rho)E[I|Q] = \tilde{\beta}\frac{\sum_L \epsilon^i + nI}{n} \quad with \quad \tilde{\beta} = (1 - \rho)\frac{\sigma_I^2}{\sigma_I^2 + \sigma_\epsilon^2/n}. \tag{8}$$

The econometrician can only observe average returns that include all assets. After normalizing all $t = 0$ prices to 1, average returns are

$$\bar{R_1} = \frac{\sum_N \epsilon_i + nI + (N - n)(1 - \rho)E[I|Q]}{N}. \tag{9}$$

Using the above, we can compute the required variances and covariances as follows:

$$Var(R_1^{Lead}) = \sigma_\epsilon^2 + \sigma_I^2 \quad and \quad Var(R_1^{Lag}) = \sigma_\epsilon^2 + \tilde{\beta}^2(\sigma_I^2 + \sigma_\epsilon^2/n) \tag{10}$$

$$Var(\bar{R_1}) = \frac{1}{N^2}\left[N\sigma_\epsilon^2 + (N - n)\tilde{\beta}\left(2 + \frac{(N - n)\tilde{\beta}}{n}\right)\sigma_\epsilon^2 + (n + (N - n)\tilde{\beta})^2\sigma_I^2\right] \tag{11}$$

$$Cov(R_1^{Lead}, \bar{R_1}) = \frac{1}{N}\left[\left(1 + \frac{(N - n)\tilde{\beta}}{n}\right)\sigma_\epsilon^2 + (n + (N - n)\tilde{\beta})\sigma_I^2\right] \tag{12}$$

$$Cov(R_1^{Lag}, \bar{R_1}) = \frac{1}{N}\left[\left(1 + \tilde{\beta} + \frac{(N - n)\tilde{\beta}^2}{n}\right)\sigma_\epsilon^2 + \tilde{\beta}(n + (N - n)\tilde{\beta})\sigma_I^2\right] \tag{13}$$

Using the above, the bivariate distribution of $(R_1^{Lead}, \bar{R}_1)$ follows a bivariate normal with mean zero and covariance matrix

$$\Sigma_L = \begin{pmatrix} Var(R_1^{Lead}) & Cov(R_1^{Lead}, \bar{R}_1) \\ Cov(R_1^{Lead}, \bar{R}_1) & Var(\bar{R}_1) \end{pmatrix}, \tag{14}$$

while the bivariate distribution of $(R_1^{Lag}, \bar{R}_1)$ follows a bivariate normal with mean zero and covariance matrix

$$\Sigma_{Lag} = \begin{pmatrix} Var(R_1^{Lag}) & Cov(R_1^{Lag}, \bar{R}_1) \\ Cov(R_1^{Lag}, \bar{R}_1) & Var(\bar{R}_1) \end{pmatrix}. \tag{15}$$

The econometrician observes the return of a given asset i in addition to the average return. It follows that the posterior probability of asset i being a Leader equals to:

$$Prob[Asset\ i\ is\ Leader|R_1^i, \bar{R}_1] = \frac{n\phi(R_1^i, \bar{R}_1, \Sigma_L)}{n\phi(R_1^i, \bar{R}_1, \Sigma_L) + (N-n)\phi(R_1^i, \bar{R}_1, \Sigma_F)}, \tag{16}$$

where $\phi()$ denotes the probability density function of the mean zero bivariate normal distribution.

The general solution of (17) takes the form of

$$Prob[Asset\ i\ is\ Leader|R_1^i, \bar{R}_1] = \frac{1}{1 + ae^{bR_1^{i2} + c\bar{R}_1{}^2 + dR_1^i\bar{R}_1}}, \tag{17}$$

with constants a, b, c, d depending on parameters $\sigma_\epsilon^2, \sigma_I^2, N, n$ and ρ. The solution greatly simplifies if one assumes that there is an equal number of Leaders and Laggards, i.e., $n = N/2$. In this case the solution follows the form in (6), with a more involved γ parameter. In this case it can be shown that $a = 1$, $b = 0$ and $c = -d$.