Short-Term Return Reversals and Underreaction to Industry Information

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Abstract

We present a model featuring industry lead-lag effects in which some stocks underreact to industry information. This single friction generates both industry momentum and short-term reversals. Industry momentum is a direct implication of some stocks being slower than others when pricing industry information. However, short-term reversals emerge as underreacting stocks systematically cluster in the return distribution, i.e., they cluster in the left tail after good industry news and in the right tail after bad news. We use the model to motivate a novel return-based proxy for identifying stocks that underreact to industry information (who we label Laggards) and those that do not (who we label Leaders). Our empirical results confirm the model's predictions: long-short strategies trading Laggards doubles the profitability of industry momentum and short-term reversal strategies, while implementing these strategies on Leader stocks is typically not profitable.

1 Introduction

Investor underreaction has traditionally served as a mechanism to explain return continuation, also known as momentum. Jegadeesh and Titman (1993) conjecture that momentum profits, a trading strategy that buys past winner stocks and short-sells recent loser stocks, arise due to "market underreaction to firm-specific information". Likewise, a number of articles document that stock returns tend to persistently "drift" in the direction of the initial surprise after information events, the post-earnings announcement drift being the leading example (Bernard and Thomas, 1989; Chan et al., 1999). Again, the main hypothesis is that sluggish markets lead to prices that are subject to momentum.

In this paper we argue that market underreaction can also manifest in return reversals. We start off with a model featuring industry lead-lag effects which arise due to the slow diffusion of *common* information. The stocks who we call *Leaders* are priced efficiently: their prices reveal the combined value of the common (industry) information and idiosyncratic information. However, when pricing all other stocks, who we call *Laggards*, investors are required to make an inference from Leader prices about the industry information. When investors underweight Leader prices, industry momentum follows because Laggards' stock price initially underreacts to industry information. In addition to this (and more surprisingly), within-industry return reversals emerge as Laggards are disproportionately clustered at either the left or the right tail of the industry's return distribution depending on the sign of the common shock realization. In particular, they concentrate in the left (right) tail after underreacting to a positive (negative) common shock and hence will outperform (underperform) Leaders in the subsequent period. In both of these cases stocks in the left tail perform relatively better in the subsequent period than stocks in the right tail giving us within-industry return reversals.

We use the model to motivate a simple non-parametric approach to classify stocks as Leaders and Laggards. We first assign stocks into the 12 industries using the classification on Kenneth R. French's website.[1] Then, we double sort stocks based on their respective industry's prior month average return and their own prior month stock return. A stock is a Laggard if it belongs to one of the two winner industries with its return below the 30th within-industry return percentile (loser stocks of winner industries), or, symmetrically, if it belongs to one of the two loser industries with its return above the 70th within-industry return percentile (winners of loser industries).[2]

A long-short strategy implemented on Laggards can be interpreted as *both* a short-term reversal strategy and also as a short-term industry momentum strategy. Table 1 illustrates. Consider a strategy that buys $Laggards_{W,L}$ (winner stocks of loser industries) and short-sells $Laggards_{L,W}$ (loser stocks of winner industries). This corresponds to an industry momentum strategy (times -1, to be precise) as the winner and loser industries are on the opposite legs of the strategy. However, it is also a short-term reversal strategy (times -1, to be precise), because, winner and loser stocks are also on the opposite legs of the strategy.

Our main empirical result is that a long-short strategy implemented on Laggards (a

[1] We use the 12 industry classification scheme published on Kenneth R. French's website in our benchmark specification and use the 49 industry classification to check robustness.

[2] Similarly, a stock is a Leader if it belongs to one of the two winner industries and its own return is in the highest 30 percentiles within their respective industry's return distribution, or, symmetrically, if it belongs to one of the two loser industries and its own return is in the lowest 30 percentiles within their respective industry.

	Loser industries (i.e., bottom 2/12)	Winner industries (i.e., top 2/12)
Loser stocks $R_{it} < 30th\ percentile$ within industry	$Leaders_{L,L}$	$Laggards_{L,W}$
Winner stocks $R_{it} > 70th\ percentile$ within industry	$Laggards_{W,L}$	$Leaders_{W,W}$

Table 1: Caption

strategy that we refer to as *Laggards' reversal*) outperforms both the short-run industry momentum strategy (Moskowitz and Grinblatt, 1999) and also the short-run intra-industry reversal strategy (Da et al., 2014b; Hameed and Mian, 2015). Using our baseline specification, it yields a highly significant value-weighted and risk-adjusted return of -1.28% per month (t=-7.87). The corresponding return on the unconditional within-industry reversal strategy (a strategy that uses within-industry winners and losers from *all* industries) is -0.664% per month (t=-6.08), while an industry momentum strategy that buys the top two industries and short-sells the bottom two industries each month (using *all* the stocks from the respective industries) yields a value-weighted return of 0.658% per month (t=4.33). We label this strategy "Laggards' reversal" to emphasize that returns reverse at the stock level: Fama and MacBeth (1973) regressions show that a one standard deviation increase in raw returns during the formation month is associated with a decrease in expected returns for the subsequent month by 0.9% for Laggards, while the same association is insignificant for Leaders.

In principle, two distinct empirical patterns are consistent with the above findings. Either (i) industry momentum is stronger in Laggards than in Leaders in line with our model's predictions or (ii) intra-industry reversals are stronger in the winner and loser industries compared to all other industries. We only find evidence for the former. A long-short strategy implemented using Leaders yields small and insignificant returns. That is, buying the winner stocks of winner industries ($Leaders_{W,W}$) and short-selling the loser stocks of loser industries ($Leaders_{L,L}$) is not profitable – which is consistent with our model where Leaders are correctly priced by assumption.

Interestingly, Laggards contribute to the performance of conventional short-term reversal strategies. While removing stocks randomly from a strategy should leave its average performance unchanged, removing Laggards from a strategy that only sorts stocks on their own prior month returns (the STREV strategy on Kenneth French's website) decreases its performance from 0.56% per month to 0.45% per month.[3] This suggests that some stocks find

[3] Kenneth French's website provides the following definition for the STREV strategy: "We use six value-

their ways to the tails of the return distribution by underreacting to common information that would otherwise ease the impact of stock specific information.

Our results remain significant after mitigating market microstructure biases, removing microcaps or using alternative industry classification schemes. For instance, Laggards' reversal produces statistically significant equal-weighted returns up to the 6th week after portfolio formation. Results are also robust to skipping a day between the formation month and the holding month or dropping stocks with a share price under $5. Using the 10 winner and loser industries based on the 49 industry classification scheme from Kenneth French's website leaves our results unchanged.

We provide additional results and robustness tests to enlighten potential economic mechanisms. The most prominent explanation for short-term reversals is based on liquidity provision, which we view as complementary to our findings (Lehmann, 1990). As liquidity providers are risk-averse when taking on inventory, they require compensation for immediacy, leading to return reversals (Grossman and Miller, 1988). Empirically, Nagel (2012) argues that the jump in the profitability of reversal strategies during the financial crisis of 2007-2009 indicates that the providers of liquidity faced binding capital constraints. Hameed and Mian (2015) supports this view by showing that order imbalances drive intra-industry reversals. In principle, while illiquidity should symmetrically impact both Laggards' and Leaders' reversal, we find that it is more closely related to Laggards' reversal both in the cross-section and also in the time-series domain. For instance, time-series results suggest that measures of aggregate liquidity can predict the performance of Laggards' reversal, but never predict the performance of Leader's reversal. Also, while illiquidity should, in principle, affect Leaders and Laggards symmetrically in the cross-section, we find that Laggards' reversal is influenced more by common proxies for illiquidity, like size, turnover or Amihud (2002)'s measure. These suggest that the underlying frictions causing lead-lag effects, if anything, are amplified by illiquidity.

An equally appealing explanation for short-term reversals relates to sentiment and investor overreaction (e.g., Shiller (1984), De Bondt and Thaler (1985b), Subrahmanyam (2005), Stambaugh et al. (2012), Da et al. (2014b)) which suggest that short-term reversals are a result of mispricing. We argue that the mispricing of Laggards occurs due to investor underreaction, which generates intra-industry lead-lag effects. Empirically, mea-

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". By dropping Laggards we have removed less than 10% of stocks from the STREV strategy.

sures of sentiment, like the equity share of total equity and debt issuances as in Baker and Wurgler (2000) does seem to predict the Laggards' reversal, which viewed through the lens of our model would imply that the diffusion of common information slows down during periods of higher sentiment. However, the equity share has a notable downward trend over our sample period, as does the profitability of Laggards' reversal, and once we use detrended sentiment measures, including the sentiment index of Baker and Wurgler (2006), the relation becomes economically and statistically insignificant.

The paper is closely related to the literature that has shown how stock characteristics like size, turnover, institutional ownership and analyst coverage contribute to lead-lag effects (Lo and MacKinlay, 1990; Brennan et al., 2015; Badrinath et al., 2015; Chordia and Swaminathan, 2000). Hou (2007) argues that the predictive power of such characteristics to identify lead and lag stocks primarily works within industries. This is consistent with the idea that common information typically relates to industry information.[4] Our results imply that there are likely to be important, but temporary cross-autocorrelations among individual stocks that firm size or turnover (or, in fact, any other persistent characteristic) cannot fully capture, but the joint return distribution of stocks and their respective industry's could.

2 A lead-lag model

There are two assets, *Lead*(er) and *Lag*(gard) and they pay a final dividend in $t = 2$, 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 *Lead* the asset whose news reveals its dividend and *Lag* 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 *Lead* and the *Lag*, efficient prices of both assets should contain all information revealed by news. With risk-neutrality and a unit discount factor, the price of *Lead* at $t = 1$ is $P_1^{Lead} = D^{Lead}$ 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 *Lead* does not contain additional information to predict the *Lag*'s dividend.

We now introduce the friction in the model, which we label cross-asset underreaction.

[4] Besides industry, it has also been shown that other fundamental links, like geography, shared analyst coverage or customer-supplier links all generate lead-lag effects (Parsons et al., 2020; Ali and Hirshleifer, 2020; Cohen and Frazzini, 2008).

Formally, cross-asset underreaction occurs when instead of using β, markets price the *Lag* with some $\tilde{\beta} = (1-\rho)\beta$, with $\rho \in [0,1]$ being the measure of underreaction. With $\rho > 0$ *Lag* is mispriced at $t = 1$ as it underreacts to information about I revealed in the *Lead*'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 such an underreaction. 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. In turn, stocks that are scrutinized by a wider set of investors may lead those that are only analysed by a smaller set of investors. The gradual diffusion of information (Hong and Stein, 1999) would plausibly imply that stocks are quicker to react to news released about their own companies than to news about their peers. Limited investor attention (Hirshleifer and Teoh, 2003; Da et al., 2014b) could also imply that investors prioritize less the processing of news released by other companies, like industry peers. In addition, limits to arbitrage (Shleifer and Vishny, 1997) may prevent sophisticated investors from exploiting cross-asset mispricings.

Cross-asset underreaction generates both industry momentum and intra-industry reversals as *Lag*'s price does not instantly reveal the information revealed by the *Lead*'s price ($\rho > 0$). 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, while defining reversals as the autocovariance of a strategy that is long in one stock and short in the other, yields:

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

$$Reversals : Cov(R_2^{Lead} - R_2^{Lag}, R_1^{Lead} - R_1^{Lag}) = -\rho\sigma_I^2(1-\tilde{\beta}) \leq 0. \qquad (2)$$

Both of the above directly follow from *Lag*'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 due to symmetry.

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.

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 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 (below we investigate the implications of this assumption). 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

$$\frac{\phi(R_1^i, \bar{R}_1, \Sigma_{Lead})}{\phi(R_1^i, \bar{R}_1, \Sigma_{Lead}) + \phi(R_1^i, \bar{R}_1, \Sigma_{Lag})} = \frac{1}{1 + e^{-\gamma \frac{\bar{R}_1(R_1^i - \bar{R}_1)}{\sigma_\epsilon^2}}}, \tag{6}$$

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 posterior probability in (6) is increasing in

$$\psi^{Leader} = \bar{R}_1(R_1^i - \bar{R}_1), \tag{8}$$

which we use to motivate our portfolio sorts below. In particular, winner stocks of winner industries ($R_1^i >> \bar{R}_1$ and $\bar{R}_1 >> 0$) together with loser stocks of loser industries ($R_1^i << \bar{R}_1$ and $\bar{R}_1 << 0$) are likely to be Leaders while the loser stocks of winner industries ($R_1^i << \bar{R}_1$ and $\bar{R}_1 >> 0$) together with the winner stocks of loser industries ($R_1^i >> \bar{R}_1$ and $\bar{R}_1 << 0$) are likely to be Laggards.[5][6]

3 Data

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

[5]The above assumes only two assets, which is arguably restrictive. In Appendix A we generalize the model and present a setup in which there are N assets and $0 < n < N$ are Leaders, while $N - n$ assets are Laggards. We show that the posterior of being a Leader is still proportional to ψ^{Leader} as long as $n \approx N/2$.

[6]The constant γ determines the extent to which the observed returns are informative about 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 underreaction, ρ. Note that even in the case of no underreaction ($\rho = 0$), $\gamma \geq 0$ as 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 factors.

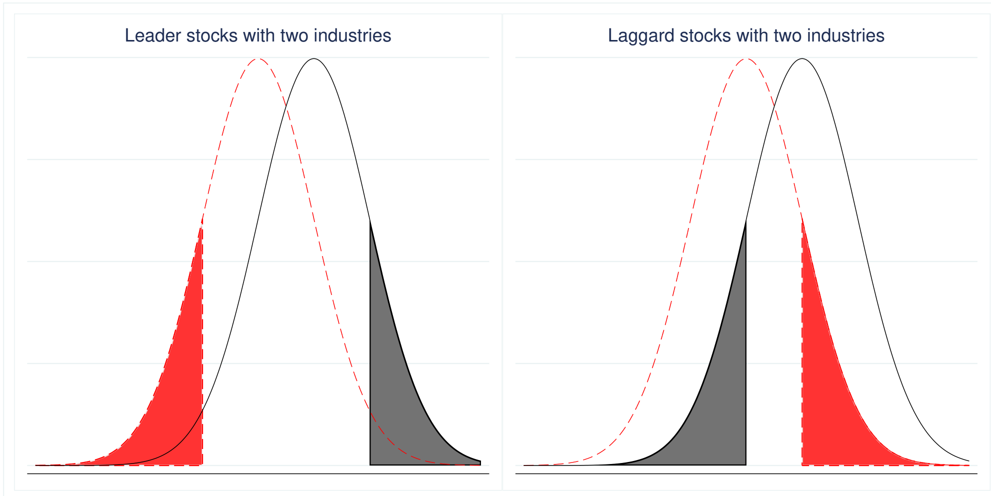

Figure 1: Classifying stocks as Leaders and Laggards.

available on Kenneth R. French's website.[7] 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 Amihud (2002)'s illiquidity measure and size can be computed) in addition to 12 months of consecutive returns (so stock momentum can also be computed), from the monthly CRSP files.[8] We filter out stocks for which we cannot compute their respective 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?

Table 2 reports the 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. Then, we double sort stocks based on their industry's monthly equal-weighted average return and their own monthly stock return. A stock is a Leader if it's return either falls above the 70th return percentile within the two best performing industries or if their return falls below the 30th return percentile within the two worst performing industries. At the same time, a stock is a Laggard if it's return either falls above the 70th return percentile within the two worst performing industries or if their return fall below the 30th return percentile within the two best performing industries. Figure 3 shows how we classify stocks as Leaders and

[7] We primarily rely on CRSP SIC codes as COMPUSTAT only reports the most recent SIC.

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

Laggards in a stylized way.

While Leaders and Laggards appear to be similar in terms of size, book-to-market and many other characteristics, Leaders experience significantly larger turnover than Laggards do. Based on the literature it is not trivial what this difference should imply for reversals. For example, Avramov et al. (2006) show that reversals are strongest in high turnover and low liquidity stocks – characteristics that appear similar to that of Leaders. To the contrary, Medhat and Schmeling (2021) find short-term momentum for high turnover stocks when double sorting stocks on prior month return and turnover. Also, the relatively low turnover of Laggards could indicate lower investor attention (Barber and Odean, 2008; Da et al., 2014a). Leaders have typically performed better on average and their return distribution also shows larger variation during the formation month. This latter finding directly follows from our classification (Figure 3 illustrates the intuition): as Leader stocks are placed in the top 30% of winner industries and bottom 30% of loser industries they will naturally have larger return variance compared to Laggards.[9]

As Leaders and Laggards are only selected from winner and loser industries, there is a concern that given the large variation in the number of industry constituents across industries, only industries with a relatively low number of constituents drive our results. A priori we would expect 9.67% of stocks to be classified as Leaders and Laggards each. Empirically, 8.8% of stocks enter these portfolios due to smaller industries making it slightly more frequently to winner and loser status.[10]

Table 3 shows Fama and MacBeth (1973) regressions where we predict Laggard and Leader status using lagged variables (except for releasing a quarterly earnings announcement which can be predicted with very high certainty). Columns (1)-(2) use our benchmark classification for Laggards and Leaders based on the two winner and two loser industries while columns (3)-(4) use a broader classification based on the six winner and six loser industries.[11] All predictors are coded as categorical variables where the "low" ("high")

[9]Understanding the higher average performance of Leaders (e.g., 3.18% as opposed to 0.91%) is less trivial. It follows from the positive cross-sectional relation between the within-industry variance of stock returns and average industry returns. I.e., the variance of returns is increasing in the mean of stock returns across industries. During our sample period the average standard deviation of stock returns for stocks in the loser (winner) industry was 12% (16%) and the relation between industry ranks and return standard deviation is approximately monotonic. In turn, winner industries have a larger influence on the average returns of Leaders and Laggards. As Leaders (Laggards) come from the top (bottom) end of the distribution within winner industries, Leaders have larger average returns.

[10]During our sample period, the industry with the smallest average number of constituents had 65 (Telcm) while the industry with the largest number of average constituents had 515 (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, reassuringly, Other (77 months).

[11]I.e., we double sort stocks based on their industry's monthly equal-weighted average return and their

indicator corresponds to the lowest (highest) 30 percentiles in the given month's respective distribution.

Again, lagged turnover stands out as one of the best predictors for becoming a Leader. In addition, to proxy for fluctuations in liquidity provision we follow Cheng et al. (2017) and compute the prior quarter's return ("3M return") and find that stocks experiencing poor performance during the prior quarter (indicative of relatively low liquidity) have a larger probability of becoming a Leader. At the same time, the partial relation between Amihud (2002)'s illiquidity measure (lagged) and Leader status is insignificant in column (2) implying that illiquidity is unlikely to play a major role here.[12]

Other proxies for investor attention, like releasing a quarterly earnings announcement or the information discreetness ("Info discreetness") measure of Da et al. (2014a) appear to be more important predictors of Leader status than of Laggard status.[13] This is consistent with our framework in which Leaders are typically priced more efficiently than Laggards as these proxies are thought to be increasing with investor attention.

Finally, we note that Laggard and Leader status is persistent to some extent. I.e., a Laggard is approximately 70% more likely to become a Laggard compared to the unconditional probability using our benchmark classification and the same holds for Leaders. This largely follows from the persistence of industry winner/loser status. Columns (3)-(4) show that persistence remains statistically significant even with the broader Laggard* and Leader* classification using all industries.

4 Results

This section presents our main results. We first show that a long-short strategy implemented on Laggards yields strong reversals while a similar strategy implemented on Leaders does not earn significant returns. Standard factors together with an industry momentum factor and a short-term reversal factor cannot fully account for this. Then, we show that industry momentum, industry reversals and short-term reversals are all significant predictors for Laggards' future stock returns – and not for Leaders'. Finally, we show that characteristics

own monthly stock return. A stock is a Leader* if it's return either falls above the 70th return percentile within the six best performing industries or if their return falls below the 30th return percentile within the six worst performing industries. At the same time, a stock is a Laggard* if it's return either falls above the 70th return percentile within the six worst performing industries or if their return fall below the 30th return percentile within the six best performing industries.

[12] We use daily returns, volume and price to compute Amihud (2002)'s illiquidity measure by averaging the daily values of $|R_{i,d}|/(vol_{i,d} * prc_{i,d})$ for each month for each stock.

[13]Info discreetness is defined as $sign(R_{t-2:t})(\%neg - \%pos)$ where $sign(R_{t-2:t}$ is the sign of a stock's cumulative return during the prior quarter, $\%neg$ ($\%pos$) is the percent of days with negative (positive) returns during the prior quarter.

indicative of illiquidity and/or information frictions amplify Laggards' reversals more than they amplify Leaders' reversals in both the cross-section and the time-series domains.

4.1 Laggards' and Leaders' reversals

Our benchmark results in Table 4 Panel B show that a long-short strategy trading Laggards generates reversal returns of -2.83% per month with equal-weighted portfolios or -1.36% with value-weighted portfolios. This clearly exceeds the performance of the corresponding strategy implemented using Leader stocks – the latter's performance being statistically insignificant. The intra-industry reversal strategy that uses stocks from all industries gives comparable results to the ones in the literature, e.g., our estimate of -1.45% per month is close to the one in Da et al. (2014b) who report a raw performance of 1.20% per month for a similar strategy using a slightly different specification. Adjusting for standard risk factors, like a four factor model, does not lead to noticeable differences.

The fact that Laggards produce large and significant reversals, while Leaders do not is a striking result. While Leaders and Laggards are similarly illiquid during the formation month based on Table 2, Leaders experience more extreme returns as shown on Panel A of Table 4. Hence, Leaders would appear more likely to experience price pressure or investor overreaction. While these mechanisms are likely at play to some extent, the results suggest that industry links play at least an equally important role here.

To illustrate this point, we repeat the analysis using placebo industries. In particular, we take the annual empirical distribution of the number of industry constituents and use it to classify stocks into 12 placebo industries each year (we reclassify stocks every year). Using these, we compute the placebo industry average returns and use those together with the individual stock returns to classify stocks as (placebo) Laggards and Leaders following the same procedure as with "true" industries. We repeat this 1000 times and report statistics from these trials in Table 5. Not surprisingly, placebo Leaders produce slightly, though often not significantly, larger reversals than placebo Laggards. More importantly, even the most extreme estimates obtained from 1000 trials fail to come close to our results based on "true" industries. E.g., the largest reversal of placebo Laggards out of 1000 trials gives an average equal-weighted return of -1.28% per month, whereas with "true" industries the corresponding estimate is -2.83%. Figure 5 illustrates the distribution of t-statistics obtained from the 1000 trials corresponding to the null hypothesis that Laggards' and Leaders' equal-weighted reversal perform equally. While with "true" industries we reject this hypothesis with a Newey-West t-statistic of -6.84, the 1000 Newey-West t-statistics based on placebo industries have a mean of 2.35 with a standard deviation of 1.00 – placing our estimate over 9 standard deviations away from the placebo mean. Taken together, these suggest that industry links play an essential role in our setting.

We do 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 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 only 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 6 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. 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 specifications presented in Table 6 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.

We round off this section with spanning tests to investigate how Laggards' reversal relates to common risk factors, conventional reversal strategies and to industry momentum. Table 7 reports the results for both equal-weighted and value-weighted results. First, common risk factors like 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.[14] Finally, other factors like

[14] See STREV's definition in footnote 3. Note that in line with our definition of reversals, we multiply the returns of STREV by -1, so negative profits are associated with reversals. IMOM buys a value-weighted

the long-term reversal factor (LTREV) of De Bondt and Thaler (1985a) and the short-term reversal and short-term momentum strategies of Medhat and Schmeling (2021) show little to no partial correlations with Laggards' reversal.[15]

Interestingly, columns (2) and (6) reveal that when excluding industry momentum controls, the partial relation between STREV and Laggards' reversal is negative, i.e., when cross-sectional reversals are larger, Laggards' reversal is weaker. However, controlling for industry momentum flips these relations, which shows that industry momentum and short-term reversals are moderately correlated. The correlation coefficient between STREV and IMOM is, in fact, 0.70, which tells us that these strategies are intimately related. In particular, stronger industry momentum is associated with weaker cross-sectional reversals – a noteworthy finding we believe has not yet been highlighted in the literature.[16]

4.2 Relation to short-term reversal and industry momentum

Table 8 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 do not expect significant changes to its mean return. However, when we drop Laggards (following our benchmark definition as in Table 2), 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 STREV (IMOM) strategy.

To the contrary, dropping Leaders improves the performance of these portfolios. While this directly follows from our previous result in case of IMOM, it is somewhat surprising for STREV. Moreover, Leaders also do not appear to be contributing by providing added diversification, as dropping them *decreases* the standard deviations of these long-short portfolios.[17] Again, Leaders are relatively illiquid 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 4. This modest return continuation significantly hinders the performance of both STREV (because it is a return continuation)

portfolio of the 2 winner industries and short-sells a value-weighted portfolio of the 2 loser industries each month using the 12 industry classification on Kenneth French's website.

[15] 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.

[16] The positive correlation in this case implies that when the industry momentum performs well (yields positive returns), STREV performs relatively poorly (i.e., does not yield large and negative returns)

[17] 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%.

and IMOM (because it is only modest).

We also perform cross-sectional tests to illustrate that both reversals towards industry averages as well as industry momentum effects are strongest in Laggards. Table 9 shows results from estimating Fama and MacBeth (1973) regressions using one month lagged market capitalisation 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 2) 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 intra-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 intra-industry reversals 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.

To investigate the return persistence of the various portfolios, we compute Wednesday to Tuesday weekly stock returns to track the performance of Laggards' reversal, Leaders' reversal, industry momentum and STREV. 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 continue to track the performance of the long-short strategies during each of the 11 weeks after portfolio formation. Since our weekly returns always start on Wednesdays, we skip 1-7 days between the end of the formation month and the first holding period week[18]

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. This apparent persistence, which resembles that persistence of the equal-weighted industry momentum portfolio also shown on Figure 4, further supports the notion that Laggards' reversal is driven by these stocks' initial underreaction to industry information.

4.3 Exploring heterogeneity

The previous literature has found that smaller and more illiquid stocks exhibit stronger reversals (Nagel, 2012; Hameed and Mian, 2015) while higher turnover can signal short-term

[18]E.g., if the first trading day in a month is Monday, we skip Tuesday, but if the first trading day is a Tuesday, we skip an entire week.

momentum (Medhat and Schmeling, 2021). To address the concern that our findings are not trivial implications of these associations we first find the median value of size (market equity) within each industry and month to sort stocks into two groups (small caps and large caps). Then, we find the 30th and 70th percentile of the return distribution within each industry, month and size group and use these breakpoints to classify stocks as Leaders and Laggards. We also repeat this with turnover, Amihud's illiquidity measure (as defined in footnote 12) and the previous quarter's return prior to the formation month as in Cheng et al. (2017) to proxy for fluctuations in liquidity provision. As expected, Table 10 shows that smaller stocks, stocks experiencing less trading, relatively illiquid stocks and stocks that have experienced smaller returns during the previous quarter all show stronger reversals.

However, Table 10 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. Through the lens of our model, these suggest that adverse trading/stock characteristics amplify investor underreaction.

Interestingly, turnover does not seem to be associated with the reversal of Leaders, while market equity (size) is also only weakly related to Leaders' reversals. This is surprising given the evidence that reversals decrease with turnover (Medhat and Schmeling, 2021) and decrease with size (Nagel, 2012). On the other hand, sorting on the prior quarter's return leads to a large and significant difference. One possibility is that proxies such as size or turnover capture multiple adverse effects potentially pointing in opposite directions. That is, one group of Leaders could potentially overshoot due to illiquidity during the formation month while another group of Leaders underreact to industry news.[19] While both of these effects could be larger for stocks with small market capitalisation or smaller turnover, they offset each other, making Leaders appear to be priced more efficiently, on average. On the other hand, using proxies for illiquidity, like Amihud's measure (Amihud, 2002) or the measure for liquidity provision as in Cheng et al. (2017) suggest that, in fact, illiquid Leaders tend to reverse while relatively liquid Leaders may even be subject to significant return continuation.

Time-series tests focusing on adverse market conditions lead to similar conclusions. Table 11 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,

[19] This would also be in line with the result of the strong negative time-series association between the performances of IMOM and STREV noted above.

which is in line with investors allocating more attention to market news, e.g., an implication of category learning (Peng and Xiong, 2006).

Comparing the results in Tables 11 and 12 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.[20] As there is a significant downward trend in the illiquidity series, we compute innovations from it by computing 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 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 11 implies that a one standard deviation increase in aggregate illiquidity increases reversals by -0.60% 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 only the reversals of small market capitalisation stocks are influenced by market illiquidity.

Finally, market sentiment is known to influence many asset pricing anomalies (Stambaugh et al., 2012), and also reversals in particular (Da et al., 2014b). In column (5) of Tables 11-12 we also find that one measure of sentiment, lagged equity share (equity issuance over the issuance of debt plus equity during the past 12 months) as in Baker and Wurgler (2000) increases reversals for both Laggards and Leaders. However, equity share – similarly to the performance of Laggards' reversal – trends over our sample period implying that the results are likely to be spurious. In fact, with stationary measures, like the sentiment index of Baker and Wurgler (2006), we do not find evidence for an association between sentiment and reversals.[21]

5 Conclusions

We consider a simple model featuring lead-lag effects and use it to motivate a proxy for Laggards (stocks that are likely to underreact to common information) and Leaders (stocks

[20] We only include NYSE and AMEX stocks here due to the differences in how volume is reported across exchanges.

[21] Given that sentiment typically amplifies the performance of anomalies through their short-legs (Stambaugh et al., 2012), we repeat the analysis of Tables 11- 12 separately for the long and short legs of the respective strategies but do not find significant relations.

that react in a timely way to common information). Applying the model to industry information, we classify winner stocks of loser industries and loser stocks of winner industries as Laggards, while Leaders are the winner stocks of winner industries and loser stocks of loser industries.

A long-short strategy implemented on Laggards reveals that industry momentum (Moskowitz and Grinblatt, 1999) is mainly driven by Laggards. More importantly, Laggards also contribute to the performance of short-term reversal strategies (Lehmann, 1990) as the common (industry) information which is being priced with a delay is initially offset by stock specific information.

There is surprisingly little that predicts a stock becoming a Laggard. Measures of illiquidity or investor attention measures like turnover or the information discreetness measure of Da et al. (2014a) are not relevant predictors. At the same time, Laggard status is persistent to some extent even after considering the persistence in industry performances. This suggests that some stocks experience sustained periods during which they become slower at incorporating common information.

The profitability of Laggards' reversal during our sample period 1962-2022 is striking. While some of this performance can be attributed to the profitability of industry momentum (Moskowitz and Grinblatt, 1999) and short-term reversals (Lehmann, 1990), these documented strategies together with conventional risk factors (Fama and French, 2015) do not seem to span the performance of Laggards' reversal. We also find that illiquidity amplifies Laggards' reversal more than it amplifies Leaders' reversal in the cross-section, while aggregate illiquidity and market uncertainty as measured by the VIX only predict Laggards' reversal. Taken together, these suggest that underreaction to common information is deepened by illiquidity and market uncertainty.

Our direction of future research is to further explore the links between momentum and reversals. The results in this paper suggest that investor underreaction to common information is a friction that influences the performances of both short-term industry momentum but also short-term reversals. Future research could investigate the links between these with a unified framework accounting for both investor underreaction and variation in liquidity provision.

Table 2: 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. Then, we double sort stocks based on their industry's 1 month equal-weighted average return and their 1 month stock return. A stock is a Leader if it's return either falls above the 70th return percentile within the two best performing industries or if their return falls below the 30th return percentile within the two worst performing industries. At the same time, a stock is a Laggard if it's return either falls above the 70th return percentile within the two worst performing industries or if their return fall below the 30th return percentile within the two best performing industries. For number of analysts following a stock (Analyst coverage) the sample begins from 1982m7, while for the earnings announcement indicator (EA) it is available from 1973m1. Information discreetness is the ID measure of Da et al. (2014a) using past three months of daily data (times 100). For other variables, the sample period is 1962m7-2022m3.

	Leaders	Laggards	Other
N	302.05	300.31	2792.20
R_{it}	3.18	0.91	1.10
$\sigma(R_{it})$	22.03	12.90	13.13
5th percentile of R_{it}	-23.04	-16.64	-16.01
95th percentile of R_{it}	34.54	20.28	20.08
Log market cap	4.93	4.99	4.99
Log BM	-0.55	-0.54	-0.50
MOM	0.14	0.14	0.14
Turnover	0.13	0.10	0.09
Amihud	4.79	4.72	4.27
IO	0.22	0.23	0.25
Analyst coverage	1.62	1.53	1.49
EA	0.30	0.30	0.28
Information discreetness	1.54	1.26	1.03

Table 3: Cross-sectional regressions to predict Laggard and Leader status. This table shows Fama and MacBeth (1973) regressions with binary dependent variables in month t (indicators for Laggards and Leaders) and binary independent variables computed using information up to the end of month $t-1$ (except for the earnings announcement indicator). Columns (1)-(2) use our benchmark classification of Laggards and Leaders while columns (3)-(4) use a similar classification but instead of only using the two winner and two loser industries, it uses six winner and six loser industries. Each month we find the 30th and 70th percentile of our predictors and transform them into "low" and "high" indicators if they are below the 30th percentile or above the 70th percentile of their respective distributions. "Ret 3M" is the cumulative stock return during the prior quarter as in Cheng et al. (2017). "Info discreetness" is the information discreetness measure of Da et al. (2014a). The sample period is 1973m1-2022m3. Newey and West (1987) adjusted t-statistics are in parenthesis.

	(1)	(2)	(3)	(4)
	Laggard	Leader	Laggard*	Leader*
Lag Amihud low	0.0017	-0.0016	-0.0174	-0.0212
	(1.17)	(-0.80)	(-9.46)	(-8.17)
Lag Amihud high	0.0027	0.0009	0.0193	0.0192
	(2.22)	(0.63)	(12.80)	(8.37)
Lag Size low	0.0051	0.0051	0.0208	0.0224
	(4.30)	(3.87)	(11.17)	(12.72)
Lag Size high	-0.0010	-0.0048	-0.0177	-0.0211
	(-0.80)	(-3.86)	(-9.67)	(-9.41)
Lag Turnover low	0.0010	-0.0060	-0.0115	-0.0270
	(0.80)	(-3.98)	(-9.17)	(-17.04)
Lag Turnover high	0.0018	0.0175	0.0156	0.0416
	(1.76)	(9.86)	(11.96)	(19.65)
Earnings Announcement	0.0034	0.0067	0.0222	0.0286
	(3.56)	(5.05)	(9.83)	(11.47)
Lag Analyst coverage low	0.0001	-0.0000	-0.0001	-0.0000
	(0.62)	(-0.32)	(-1.45)	(-1.20)
Lag Analyst coverage high	-0.0034	-0.0033	-0.0069	-0.0057
	(-4.07)	(-3.94)	(-6.37)	(-5.50)
Lag 3M return low	0.0037	0.0102	0.0131	0.0281
	(4.22)	(8.80)	(8.14)	(13.44)
Lag 3M return high	0.0014	0.0038	0.0118	0.0171
	(1.54)	(3.40)	(8.55)	(11.69)
Lag Info discreetness low	-0.0005	-0.0018	-0.0058	-0.0070
	(-0.90)	(-2.57)	(-5.84)	(-5.93)
Lag Info discreetness high	0.0011	0.0035	0.0051	0.0086
	(1.75)	(4.47)	(5.11)	(6.96)
Lag Laggard	0.0639	0.0481		
	(12.34)	(12.98)		
Lag Leader	0.0494	0.0627		
	(13.14)	(12.11)		
Lag Laggard*			0.0242	0.0136
			(14.21)	(9.23)
Lag Leader*			0.0155	0.0251
			(10.99)	(13.25)
Constant	0.0724	0.0687	0.2719	0.2623
	(43.10)	(41.83)	(184.87)	(159.08)
Observations	2,237,699	2,237,699	2,237,699	2,237,699
Avg. R-squared	0.036	0.043	0.016	0.021
Number of months	591	591	591	591

Table 4: Portfolios of Leaders and Laggards. Stocks are sorted as described in Table 2. 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	Equal-weighted				Value-weighted			
group	All	Laggards	Leaders	Diff	All	Laggards	Leaders	Diff
Panel A: Formation month returns								
Bottom 30	-11.77	-8.28	-14.55		-8.08	-5.14	-11.52	
Middle 40	-0.04	.	.		0.27	.	.	
Top 30	14.85	9.51	19.84		9.94	5.96	14.35	
Panel B: 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	-1.45	-2.83	0.31	-3.14	-0.66	-1.36	0.26	-1.62
- Bottom	(-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)

Table 5: Results with placebo industries. We repeat the analysis presented in Table 4 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 4 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
Statistics of Top-Bottom reversals 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
Statistics of Top-Bottom 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

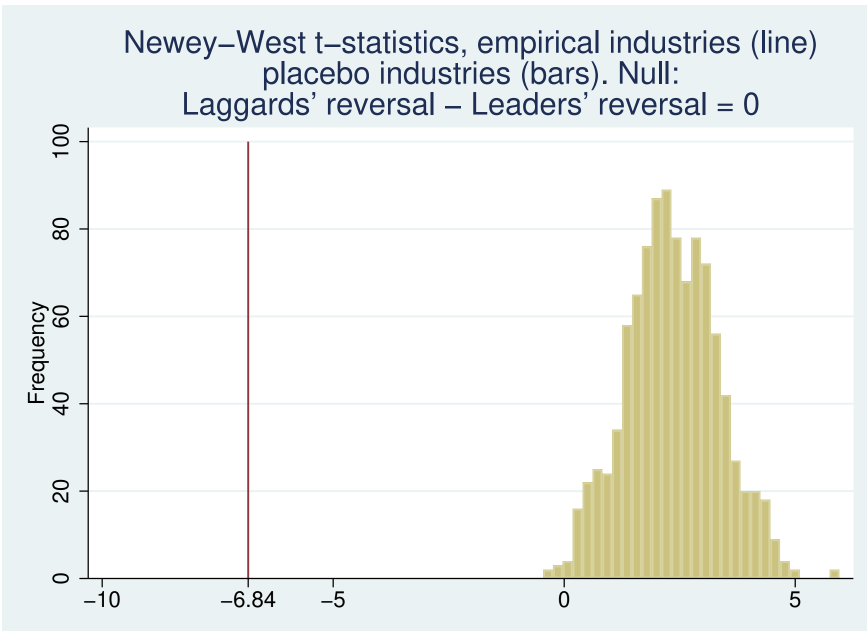

Figure 2: Histogram of t-statistics with sorting stocks into placebo industries. We repeat the analysis presented in Table 4 with placebo industries. Using the respective annual empirical distribution of stocks across the 12 Fama-French industries to randomly assign stocks into 12 placebo industries, 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 4 with placebo industries. We repeat this 1000 times and compute the statistic corresponding to the "Top-Bottom" row and equal-weighted "Diff" column in Table 4. The vertical line shows the t-statistic based on actual industries while the bars show the distribution of the 1000 t-statistics based on placebo industries.

Table 6: Results with limiting market microstructure biases and alternative industry classifications. This table repeats the analysis of Table 4 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
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)

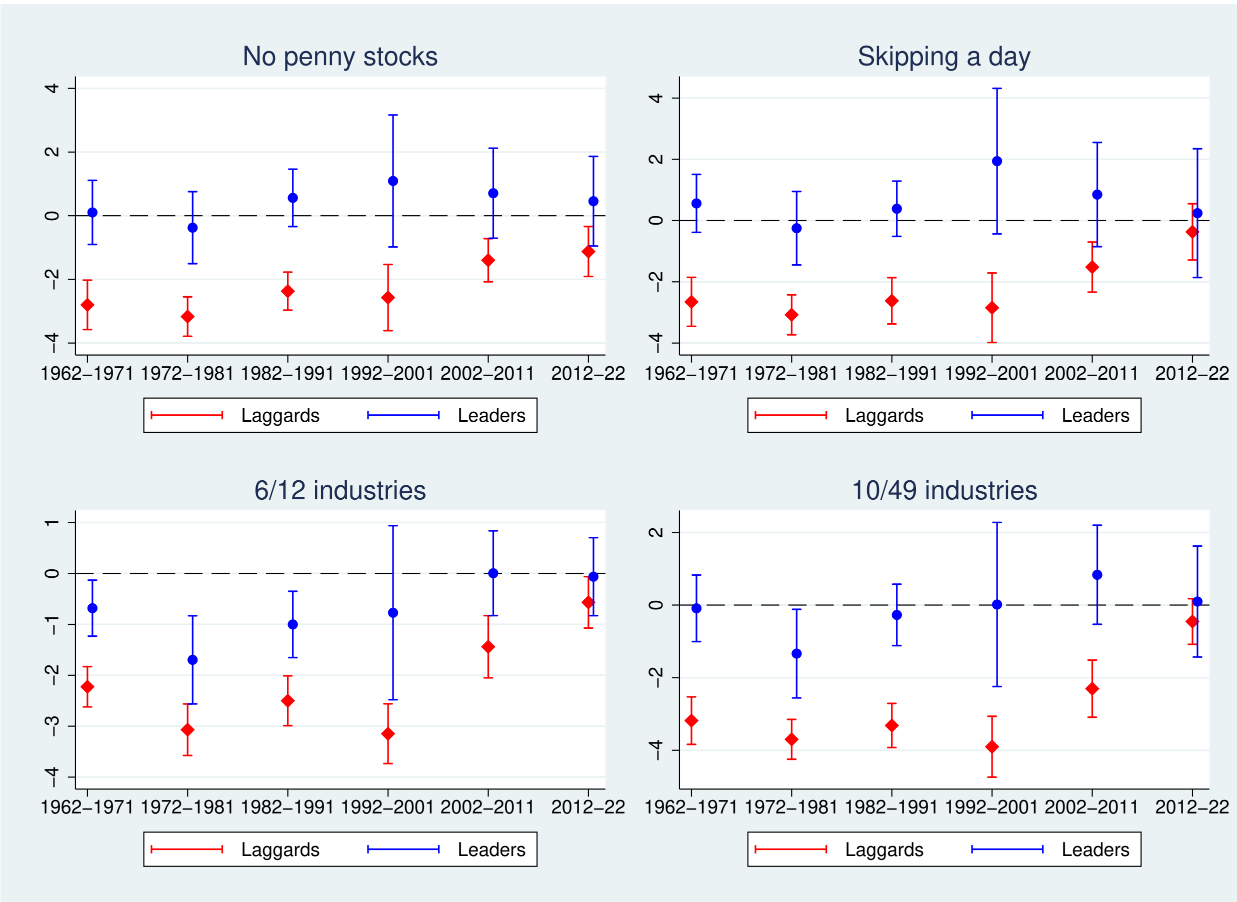

Figure 3: Reversals of Laggards (diamonds) and Leaders (circles) per decade. The figures show equal-weighted return reversals for the four specifications tabulated in Table 6 for each decade separately in our sample together with their 95% confidence intervals. The four panels correspond to (i) dropping 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").

Table 7: 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 (1985a), 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 8: 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 3. 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 stocks	-0.56 (-5.20)	0.66 (4.33)
Dropping Laggards	-0.45 (-3.73)	0.52 (3.14)
Dropping Leaders	-0.70 (-7.10)	0.84 (4.56)
Difference	0.25 (5.00)	-0.32 (-3.63)

Table 9: 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 2. 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

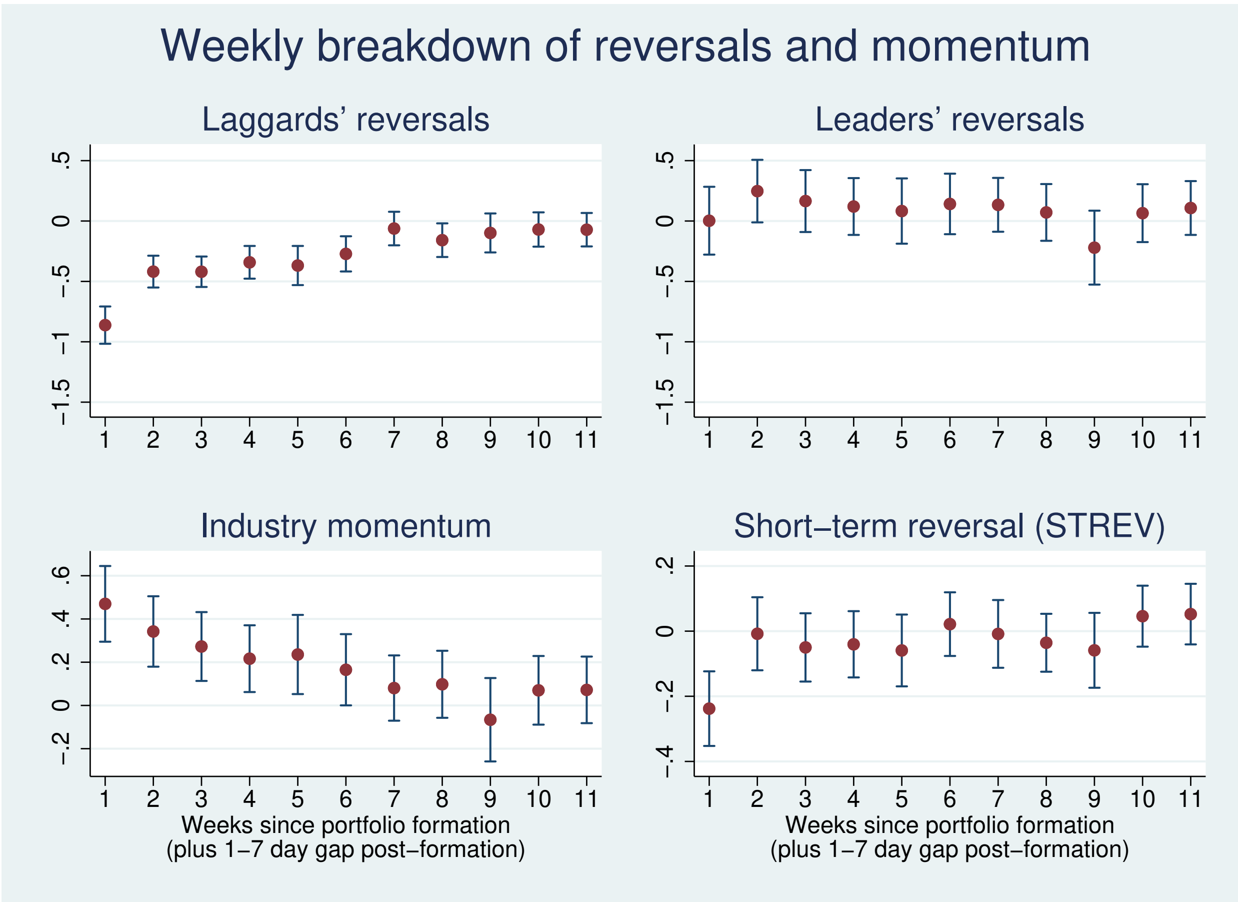

Figure 4: Persistence of the performance of reversals and industry momentum. We compute Wednesday to Tuesday weekly stock returns and use these to track the performance and their 95% confidence intervals of the various strategies based on monthly sorts. We skip 1-7 day(s) between portfolio formation and the holding period depending on the first day of the holding period month (i.e., 7 for Wednesdays, 6 for Thursdays ... and 1 for Tuesdays). Laggards' and Leaders' reversals are based on equal-weighted portfolios. Industry momentum is the equal-weighted strategy that buys (short-sells) the top (bottom) 2 industries each month using the 12 industry classification on Kenneth French's website. STREV is the conventional short-term reversal strategy (see definition in footnote 3) computed from our sample.

Table 10: 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 11: Laggards' reversal and market states. Laggards' reversal is computed as the equal-weighted long-short strategy as in Table 4. 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 month $t-1:t-24$. PS INNOV LIQ are the innovations from Pastor and Stambaugh (2003)'s aggregate liquidity measure obtained from WRDS. EquityShare is the total volume of equity issues over the prior twelve months divided by the total volume of equity and debt issues over the prior twelve months from Federal Reserve Bulletin as in Baker and Wurgler (2000). SENT is the sentiment index of Baker and Wurgler (2006). SENT and EquityShare are 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)	(6)
Mkt-rf	0.07	-0.00	0.00	-0.00	0.01	0.06
	(0.78)	(-0.05)	(0.03)	(-0.07)	(0.13)	(0.63)
SMB	-0.06	-0.13	-0.13	-0.13	-0.12	-0.06
	(-0.43)	(-1.41)	(-1.44)	(-1.54)	(-1.35)	(-0.43)
HML	0.04	0.07	0.10	0.13	0.11	0.06
	(0.28)	(0.57)	(0.81)	(1.08)	(0.90)	(0.42)
RMW	0.31	0.27	0.26	0.25	0.27	0.35
	(1.73)	(1.78)	(1.73)	(1.59)	(1.66)	(1.86)
CMA	-0.19	-0.19	-0.22	-0.23	-0.22	-0.15
	(-0.59)	(-0.88)	(-1.06)	(-1.07)	(-1.01)	(-0.49)
UMD	-0.03	-0.05	-0.03	-0.02	-0.02	-0.02
	(-0.27)	(-0.63)	(-0.37)	(-0.28)	(-0.29)	(-0.17)
lag VIX	-0.10					-0.02
	(-2.32)					(-0.35)
lag Amihud INNOV ILLIQ		-1.20				-1.00
		(-3.10)				(-1.39)
lag PS INNOV LIQ			5.81			3.46
			(1.83)			(0.70)
lag EquityShare				-8.13		-15.51
				(-3.49)		(-2.35)
lag SENT					-0.10	-0.58
					(-0.43)	(-0.96)
Constant	-0.65	-2.90	-2.85	-1.51	-2.91	-0.40
	(-0.69)	(-10.56)	(-10.14)	(-2.89)	(-9.77)	(-0.33)
Observations	387	705	705	705	681	387
R-squared	0.04	0.04	0.03	0.05	0.03	0.06

Table 12: Leaders' reversal and market states. Leaders' reversal is computed as the equal-weighted long-short strategy as in Table 4. For variable definitions see the caption of Table 11.

	Leaders' reversal, equal-weighted					
	(1)	(2)	(3)	(4)	(5)	(6)
Mkt-rf	-0.39	-0.25	-0.25	-0.25	-0.25	-0.37
	(-1.56)	(-1.69)	(-1.68)	(-1.73)	(-1.69)	(-1.44)
SMB	-0.10	-0.13	-0.14	-0.14	-0.14	-0.07
	(-0.37)	(-0.79)	(-0.81)	(-0.82)	(-0.79)	(-0.27)
HML	-0.19	-0.27	-0.26	-0.23	-0.25	-0.16
	(-0.72)	(-1.22)	(-1.19)	(-1.07)	(-1.15)	(-0.54)
RMW	-0.48	-0.23	-0.24	-0.25	-0.25	-0.44
	(-1.17)	(-0.67)	(-0.68)	(-0.71)	(-0.68)	(-0.98)
CMA	0.86	0.63	0.62	0.61	0.60	0.89
	(1.79)	(1.77)	(1.74)	(1.70)	(1.58)	(1.73)
UMD	0.54	0.59	0.60	0.61	0.60	0.57
	(1.54)	(2.41)	(2.40)	(2.44)	(2.39)	(1.60)
lag VIX	-0.08					-0.14
	(-0.67)					(-1.21)
lag Amihud INNOV ILLIQ		-0.72				0.90
		(-0.63)				(0.60)
lag PS INNOV LIQ			5.02			-4.72
			(0.60)			(-0.41)
lag EquityShare				-6.64		13.83
				(-2.50)		(1.06)
lag SENT					0.08	-1.34
					(0.14)	(-0.84)
Constant	2.46	0.08	0.11	1.21	0.16	2.33
	(1.08)	(0.17)	(0.24)	(1.99)	(0.31)	(1.33)
Observations	387	705	705	705	681	387
R-squared	0.14	0.13	0.13	0.13	0.13	0.15

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, 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

$$(1-\rho)E[I|Q] = \tilde{\beta}\frac{\sum_L \epsilon^i + nI}{n} \quad with \quad \tilde{\beta} = (1-\rho)\frac{\sigma_I^2}{\sigma_I^2 + \sigma_\epsilon^2/n}. \tag{9}$$

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

$$\bar{R_1} = \frac{\sum_N \epsilon_i + nI + (N-n)(1-\rho)E[I|Q]}{N}. \tag{10}$$

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

$$Var(R_1^{Lead}) = \sigma_\epsilon^2 + \sigma_I^2 \quad and \quad Var(R_1^{Lag}) = \sigma_\epsilon^2 + (1-\rho)\tilde{\beta}\sigma_I^2 \tag{11}$$

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

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

$$Cov(R_1^{Lag}, \bar{R_1}) = \frac{1}{N}\left[\left(1 + \tilde{\beta} + \frac{(N-n)\tilde{\beta}^2}{n}\right)\sigma_\epsilon^2 + \tilde{\beta}(n + (N-n)\tilde{\beta})\sigma_I^2\right] \tag{14}$$

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

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

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

$$\Sigma_{Lag} = \begin{pmatrix} Var(R_1^{Lag}) & Cov(R_1^{Lag}, \bar{R}_1) \\ Cov(R_1^{Lag}, \bar{R}_1) & Var(\bar{R}_1) \end{pmatrix}. \tag{16}$$

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:

$$Prob[Asset\ i\ is\ Leader|R_1^i, \bar{R}_1] = \frac{n\phi(R_1^i, \bar{R}_1, \Sigma_L)}{n\phi(R_1^i, \bar{R}_1, \Sigma_L) + (N-n)\phi(R_1^i, \bar{R}_1, \Sigma_F)}, \tag{17}$$

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

The general solution of (18) takes the form of

$$Prob[Asset\ i\ is\ Leader|R_1^i, \bar{R}_1] = \frac{1}{1 + ae^{bR_1^{i2} + c\bar{R}_1^{\,2} + dR_1^i \bar{R}_1}}, \tag{18}$$

with constants a, b, c, d depending on parameters $\sigma_\epsilon^2, \sigma_I^2, N, n$. 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 $c = d$.

References

Ali, Usman and David Hirshleifer (2020), “Shared analyst coverage: Unifying momentum spillover effects.” *Journal of Financial Economics*, 136, 649–675, URL `https://ideas.repec.org/a/eee/jfinec/v136y2020i3p649-675.html`.

Amihud, Yakov (2002), “Illiquidity and stock returns: cross-section and time-series effects.” *Journal of Financial Markets*, 5, 31–56.

Avramov, Doron, Si Cheng, and Allaudeen Hameed (2016), “Time-Varying Liquidity and Momentum Profits.” *Journal of Financial and Quantitative Analysis*, 51, 1897–1923, URL `https://ideas.repec.org/a/cup/jfinqa/v51y2016i06p1897-1923_00.html`.

Avramov, Doron, Tarun Chordia, and Amit Goyal (2006), “Liquidity and autocorrelations in individual stock returns.” *The Journal of Finance*, 61, 2365–2394, URL `http://www.jstor.org/stable/3874713`.

Badrinath, S.G., Jayant R. Kale, and Thomas H. Noe (2015), “Of Shepherds, Sheep, and the Cross-autocorrelations in Equity Returns.” *The Review of Financial Studies*, 8, 401–430, URL `https://doi.org/10.1093/rfs/8.2.401`.

Baker, Malcolm and Jeffrey Wurgler (2000), “The equity share in new issues and aggregate stock returns.” *The Journal of Finance*, 55, 2219–2257, URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/0022-1082.00285`.

Baker, Malcolm and Jeffrey Wurgler (2006), “Investor sentiment and the cross-section of stock returns.” *Journal of Finance*, 61, 1645–1680.

Barber, Brad M and Terrance Odean (2008), “All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors.” *Review of Financial Studies*, 21, 785–818.

Bernard, Victor L. and Jacob K. Thomas (1989), “Post-earnings-announcement drift: Delayed price response or risk premium?” *Journal of Accounting Research*, 27, 1–36, URL `http://www.jstor.org/stable/2491062`.

Brennan, Michael J., Narasimhan Jegadeesh, and Bhaskaran Swaminathan (2015), “Investment Analysis and the Adjustment of Stock Prices to Common Information.” *The Review of Financial Studies*, 6, 799–824, URL `https://doi.org/10.1093/rfs/6.4.799`.

Carhart, Mark M (1997), “On persistence in mutual fund performance.” *Journal of Finance*, 52, 57–82.

Chan, Louis K. C., Narasimhan Jegadeesh, and Josef Lakonishok (1999), "The profitability of momentum strategies." *Financial Analysts Journal*, 55, 80–90, URL `http://www.jstor.org/stable/4480210`.

Cheng, Si, Allaudeen Hameed, Avanidhar Subrahmanyam, and Sheridan Titman (2017), "Short-Term Reversals: The Effects of Past Returns and Institutional Exits." *Journal of Financial and Quantitative Analysis*, 52, 143–173, URL `https://ideas.repec.org/a/cup/jfinqa/v52y2017i01p143-173_00.html`.

Chordia, Tarun and Bhaskaran Swaminathan (2000), "Trading volume and cross-autocorrelations in stock returns." *The Journal of Finance*, 55, 913–935, URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/0022-1082.00231`.

Cohen, Lauren and Andrea Frazzini (2008), "Economic links and predictable returns." *The Journal of Finance*, 63, 1977–2011, URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.2008.01379.x`.

Conrad, Jennifer, Mustafa N. Gultekin, and Gautam Kaul (1997), "Profitability of short-term contrarian strategies: Implications for market efficiency." *Journal of Business Economic Statistics*, 15, 379–386, URL `http://www.jstor.org/stable/1392341`.

Da, Zhi, Umit G. Gurun, and Mitch Warachka (2014a), "Frog in the Pan: Continuous Information and Momentum." *Review of Financial Studies*, 27, 2171–2218, URL `https://ideas.repec.org/a/oup/rfinst/v27y2014i7p2171-2218..html`.

Da, Zhi, Qianqiu Liu, and Ernst Schaumburg (2014b), "A Closer Look at the Short-Term Return Reversal." *Management Science*, 60, 658–674, URL `https://ideas.repec.org/a/inm/ormnsc/v60y2014i3p658-674.html`.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam (1998), "Investor psychology and security market under- and overreactions." *The Journal of Finance*, 53, 1839–1885, URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/0022-1082.00077`.

De Bondt, Werner F M and Richard Thaler (1985a), "Does the Stock Market Overreact?" *Journal of Finance*, 40, 793–805, URL `https://ideas.repec.org/a/bla/jfinan/v40y1985i3p793-805.html`.

De Bondt, Werner FM and Richard Thaler (1985b), "Does the stock market overreact?" *Journal of Finance*, 40, 793–805.

Fama, Eugene F and Kenneth R French (1992), "The cross-section of expected stock returns." *Journal of Finance*, 47, 427–465.

Fama, Eugene F. and Kenneth R. French (2015), "A five-factor asset pricing model." *Journal of Financial Economics*, 116, 1–22, URL https://ideas.repec.org/a/eee/jfinec/v116y2015i1p1-22.html.

Fama, Eugene F and James D MacBeth (1973), "Risk, return, and equilibrium: Empirical tests." *Journal of Political Economy*, 81, 607–636.

Grossman, S.J. and M.H. Miller (1988), "Liquidity And Market Structure." *Journal of Finance*, 43, 617–633.

Hameed, Allaudeen and G Mujtaba Mian (2015), "Industries and stock return reversals." *Journal of Financial and Quantitative Analysis*, 50, 89–117.

Hirshleifer, David and Siew Hong Teoh (2003), "Limited attention, information disclosure, and financial reporting." *Journal of Accounting and Economics*, 36, 337–386, URL https://www.sciencedirect.com/science/article/pii/S0165410103000648. Conference Issue on.

Hong, Harrison and Jeremy C. Stein (1999), "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets." *Journal of Finance*, 54, 2143–2184, URL https://ideas.repec.org/a/bla/jfinan/v54y1999i6p2143-2184.html.

Hou, Kewei (2007), "Industry Information Diffusion and the Lead-lag Effect in Stock Returns." *Review of Financial Studies*, 20, 1113–1138, URL https://ideas.repec.org/a/oup/rfinst/v20y2007i4p1113-1138.html.

Jegadeesh, Narasimhan and Sheridan Titman (1993), "Returns to buying winners and selling losers: Implications for stock market efficiency." *Journal of Finance*, 48, 65–91.

Lehmann, Bruce N. (1990), "Fads, Martingales, and Market Efficiency." *The Quarterly Journal of Economics*, 105, 1–28, URL https://ideas.repec.org/a/oup/qjecon/v105y1990i1p1-28..html.

Lo, Andrew W. and A. Craig MacKinlay (1990), "When are contrarian profits due to stock market overreaction?" *The Review of Financial Studies*, 3, 175–205, URL http://www.jstor.org/stable/2962020.

Luo, Jiang, Avanidhar Subrahmanyam, and Sheridan Titman (2021), "Momentum and Reversals When Overconfident Investors Underestimate Their Competition [The financial crisis of 2007–2009: Causes and remedies]." *Review of Financial Studies*, 34, 351–393, URL `https://ideas.repec.org/a/oup/rfinst/v34y2021i1p351-393..html`.

Medhat, Mamdouh and Maik Schmeling (2021), "Short-term Momentum." *The Review of Financial Studies*, 35, 1480–1526, URL `https://doi.org/10.1093/rfs/hhab055`.

Merton, Robert C. (1987), "A simple model of capital market equilibrium with incomplete information." *The Journal of Finance*, 42, 483–510, URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1987.tb04565.x`.

Moskowitz, Tobias J. and Mark Grinblatt (1999), "Do Industries Explain Momentum?" *Journal of Finance*, 54, 1249–1290, URL `https://ideas.repec.org/a/bla/jfinan/v54y1999i4p1249-1290.html`.

Nagel, Stefan (2012), "Evaporating Liquidity." *Review of Financial Studies*, 25, 2005–2039, URL `https://ideas.repec.org/a/oup/rfinst/v25y2012i7p2005-2039.html`.

Newey, Whitney K and Kenneth D West (1987), "A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix." *Econometrica*, 55, 703–708.

Parsons, Christopher A, Riccardo Sabbatucci, and Sheridan Titman (2020), "Geographic Lead-Lag Effects." *Review of Financial Studies*, 33, 4721–4770, URL `https://ideas.repec.org/a/oup/rfinst/v33y2020i10p4721-4770..html`.

Pastor, Lubos and Robert F. Stambaugh (2003), "Liquidity Risk and Expected Stock Returns." *Journal of Political Economy*, 111, 642–685, URL `https://ideas.repec.org/a/ucp/jpolec/v111y2003i3p642-685.html`.

Peng, Lin and Wei Xiong (2006), "Investor attention, overconfidence and category learning." *Journal of Financial Economics*, 80, 563–602, URL `https://ideas.repec.org/a/eee/jfinec/v80y2006i3p563-602.html`.

Shiller, Robert J. (1984), "Stock Prices and Social Dynamics." *Brookings Papers on Economic Activity*, 15, 457–510, URL `https://ideas.repec.org/a/bin/bpeajo/v15y1984i1984-2p457-510.html`.

Shleifer, Andrei and Robert W. Vishny (1997), "The limits of arbitrage." *The Journal of Finance*, 52, 35–55, URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1540-6261.1997.tb03807.x`.

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

Subrahmanyam, Avanidhar (2005), "Distinguishing Between Rationales for Short-Horizon Predictability of Stock Returns." *The Financial Review*, 40, 11–35, URL `https://ideas.repec.org/a/bla/finrev/v40y2005i1p11-35.html`.