# Cross-Firm Information Flows and the Predictability of Stock Returns

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First draft: April 10, 2013
This draft: January 7, 2015

**ABSTRACT**

We use Granger causality tests to identify all return leader-follower pairs among individual stocks. Thus-identified leaders can reliably predict their followers' returns out of sample, and the return predictability works at the level of individual stocks rather than industries. We show that small stocks can lead the returns of large stocks and conjecture that a firm may emerge as a return leader when it is at the center of an important news development that has ramifications for other firms. Support for this conjecture is found by showing that, all else equal, firms with more news stories written about them lead the returns of a larger number of other stocks. Consistent with the view that the magnitude of mispricing is related to arbitrage costs, we observe that less liquid stocks react to their leaders' return signals with a longer delay.

**JEL classification:** G10, G12, G14, G17

**Keywords:** Information Leadership, Lead-Lag Effect, Corporate News Announcements, Limited Attention, Market Efficiency

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The views expressed in this paper are those of the authors and not necessarily those of the Board of Governors, other members of its staff, or the Federal Reserve System. Anna Scherbina acknowledges the support of the Q Group.

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# I. Introduction

In early 1994, six African-American employees of Texaco Inc. filed a racial discrimination lawsuit against their employer claiming that they were discriminated against in salaries and promotions. In an attempt to expedite a resolution, Reverend Jesse Jackson called for a national boycott of Texaco Inc. The lawsuit was eventually settled in late 1996 for over $140 million, making it the largest settlement for a racial discrimination case at the time. As described in a November 17, 1996, *New York Times* article, the lawsuit potentially affected other companies as well.[1] In particular, Rev. Jackson announced not only that the Texaco boycott would continue but also that his organization, the Rainbow PUSH Action Network, would study the affirmative action policies of other companies that shared directors with Texaco Inc., such as Gillette, Johnson & Johnson, and Campbell Soup. The article also quoted a lawyer representing firms in discrimination lawsuits as saying, "If you are a consumer-product company, you are quite vulnerable. If you're an Exxon, or an American Express, or a Texaco, it's a big exposure."

While prior literature has shown that a stock with a high level of investor attention can lead returns of stocks with low levels of investor attention by being the first to react to common macroeconomic news, the evidence in this paper suggests that a stock can also lead returns of other stocks by being at the center of a news development that has ramifications for other firms. There are many instances in which firm-specific news could affect other companies. For example, a discovery of questionable accounting practices at one firm can cause investors to lose faith in financial statements of other firms that apply similar accounting techniques. Labor scandals or product safety concerns may negatively impact other firms with comparable production processes. When a firm expands to a new country with an unproven track record of dealing with foreign businesses, news about that firm's experience may be relevant for other firms also seeking to expand to that country. Consequently, we

[1] "Size of Texaco Discrimination Settlement Could Encourage More Lawsuits," by Steven A. Holmes, *New York Times*, November 17, 1996.

demonstrate that an individual stock can have a collection of "bellwether" stocks that can forecast that stock's return.[2]

The direction of a stock's return leadership may be positive or negative, depending on the circumstances. For example, bankruptcy rumors will have a negative impact on customers, suppliers, and providers of capital, but a positive impact on the firm's competitors. Labor scandals in developing countries that involve U.S. corporations may spread to other U.S. firms that use cheap foreign labor, but corporations based entirely in the United States could benefit by attracting socially-minded investors and consumers. Similarly, some firms stand to lose and some to win depending on how a patent infringement lawsuit is resolved.[3]

These examples illustrate that information can flow in unexpected directions. We argue that a stock can lead the returns of other stocks by being at the center of a valuation-relevant issue. To that extent, we show that stocks can lead the returns of stocks that are larger and operate in a different industry. Return leadership can be short-lived and disappear once the issue is resolved. News coverage data obtained from Thomson-Reuters News Analytics enable us to confirm that, all else equal, firms with more news stories written about them tend to lead the returns of a larger number of other firms.

This paper contributes to the literature on slow information diffusion. There is ample evidence in the literature that prices react slowly to a firm's own news (e.g., the post-earnings

[2] Of course, the bellwether stocks do not have to be limited to the firms in the news and may comprise firms with high levels of investor attention, single-segment firms, or firms in the same supply chain, as per the earlier literature reviewed later in the paper.

[3] This is illustrated by a recent copyright infringement lawsuit that was initiated by publisher John Wiley & Sons and eventually tried by the Supreme Court. The case was determining whether it is allowed to purchase a copyrighted item in one market and then undersell the copyright owner's local price in another, more expensive, market. In that case, the petitioner in the Supreme Court case, Surap Kirtsaeng, resold John Wiley & Sons' foreign-edition textbooks in the United States at a higher price than the purchase price he paid for them elsewhere and was subsequently sued by John Wiley & Sons, the respondent in the Supreme Court case. A diverse set of firms, spanning several industries, filed amicus briefs in this case. In particular, the Association of American Publishers, the Motion Pictures Association of America, the Business Software Alliance, and the Software and Information Industry Association, among others, which prefer that goods may be sold at different prices in different markets without anyone engaging in price arbitrage, filed amicus briefs in support of John Wiley & Sons, while Ebay, Costco, Google, the American Library Association, the Association of Art Museum Directors, Powell's Books Inc., the Association of Service and Computer Dealers International, and other organizations that prefer goods to be purchased and resold freely across markets filed amicus briefs in support of the opponent.

announcement drift). Prices may react slower still when the relevant news is announced by a different firm, especially when that news is of non-routine nature, making it difficult to immediately assess its effect on the firm's value. Every day, a large number of firms release new information. Using a near-complete sample of corporate press releases issued between April 2006 and August 2009, Neuhierl, Scherbina, and Schlusche (2013) estimate that, in the aggregate, about 218 value-relevant news are announced by firms each day. Of these, only 19.61% announce relatively routine financial news (such as earnings, sales, dividends, plans to raise or return capital, etc.), while the rest make less routine announcements about products, partnerships, strategic plans, corporate lawsuits, and so on. These news announcements have the potential to affect valuations of other firms, but reaction time may be slow if investors (1) overlook relevant news announcements by other firms due to limited attention or (2) are unable to quickly assess the degree of relevance of other firms' news due to slow processing of complex information.

Employing Granger causality tests to identify leader-follower pairs allows us to approach the question of how information flows across stocks purely empirically, without the need to first postulate the direction of the information flow. The results of this approach, therefore, could help uncover new patterns of information flows. The methodology is implemented as follows. In every month (week) and for each combination of stocks $i$ and $j$, we regress monthly (weekly) returns of stock $i$ on the lag of its own return, the lag of stock $j$'s return, and the lag of the market return, using rolling regression windows that are at least one year long. Stock $j$ is said to Granger-cause the return of stock $i$ if the absolute value of the $t$-statistic on stock $j$'s lagged return exceeds 2.00 (or 2.57 in a robustness check). Having run these rolling regressions for all stock pairs, we are able to identify a set of leaders for each stock in each month (week), if such leaders exist. We hypothesize that the leaders' ability to forecast the return of their followers will persist for at least another month (week). Hence, we proceed to calculate an aggregate predictive signal from all leaders for a follower's return. To calculate the aggregate leader signal, we first multiply the estimated regression coefficient on a leader's lagged return by its current-month's return to obtain the individual leader signal and then calculate the weighted average of all leaders' individual signals.

We confirm that this methodology is indeed able to identify legitimate return leaders. We show that stocks with high aggregate leader signals earn high returns and stocks with low aggregate leader signals earn low returns in the subsequent month (week), controlling for other factors known to predict returns.[4] The leaders' documented ability to predict their followers' returns is unlikely to be explained by data snooping. To illustrate that, we scramble our panel data along the time dimension while preserving each cross section. The leaders that we identify using this dataset are therefore all false leaders that should not possess any predictive ability for their followers' returns, and we show that they indeed do not. Moreover, the return differential between high- and low-leader-signal portfolios exhibits the properties of other documented anomalies: Its magnitude declines over time and it is stronger for smaller, more neglected stocks. Finally, we show that short sellers increase their shorting demands for stocks that receive low leader signals, which suggests that sophisticated investors trade on leader signals.

This paper presents novel evidence of slow information diffusion by showing that stock prices are slow to incorporate information originating at other firms, and our setting lends itself well to investigating the speed of price discovery. Our analysis of break-even transaction costs suggests that the economic benefit of trading on this form of delayed information processing is not very high. In order to exploit the slow information diffusion, the long-short portfolios need to be formed quickly. As a result, the price impact of trade is likely to be high due to the inability to spread trades over time, which limits the dollar amount that could be profitably invested in the strategy. While price impacts for more heavily traded stocks will be lower, we show that these stocks incorporate their leader signals with a shorter delay, weakening the profitability of the trading strategy. These results support the view that the market, although not perfectly efficient, is competitive, and that stock prices tend to fall

[4]Moreover, we show that leaders identified at a monthly frequency and leaders identified at a weekly frequency have an independent forecasting ability.

within no-arbitrage bounds around the fair value (see, e.g., Shleifer and Vishny (1997) and Lo (2004)).

To sum up, the paper's contribution to the literature is three-fold. First, it uses Granger causality tests to identify leader/follower pairs among individual stocks and shows that this methodology uncovers legitimate leaders with a reliable out-of-sample forecasting ability for their followers' returns. This hypothesis-free approach could help uncover new channels of information flows. Second, the paper documents that leaders can be smaller and can belong to a different industry than their followers. This finding suggests that stocks can lead other stocks by being at the center of an important valuation-relevant news development. This hypothesis is confirmed by showing that, all else equal, stocks that receive more news coverage lead returns of a larger number of other stocks. Third, the paper shows that the speed of information diffusion is related to arbitrage costs by documenting that information is incorporated more quickly into prices of the more liquid stocks.

## Relation to the existing literature

This paper is related to the lead-lag literature, which has documented that some stocks (leaders) react faster than other stocks (followers) to common macroeconomic shocks. Lo and MacKinlay (1990) document that leaders are large firms and followers are small firms by showing that large firms predict returns of small firms, but not vice versa. Although non-synchronous trading or time-varying expected returns could give rise to the lead-lag effect, Lo and MacKinlay (1990), Chordia and Swaminathan (2000), and Anderson, Eom, Hahn, and Park (2012) determine that only a small fraction of the effect can be attributed to these explanations. Subsequent studies have shown that other ex-ante stock characteristics that proxy for investor attention are also positively associated with information leadership. These characteristics include analyst coverage (Brennan, Jegadeesh, and Swaminathan (1993)), institutional ownership (Badrinath, Kale, and Noe (1995)), and trading volume (Chordia and Swaminathan (2000)).

We take steps to ensure that the predictive ability of leaders cannot be attributed to non-synchronous trading. We limit the sample of followers to only the stocks that traded on the last day of the previous period, thus largely eliminating the concern about non-synchronous trading. Additionally, for the portfolio results, we require that all followers be priced above $5 per share, which ensures that portfolios are comprised of rather liquid stocks. Moreover, the predictive ability of the monthly strategy survives skipping one month before portfolio formation for equal-weighted portfolios, and the weekly strategy survives skipping up to three weeks for equal-weighted and up to two weeks for value-weighted portfolios.

As one may expect, leaders' predictive power is stronger for smaller followers. Yet, in contrast to the results in the lead-lag literature, the strategy works better when leaders are small rather than large stocks: Equal-weighting signals across leader stocks results in a stronger predictive power for the followers' returns than value-weighting signals across leaders. This finding suggests that information flowing from large firms is incorporated into the followers' prices faster than information flowing from small firms. This is not surprising. While large firms may be quicker to react to common market- or industry-wide news, small firms can themselves be the originators of relevant news. Yet investors initially are more likely to underreact to small-firm news due to limited attention. We further illustrate that leaders may be small stocks by restricting the set of leaders to stocks that are smaller than their followers and showing that the strategy works almost as well. Since firms may lead returns of other firms by originating valuation-relevant news, leaders may be small firms and followers may be large firms.

Thus, the first important distinction from the lead-lag literature is that small firms can lead returns of larger firms. The second distinction is that we are able to make within-industry long-short bets. In contrast, Hou (2007) documents that large firms in a particular industry lead small firms in that industry, but not small firms in a different industry. Relying on this kind of large-firm signal would preclude making long-short bets *within* industries, as all stocks in the same industry will receive the same signal. Moreover, in a robustness check, we require that leaders reside in a different industry than their followers and show that the strategy still works. From an investor's perspective, intra-industry long-short bets are industry-neutral, ensuring lower volatility of the long-short return differential and therefore offer a better hedge than long-short bets made over the entire stock sample without regard for portfolios' industry composition.

Recent papers have uncovered new channels of cross-firm information flows. In particular, Menzly and Ozbas (2010) document that information travels between supplier and customer industries, and Hong, Torous, and Valkanov (2007) present evidence that some industries even have the ability to lead the entire market. The information transfer literature in accounting shows that early earnings announcers predict earnings surprises of late announcers within the same industry.[5] Again, these signals will be correlated for all followers within an industry, precluding within-industry long-short bets. Cohen and Lou (2012) show that information diffuses slowly from single-segment firms to multi-industry conglomerates. In this setting, the signals would also be correlated within an industry. Cohen and Frazzini (2008) find that information travels slowly through the supply chain; in that setup, followers in the same industry may receive uncorrelated signals, but, similarly to the lead-lag literature, leaders tend to be larger firms.[6]

These aforementioned papers assume that the set of leaders for a given firm is predetermined by the firm's customer/supplier ties or by the industry affiliation of its segments. The advantage of Granger causality tests used in this paper is its ability to identify both stable (or recurring) leaders, such as those determined by supply-chain links, and transitory (or non-recurring) leaders, whose leadership for a given firm may be short-lived and disappears

[5]In contrast to the information transfer literature, the leaders' predictive ability documented here is not tied to their earnings announcement activity: When we limit the set of leaders to those that are not announcing earnings in the current month, they still reliably predict their followers' returns in the following month.

[6]More recent work documents excessive contemporaneous return correlations among stocks with common institutional ownership (Anton and Polk (2014)) and common analyst coverage (Israelsen (2013); Gao, Moulton, and Ng (2014) show that stocks with common institutional ownership cross-predict each other's returns. Since our dataset starts in 1929, which predates widespread institutional owners and analyst coverage, we believe that our results are independent of these phenomena.

once a news development is resolved. Moreover, this methodology is not limited by data availability (for example, firms are required by the SEC to report only the identity of any customer that comprises more than 10% of a firm's consolidated sales revenues, and hence the less prominent customers will be missing from the dataset, which would make it impossible to identify all customer/supplier pairs).

The paper proceeds as follows: Section II explains the methodology used to identify information leaders. Section III documents the ability of leaders to predict the returns of their followers out-of-sample. Section IV provides evidence that sophisticated investors trade on the strategy described in this paper. Section V investigates the determinants of leadership. Section VI concludes.

## II. Identifying Information Leaders

We identify information leaders for each stock $i$ based on its leaders' ability to Granger-cause stock $i$'s return. Specifically, using a rolling window of 12 months (or 36 months) including the current month $\tau$ we run the following monthly regression for each combination of stocks $i$ and $j$:[7]

$$Ret_t^i = b_0^{ij} + b_1^{ij} Ret_{t-1}^{mkt} + b_2^{ij} Ret_{t-1}^i + b_3^{ij} Ret_{t-1}^j + \epsilon_t^{ij}, \tag{1}$$

where we require that both stocks $i$ and $j$ have 12 (36) monthly return observations available. Stock $j$ is assumed to Granger-cause the return of firm $i$ if the absolute value of the $t$-statistic for the estimated regression coefficient $\hat{b}_3^{ij}$ is greater than 2.00 (or 2.57 in a robustness check). Furthermore, if the estimated coefficient $\hat{b}_3^{ij}$ is positive, we say that stock $j$ is a positive leader of stock $i$, and if negative, a negative leader.[8]

[7] For the ease of exposition, all descriptions in this section are for monthly return frequencies. However, we also consider weekly return frequencies.

[8] We were able to verify on a subsample of data that our results are about the same if we estimate regression (1) and compute leader signals with factor-adjusted instead of raw returns $Ret_t^i$ and $Ret_t^j$. The reasons are that, firstly, factor loadings are typically unable to explain extreme leader returns that produce leader signals in the top or bottom signal deciles and, secondly, any tilt in factor loadings in the follower portfolios that may occur is adjusted for when the follower portfolio returns are subsequently regressed on factors in order

When choosing the length of the estimation window, two considerations need to be balanced. On the one hand, it is beneficial to have a longer regression period to reduce noise. On the other hand, making the rolling window overly long will prevent us from uncovering relatively short-lived leader-follower pairs. We therefore settle for two rolling window lengths, 12 months and 36 months.[9]

Many leaders are misidentified as such due to estimation noise. The following quick calculation illustrates how many stocks are likely to be falsely identified as leaders for each stock $i$. For each potential follower $i$, the average number of cross-sectional regressions (1) being run every month equals the average size of the monthly cross section of stocks minus one for stock $i$ itself, or $3,304.68 - 1$. Under the assumption that the leaders for stock $i$ are all stocks $j$ for which $|t\text{-statistic}(\hat{b}_3^{ij})| \geq 2.00$, if the distribution of the estimated coefficients $\hat{b}_3^{ij}$ is perfectly normal, the associated likelihood of falsely identifying as leaders stocks whose true coefficient $\hat{b}_3^{ij}$ equals zero is 4.55% (the two-tailed p-value corresponding to a $t$-statistic with an absolute value of 2.00). On average, this amounts to about 150 false leaders per follower.[10]

Table 1 provides descriptive statistics for leaders and followers. The data are calculated as of January 31 of each year. Leaders are drawn from an unrestricted dataset that includes all stocks in the CRSP universe. We restrict the set of potential followers to domestic common stocks with share codes 10 or 11 that had a trade on the last day of the previous month and are priced at or above \$5 per share in 2011 inflation-adjusted dollars. Hence, leaders are drawn from a somewhat larger set of stocks than followers.[11] The table shows that

to calculate abnormal returns. Since factor adjustment introduces noise, we report the results based on identifying leaders with raw returns.

[9]In the Texaco example from the introduction, during the period from January 1994 to December 1997 when the lawsuit was ongoing, Texaco is identified as a positive leader for Gillette in January 1994 and from July to October 1994, as a positive leader for Campbell Soup from February to April 1994 and again in January 1996, as a negative leader for American Express from July to September 1995, and as a positive leader for American Express from April to July 1997 when the 12-month rolling regression window is used.

[10]As will be discussed later in the paper, the actual distribution is more fat-tailed, resulting in somewhat more false leaders.

[11]Our results are only slightly weakened when we limit the set of potential leaders to common stocks of U.S.-incorporated firms.

every stock eligible to be classified as a follower has, on average, 287 leaders (stock-month observations with no leaders are assigned a value of zero). This does not imply that the difference between 287 and 150 equals the number of independent leaders. Many "true" leaders, especially large leaders for small followers, are likely to offer correlated signals by virtue of reacting to common information shocks ahead of the followers. Hence, the number of "independent" leaders is likely to be smaller. Finally, a vast majority, 84% of all firm-month observations, have at least one leader.

When focusing on stocks that have at least one leader, the table shows that positive leaders slightly outnumber negative leaders. The absolute value of the coefficient $\hat{b}_3^{ij}$ is about 0.9 for both positive and negative leaders. For a given follower, its leaders do not typically belong to the same industry, but more positive than negative leaders do. Finally, despite the share price restriction on the followers and none on the leaders, the table shows that a follower stock tends to be smaller, to have a lower turnover, and to be younger than its average leader stock. The last sub-table sorts, every month, all followers into quintiles based on the number of leaders that a follower has. It can be seen that the stocks with the smallest number of leaders tend to be larger and more heavily traded than other stocks; this is consistent with the result form the lead-lag literature that smaller and less liquid stocks typically have more liquid, large-stock leaders, which are simply the first to react to common macro news.

Table A1 in the Online Appendix reports the persistence of leader-follower pairs over time. The results for the 12-month and 36-month rolling regression windows are reported in Panels A and B, respectively. Having identified a leader-follower pair on January 31 of year $t$, we calculate the probability that this leader-follower pair also existed up to 10 years back—in January of year $t - \tau$, with $\tau \in \{1, ..., 10\}$—conditional on both the leader and the follower being present in the CRSP dataset at least 12 months or 36 months, respectively, prior to January of year $t - \tau$. The panels present these probabilities separately for all leaders, independent of the leadership sign in year $t$, requiring that the leadership sign be preserved in year $t - \tau$, and for positive and negative leaders only, analogously requiring that the positive (negative) leadership sign be preserved in year $t-\tau$. We use as a baseline the probability that a leader-follower pair also existed 10 years earlier and report, for every year $t-\tau$, the "excess" probability relative to this baseline (probability in $t-\tau$ minus probability in $t-10$).[12]

The table shows that the probability of a leader-follower relation also existing up to five years prior is significantly higher than the baseline probability. Moreover, as expected, these probabilities decline smoothly when moving further back in time since the firm pairs are likely to have fewer similarities. In Panel B, the estimated probabilities of leader-follower pairs being identified as such are substantially higher for prior years 1 and 2 than in Panel A because of the overlapping estimation windows. Positive leader-follower pairs are somewhat more persistent than negative leader-follower pairs. When compared to the baseline number of year $t-10$, the persistence of a leader-follower pair disappears around year 5 for all leader-follower pairs, and around year 7 for positive leader-follower pairs when leaders are identified with a 12-month estimation window; in case of a 36-month leader estimation window, the persistence disappears around years 7 and 8, respectively.[13]

# III. Return Predictability

Having obtained a set of $J_\tau^i$ leaders for each stock $i$ in month $\tau$, if such leaders exist, we proceed to calculate the aggregate leader signal. We do so by simply summing up the products of each current month's (or week's) leader return and the corresponding coefficient estimate $\hat{b}_3$:

$$Signal_\tau^i = \sum_{j=1}^{J_\tau^i} w_j \hat{b}_{3\tau}^{ij} Ret_\tau^j, \tag{2}$$

[12]We do so to adjust for the likelihood of identifying a "false leader," as discussed above. Instead of this adjustment, we could have used the $p$-value corresponding to the $t$-statistic with an absolute value of 2.00 to capture the probability of identifying a "false leader." However, this approach could produce misleading results if the true empirical distribution of the estimated coefficients $b_3$ is non-normal.

[13]Years $t-6$ through $t-9$ are omitted due to space constraints but are available upon request.

where $w_j$ is the weight on leader $j$'s signal. In our baseline set of results, signals are equal-weighted across stock $i$'s leaders, in which case ($w_j = 1/J^i_\tau$). The inset box in Figure 1 illustrates how the aggregate equal-weighted leader signal is computed.[14]

In the following, we present results based on portfolio sorts and cross-sectional return regressions. As mentioned earlier, though our leaders can be any stocks, we restrict the set of potential followers to domestic common stocks with share codes 10 or 11 that had a trade on the last day of the previous month (or on the last day of the previous week for weekly-frequency portfolios).[15] In all portfolio results, we require that followers be priced above \$5 per share in 2011 inflation-adjusted dollars at the end of the last period. The data used in the paper are described in Section A1 of the Online Appendix.

## A. Monthly portfolio returns

### 1. Baseline specification

In the baseline specification, we identify leaders with 12-month rolling regression windows and equal-weight signals across leaders. Having estimated signals for each follower stock in month $\tau$, within each of the 36 industries that remain after the industry "Irrigation Systems" drops out and the stocks in the industry labeled "Other" are discarded we sort followers into

[14]The advantage of the equal- or value-weighted signal aggregation method is its simplicity. However, improvements can be made along two dimensions. The first dimension of improvement would be to devise a more efficient weighting scheme that takes into account historical correlations between leaders' signals and the confidence with which coefficients $\hat{b}_3$ are estimated. Leaders could produce perfectly correlated signals when (1) they simply react with a shorter delay than their followers to common economy- or industry-wide shocks or (2) a subset of stocks reacts with a shorter delay than their followers to the news of a sole original leader. Currently, the weights on leaders' signals are independent of the leaders' return correlations or their relative forecasting ability. A more efficient weighting method would aim to underweight signals that had large prediction errors and high correlations with other signals over the estimation window and overweight signals that were more precise and had low correlations with other signals; this can be accomplished by choosing the optimal weights that would minimize the expected variance of the aggregate signal using signal precision and correlation parameters estimated over the rolling window. The second dimension of improvement would focus on eliminating misidentified leaders. For example, leaders that lead very few stocks in a given period are likely to be "false" leaders, and their signals should be ignored. In the remainder of this section, we will show that our simple weighting schemes work well in predicting followers' returns, and, hence, we will leave the improvements in signal aggregation to future research.

[15]Our results are virtually unchanged when we also require that leaders be common stocks with share codes 10 or 11.

deciles based on the aggregate leader signal. We form portfolios at the beginning of month $\tau + 1$ and hold them for one month. In the following month, new portfolios are formed based on the new set of leader signals. Figure 1 illustrates the timeline for our regression windows and portfolio formation.

Panel A of Figure 2 plots the value of $1 invested in February 1929 at a monthly return equal to that earned on the zero-investment strategy of holding a long position in the decile-10 portfolio and a short position in the decile-1 portfolio. The solid line represents the cumulative return for value-weighted portfolios and the dashed line that for equal-weighted portfolios. The initial investment of $1 would have turned into $2,010.09 by December 31, 2011, for the equal-weighted strategy. For the value-weighted strategy, it would have turned into only $75.26. For the equal-weighted strategy, the cumulative return reached its peak in July 2008, at which point the initial investment of $1 was worth $2,515.95; for the value-weighted strategy, the maximum of $137.86 is reached in November 1998. The equal-weighted strategy experienced seven consecutive months of negative returns from July 1999 to January 2000 and five consecutive months of negative returns from August to December 2008. The value-weighted strategy experienced six consecutive months of negative returns from May to October 1999 and four consecutive months of negative returns from August to November 2008. During the market crashes of October 1929 and October 1987, both sets of returns were highly positive (they were 7.1% and 17.7% in October 1929, and 1.3% and 2.5% in October 1987, for equal-weighted and value-weighted portfolios, respectively).

Table 2 presents average monthly excess returns for various deciles of equal- and value-weighted follower portfolios (Panels A and B, respectively), along with return differentials between the high- and low-signal portfolios.[16] Over the 1929-2011 period, leaders possess significant out-of-sample predictive ability. Low-signal portfolios earn low returns and high-signal portfolios earn high returns, and returns increase smoothly in magnitude with the signal

[16] All $t$-statistics are adjusted for autocorrelation in returns using the Newey and West (1987) methodology, and, for each specification, the number of lags is determined as the third root of the number of observations in the time series.

for both return-weighting methods. Moreover, the alphas of the lowest-signal portfolio (decile 1) are significantly negative for both equal- and value-weighted returns, and the alphas for the highest-signal portfolio (decile 10) are significantly positive when equal-weighted, but not when value-weighted. The lack of significance of the value-weighted alpha on the high-signal portfolio suggests that positive information is incorporated faster than negative information, at least for larger stocks. This observation is consistent with the evidence of Hong, Lim, and Stein (2000) that bad news diffuses more slowly than good news. The return differentials between high- and low-signal portfolios are significantly greater than zero for both equal- and value-weighted portfolios and for all return measures (i.e., excess returns, alphas relative to the market, or three- or four-factor alphas). The monthly four-factor alphas on the return differentials are equal to 0.64%, with a $t$-statistic of 5.73, and 0.38%, with a $t$-statistic of 2.98, for equal- and value-weighted portfolios, respectively. Since our portfolios are constructed to have the same industry loadings, industry-wide movements are canceled out for the return differentials, thereby reducing their volatility and increasing the Sharpe Ratio.

Table A2 in the Online Appendix presents factor loadings on the four-factor model for equal- and value-weighted portfolios in Panels A and B, respectively. The panels show that, compared to the lowest signal-sorted decile portfolio, the highest signal-sorted decile portfolio has significantly higher loadings on the size, book-to-market, and momentum factors, indicating that high-signal firms behave like small value winners. Yet, these loading differentials do not subsume the predictive ability of the leader signal. Panel C of Table A2 presents portfolio transition probabilities between the current and the future portfolio assignment, one, two, and 12 months ahead. In the calculations, we only consider those stocks that are present in the sample in both time periods and, as before, we form leader-signal-based portfolios within each of the 36 industries. The table shows that there is some persistence in portfolio assignments in the next two months, with somewhat U-shaped transition probabilities, which indicate that the stocks in the high- and low-signal portfolios have a higher chance of remaining in their respective deciles relative to other portfolio assignments. However, this stickiness in the portfolio assignments disappears 12 months into the future.

Table 3 presents monthly portfolio returns for the specification in which leaders are identified using 36-month rolling windows. Returns are equal-weighted in Panel A and value-weighted in Panel B. With a longer rolling regression window, regression coefficients can be estimated more precisely, but there is a smaller chance of identifying short-term leaders. It can be seen that this methodology produces very similar returns to the baseline specification. Some differences between these two methods will be revealed in the robustness checks and the Fama-MacBeth cross-sectional regressions presented later in the paper.

In order to check how the leaders' return predictability is related to the followers' size, every month and within each industry, we sort stocks into size terciles. Then, within each size tercile and industry group, we form decile portfolios based on the leader signal in that month. As before, first sorting on industry exploits only the within-industry return predictability and, by this, eliminates industry-specific movements from the portfolio return differentials. Table A3 in the Online Appendix reports four-factor alphas for the low- and high-signal portfolios (deciles 1 and 10) and for the return differentials between portfolios 10 and 1. The results show that the return differentials are significant for all size terciles but the magnitudes steadily decline as the average size of the followers increases and that the positive alphas of portfolio 10 are only significant for the lowest-size terciles. Both results are consistent with the results of the lead-lag literature that large stocks, by virtue of having more attention, react faster to new information. However, significantly negative alphas of portfolio 1 suggest that stocks across all size groups are slow to react to negative information due to short-sale constraints.

### 2. How quickly are leader signals incorporated?

We check how long it takes for the leader signals to be incorporated into their followers' prices. Specifically, we skip one month between the month in which the leader signals are computed and the month in which portfolios are formed. Panels A and B of Table 4 present the results for the 12-month and the 36-month rolling regression windows, respectively. The return differential is still significant for equal-weighted portfolios but is no longer significant for value-weighted portfolios. Moreover, the significance for the equal-weighted portfolios is largely explained by the significantly negative alphas of the low-signal portfolios. The alphas of the high-signal portfolios are no longer significantly positive. When two months are skipped from the month in which leader signals are calculated, none of the methods produces significant return differentials, suggesting that information is fully transmitted from leaders to followers within one month for value-weighted portfolios and within two months for equal-weighted portfolios.

## 3. Alternative methods for aggregating leader signals

We also try four alternative methods of aggregating leader signals. Unlike the baseline specification (2), these methods do not involve the magnitude of the estimated regression coefficient $\hat{b}_3$, but only its sign: $Signal^i_\tau = \sum_{j=1}^{J^i_\tau} w_j \text{sign}(\hat{b}^{ij}_3) Ret^j_\tau$. Throughout the paper, we will refer to the leader-return weighting methods that do not rely on the magnitude of $\hat{b}_3$ as "non-parametric" weighting methods. Specifically, we use the following four non-parametric leader return weighting methods: (1) equal-weighting; (2) weighting by the leaders' market capitalization as of the end of month $\tau - 1$; (3) weighting by the absolute value of the $t$-statistic of $\hat{b}_3$; and (4) weighting by the absolute value of $\hat{b}_3$.

The results are presented in Panel A of Table 5. A comparison with the results in Table 2 shows that the original specification produces more significant return differentials for value-weighted portfolios, while weighting by the absolute value of the $t$-statistics of $\hat{b}_3$ works best for equal-weighted portfolios. Value-weighting leader returns produces the lowest return differentials, which suggests that signals from large leaders that are overweighted in this weighting scheme are incorporated by the followers faster than signals from small leaders, likely because large leaders are more visible.

Panel B of the table skips one month between the month in which leader signals are calculated and the month in which portfolios are formed, as in Table 4. With the exception of the method in which leader signals are non-parametrically value-weighted, the predictive ability of leaders persists for equal-weighted return differentials but not for value-weighted return differentials. And, as with the baseline weighting scheme, none of the return differentials are significant when two months are skipped before portfolio construction.

## 4. Alternative methods of portfolio construction and other robustness checks

The predictive power of leader signals is robust to a number of other variations of how portfolios are constructed or how leader signals are calculated. The results for these alternative specifications are reported in Table 6.

We begin by sorting followers on the leader signal, not within each industry, but over the *entire sample*. Portfolio returns are reported in Panel A of the table for the specification in which leaders are determined using 12-month rolling regressions and in Panel B for the specification that uses 36-month rolling regressions to identify leaders. The returns are similar to those reported for within-industry sorts (Tables 2 and 3). However, here, for a given return magnitude, the $t$-statistics are somewhat lower because portfolio returns tend to be more volatile. The reason is that the long and short portfolios are likely to have unequal industry loadings, which will result in the long-short portfolio that is not industry-neutral.

The next two panels present portfolio returns for value-weighted leader signals, computed according to formula (2). In Panel C, a 12-month rolling regression window is used, and in Panel D, a 36-month window. The results are not as strong as in the specification in which the leader signals are equal-weighted, which implies that signals from large stocks are incorporated more quickly than with a one-month delay. (Incidentally, the lead-lag literature uses weekly return frequencies.)

Panels E and F present results for the 1990-2011 subperiod for both lengths of the rolling regression windows. Leaders identified with 36-month rolling regression windows have more significant predictive power in that time period than leaders identified with 12-month rolling regression windows. However, neither method produces significant four-factor alphas for value-weighted portfolios. Similarly to many other return anomalies, this return anomaly diminishes over time, especially for large stocks.

In order to conserve space, the remainder of the robustness tests are presented only for leaders identified with 12-month rolling regressions. In Panel G, signals exclusively from positive leaders are used in portfolio formation, and in Panel H, signals exclusively from negative leaders are used. In Panel G, both equal- and value-weighted portfolio return differentials are significant, suggesting that positive leaders lead returns for both small and large stocks. In Panel H, the return differentials are only marginally significant for equal-weighted portfolios and insignificant for value-weighted portfolios, which implies that the predictive ability of negative leaders is rather weak, at least for intra-industry sorts.

To illustrate that leaders need not belong to the same industry as their followers, we compute signals only from the leaders that belong to a different industry than the follower stock. As shown in Panel I, the signal from this restricted set of leaders works nearly as well as the signal from the unrestricted set of leaders.

In Panel J, in order to further distinguish our results from those in the lead-lag literature, we limit the set of leaders to stocks that are smaller than the follower. The significantly positive return differentials indicate that smaller leaders can indeed lead returns of larger followers.

Next, we study the predictive ability of recurring and non-recurring leaders. In Panel K, for each follower, we consider only the leaders that were not identified as that follower's leaders in any month over the previous three years (non-recurring leaders). In Panel L, for each follower, we consider only the leaders that were identified as that follower's leaders in at least one month over the previous three years (recurring leaders), requiring that both stocks existed in CRSP for the past three years. Signals from recurring leaders have a higher forecasting power than signals from non-recurring leaders, especially for value-weighted portfolios. One explanation for the weaker predictive ability of non-recurring leaders is that this set of leader stocks likely contains more noise, i.e., non-leaders that are mistakenly identified as leaders.

In order to make a distinction between our results and those in the information transfer literature and in Cohen and Frazzini (2008), which describe an underreaction to relevant earnings information announced by other firms, we include, in Panel M, only leaders that are *not* announcing earnings in the current month. Hence, the information in the leaders' current returns is likely unrelated to their earnings news. However, these leaders still forecast their followers' returns in the next month (the return differentials are somewhat lower than in earlier tables because the results in Panel M are based on the more recent sample period). In Panel N, we use only leaders that announce their quarterly earnings in the current month. The return differentials in this panel are somewhat lower in magnitude for equal-weighted portfolios than those in Panel M and are insignificant for value-weighted portfolios, probably because firms announcing earnings typically attract news coverage, which would lead follower stocks to react to the leaders' news with a shorter delay.

In Panels O and P, we introduce an alternative cutoff value for the absolute value of the $t$-statistic on the regression coefficient $\hat{b}_3$ used to identify leaders. Instead of 2.00, we use a 2.57 cutoff, which corresponds to the two-tailed significance level of 1%. In Panel O, portfolios are formed within industries, and in Panel P, over the entire sample. It can be seen that the results are very similar to those that use a cutoff of 2.00 (see Panels A and B of Table 2 and Panel A of Table 6, respectively).

Finally, in Panels Q and R, we allow some time to pass between the month in which leaders are identified and the month in which these leaders are used to calculate the aggregate leader signal. In Panel Q, we skip one month, which lowers the return differentials by a factor of about 44% compared to those in Panels A and B of Table 2. In Panel R, we skip 60 months, which renders the return differentials insignificant as the leader-follower relation is unlikely to survive such a long period.

In Section A2 of the Online Appendix, we show that our results are unlikely to be explained by some omitted cross-sectional stock characteristic. Specifically, we show that when the cross-sectional dimension of the data is preserved but the time-series dimension used for identifying leaders is broken by scrambling the dataset along the time dimension, the signals from newly identified but, in this case, definitely false leaders no longer predict their followers' returns.

## B. Weekly portfolio returns

As previously discussed, one reason to switch our analysis to higher frequencies is that signals from leaders may be incorporated into their followers' prices faster than with a one-month delay. (Tellingly, the lead-lag literature uses weekly return frequencies to document the delayed price reaction of small relative to large firms.) Additionally, higher frequencies will generate more data points, which will allow us, in later sections, to study the interaction between leadership and news coverage as well as leadership and short selling (the news dataset is relatively short, starting in April 1996, and the short selling dataset is shorter still, starting only in July 2006). In this subsection, we therefore work only with weekly return frequencies. Weekly returns are computed as Monday-to-Friday returns, using the CRSP Daily Stock file, thereby aligning returns with the weekly factors obtained from Kenneth French's web site.

The weekly portfolio construction methodology is similar to the monthly one. We run regression (1) with weekly returns using 52-week rolling regression windows. Even though the window length is still about 12 months, we are able to estimate regression coefficients with greater precision. Once leaders are identified, we form portfolios every Monday using the equal-weighted aggregate leader signal from the previous week, computed as per equation (2), and hold stocks in the portfolios for one week.

Panels A and B of Table 7 present weekly portfolio returns for equal- and value-weighted portfolios, respectively. The results show that the weekly strategy produces highly significant return differentials for both equal- and value-weighted portfolios over the period 1980-2011. These returns are also highly economically significant, amounting to about 28% per year for equal-weighted and 15% per year for value-weighted long-short portfolios.

Panels A and B of Table A4 in the Online Appendix reports four-factor loadings (using weekly factor returns) for equal- and value-weighted portfolios, respectively. The long-short portfolio loads negatively on the market factor, and, when returns are value-weighted, the long-short portfolio additionally has a negative loading on the HML factor but a positive loading on the momentum factor. Overall, the four factors have little explanatory power for the return differentials, and the resulting alphas are close in magnitude to the raw return differential. Panel C of Table A4 presents portfolio transition probabilities between the current and the future portfolio assignment, one, two, and 52 weeks ahead. As in the case of monthly-frequency transition probability calculations, we only consider those stocks that are present in the sample in both time periods and form leader-signal-based portfolios within each of the 36 industries. Again, the tables show that there is persistence in the portfolio assignments in the next two weeks but that it disappears 52 weeks into the future.

Panel B of Figure 2 plots the value of $1 invested on January 18, 1980, at a weekly return equal to that earned on the zero-investment strategy of holding a long position in the decile-10 portfolio and a short position in the decile-1 portfolio. The solid line represents the cumulative return for value-weighted portfolios and the dashed line that for equal-weighted portfolios. The initial investment of $1 would have turned into $5,649.56 on December 30, 2011, for the equal-weighted strategy. For the value-weighted strategy, it would have turned into only $77.74.

Next, as we did for monthly-frequency leader signals, we try alternative methods for aggregating weekly leader signals and check their forecasting ability for various lags between the week in which the signals are computed and the week in which portfolios are formed. (The four alternative non-parametric methods of aggregating leader returns are described in Section A.3). The results are shown in Table A5 in the Online Appendix. As in the case of monthly-frequency signals, the baseline method works best for value-weighted portfolios, while weighting leader returns by the absolute value of the $t$-statistics of $\hat{b}_3$ works best for equal-weighted portfolios; as before, value-weighting leader returns produces the worst return predicability. This quick analysis shows that leader signals are fully incorporated into equal-weighted portfolios within the subsequent four weeks, and into value-weighted portfolios within the subsequent two to three weeks, depending on the specification.

The analysis presented in the remainder of this subsection is conducted at weekly frequencies to conserve space and to better match the availability of news and trading cost data, but the results are qualitatively similar when the analysis is performed at monthly frequencies.

### 1. The speed of information diffusion and stock liquidity

The results in this subsection show that leader signals are incorporated more slowly by prices of less liquid stocks, and we, therefore, argue that trading costs represent an important impediment to implementing the leader-signal-based trading strategy. (For the remainder of the section, we consider only our baseline leader-signal aggregation specification, with equal-weighted leader signals.) We use turnover as a proxy for stock liquidity. At the end of the week in which the leader signal is computed, we sort stocks into quintiles based on their turnover over the previous 12 months (using the most recent month-end), and then, within each turnover quintile, into leader-signal deciles. Table 9 presents the four-factor alphas of the high-minus-low decile return differentials for equal-weighted portfolios. The rows of the table are organized by the number of weeks skipped after the week in which the leader signal is calculated.

The results indicate that the more liquid stocks tend to incorporate their leader signals faster—the long-short strategy's profits are lower for high-turnover stocks across most specifications.[17] Overall, the results are consistent with our conjecture that information diffuses more slowly for stocks with higher impediments to trade.

## 2. The interaction between leader signals and followers' concurrent returns

Once a stock's leadership for a follower stock has become apparent to investors, the follower will start to react to the leader's signal with a shorter delay or no delay at all. In the latter case, a leader's signal will lose its ability to forecast returns. Moreover, conditioning future returns on the past leader signal may even become counterproductive due to the return reversal effect, which is strongly present at both monthly and weekly frequencies. Thus, if a follower's price has already moved in the same direction as the signal this week, it will likely move in the opposite direction in the subsequent week.

Since the predictive ability of the leader signal should be the strongest among followers whose prices have not yet co-moved with the signal, conditioning on the correlation between the leader signal and the follower's contemporaneous return would improve the leader signals' predictive ability. We check whether this is the case. Every week, all follower stocks are sorted into quintiles based on their leader signal and then, within each leader-signal quintile, into further quintiles based on their return in that week.

Table 8 presents four-factor alphas of the subsequent week's portfolio returns. It can be seen that the leader-signal strategy works within each reversal quintile; it generates a return equal to, on average, about 40% of the return of the reversal-based strategy.[18] As expected, the highest-leader-signal/lowest-prior-week return portfolio (portfolio 51) generates the highest return in the subsequent week, and the lowest-leader-signal/highest-prior-week return portfolio (portfolio 15) generates the lowest return in the subsequent week. The four-factor alphas of the return differential between portfolios 51 and 15 is 1.69% per week

[17]To explain the somewhat surprising result that the speed of information diffusion is the slowest among the stocks in the second-lowest (but not the lowest) turnover quintile, it helps to remember that turnover is not a perfect proxy for liquidity. In addition to trading costs, turnover is also influenced by the level of investor disagreement.

[18]Sorting independently on reversals and leader signals produces very similar results.

($t$-statistic=20.51) for equal-weighted portfolios and 1.03% per week ($t$-statistic=13.73) for value-weighted portfolios.[19] These results show that the performance of the leader-signal strategy can be substantially improved by conditioning on whether or not the followers' prices have likely already reacted to the leader signal.

Section A3 of the Online Appendix shows that the trading strategies based on leader signals have rather low break-even trading costs. Since large investment amounts will entail high price impacts, leader-signal-based strategies can support only small investment amounts. Therefore, the arbitrage profits left on the table are small, which suggests that even though the market is not perfectly efficient, it is approximately efficient once trading costs are taken into account.

## C. Cross-sectional regressions

The ability of leader signals to predict followers' returns in the subsequent month (week) is further confirmed with a set of Fama and MacBeth (1973) cross-sectional regressions. The regression setting allows us to add various control variables that are known to forecast returns in order to check that we have identified an independent source of return predicability. (The control variables are described in detail in the appendix.) The regression results are presented in Table 10.

In Panel A, regressions are run for the period 1929-2011 (or the period 1930-2011 when 36-month rolling regression windows are used to identify leaders). In addition to the equal-weighted leader signals, we include the following cross-sectional return predictors that are available over the entire sample period: the previous month's stock return, the previous month's industry return, and the stock's momentum return and market capitalization computed at the end of the previous month. Specification (3) also includes the interaction between the previous month's signal and the previous month's stock return. We expect the coefficient on the interaction variable to be negative because the magnitude of the reaction

[19] As before, forming within-industry portfolios helps eliminate industry-wide price movements and thereby achieve higher $t$-statistics.

in the following month would be lower if the follower has already reacted to the leaders' news signal in the previous month (which would make the value of the interaction variable high). In specifications (1)-(7), leaders are identified with 12-month rolling regressions, and in specification (8), leaders are identified with 36-month rolling regressions. In all specifications except specification (7), the dependent variable is the follower's return, and in specification (7), the dependent variable is the follower's return in excess of the contemporaneous value-weighted return of its industry. Specifications (4)-(6) include only firms that are above the median in size, turnover, and age, respectively.

In all regression specifications and in all subsamples, the coefficient on the aggregate leader signal is highly statistically significant; it varies in magnitude between 0.080 and 0.240. The highest coefficient estimate is obtained for the specification in which leaders are determined with 36-month regression windows, which is not surprising as the range of aggregate leader signals is much narrower for the 36-month specification than for the 12-month specification (compare the second column of Panel A of Table 3 to the second column of Panel A of Table 2). The reported range of the regression coefficients on the leader signal implies that if two otherwise identical stocks have leader signals that are different by, for example, 0.10, then their next month's returns would differ by between 0.008 to 0.024. As we expected, the coefficient on the interaction between the leader signal and the previous month's return is negative and significant at the 10% level.

Regressions in Panel B include more controls. These regressions are run for a shorter time period, 1963 to 2011, since Compustat variables and daily return data are not available in the earlier period. Specifications (3) and (4) use signals from leaders that are identified with 36-month rolling regressions. The coefficients on the leader signal are somewhat lower than those in the longer sample, but nevertheless highly significant across all specifications. Consistent with the results in Panels E and F of Table 6 that show that signals from leaders identified with 36-month rolling regressions work better in the later part of our sample for equal-weighted portfolios, the $t$-statistics on these signals are almost twice as high as those on the signals from leaders identified with 12-month rolling regressions. In unreported results, we included a quarterly earnings announcement dummy interacted with the leader signal, hypothesizing that the coefficient on this interaction term should be negative since earnings announcements typically increase the level of investor attention and may additionally reveal the information embedded in the leader signal. As expected, the regression coefficient is negative but statistically insignificant.[20]

In Panel C, regressions are run for weekly returns over the period 1980 to 2011. However, in specifications that use analyst coverage and news indicators the sample period is shorter, as described in the footnotes to the panel. All return-based explanatory variables are computed at weekly frequencies, while all other controls are computed as of the end of the previous month. It can be seen that in all regression models, the coefficient on the weekly leader signal is highly statistically significant, and its range of magnitudes implies that a difference of 0.10 in the weekly leader signal would produce a difference in the otherwise identical followers' returns of between 0.03 and 0.07 in the subsequent week.

In specifications (4)-(12), we include a number of interactions between the weekly leader signal and various variables of interest (these variables are also included in the regressions as independent controls). As in the monthly regression specification, specification (4) shows that the coefficient on the interaction between the weekly leader signal and the follower's prior-week return is negative and significant. Specification (5) includes the interaction with the quarterly earnings announcement dummy that equals one if the follower made a quarterly earnings announcement in the previous week and zero otherwise. As in the monthly regression case, we hypothesize that the coefficient on this interaction variable is negative, and this is what we find; here, the interaction term is significant at the 10% level. We are guided by the same logic when including another interaction with a dummy variable that equals one if the TRNA dataset contains a news story with a relevance score of one written about the follower firm in the previous week and zero otherwise. The coefficient on this interaction term is

[20]These results are available upon request.

also negative but not significant. In specifications (7)-(10), we include interactions between the weekly leader signal and dummy variables indicating relatively high levels of investor attention (we hypothesize that stocks that rank above the median in institutional ownership, analyst coverage, size, and turnover enjoy higher levels of attention than stocks that rank below the median on these measures). Stocks with higher levels of investor attention may react to leader signals more quickly than with a one-week delay, and, hence, we expect the coefficients on these interaction terms to be negative. And indeed, all these coefficients are significantly negative. In specification (11), we include an interaction between the leader signal and a dummy variable for whether the follower's firm age is higher than the median firm age. We hypothesize that the predictive ability of the leader signal may not be as high for followers that have been around longer. Though, as anticipated, the coefficient on the interaction is negative, it is insignificant. In specification (12), we include, in addition to the weekly signal, a *monthly* leader signal computed at the end of the previous month to check whether or not it has incremental predictive power for a follower's weekly returns. And indeed it does. Controlling for the weekly aggregate leader signal, as well as other characteristics, a spread of 0.10 in the monthly signal generates an average difference in the next week's returns of almost 0.002.

All these results confirm that the aggregate leader signal has an independent predictive ability for followers' returns at both monthly and weekly horizons. Moreover, the results show that leader signals work best for followers with lower levels of investor attention. Lastly, we find that monthly- and weekly-frequency leaders have an independent predictive ability at weekly return horizons.

# IV. Do Sophisticated Investors Trade on Leader Signals?

If sophisticated investors trade on leader signals, one should observe that stocks receiving low signals experience increased short-selling activity. In order to check whether this is the case, we have obtained data from Markit (formerly, Data Explorers), which collects information on total loanable stock inventory, the amount on loan to short sellers, and loan fees (which are calculated as the average of all applicable loan fees weighted by loan value). The data frequency is daily from July 3, 2006, to present; weekly from August 8, 2004, to June 28, 2006; and monthly from June 19, 2002, to July 21, 2004. Since we are interested in short-selling activity in response to the weekly signal, and Markit's weekly-frequency dates do not align with the dates on which the leader signal is calculated, we will only consider the daily-frequency data Markit sample.

Markit claims to capture stock loan trading information on over 85% of the OTC securities lending market; it is worthwhile to note that its universe of reporting participants (custodians and short sellers, from whom Markit gathers the information on the number of shares available for lending, the number of shares borrowed, and lending fees on borrowed shares) is unstable and tends to grow over time. As a result, short interest, which is defined as the number of shares sold short scaled by the number of shares outstanding, would mechanically increase over time if calculated using Markit's data on loaned shares. To avoid this concern, we use utilization as a measure of short-selling activity. Utilization is calculated by Markit as the percentage of the stock inventory available for lending to short sellers that is currently on loan. This measure of short-selling activity is not mechanically determined by the fluctuations in the number of participating short sellers and lenders.

The average utilization over time is plotted in Figure A1. Utilization exhibits a sharp drop on September 18, 2008, the date on which the short-selling ban on almost 1,000 financial stocks came into effect, as well as the ban on all naked short selling.[21] Even though the ban on short selling of financial stocks was lifted on October 8, 2008, the utilization number did not rebound. (The ban on naked short selling remains in effect.)

In addition to weekly leader signals, short-selling activity is potentially influenced by a number of slower-moving factors, such as momentum or book-to-market characteristics. Since we would like to isolate the effect of weekly leader signals on short-selling activity, our regression is set up to explain week-to-week changes in utilization, $\Delta utilization$, and includes controls for other potential weekly-frequency drivers of short-selling demand. The variables of interest are the two indicator variables indicating whether the stock enters or exists the bottom weekly leader-signal decile as of Friday of each week. The indicator variable for entering the bottom signal decile is set to zero if the stock was already in the bottom leader signal decile as of Friday of the previous week. Four other control variables are calculated in a similar fashion. These are indicators for whether a stock enters or exits the bottom weekly industry-return decile and for whether the stock enters or exits the top decile of all weekly returns (this indicator is intended to capture possible short-selling activity aimed to profit from the weekly-frequency return reversal effect). Specifically, we run the following Fama-MacBeth regression at a weekly frequency:

$$\begin{aligned}\Delta utilization_{it} = \alpha &+ \beta_1 \cdot \mathbb{1}_{it}\{\text{Enters bottom signal decile}\} + \beta_2 \cdot \mathbb{1}_{it}\{\text{Exits bottom signal decile}\} \\ &+ \gamma_1 \cdot \mathbb{1}_{it}\{\text{Enters bottom ind. ret. decile}\} + \gamma_2 \cdot \mathbb{1}_{it}\{\text{Exits bottom ind. ret. decile}\} \\ &+ \mu_1 \cdot \mathbb{1}_{it}\{\text{Enters top return decile}\} + \mu_2 \cdot \mathbb{1}_{it}\{\text{Exits top return decile}\} + \epsilon_{it}. \qquad (3)\end{aligned}$$

In accordance with the SEC's T+3 rule, all security transactions must be settled within three business days after the transaction day.[22] Since the weekly leader signal is calculated

[21] The ban on naked short selling should not affect the utilization numbers given that naked short sellers do not borrow the stock. (The ban on naked short selling on 19 financial firms came into effect on July 21, 2008, and ended on August 12, 2008 (`https://www.sec.gov/rules/other/2008/34-58166.pdf`).)

[22] See `http://www.sec.gov/investor/pubs/tplus3.htm` for a detailed description.

after market close on Friday, short sellers would be able to trade on the signal on Monday of the following week. In accordance with the T+3 rule, shares sold short on Monday must be borrowed and delivered to the buyers by the close of business on Thursday. Therefore, we calculate the difference in utilization between the Thursday that comes six days after the Friday when the leader signal was computed and Thursday of the previous week.

At any given time, a small number of stocks have relatively high lending fees; these stocks are said to be "on special."[23] D'Avolio (2002) reports that at any given time, 91% of all stocks in the loanable universe have lending fees below 1% per annum, while the remaining 9% have fees above 1% per annum, with the lending fee for this set of stocks averaging 4.3% per annum. Reed (2001) estimates that 5.74% of all loans have fees that exceed the prevailing fee levels by at least 1% per annum. Since short sellers may want to avoid stocks that are on special, in one regression specification we remove stocks with high lending fees. Our version of the Markit dataset does not report the actual average loan fee for each stock but rather provides six loan fee buckets, ranging from 0 to 5, with 0 being the cheapest and 5 the most expensive to borrow.[24] As would be expected, utilization rates increase steadily across the loan fee buckets, with the utilization rate averaging 15.90% for the zero-bucket, and 31.19%, 36.51%, 42.47%, 48.07%, and 59.24% for the next five fee buckets, that is, buckets 1 to 5, respectively. Bucket zero contains 81.78% of all stocks in the sample, and the next five fee buckets contain 6.23%, 2.89%, 2.03%, 2.01%, and 2.78% of the stocks in our sample, respectively.

We modify our sample in the following ways. In order to control for outliers, we trim the dataset at the 1st and 99th percentiles of the variable $\Delta utilization$ on each date. We start the regression sample period after October 8, 2008, the end of the short selling ban on financial stocks that coincides with the start of the ban on naked short selling, which is still in effect at the end of the sample period. The sample ends on December 31, 2011. Moreover, as in the

[23]The lending fee is the difference between the interest rate that is typically earned on a cash collateral and the interest rate that the stock's borrower receives on her cash collateral posted for the short sale.

[24]We drop 2.28% of all observations in our sample that have a missing value for the loan fee bucket assigned. The results are nearly unchanged when these observations are kept.

portfolio results, we drop all stocks priced at less than \$5 per share in 2011 inflation-adjusted dollars. The average utilization in the resulting sample is 19.93%.

We run the regression on three data samples. The first sample contains all observations. In the second sample, we remove stocks that are expected to announce quarterly earnings in the following week. We hypothesize that short sellers may be more reluctant to sell short these stocks because of the high expected return volatility associated with the price reaction to earnings news. Earnings announcement dates are highly predictable by the previous year's earning announcement dates; therefore, we construct this sample by dropping stocks that made quarterly earnings announcements in the same week of the previous year. Finally, in the third sample, we remove all stock-week observations with the average loan fees in the three highest loan fee buckets, thus dropping 6.98% of the stocks that are likely to be "on special" according to the estimates of D'Avolio (2002) and Reed (2001). The average utilization in that sample decreases slightly, to 17.60%.

The regression results, reported in Table 11, show that short-selling activity indeed increases after a stock enters the bottom leader-signal decile: on Monday following the Friday on which the leader signal is computed, utilization goes up by between 0.075% and 0.084%, depending on the sample restrictions. Though these magnitudes may be economically small, they are statistically significant, indicating that the leader signal is one of the inputs that short-sellers use. Short-selling demand, however, does not significantly decrease following a stock exiting the bottom signal decile. This is consistent with the evidence presented earlier in the paper that leader signals continue to forecast followers' returns for up to four weeks into the future. All told, the results show that sophisticated traders, such as short sellers, seemingly do trade on leader signals.

## V. Leadership and News

In this section, we investigate our conjecture that return leadership is associated with noteworthy news developments at the firm level. For that purpose, we again use the TRNA dataset. Here, we limit the set of potential leaders to common stocks with share codes 10 or 11, since our version of the TRNA dataset covers only U.S.-based firms. We use the first year of the TRNA sample to form the first annual cumulative news count, which reduces the regression sample to the period from April 1997 to December 2011.

The distribution of the number of followers for each stock in our dataset, which is computed using only end-of-year observations and which also includes stocks with zero followers, is plotted in Figure A2. In Panel A, the monthly leadership specification with 12-month rolling regressions is used, and in Panel B, the weekly leadership specification with 52-week rolling regressions is used. Since the number of followers is a count variable, the distributions are non-negative and right-skewed. The requirement that a potential follower traded on the last day of the week, which we impose at weekly frequencies, eliminates more stocks than the requirement that a potential follower traded on the last day of the month, which we impose at monthly frequencies. The average and median numbers of followers in Panel A (357.2 and 329, respectively) are, hence, greater than those in Panel B (299.9 and 269, respectively).

In order to assess whether a firm's capacity to lead is related to the intensity of its news coverage, we regress the number of followers that a firm has on its news coverage and a set of firm characteristics that determine a firm's steady-state news coverage. We estimate our regressions using quasi-maximum likelihood, which is appropriate for a count variable; this estimation method produces consistent and asymptotically normal coefficient estimates even if the underlying distribution is not Poisson (Wooldridge (2002)).[25] Since leadership is determined over a one-year window, we use rolling one-year averages for all explanatory variables; for news, we calculate rolling *total* news counts over the previous year.

[25] In our case, the underlying distribution is not Poisson because its variance is significantly larger than its mean. We experimented with assuming that the underlying distribution is negative gamma and obtained qualitatively similar results.

The regressions are run at a monthly frequency, and the standard errors are clustered by firm.[26] Because news coverage increases over time and may be uneven across industries, we also include year and industry dummies.

The regression results are reported in Table 12. Pairwise correlations between the control variables are reported in Panel C. We use two measures of news. In specifications (1)-(3), $News$ is the count of all "highly relevant news," or news with a relevance score of one. In specifications (4)-(6), $News$ is the count of only "highly relevant corporate news," or news stories with a relevance score of one that report on new corporate developments such as lawsuits, product recalls, corporate actions, and so on, as opposed to news stories that report on trade order imbalances, mutual fund trades, market trends, etc. (more details are provided in Section A4 of the Online Appendix). For firms with no news stories over the previous year when using a particular news count methodology or for firms not present in the TRNA dataset, we set $News = 0$ (we include the latter set of firms because it is still potentially on Reuters' radar screen). In Panel A, leaders are identified with monthly regressions, and in Panel B, with weekly regressions. It can be seen that the variable $News$ is highly statistically significant in both panels. When the variable $News^2$ is included in the regression, the coefficient on that variable is significantly negative, indicating non-linearity: Even though leaders tend to have more news stories written about them, those firms that receive very intensive news coverage start to drop followers, as followers' prices begin to react to the leaders' news with shorter delays.

The economic interpretation of the regression coefficients on news is as follows. In specifications (1) and (2) of Panel A, the coefficient on $News$ ranges from $0.0056 \times 10^{-2}$ to $0.0075 \times 10^{-2}$. This implies that when a firm moves from the 5th to the 95th percentile of news coverage, or from 0 to 232 highly relevant news items per year (see the last row of Table A8), its number of followers increases by between 1.3% and 1.7%, which amounts to between 4 and 6 additional followers for a median stock (see the box in Figure A2). Redoing these

[26]Clustered OLS regressions produce qualitatively similar results.

calculations, but now taking the squared news term of model (3) into account, produces an increase of 8 followers. These magnitudes are very similar for specifications (4)-(6) of Panel A. For specifications (1)-(3) of Panel B, analogous calculations imply a gain of between 2 and 4 followers, and for specifications (4)-(6), a gain of between 3 and 5 followers. Though the economic magnitudes are not large, they could possibly be increased with a more careful analysis of the contents of the news articles.

The results for the control variables show that, for both monthly and weekly leadership specifications, stocks with high institutional ownership and high analyst coverage tend to have significantly more followers. This result is consistent with the findings of the lead-lag literature that stocks with higher levels of attention react faster to common shocks, and, hence, they would appear to have more followers. Institutional investors are sophisticated and react to new common information faster than retail investors, while analysts help uncover and publicize relevant news developments reported by other firms.

Overall, these results indicate that the scope of a firm's leadership is indeed positively related to news developments at the firm level. A more precise news classification could provide better insights into the news categories that have the most ramifications for other firms. Such an analysis is, however, beyond the scope of this paper.

# VI. Conclusion

In this paper, we use Granger causality tests to identify all leader-follower pairs among individual stocks. We show that the returns of thus-identified leaders have a real and robust out-of-sample forecasting ability for their followers' returns. Relying on Granger causality tests to identify return leaders allows for a hypothesis-free approach to the question of return leadership, without having to first posit the direction of information flows in the stock market. By analyzing the leader-follower pairs that we uncovered, we find that leaders can be smaller stocks and belong to a different industry than their followers. This finding gives rise to the conjecture that stocks can lead returns of other stocks not only because they are quicker to react to common market- or industry-wide news, but also because they might be at the center of an important news development that has ramifications for other firms. We find support for this conjecture by showing that, all else equal, stocks with more news stories written about them tend to lead returns of a greater number of other stocks. It is left to future research to investigate what types of firm-level news are most likely to affect other firms.

Our setting also allows us to investigate impediments to information diffusion. First, we find that leaders' return signals are incorporated into followers' prices relatively quickly (within less than three months). A strategy designed to trade on leader signals will therefore entail high portfolio turnover and, consequently, high trading costs. Given the trading cost incurred by a typical trader, prices appear to lie within the no-arbitrage bounds. Thus, the market is approximately efficient. (To that extent, we also show that more liquid stocks incorporate information faster than less liquid stocks and that the speed of information diffusion has increased over our sample period.) However, highly-skilled traders adept at minimizing trading costs can profit from the delayed information diffusion, and we show that short-sellers do increase their shorting demands in response to negative leader signals.

Finally, our results suggest that individual stocks are highly interconnected (by permanent or temporary business ties, similar legal liabilities, and similar dependence on product safety controls, consumer tastes, labor market rules, etc.). Hence, it is natural that stock prices will react not only to own news and to market- and industry-wide news but also to relevant news of other firms. This observation can help resolve the $R^2$ puzzle articulated by Roll (1988), which states that asset pricing models do about as well in explaining individual stock returns on non-news days as they do on news days.[27] Our results suggest that the difference in $R^2$s

[27] Specifically, that paper investigates whether traditional asset pricing models can explain reasonably well daily stock price movements of 96 large firms and finds that the traditional pricing factors used in return regressions produce low $R^2$s. The $R^2$s computed for the subsample of non-news days are only slightly higher than the $R^2$s computed for the subsample of news days. This is surprising because one would expect large news-induced idiosyncratic price movements to result in low model $R^2$s on news days, with model $R^2$s being high on non-news days. News days are defined as days on which the firm appeared in the Dow-Jones news service or in *The Wall Street Journal*.

between no-news and news days can be increased by adding to the set of news days the days on which a firms' return leaders experience significant news events.

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# Appendix: Variable definition and estimations

This appendix provides detailed descriptions of the variables used in our cross sectional regressions. Unless specified otherwise, all variables are calculated at the month-end as described below. Weekly-frequency variables are computed analogously.

**Amihud's illiquidity measure** *(Illiq).* Following Amihud (2002), we measure illiquidity for each stock in month $t$ as the average daily ratio of the absolute stock return and the dollar trading volume within the day:

$$Illiq_{i,t} = \text{Avg}_t \left[ \frac{|R_{i,d}|}{Volume_{i,d}} \right], \tag{4}$$

where $R_{i,d}$ is the return and $Volume_{i,d}$ is the dollar trading volume for stock $i$ on day $d$.

**Analyst Coverage** *(Analyst Coverage)* is defined as the number of analysts issuing annual earnings forecasts for the current fiscal year, computed using the I/B/E/S dataset.

**Beta** *(Beta).* Following Fama and French (1992), the market beta of individual stocks is estimated by running a time-series regression based on the monthly return observations over the prior 60 months if available (or a minimum of 24 months):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^1 \left(R_{m,t} - R_{f,t}\right) + \beta_i^2 \left(R_{m,t-1} - R_{f,t-1}\right) + \epsilon_{i,t}, \tag{5}$$

where the market beta of stock $i$ is the sum of the slope coefficients on the current and lagged excess market returns, i.e., $Beta = \hat{\beta}_i^1 + \hat{\beta}_i^2$.

**Book-to-market ratio** *(Book/Market).* Following Fama and French (1992, 1993, and 2000), the book-to-market equity ratio is computed at the end of June of each year as the book value of stockholders' equity, plus deferred taxes and investment tax credit (if available), minus the book value of preferred stock, scaled by the market value of equity. Depending on availability, we use the redemption, liquidation, or par value (in that order) to estimate the book value of preferred stock for the last fiscal-year end. The market value of equity is the product of share price and the number of shares outstanding at the end of December of the previous fiscal year.

**Firm age** *(Age)* is the number of months since the firm's IPO.

**Idiosyncratic volatility** *(IVOL)*. Following Ang, Hodrick, Xing, and Zhang (2006), we estimate idiosyncratic volatility of stock $i$ each month as the standard deviation of the daily regression residuals, $\epsilon_{i,d}$, within a month. Specifically, the regression residuals are obtained from the following regression run every month with daily returns:

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i(R_{m,d} - R_{f,d}) + \eta_i \mathrm{SMB}_d + \delta_i \mathrm{HML}_d + \epsilon_{i,d}, \tag{6}$$

where $R_{i,d}$ is the return on stock $i$ on day $d$, $R_{f,d}$ is the risk-free return (proxied by the return on a one-month T-bill), $R_{m,d}$ is the daily return on the market portfolio (proxied by the return on the CRSP value-weighted index), and $\mathrm{SMB}_d$ and $\mathrm{HML}_d$ are the daily returns on the size and book-to-market factors. We then convert the idiosyncratic volatility of each stock into a monthly measure by multiplying the estimate by the number of trading days in the month: $IVOL_{i,t} = st.dev._t(\epsilon_{i,d}) \times$ no. of trading days. At least 15 daily return observations in a month are required to estimate IVOL.

**Institutional Ownership** *(Inst. Ownership)* is defined as the percentage of total shares outstanding owned by institutions, computed using the data in the Institutional Holdings (13F) dataset.

**Previous month's return** *($Ret_{t-1}$)*. Following Jegadeesh (1990), this short-term reversal predictor is defined as the stock return over the previous month.

**Momentum return** *(Momentum)*. Following Jegadeesh and Titman (1993), momentum is defined as the cumulative return of a stock over a period from the beginning of month $t-13$ to the end of month $t-2$.

**Previous month's industry return** *(Ind. $Ret_{t-1}$)* is defined as the value-weighted industry return over the previous month.

**Size** *(Size)*. A stock's size is defined as the product of the price per share and the number of shares outstanding, expressed in thousands of dollars.

**Turnover** *(Turnover)* is the monthly turnover, scaled by the end-of-month number of shares outstanding.

**Example:** Leader stocks B and C for follower stock A

Regression estimated at $\tau$: $Ret_t^A = b_0^{Aj} + b_1^{Aj} Ret_{t-1}^{mkt} + b_2^{Aj} Ret_{t-1}^A + b_3^{Aj} Ret_{t-1}^j + \epsilon_t^{Aj}$, $j = \{B, C\}$
Estimates: $\hat{b}_3^{AB} = 1$ and $\hat{b}_3^{AC} = 1$
Leader returns: $Ret_\tau^B = 1\%$, $Ret_\tau^C = 3\%$
Leader signal: $Signal_\tau^A = \frac{1}{2}(1 \cdot 1\% + 1 \cdot 3\%) = 2\%$

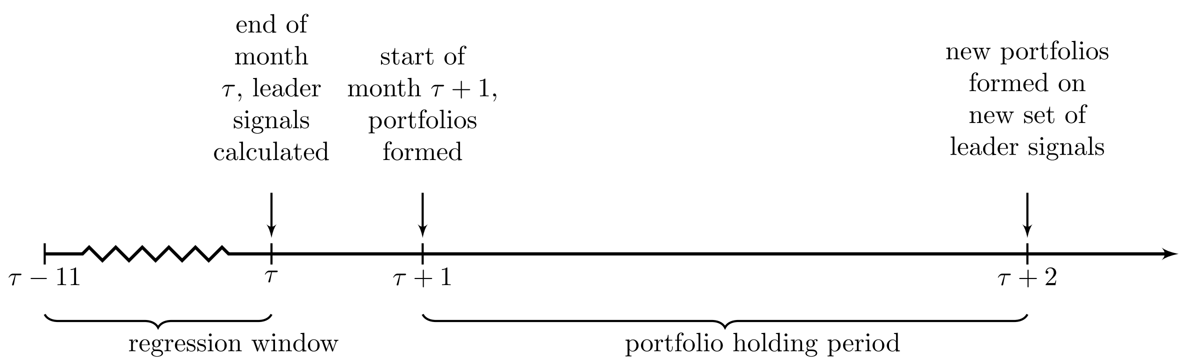
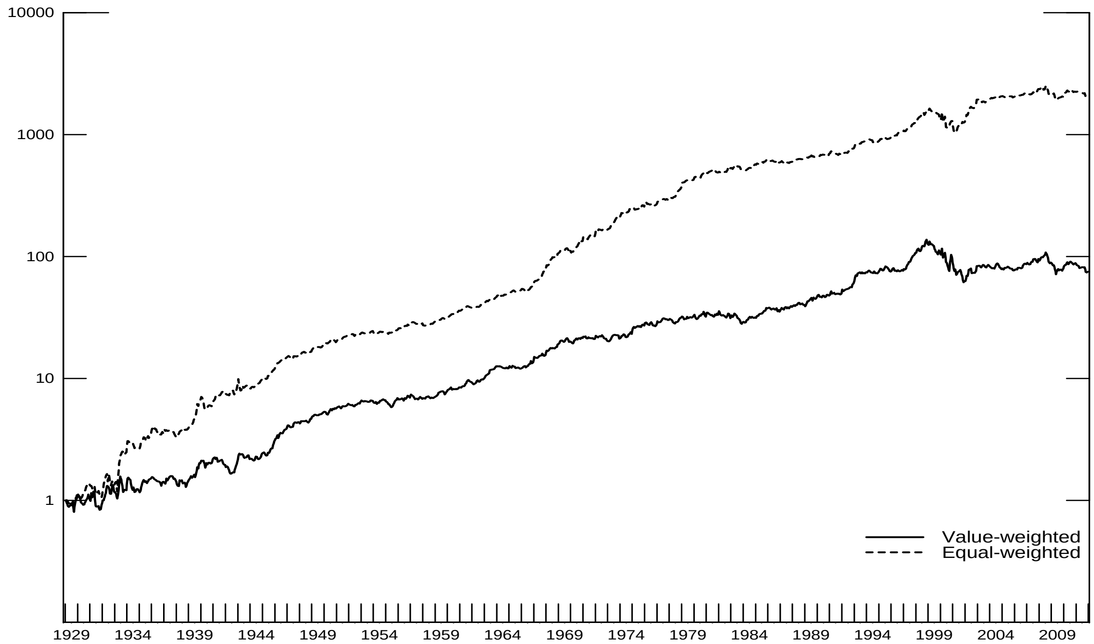



**Figure 1. Timeline**. This figure presents the timeline for our computations and an example for how an aggregate leader signal is computed.

Panel A: Monthly portfolios




Panel B: Weekly portfolios

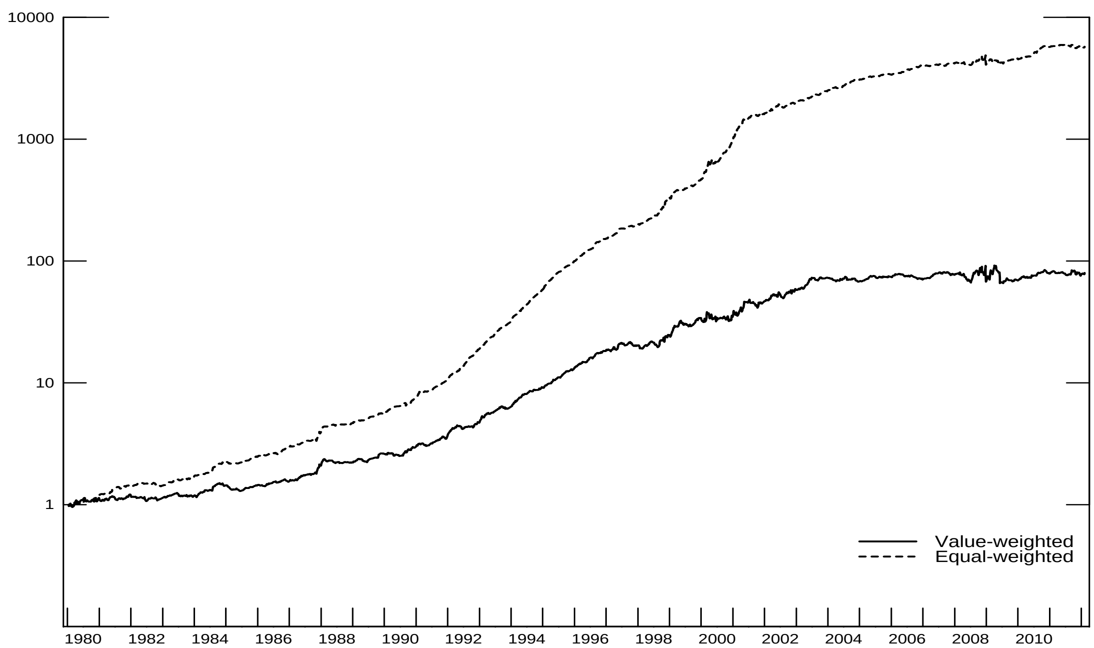



**Figure 2. Cumulative returns**. The charts plot, for equal- and value-weighted portfolios, the value of $1 invested in the beginning of the period at the return earned on a zero-investment strategy of buying stocks in the top and selling short stocks in the bottom leader signal decile. In Panel A, leaders are identified with monthly regressions and portfolios are formed monthly. In Panel B, leaders are identified with weekly regressions and portfolios are formed weekly. The axes are in log-scale. The time periods are February 28, 1929, to December 31, 2011, and January 18, 1980, to December 30, 2011, respectively.

**Table 1**
**Descriptive statistics on followers**

This table presents characteristics of follower stocks. Followers are stocks whose returns were shown to be Granger-caused by their leaders' returns, as described in the text. The set of possible followers is limited to stocks that traded on the last day of the previous month and were priced above $5 per share in 2011 inflation-adjusted dollars. Both leaders and followers are limited to common shares of U.S.-incorporated firms. The statistics are calculated as of January 31 of each year. The sample period is 1929-2011.

**The entire sample**

| | |
|---|---|
| Average number of leaders (including observations with no leaders) | 286.89 |
| Fraction of stock-month observations with at least one leader | 84.00% |

**The sample limited to stocks with existing leaders (or existing followers)**

| | |
|---|---|
| Fraction of leaders that are positive leaders | 53.03% |
| Average regression coefficient on a positive leader's lagged return | 0.89 |
| Average regression coefficient on a negative leader's lagged return | -0.91 |
| | |
| Average fraction of a followers' leaders in the same industry, using 12 ind. classifications† | |
| – positive leaders | 15.28% |
| – negative leaders | 13.77% |
| Average fraction of a followers' leaders in the same industry, using 38 ind. classifications† | |
| – positive leaders | 8.25% |
| – negative leaders | 7.27% |
| | |
| Fraction of followers larger than its average leader | 22.07% |
| Fraction of followers with greater turnover than its average leader | 37.94% |
| Fraction of followers older than its average leader | 44.94% |

†The industry classification "Other" is excluded.

| | Number of leaders | | | | |
|---|---|---|---|---|---|
| | 1 (low) | 2 | 3 | 4 | 5 (high) |
| Avg. number of leaders in quintile | 234.37 | 268.14 | 299.82 | 338.71 | 427.90 |
| Market capitalization (in $ million) | 158.81 | 154.48 | 153.19 | 154.74 | 138.79 |
| Share turnover over the past 12 months | 1.03 | 1.00 | 0.99 | 0.99 | 1.00 |
| Firm age (in years) | 16.86 | 17.00 | 17.00 | 16.66 | 16.08 |

**Table 2**

**Portfolios sorted on the equal-weighted leader signal within 36 industries, 1929-2011**

This table presents monthly abnormal returns of leader-signal-sorted portfolios. Leaders for each stock are identified using 12-month rolling regressions, as described in the text. At the beginning of each month, all stocks that traded on the last day of the prior month, that were priced above $5 per share in 2011 inflation-adjusted dollars, and that had leader stocks are sorted into decile portfolios within each of the 36 industries based on the last month's equal-weighted aggregate leader signal, computed as described in the text. Portfolio returns are equal-weighted in Panel A and value-weighted in Panel B. The second column reports the weighted-average leader signal, which is equal-weighted across followers in each portfolio in Panel A and value-weighted across followers in Panel B; the third column reports the average portfolio return in excess of the risk-free rate; the fourth column reports the market alpha; the fifth column reports the alpha of the Fama and French (1993) three-factor model; and the sixth column reports the alpha of the four-factor model that also includes the Carhart (1997) momentum factor. The last row reports the return differential between the high- and the low-signal portfolios (deciles 10 and 1). Newey-West-adjusted $t$-statistics are reported in parentheses. Panel E reports portfolio transition probabilities.

Panel A: Equal-weighted portfolios

| Decile | Leader signal | Excess return | Market alpha | 3-factor alpha | 4-factor alpha |
|---|---|---|---|---|---|
| 1 | -3.58% | 0.52% | -0.27% | -0.47% | -0.37% |
| | | (1.93) | (-2.25) | (-5.81) | (-4.61) |
| 2 | -1.99% | 0.71% | 0.00% | -0.16% | -0.10% |
| | | (3.02) | (0.03) | (-2.78) | (-1.62) |
| 3 | -1.26% | 0.80% | 0.10% | -0.08% | 0.02% |
| | | (3.44) | (1.13) | (-1.75) | (0.44) |
| 4 | -0.72% | 0.87% | 0.19% | 0.02% | 0.10% |
| | | (3.89) | (2.40) | (0.47) | (2.37) |
| 5 | -0.28% | 0.86% | 0.20% | 0.04% | 0.09% |
| | | (3.97) | (2.61) | (0.94) | (1.81) |
| 6 | 0.14% | 1.01% | 0.33% | 0.15% | 0.22% |
| | | (4.50) | (4.05) | (3.32) | (4.71) |
| 7 | 0.63% | 1.05% | 0.35% | 0.14% | 0.23% |
| | | (4.49) | (3.82) | (2.89) | (4.69) |
| 8 | 1.14% | 1.13% | 0.40% | 0.18% | 0.26% |
| | | (4.62) | (4.06) | (3.53) | (5.14) |
| 9 | 1.88% | 1.21% | 0.45% | 0.21% | 0.29% |
| | | (4.68) | (4.07) | (3.62) | (5.04) |
| 10 | 3.54% | 1.35% | 0.52% | 0.25% | 0.27% |
| | | (4.68) | (3.82) | (3.29) | (3.52) |
| 10-1 | | 0.83% | 0.79% | 0.71% | 0.64% |
| | | (7.35) | (7.03) | (6.48) | (5.73) |

Panel B: Value-weighted portfolios

| Decile | Leader signal | Excess return | Market alpha | 3-factor alpha | 4-factor alpha |
|---|---|---|---|---|---|
| 1 | -2.85% | 0.34% | -0.36% | -0.39% | -0.34% |
| | | (1.46) | (-4.37) | (-4.67) | (-4.07) |
| 2 | -1.70% | 0.49% | -0.12% | -0.13% | -0.10% |
| | | (2.50) | (-2.02) | (-2.14) | (-1.68) |
| 3 | -1.09% | 0.53% | -0.04% | -0.05% | -0.02% |
| | | (2.88) | (-0.85) | (-0.88) | (-0.29) |
| 4 | -0.65% | 0.60% | 0.04% | 0.05% | 0.03% |
| | | (3.34) | (0.80) | (0.93) | (0.61) |
| 5 | -0.25% | 0.56% | -0.01% | -0.01% | 0.01% |
| | | (3.08) | (-0.20) | (-0.31) | (0.29) |
| 6 | 0.10% | 0.61% | 0.07% | 0.06% | 0.06% |
| | | (3.55) | (1.60) | (1.28) | (1.37) |
| 7 | 0.51% | 0.62% | 0.06% | 0.06% | 0.06% |
| | | (3.45) | (1.18) | (1.25) | (1.15) |
| 8 | 0.99% | 0.71% | 0.12% | 0.08% | 0.07% |
| | | (3.71) | (1.98) | (1.28) | (1.17) |
| 9 | 1.58% | 0.77% | 0.14% | 0.09% | 0.10% |
| | | (3.77) | (2.21) | (1.45) | (1.67) |
| 10 | 2.81% | 0.85% | 0.16% | 0.07% | 0.04% |
| | | (3.68) | (1.76) | (0.83) | (0.48) |
| 10-1 | | 0.52% | 0.52% | 0.45% | 0.38% |
| | | (4.08) | (4.09) | (3.60) | (2.98) |

**Table 3**

**Portfolios sorted on the equal-weighted leader signal within 36 industries; leaders are identified using 36-month rolling regressions, 1930-2011**

This table presents monthly abnormal returns of leader-signal-sorted portfolios. Leaders for each stock are identified using 36-month rolling regressions, as described in the text. At the beginning of each month, all stocks that traded on the last day of the prior month, that were priced above $5 per share in 2011 inflation-adjusted dollars, and that had leader stocks are sorted into decile portfolios within each of the 36 industries based on the last month's equal-weighted aggregate leader signal, computed as described in the text. Portfolio returns are equal-weighted in Panel A and value-weighted in Panel B. The second column reports the weighted-average leader signal, which is equal-weighted across followers in each portfolio in Panel A and value-weighted across followers in Panel B; the third column reports the average portfolio return in excess of the risk-free rate; the fourth column reports the market alpha; the fifth column reports the alpha of the Fama and French (1993) three-factor model; and the sixth column reports the alpha of the four-factor model that also includes the Carhart (1997) momentum factor. The last row reports the return differential between the high- and the low-signal portfolios (deciles 10 and 1). Newey-West-adjusted $t$-statistics are reported in parentheses.

Panel A: Equal-weighted portfolios

| Decile | Leader signal | Excess return | Market alpha | 3-factor alpha | 4-factor alpha |
|---|---|---|---|---|---|
| 1 | -2.13% | 0.55% | -0.29% | -0.53% | -0.38% |
| | | (2.01) | (-2.34) | (-6.58) | (-4.80) |
| 2 | -1.20% | 0.77% | 0.03% | -0.15% | -0.11% |
| | | (3.26) | (0.36) | (-2.32) | (-1.64) |
| 3 | -0.75% | 0.82% | 0.10% | -0.09% | 0.01% |
| | | (3.57) | (1.12) | (-1.80) | (0.11) |
| 4 | -0.40% | 0.90% | 0.21% | 0.04% | 0.10% |
| | | (4.14) | (2.75) | (0.82) | (2.14) |
| 5 | -0.12% | 0.94% | 0.22% | 0.02% | 0.09% |
| | | (4.13) | (2.64) | (0.50) | (1.72) |
| 6 | 0.14% | 1.01% | 0.30% | 0.11% | 0.16% |
| | | (4.51) | (3.69) | (2.47) | (3.65) |
| 7 | 0.46% | 1.14% | 0.41% | 0.20% | 0.26% |
| | | (4.92) | (4.75) | (4.41) | (5.54) |
| 8 | 0.79% | 1.20% | 0.45% | 0.22% | 0.25% |
| | | (4.94) | (4.53) | (3.86) | (4.37) |
| 9 | 1.25% | 1.36% | 0.58% | 0.32% | 0.39% |
| | | (5.35) | (5.36) | (6.01) | (7.22) |
| 10 | 2.24% | 1.45% | 0.58% | 0.27% | 0.36% |
| | | (4.98) | (4.23) | (3.59) | (4.71) |
| 10-1 | | 0.89% | 0.86% | 0.80% | 0.74% |
| | | (8.18) | (7.86) | (7.40) | (6.72) |

Panel B: Value-weighted portfolios

| Decile | Leader signal | Excess return | Market alpha | 3-factor alpha | 4-factor alpha |
|---|---|---|---|---|---|
| 1 | -1.69% | 0.37% | -0.33% | -0.37% | -0.30% |
| | | (1.67) | (-3.98) | (-4.48) | (-3.56) |
| 2 | -1.02% | 0.56% | -0.09% | -0.13% | -0.11% |
| | | (2.75) | (-1.45) | (-2.12) | (-1.74) |
| 3 | -0.65% | 0.43% | -0.17% | -0.16% | -0.15% |
| | | (2.33) | (-2.98) | (-2.97) | (-2.68) |
| 4 | -0.35% | 0.53% | -0.07% | -0.06% | -0.06% |
| | | (2.90) | (-1.28) | (-1.26) | (-1.12) |
| 5 | -0.12% | 0.54% | -0.05% | -0.05% | -0.05% |
| | | (2.99) | (-1.02) | (-1.02) | (-1.05) |
| 6 | 0.11% | 0.62% | 0.05% | 0.05% | 0.05% |
| | | (3.59) | (1.21) | (1.09) | (1.18) |
| 7 | 0.39% | 0.60% | 0.02% | 0.02% | 0.03% |
| | | (3.39) | (0.47) | (0.35) | (0.50) |
| 8 | 0.67% | 0.84% | 0.23% | 0.19% | 0.19% |
| | | (4.44) | (4.02) | (3.44) | (3.35) |
| 9 | 1.04% | 0.83% | 0.18% | 0.12% | 0.13% |
| | | (4.11) | (2.84) | (1.97) | (2.12) |
| 10 | 1.76% | 0.94% | 0.21% | 0.10% | 0.08% |
| | | (4.03) | (2.34) | (1.26) | (0.99) |
| 10-1 | | 0.56% | 0.54% | 0.47% | 0.38% |
| | | (4.45) | (4.21) | (3.71) | (2.94) |

**Table 4**

**One-month waiting period before portfolio formation**

This table presents monthly abnormal returns of leader-signal-sorted portfolios. The sample consists of stocks that traded on the last day of the prior month, that were priced above $5 per share in 2011 inflation-adjusted dollars, and that had leaders. One month is skipped between the month in which leader signals are calculated and the time of portfolio formation. In Panel A, leaders are identified with 12-month rolling regressions and in Panel B, leaders are identified with 36-month rolling regressions. Portfolios are formed within 36 industries based on the equal-weighted leader signal computed at the end of the previous month. Each panel reports excess returns and four-factor alphas for equal- and value-weighted portfolios and, in the last row, the return differentials between the high- and low-signal portfolios. Newey-West-adjusted $t$-statistics are reported in parentheses.

Panel A: Leaders are identified with 12-month rolling regressions

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.71% | -0.22% | 0.55% | -0.12% |
| | (2.64) | (-2.77) | (2.39) | (-1.38) |
| 2 | 0.87% | 0.03% | 0.63% | -0.01% |
| | (3.48) | (0.51) | (3.02) | (-0.16) |
| 3 | 0.87% | 0.06% | 0.61% | 0.03% |
| | (3.68) | (1.11) | (3.22) | (0.55) |
| 4 | 0.88% | 0.08% | 0.65% | 0.09% |
| | (3.85) | (1.62) | (3.44) | (1.55) |
| 5 | 0.83% | 0.06% | 0.62% | 0.11% |
| | (3.70) | (1.15) | (3.44) | (2.21) |
| 6 | 0.82% | 0.05% | 0.58% | 0.05% |
| | (3.76) | (1.21) | (3.36) | (0.98) |
| 7 | 0.88% | 0.10% | 0.59% | 0.04% |
| | (4.01) | (2.21) | (3.35) | (0.79) |
| 8 | 0.85% | 0.03% | 0.52% | -0.03% |
| | (3.74) | (0.69) | (2.85) | (-0.58) |
| 9 | 0.90% | 0.03% | 0.52% | -0.14% |
| | (3.72) | (0.50) | (2.63) | (-2.36) |
| 10 | 1.05% | -0.00% | 0.73% | -0.06% |
| | (3.68) | (-0.03) | (3.23) | (-0.78) |
| 10-1 | 0.33% | 0.21% | 0.18% | 0.05% |
| | (2.89) | (1.81) | (1.43) | (0.42) |

Panel B: Leaders are identified with 36-month rolling regressions

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.78% | -0.18% | 0.58% | -0.14% |
| | (2.85) | (-2.49) | (2.49) | (-1.61) |
| 2 | 0.88% | 0.00% | 0.68% | 0.04% |
| | (3.46) | (0.06) | (3.22) | (0.65) |
| 3 | 0.88% | 0.05% | 0.65% | 0.05% |
| | (3.75) | (0.96) | (3.38) | (0.96) |
| 4 | 0.85% | 0.02% | 0.61% | 0.05% |
| | (3.81) | (0.54) | (3.41) | (1.04) |
| 5 | 0.92% | 0.07% | 0.60% | 0.01% |
| | (4.09) | (1.40) | (3.27) | (0.17) |
| 6 | 0.92% | 0.11% | 0.58% | 0.04% |
| | (4.19) | (2.55) | (3.46) | (0.80) |
| 7 | 0.94% | 0.11% | 0.54% | -0.04% |
| | (4.30) | (2.30) | (3.02) | (-0.72) |
| 8 | 0.99% | 0.08% | 0.76% | 0.13% |
| | (4.20) | (1.49) | (4.03) | (2.38) |
| 9 | 1.00% | 0.07% | 0.61% | -0.06% |
| | (4.19) | (1.12) | (3.19) | (-0.97) |
| 10 | 1.10% | 0.01% | 0.67% | -0.16% |
| | (4.01) | (0.15) | (3.04) | (-1.96) |
| 10-1 | 0.32% | 0.19% | 0.09% | -0.03% |
| | (3.03) | (1.80) | (0.73) | (-0.22) |

**Table 5**

**Alternative methods for aggregating leader signals**

This table presents monthly abnormal return differentials between the highest- and lowest-signal decile portfolios. The sample consists of stocks that traded on the last day of the prior month, that were priced above $5 per share in 2011 inflation-adjusted dollars, and that had leaders. Leader signals are computed "non-parametrically," by multiplying the past-month's leader returns by the sign($\hat{b}_3$) and weighting them as described above each set of results. In Panel B, one month is skipped between the time that leader signals are calculated and portfolio formed. Leaders are identified with 12-month rolling regressions. Portfolios are formed within 36 industries based on the equal-weighted leader signal. Newey-West-adjusted $t$-statistics are reported in parentheses.

Panel A: Portfolios are formed based on month $t-1$ leader signals, corresponding to Table 2

| Return Differentials (Portfolio 10−Portfolio 1) | | | |
|---|---|---|---|
| Equal-weighted | | Value-weighted | |
| Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| Non-parametric signals are equal-weighted | | | |
| 0.83% | 0.66% | 0.35% | 0.26% |
| (8.35) | (6.65) | (3.31) | (2.38) |
| Non-parametric signals are value-weighted | | | |
| 0.29% | 0.24% | 0.23% | 0.22% |
| (4.07) | (3.34) | (2.75) | (2.50) |
| Non-parametric signals are weighted by $\lvert t\text{-stat}(\hat{b}_3)\rvert$ | | | |
| 0.87% | 0.70% | 0.37% | 0.28% |
| (8.79) | (7.13) | (3.24) | (2.37) |
| Non-parametric signals are weighted by $\lvert\hat{b}_3\rvert$ | | | |
| 0.74% | 0.56% | 0.21% | 0.12% |
| (7.67) | (5.85) | (1.90) | (1.05) |

Panel B: Portfolios are formed based on month $t-2$ leader signals, corresponding to Table 4

| Return Differentials (Portfolio 10 - Portfolio 1) | | | |
|---|---|---|---|
| Equal-weighted | | Value-weighted | |
| Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| Non-parametric signals are equal-weighted | | | |
| 0.31% | 0.25% | 0.04% | -0.01% |
| (3.76) | (2.95) | (0.44) | (-0.11) |
| Non-parametric signals are value-weighted | | | |
| 0.07% | -0.03% | 0.03% | -0.05% |
| (0.95) | (-0.48) | (0.34) | (-0.56) |
| Non-parametric signals are weighted by $\lvert t\text{-stat}(\hat{b}_3)\rvert$ | | | |
| 0.29% | 0.23% | 0.11% | 0.05% |
| (3.52) | (2.75) | (1.03) | (0.49) |
| Non-parametric signals are weighted by $\lvert\hat{b}_3\rvert$ | | | |
| 0.28% | 0.20% | 0.08% | 0.01% |
| (3.20) | (2.25) | (0.80) | (0.11) |

**Table 6**

**Alternative specifications and robustness checks**

This table presents monthly abnormal returns of leader-signal-sorted portfolios. The sample consists of stocks that traded on the last day of the prior month, that were priced above $5 per share in 2011 inflation-adjusted dollars, and that had leaders. In the baseline specification, leaders are identified with 12-month rolling regressions and portfolios are formed within 36 industries based on the equal-weighted leader signal computed at the end of the previous month. Variations on this baseline specification are described in each panel heading. Each panel reports excess returns and four-factor alphas for equal- and value-weighted portfolios and, in the last row, the return differentials between the high- and low-signal portfolios. Newey-West-adjusted $t$-statistics are reported in parentheses.

Panel A: Stocks are sorted over the entire sample and *not* within each industry

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.54% | -0.36% | 0.31% | -0.41% |
| | (1.91) | (-4.13) | (1.26) | (-4.03) |
| ... | | | | |
| 10 | 1.34% | 0.23% | 0.97% | 0.07% |
| | (4.39) | (2.69) | (3.77) | (0.74) |
| 10-1 | 0.80% | 0.59% | 0.66% | 0.48% |
| | (6.45) | (4.82) | (4.40) | (3.16) |

Panel B: Stocks are sorted over the entire sample and *not* within each industry; leaders are identified with 36-month rolling regressions

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.58% | -0.37% | 0.43% | -0.29% |
| | (1.99) | (-3.79) | (1.63) | (-2.62) |
| ... | | | | |
| 10 | 1.50% | 0.38% | 1.03% | 0.09% |
| | (4.99) | (4.28) | (3.88) | (0.86) |
| 10-1 | 0.93% | 0.75% | 0.60% | 0.38% |
| | (6.96) | (5.49) | (3.61) | (2.25) |

Panel C: Leader signals are value-weighted

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.82% | -0.11% | 0.45% | -0.22% |
| | (2.97) | (-1.55) | (2.01) | (-2.95) |
| ... | | | | |
| 10 | 1.05% | 0.03% | 0.82% | 0.08% |
| | (3.75) | (0.48) | (3.62) | (0.90) |
| 10-1 | 0.23% | 0.14% | 0.37% | 0.30% |
| | (2.82) | (1.69) | (3.25) | (2.54) |

Panel D: Leader signals are value-weighted; leaders are identified with 36-month rolling regressions

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.81% | -0.19% | 0.53% | -0.21% |
| | (2.88) | (-2.65) | (2.38) | (-2.70) |
| ... | | | | |
| 10 | 1.17% | 0.09% | 0.85% | 0.01% |
| | (4.22) | (1.37) | (3.59) | (0.08) |
| 10-1 | 0.36% | 0.28% | 0.31% | 0.21% |
| | (4.30) | (3.33) | (2.72) | (1.80) |

Panel E: 1990-2011 sample period

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.33% | -0.31% | 0.24% | -0.32% |
| | (0.80) | (-2.37) | (0.60) | (-1.97) |
| ... | | | | |
| 10 | 0.81% | 0.08% | 0.53% | -0.17% |
| | (2.00) | (0.61) | (1.37) | (-0.92) |
| 10-1 | 0.48% | 0.38% | 0.30% | 0.15% |
| | (2.37) | (1.88) | (1.12) | (0.57) |

Panel F: 1990-2011 sample period; leaders are identified with 36-month rolling regressions

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.32% | -0.32% | 0.37% | -0.18% |
| | (0.78) | (-2.45) | (0.99) | (-1.16) |
| ... | | | | |
| 10 | 1.07% | 0.34% | 0.84% | 0.15% |
| | (2.70) | (2.80) | (2.30) | (0.90) |
| 10-1 | 0.75% | 0.66% | 0.47% | 0.32% |
| | (3.75) | (3.28) | (1.96) | (1.34) |

Panel G: Only signals from positive leaders are used

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.50% | -0.35% | 0.26% | -0.46% |
| | (1.95) | (-3.56) | (1.16) | (-4.72) |
| ... | | | | |
| 10 | 1.21% | 0.20% | 0.84% | 0.09% |
| | (4.31) | (1.99) | (3.48) | (0.80) |
| 10-1 | 0.71% | 0.55% | 0.58% | 0.54% |
| | (4.23) | (3.20) | (3.48) | (3.17) |

Panel H: Only signals from negative leaders are used

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.71% | -0.23% | 0.48% | -0.22% |
| | (2.54) | (-2.48) | (2.01) | (-2.17) |
| ... | | | | |
| 10 | 0.95% | 0.03% | 0.51% | -0.24% |
| | (3.62) | (0.29) | (2.25) | (-2.75) |
| 10-1 | 0.24% | 0.26% | 0.03% | -0.02% |
| | (1.51) | (1.66) | (0.20) | (-0.11) |

Panel I: Only signals from leaders in a different industry are used

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.54% | -0.36% | 0.40% | -0.31% |
| | (1.97) | (-4.42) | (1.68) | (-3.49) |
| ... | | | | |
| 10 | 1.33% | 0.25% | 0.86% | 0.10% |
| | (4.62) | (3.17) | (3.74) | (1.11) |
| 10-1 | 0.79% | 0.61% | 0.46% | 0.41% |
| | (7.00) | (5.38) | (3.59) | (3.09) |

Panel J: Only signals from leaders that are smaller than their followers are used

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.71% | -0.26% | 0.36% | -0.31% |
| | (2.44) | (-3.39) | (1.55) | (-3.57) |
| ... | | | | |
| 10 | 1.32% | 0.28% | 0.79% | 0.02% |
| | (4.60) | (3.50) | (3.36) | (0.26) |
| 10-1 | 0.61% | 0.54% | 0.42% | 0.33% |
| | (6.07) | (5.21) | (3.38) | (2.62) |

Panel K: Only signals from first-time leaders in three years are used

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.80% | -0.14% | 0.49% | -0.16% |
| | (2.94) | (-1.75) | (2.26) | (-2.16) |
| ... | | | | |
| 10 | 1.14% | 0.13% | 0.73% | 0.02% |
| | (4.10) | (2.12) | (3.28) | (0.28) |
| 10-1 | 0.34% | 0.27% | 0.24% | 0.19% |
| | (3.93) | (3.03) | (2.38) | (1.75) |

Panel L: Only signals from leaders that also led the follower at some time in the previous three years are used

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.54% | -0.37% | 0.35% | -0.31% |
| | (1.99) | (-4.84) | (1.58) | (-3.69) |
| ... | | | | |
| 10 | 1.33% | 0.27% | 0.84% | 0.03% |
| | (4.64) | (3.50) | (3.57) | (0.34) |
| 10-1 | 0.79% | 0.64% | 0.49% | 0.34% |
| | (7.59) | (6.11) | (3.79) | (2.59) |

Panel M: Only signals from leaders that are *not* announcing quarterly earnings in the current month are used (sample period: 1972-2011)

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.30% | -0.35% | 0.17% | -0.27% |
| | (0.98) | (-4.22) | (0.63) | (-2.52) |
| ... | | | | |
| 10 | 0.85% | 0.05% | 0.53% | -0.14% |
| | (2.69) | (0.56) | (1.87) | (-1.13) |
| 10-1 | 0.55% | 0.40% | 0.36% | 0.13% |
| | (4.50) | (3.20) | (2.06) | (0.76) |

Panel N: Only signals from leaders that *are* announcing quarterly earnings in the current month are used (sample period: 1972-2011)

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.37% | -0.30% | 0.34% | -0.24% |
| | (1.18) | (-3.32) | (1.24) | (-2.35) |
| ... | | | | |
| 10 | 0.80% | 0.05% | 0.50% | -0.07% |
| | (2.59) | (0.60) | (1.91) | (-0.68) |
| 10-1 | 0.42% | 0.35% | 0.15% | 0.17% |
| | (3.47) | (2.80) | (1.03) | (1.10) |

Panel O: Leaders are determined using a cutoff $t$-statistic $(\hat{b}_3) \geq 2.57$

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.58% | -0.32% | 0.34% | -0.33% |
| | (2.12) | (-4.57) | (1.43) | (-4.02) |
| ... | | | | |
| 10 | 1.32% | 0.27% | 0.87% | 0.06% |
| | (4.58) | (3.57) | (3.72) | (0.84) |
| 10-1 | 0.74% | 0.59% | 0.53% | 0.40% |
| | (7.20) | (5.69) | (4.46) | (3.24) |

Panel P: Leaders are determined using a cutoff $t$-statistic $(\hat{b}_3) \geq 2.57$; stocks are sorted over the entire sample and *not* within each industry

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.55% | -0.35% | 0.31% | -0.43% |
| | (1.96) | (-4.40) | (1.26) | (-4.49) |
| ... | | | | |
| 10 | 1.34% | 0.25% | 0.90% | 0.04% |
| | (4.35) | (3.02) | (3.51) | (0.44) |
| 10-1 | 0.79% | 0.61% | 0.58% | 0.47% |
| | (6.52) | (5.04) | (4.30) | (3.37) |

Panel Q: Skip one month between the end of the rolling regression window and the estimation of the leader signal

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.76% | -0.24% | 0.51% | -0.22% |
| | (2.78) | (-3.14) | (2.29) | (-2.71) |
| ... | | | | |
| 10 | 1.22% | 0.09% | 0.81% | 0.00% |
| | (4.27) | (1.15) | (3.42) | (0.04) |
| 10-1 | 0.45% | 0.33% | 0.30% | 0.23% |
| | (4.49) | (3.19) | (2.33) | (1.72) |

Panel R: Skip five years between the end of the rolling regression window and the estimation of the leader signal

| | EW portfolios | | VW portfolios | |
|---|---|---|---|---|
| Decile | Excess return | 4-factor alpha | Excess return | 4-factor alpha |
| 1 | 0.89% | -0.07% | 0.70% | -0.02% |
| | (3.93) | (-0.96) | (3.76) | (-0.28) |
| ... | | | | |
| 10 | 0.94% | -0.03% | 0.56% | -0.21% |
| | (4.31) | (-0.54) | (2.99) | (-3.18) |
| 10-1 | 0.05% | 0.03% | -0.15% | -0.19% |
| | (0.60) | (0.44) | (-1.53) | (-1.87) |

**Table 7**

**Weekly portfolios sorted on the equal-weighted leader signal within 36 industries, 1980-2011**

This table presents weekly abnormal returns of leader-signal-sorted portfolios. Leaders for each stock are identified using 52-week rolling regressions, as described in the text. At the beginning of each week, all stocks that traded on the last day of the prior week, that were priced above $5 per share in 2011 inflation-adjusted dollars, and that had leader stocks are sorted into decile portfolios within each of the 36 industries based on the previous week's equal-weighted aggregate leader signal, computed as described in the text. Portfolio returns are equal-weighted in Panel A and value-weighted in Panel B. The second column reports the average weekly portfolio return in excess of the risk-free rate; the third column reports the market alpha; the fourth column reports the weekly alpha of the Fama and French (1993) three-factor model; and the fifth column reports the weekly alpha of the four-factor model that also includes the Carhart (1997) momentum factor, using weekly factor returns. The last row reports the return differential between the high- and the low-signal portfolios (deciles 10 and 1). Newey-West-adjusted $t$-statistics are reported in parentheses.

Panel A: Equal-weighted portfolios

| Decile | Excess return | Market alpha | 3-factor alpha | 4-factor alpha |
|---|---|---|---|---|
| 1 | -0.15% | -0.28% | -0.31% | -0.28% |
| | (-1.74) | (-6.73) | (-12.2) | (-11.3) |
| 2 | 0.02% | -0.11% | -0.14% | -0.11% |
| | (0.24) | (-3.32) | (-7.52) | (-6.56) |
| 3 | 0.09% | -0.03% | -0.06% | -0.04% |
| | (1.28) | (-0.92) | (-3.54) | (-2.29) |
| 4 | 0.15% | 0.04% | 0.01% | 0.03% |
| | (2.33) | (1.46) | (0.73) | (1.98) |
| 5 | 0.17% | 0.06% | 0.03% | 0.05% |
| | (2.61) | (2.22) | (2.20) | (3.31) |
| 6 | 0.21% | 0.10% | 0.07% | 0.09% |
| | (3.17) | (3.49) | (4.62) | (5.59) |
| 7 | 0.25% | 0.14% | 0.11% | 0.13% |
| | (3.72) | (4.55) | (6.87) | (7.70) |
| 8 | 0.29% | 0.18% | 0.15% | 0.17% |
| | (4.13) | (5.57) | (9.45) | (9.83) |
| 9 | 0.32% | 0.21% | 0.18% | 0.20% |
| | (4.34) | (5.74) | (9.78) | (10.63) |
| 10 | 0.38% | 0.26% | 0.23% | 0.25% |
| | (4.43) | (5.54) | (8.92) | (9.48) |
| 10-1 | 0.53% | 0.54% | 0.55% | 0.53% |
| | (12.63) | (12.79) | (12.83) | (12.54) |

Panel B: Value-weighted portfolios

| Decile | Excess return | Market alpha | 3-factor alpha | 4-factor alpha |
|---|---|---|---|---|
| 1 | -0.04% | -0.19% | -0.23% | -0.18% |
| | (-0.56) | (-6.11) | (-7.11) | (-6.05) |
| 2 | 0.02% | -0.12% | -0.13% | -0.12% |
| | (0.27) | (-5.85) | (-6.05) | (-5.82) |
| 3 | 0.09% | -0.04% | -0.04% | -0.04% |
| | (1.50) | (-2.01) | (-2.43) | (-1.91) |
| 4 | 0.12% | 0.00% | 0.00% | 0.00% |
| | (2.20) | (0.19) | (0.09) | (0.11) |
| 5 | 0.11% | -0.00% | 0.00% | -0.00% |
| | (2.03) | (-0.26) | (0.07) | (-0.15) |
| 6 | 0.15% | 0.03% | 0.04% | 0.04% |
| | (2.65) | (2.25) | (2.76) | (2.57) |
| 7 | 0.14% | 0.02% | 0.02% | 0.02% |
| | (2.57) | (1.40) | (1.40) | (0.93) |
| 8 | 0.22% | 0.10% | 0.10% | 0.10% |
| | (3.68) | (5.15) | (5.45) | (5.00) |
| 9 | 0.24% | 0.11% | 0.11% | 0.11% |
| | (3.54) | (4.79) | (4.73) | (4.73) |
| 10 | 0.24% | 0.10% | 0.10% | 0.11% |
| | (3.17) | (3.23) | (3.24) | (3.44) |
| 10-1 | 0.28% | 0.29% | 0.32% | 0.29% |
| | (6.27) | (6.50) | (6.96) | (6.30) |

**Table 8**

**Weekly portfolios sorted on the equal-weighted leader signal and the previous week's return, within 36 industries, 1980-2011**

This table presents weekly four-factor alphas of portfolios sorted every week and within each of the 36 industries first into leader-signal quintiles and then into further quintiles based on the previous week's return. Leaders for each stock are identified using 52-week rolling regressions, as described in the text. The set of stocks is limited to those that have traded on the last day of the previous week, that were priced above $5 per share in 2011 inflation-adjusted dollars, and that had leaders. Portfolio returns are equal-weighted in Panel A and value-weighted in Panel B. Newey-West-adjusted $t$-statistics are reported in parentheses. The last column reports four-factor alphas of return differentials between the highest- and lowest-return-quintile portfolios. The last raw reports four-factor alphas of return differentials between the highest- and lowest-signal-quintile portfolios. Corner numbers report the four-factor alpha of the return differential between the highest-signal/lowest-return and lowest-signal/highest-return portfolios (portfolio 51−portfolio 15).

Panel A: Equal-weighted portfolios

| Signal | Prior week's return quintile | | | | | | |
|---|---|---|---|---|---|---|---|
| quintile | 1 | 2 | 3 | 4 | 5 | 5-1 | |
| 1 | 0.41% | -0.04% | -0.19% | -0.35% | **-0.78%** | -1.19% | |
| | (11.43) | (-1.80) | (-8.43) | (-13.2) | (-18.4) | (-18.74) | |
| 2 | 0.52% | 0.10% | -0.02% | -0.14% | -0.43% | -0.95% | |
| | (18.43) | (5.03) | (-1.08) | (-7.05) | (-15.4) | (-20.41) | |
| 3 | 0.55% | 0.17% | 0.05% | -0.05% | -0.33% | -0.87% | |
| | (18.70) | (7.71) | (2.57) | (-2.93) | (-14.2) | (-20.07) | |
| 4 | 0.66% | 0.26% | 0.11% | 0.03% | -0.28% | -0.94% | |
| | (19.75) | (11.98) | (5.52) | (1.35) | (-12.4) | (-20.74) | |
| 5 | **0.91%** | 0.37% | 0.19% | 0.05% | -0.34% | -1.25% | |
| | (18.52) | (13.22) | (7.56) | (2.08) | (-11.3) | (-19.99) | 51-15 |
| 5-1 | 0.50% | 0.41% | 0.38% | 0.39% | 0.44% | | **1.69%** |
| | (10.90) | (11.88) | (10.84) | (11.40) | (10.63) | | (20.51) |

Panel B: Value-weighted portfolios

| Signal | Prior week's return quintile | | | | | | |
|---|---|---|---|---|---|---|---|
| quintile | 1 | 2 | 3 | 4 | 5 | 5-1 | |
| 1 | 0.25% | 0.01% | -0.13% | -0.26% | **-0.53%** | -0.78% | |
| | (5.74) | (0.26) | (-3.87) | (-8.16) | (-11.18) | (-11.98) | |
| 2 | 0.32% | 0.09% | 0.01% | -0.14% | -0.32% | -0.64% | |
| | (9.16) | (3.48) | (0.49) | (-5.50) | (-9.37) | (-11.74) | |
| 3 | 0.41% | 0.16% | 0.04% | -0.12% | -0.31% | -0.71% | |
| | (10.27) | (5.97) | (1.66) | (-4.65) | (-9.68) | (-12.47) | |
| 4 | 0.41% | 0.20% | 0.04% | -0.10% | -0.24% | -0.65% | |
| | (10.42) | (7.26) | (1.40) | (-4.20) | (-7.92) | (-12.58) | |
| 5 | **0.49%** | 0.27% | 0.11% | -0.01% | -0.27% | -0.77% | |
| | (10.43) | (7.65) | (3.72) | (-0.25) | (-6.81) | (-12.30) | 51-15 |
| 5-1 | **0.24%** | 0.26% | 0.25% | 0.26% | 0.26% | | **1.03%** |
| | (4.16) | (5.18) | (5.14) | (5.84) | (4.35) | | (13.73) |

**Table 9**
**Portfolios double sorted on turnover and the weekly leader signal, at various weekly lags**

This table presents weekly four-factor alphas of equal-weighted return differentials between top and bottom weekly-signal decile portfolios. Within each of the 36 industries, stocks are first sorted into quintiles based on their turnover over the past 12 months and then on the leader signal. The number of weeks skipped between the week in which turnover and leader signals are calculated and the week in which portfolios are formed is indicated in each row heading. Portfolios are formed based on month-$t-Lag$ leader signals, corresponding to Table 7. Newey-West-adjusted $t$-statistics are reported in parentheses. All cells insignificant at the 10% level are shaded in grey.

Four-factor alphas of the return differentials (decile 10−decile 1)

| Stock turnover quintile | | | | |
|---|---|---|---|---|
| 1 (low) | 2 | 3 | 4 | 5 (high) |
| $Lag = 0$ weeks | | | | |
| 0.63% | 0.59% | 0.47% | 0.53% | 0.38% |
| (13.38) | (13.29) | (9.65) | (11.20) | (5.98) |
| $Lag = 1$ week | | | | |
| 0.25% | 0.24% | 0.24% | 0.25% | 0.11% |
| (5.53) | (5.73) | (5.48) | (5.27) | (1.81) |
| $Lag = 2$ weeks | | | | |
| 0.10% | 0.19% | 0.07% | 0.18% | 0.09% |
| (2.35) | (4.39) | (1.66) | (3.79) | (1.45) |
| $Lag = 3$ weeks | | | | |
| 0.12% | 0.09% | 0.08% | 0.05% | 0.08% |
| (2.54) | (2.11) | (1.87) | (1.17) | (1.33) |
| $Lag = 4$ weeks | | | | |
| 0.05% | 0.12% | -0.03% | -0.02% | -0.07% |
| (1.09) | (2.90) | (-0.73) | (-0.44) | (-1.05) |
| $Lag = 5$ weeks | | | | |
| 0.05% | 0.08% | 0.10% | 0.05% | 0.07% |
| (1.11) | (1.89) | (2.28) | (1.01) | (1.07) |
| $Lag = 6$ weeks | | | | |
| -0.01% | -0.03% | -0.05% | 0.04% | -0.07% |
| (-0.12) | (-0.70) | (-1.01) | (0.86) | (-1.11) |

**Table 10**
**Cross-sectional regressions**

This table presents the results of Fama and MacBeth (1973) regressions of stock returns on a set of explanatory variables lagged by one month in Panels A and B and by one week in Panel C. In Panels A and B, all variables are computed at monthly frequencies. In Panel C, superscript $w$ indicates leader signals and returns computed at weekly frequencies; all other variables are computed at monthly frequencies at the end of the previous month. The explanatory variables are described in the appendix. The sample consists of all common stocks of U.S.-incorporated firms that traded at the end of the previous month (the previous week in Panel C) and had leaders. *med* is the median value of each variable. Newey-West-adjusted $t$-statistics are reported in parentheses.

Panel A: Sample period: January 1929 - December 2011

| | | | | Subsamples | | | | Leaders from 36-mo. rolling windows* |
|---|---|---|---|---|---|---|---|---|
| | | | | Size>med | Turn>med | Age>med | | |
| ×100 | $Ret_t$ | $Ret_t$ | $Ret_t$ | $Ret_t$ | $Ret_t$ | $Ret_t$ | $Ret_t - Ind.Ret_t$ | $Ret_t$ |
| Specification | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Leader Signal $(\text{EW})_{t-1}$ | $10.959^a$ | $10.464^a$ | $12.190^a$ | $10.111^a$ | $8.026^a$ | $8.49^a$ | $9.408^a$ | $24.000^a$ |
| | (6.81) | (6.80) | (5.43) | (5.69) | (4.62) | (4.67) | (6.94) | (8.86) |
| $Ret_{t-1}$ | $-6.653^a$ | $-7.439^a$ | $-5.887^a$ | $-4.399^a$ | $-5.598^a$ | $-7.226^a$ | $-7.367^a$ | $-7.910^a$ |
| | (-12.45) | (-13.74) | (-11.21) | (-8.68) | (-12.12) | (-12.81) | (-14.46) | (-13.84) |
| Momentum | $0.110^a$ | $0.106^a$ | $0.060^a$ | $0.062^b$ | $0.093^a$ | $0.056^a$ | $0.101^a$ | $0.124^a$ |
| | (2.86) | (2.84) | (2.51) | (2.95) | (3.09) | (2.88) | (2.98) | (3.10) |
| Ind. $\text{Ret}_{t-1}$ | | $20.251^a$ | $18.421^a$ | $18.070^a$ | $15.634^a$ | $15.412^a$ | | $15.762^a$ |
| | | (13.13) | (13.79) | (11.79) | (13.83) | (14.39) | | (15.56) |
| Size | $0.000^c$ | 0.000 | $0.000^c$ | 0.000 | $0.000^b$ | $0.000^b$ | $0.000^c$ | $0.000^b$ |
| | (-1.77) | (-1.85) | (-1.59) | (-1.60) | (-2.34) | (-2.27) | (-1.86) | (-2.07) |
| Leader Signal $(\text{EW})_{t-1}$ | | | $-15.555^c$ | | | | | |
| $\times Ret_{t-1}$ | | | (-1.67) | | | | | |

Panel B: Sample period: August 1963 - December 2011

| | | | Leaders from 36-mo. rolling windows* | |
|---|---|---|---|---|
| ×100 | $Ret_t$ | $Ret_t$ | $Ret_t$ | $Ret_t$ |
| Specification | (1) | (2) | (3) | (4) |
| Leader Signal $(EW)_{t-1}$ | $6.354^a$ | $7.684^a$ | $18.802^a$ | $22.120^a$ |
| | (3.15) | (3.39) | (6.53) | (6.39) |
| $Ret_{t-1}$ | $-6.000^a$ | $-5.063^a$ | $-6.333^a$ | $-5.241^a$ |
| | (-11.25) | (-10.09) | (-11.72) | (-10.64) |
| Momentum | $0.050^a$ | $0.047^a$ | $0.052^a$ | $0.052^a$ |
| | (4.07) | (3.47) | (4.48) | (4.06) |
| Ind. $Ret_{t-1}$ | $17.469^a$ | | $15.212^a$ | |
| | (10.19) | | (13.02) | |
| Size | $0.000^b$ | $0.000^b$ | $0.000^b$ | $0.000^b$ |
| | (-2.49) | (-2.27) | (-2.42) | (-2.17) |
| Book/Market | $0.204^a$ | $0.113^a$ | $0.191^a$ | $0.197^a$ |
| | (3.63) | (3.94) | (3.26) | (3.23) |
| Beta | 0.126 | | 0.159 | |
| | (1.20) | | (1.42) | |
| Illiq | $0.044^b$ | $0.049^b$ | $0.038^c$ | $0.039^b$ |
| | (2.21) | (2.44) | (1.91) | (1.97) |
| IVOL | $-0.119^b$ | $-0.130^b$ | $-0.119^b$ | $-0.106^c$ |
| | (-2.57) | (-2.20) | (-2.57) | (-1.73) |

* The sample period for this regression is two years shorter.

Panel C: Weekly returns; sample period: January 1980 - December 2011

| $\times 100$ | $Ret_t^w$ | $Ret_t^w$ | $Ret_t^w$ | $Ret_t^w$ | $Ret_t^w$ | $Ret_t^{w§}$ | $Ret_t^w$ | $Ret_t^{w¶}$ | $Ret_t^w$ | $Ret_t^w$ | $Ret_t^w$ | $Ret_t^w$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Specification | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Leader Signal $(\text{EW})_{t-1}^w$ | 70.187[a] | 31.581[a] | 42.886[a] | 34.815[a] | 33.334[a] | 32.316[a] | 38.575[a] | 38.816[a] | 44.986[a] | 53.295[a] | 33.311[a] | 29.668[a] |
| | (14.15) | (10.37) | (12.17) | (11.15) | (10.77) | (8.22) | (11.49) | (11.78) | (12.04) | (13.23) | (9.05) | (9.90) |
| $\text{Ret}_{t-1}^w$ | | -8.528[a] | -8.553[a] | -8.700[a] | -8.551[a] | -5.849[a] | -8.535[a] | -8.382[a] | -8.521[a] | -8.521[a] | -8.534[a] | -8.560[a] |
| | | (-28.27) | (-27.23) | (-27.50) | (-28.62) | (-16.13) | (-28.24) | (-25.13) | (-28.24) | (-28.27) | (-28.26) | (-28.38) |
| Ind. $\text{Ret}_{t-1}^w$ | | 12.714[a] | 13.327[a] | 12.754[a] | 12.693[a] | 6.726[a] | 12.678[a] | 11.592[a] | 12.691[a] | 12.661[a] | 12.711[a] | 12.576[a] |
| | | (15.80) | (16.30) | (15.89) | (15.88) | (6.22) | (15.81) | (13.68) | (15.87) | (15.76) | (15.79) | (15.75) |
| Leader Signal $(\text{EW})_{t-1}^w$ interacted with: | | | | | | | | | | | | |
| $\times$ $\text{Ret}_{t-1}^w$ | | | | -172.794[a] | | | | | | | | |
| | | | | (-5.17) | | | | | | | | |
| $\times$ $\mathbb{1}\{Qtr.EarnAnn.\}_{t-1}$ | | | | | -2.871[c] | | | | | | | |
| | | | | | (-1.73) | | | | | | | |
| $\times\mathbb{1}\{News\}_{t-1}$ | | | | | | -2.843 | | | | | | |
| | | | | | | (-1.62) | | | | | | |
| $\times\mathbb{1}\{Inst.Ownership > med\}_{t-1}$ | | | | | | | -33.400[a] | | | | | |
| | | | | | | | (-7.32) | | | | | |
| $\times\mathbb{1}\{AnalystCoverage > med\}_{t-1}$ | | | | | | | | -37.784[a] | | | | |
| | | | | | | | | (-7.09) | | | | |
| $\times\mathbb{1}\{Size > med\}_{t-1}$ | | | | | | | | | -36.928[a] | | | |
| | | | | | | | | | (-7.96) | | | |
| $\times\mathbb{1}\{Turnover > med\}_{t-1}$ | | | | | | | | | | -37.217[a] | | |
| | | | | | | | | | | (-6.06) | | |
| $\times\mathbb{1}\{Age > med\}_{t-1}$ | | | | | | | | | | | -2.591 | |
| | | | | | | | | | | | (-0.64) | |
| Leader Signal $(\text{EW})_{t-1}^{monthly}$ | | | | | | | | | | | | 1.779[a] |
| | | | | | | | | | | | | (3.27) |
| Extended Controls[†] | Yes | Yes | No[‡] | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

[a], [b], and [c] indicate significance at the 1%, 5%, and 10% levels, respectively.

[†] Extended controls include Size, Book/Market, Momentum, Illiq, and IVOL and the dummies in the interaction terms when applicable.

[‡] Controls include Size and Book/Market.

[§] The regression sample period is April 1996 - December 2011.

[¶] The regression sample period is December 1983 - December 2011.

**Table 11**
**Short selling in response to the leader signal**

This table presents the results of the Fama-MacBeth regression of the change in utilization (defined as the number of shares on loan relative to the total number of shares available to be loaned out for short selling) on indicator functions of whether a stock enters or exits the bottom decile of the concurrent leader signal, the industry return, or the top decile of the concurrent own return on each Friday (relative to the Friday or the week before):

$$\begin{aligned}\Delta utilization_{it} &= \alpha + \beta_1 \cdot \mathbb{1}_{it}\{\text{Enters bottom signal decile}\} + \beta_2 \cdot \mathbb{1}_{it}\{\text{Exits bottom signal decile}\} \\ &+ \gamma_1 \cdot \mathbb{1}_{it}\{\text{Enters bottom ind. ret. decile}\} + \gamma_2 \cdot \mathbb{1}_{it}\{\text{Exits bottom ind. ret. decile}\} \\ &+ \mu_1 \cdot \mathbb{1}_{it}\{\text{Enters top return decile}\} + \mu_2 \cdot \mathbb{1}_{it}\{\text{Exits top return decile}\} + \epsilon_{it}\end{aligned}$$

Assuming that short sellers would set up short positions on the following Monday, utilization changes are calculated between the Thursday of the following week and the preceding Thursday, in order to account for the "t+3" security transaction settlement rule. The sample is trimmed at the top and bottom 1% of utilization, and stocks priced at less than $5/share in 2011 inflation-adjusted dollars are dropped. The sample period is October 8, 2008, to December 30, 2011. Newey-West-adjusted $t$-statistics are reported in parentheses.

| Sample selection* | (1) | (2) | (3) |
|---|---|---|---|
| $\alpha$ | -0.025 | -0.026 | -0.023 |
| | (-0.85) | (-0.88) | (-0.82) |
| $\beta_1$ | $0.075^b$ | $0.076^b$ | $0.084^b$ |
| | (2.05) | (2.06) | (2.49) |
| $\beta_2$ | -0.033 | -0.032 | 0.020 |
| | (-0.97) | (-0.95) | (0.56) |
| $\gamma_1$ | -0.021 | -0.021 | -0.014 |
| | (-0.68) | (-0.66) | (-0.45) |
| $\gamma_2$ | 0.051 | 0.052 | $0.078^a$ |
| | (1.60) | (1.63) | (2.95) |
| $\mu_1$ | 0.464 | 0.465 | 0.544 |
| | (1.18) | (1.18) | (1.37) |
| $\mu_2$ | $0.263^c$ | $0.263^c$ | 0.171 |
| | (1.74) | (1.74) | (1.15) |

*Sample selection criteria:
(1): All stocks included.
(2): Excludes stocks with quarterly earnings announcements anticipated next week.
(3): Excludes stocks with average loan fees in the top three fee buckets.

**Table 12**
**Determinants of leadership, April 1997 - December 2011**

This table presents the results of regressions of the number of followers (including zeros for the stocks that have no followers) on a set of explanatory variables, which are described in Appendices A1 and A2. The sample consists of all common shares of U.S.-incorporated firms. Panel A reports results for monthly-frequency leaders identified using 12-month rolling regressions and Panel B for weekly-frequency leaders identified using 52-week rolling regressions. In regression specifications (1)-(3), all highly relevant news and, in models (4)-(6), all highly relevant corporate news are counted over the previous 12-month period; the values of all explanatory variables are averaged over the previous 12 months. Panel C reports pairwise correlations between the control variables. Regressions are estimated with quasi-maximum likelihood and standard errors are clustered at the firm level. $z$-statistics are reported in parentheses.

Panel A: Leadership is determined with monthly rolling regressions

| | All highly relevant news | | | Highly relevant corp. events | | | | |
|---|---|---|---|---|---|---|---|---|
| Specification | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| News ($\times 10^2$) | $0.0075^a$ | $0.0056^a$ | $0.0112^a$ | $0.0100^a$ | $0.0074^a$ | $0.0123^a$ | | |
| | (6.30) | (4.19) | (6.15) | (6.50) | (4.58) | (5.40) | | |
| News$^2$ ($\times 10^4$) | | | $-0.0002^a$ | | | $-0.0002^b$ | | |
| | | | (-3.81) | | | (-2.46) | | |
| Inst. Ownership | | $0.0359^a$ | $0.0351^a$ | | $0.358^a$ | $0.0351^a$ | $0.0368^a$ | |
| | | (6.63) | (6.45) | | (6.60) | (6.45) | (6.81) | |
| Analyst Coverage | | $0.0020^a$ | $0.0018^a$ | | $0.0020^a$ | $0.0019^a$ | $0.0022^a$ | |
| | | (6.83) | (5.84) | | (6.88) | (6.24) | (7.67) | |
| Size ($\times 10^6$) | | $-0.4893^a$ | $-0.5741^a$ | | $-0.4730^a$ | $-0.5320^a$ | $-0.2241^b$ | $0.2730^b$ |
| | | (-3.98) | (-4.64) | | (-3.91) | (-4.38) | (-2.09) | (2.55) |
| Turnover | | 0.0003 | 0.0002 | | 0.0002 | 0.0001 | 0.0006 | |
| | | (0.38) | (0.24) | | (0.25) | (0.16) | (0.93) | |
| Book/Market | | $0.0031^b$ | $0.0031^b$ | | $0.0031^b$ | $0.0031^b$ | $0.0032^b$ | |
| | | (2.00) | (2.00) | | (2.00) | (2.01) | (2.01) | |
| Industry dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Panel B: Leadership is determined with weekly rolling regressions

| Specification | All highly relevant news (1) | (2) | (3) | Highly relevant corp. events (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| News ($\times 10^2$) | $0.0066^a$ | $0.0039^a$ | $0.0070^a$ | $0.0099^a$ | $0.0070^a$ | $0.0117^a$ | | |
| | (4.84) | (2.66) | (2.96) | (5.24) | (3.65) | (3.59) | | |
| News$^2$ ($\times 10^4$) | | | $-0.0001^b$ | | | $-0.0002^b$ | | |
| | | | (-2.28) | | | (-2.28) | | |
| Inst. Ownership | | $0.0483^a$ | $0.0478^a$ | | $0.480^a$ | $0.0472^a$ | $0.0489^a$ | |
| | | (7.84) | (7.74) | | (7.78) | (7.64) | (7.95) | |
| Analyst Coverage | | $0.0020^a$ | $0.0019^a$ | | $0.0020^a$ | $0.0018^a$ | $0.0021^a$ | |
| | | (6.07) | (5.70) | | (6.00) | (5.63) | (6.42) | |
| Size ($\times 10^6$) | | $-0.4242^a$ | $-0.4742^a$ | | $-0.4743^a$ | $-0.5335^a$ | $-0.2399^c$ | $0.2855^b$ |
| | | (-3.02) | (-3.28) | | (-3.24) | (-3.53) | (-1.87) | (2.15) |
| Turnover | | 0.0005 | 0.0004 | | 0.0003 | 0.0002 | 0.0007 | |
| | | (0.66) | (0.58) | | (0.40) | (0.30) | (1.02) | |
| Book/Market | | -0.0004 | -0.0005 | | -0.0005 | -0.0005 | -0.0004 | |
| | | (-0.56) | (-0.58) | | (-0.58) | (-0.60) | (-0.50) | |
| Industry dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

$^a$, $^b$, and $^c$ indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel C: Correlations between control variables[†]

| | News (all) | News (corp.) | Inst. Own. | An. Cov. | Size | Turnover | Book/Market |
|---|---|---|---|---|---|---|---|
| News (all) | 1.0000 | 0.94071 | 0.26187 | 0.4077 | 0.5072 | 0.1870 | -0.0194 |
| | | (<.0001) | (<.0001) | (<.0001) | (<.0001) | (<.0001) | (<.0001) |
| News (corp.) | | 1.0000 | 0.2659 | 0.3890 | 0.4671 | 0.1982 | -0.0150 |
| | | | (<.0001) | (<.0001) | (<.0001) | (<.0001) | (<.0001) |
| Inst. Own. | | | 1.0000 | 0.4773 | 0.1073 | 0.2586 | -0.0637 |
| | | | | (<.0001) | (<.0001) | (<.0001) | (<.0001) |
| Analyst Cov. | | | | 1.0000 | 0.4323 | 0.2831 | -0.1108 |
| | | | | | (<.0001) | (<.0001) | (<.0001) |
| Size | | | | | 1.0000 | 0.0180 | -0.0399 |
| | | | | | | (<.0001) | (<.0001) |
| Turnover | | | | | | 1.0000 | -0.0745 |
| | | | | | | | (<.0001) |

[†]p-values reported in parentheses.