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ABSTRACT

We identify all return leader-follower pairs among individual stocks using Granger causality regressions. 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. Our results indicate that, independent of its size, any firm may emerge as a return leader by being at the center of an important news development that has ramifications for other firms. Indeed, stocks undergoing news-generating developments see an increase in the number of stocks whose returns they lead.

JEL classification: G10, G12, G14, G17

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

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ABSTRACT

We identify all return leader-follower pairs among individual stocks using Granger causality regressions. 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. Our results indicate that, independent of its size, any firm may emerge as a return leader by being at the center of an important news development that has ramifications for other firms. Indeed, stocks undergoing news-generating developments see an increase in the number of stocks whose returns they lead.

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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 *New York Times* article on November 17, 1996, 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 market- or industry-wide 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, the discovery of questionable accounting practices at one firm may 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 affect other firms with plans to expand to that country. Consequently,

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

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

Depending on the circumstances, the direction of a stock's return leadership may be positive or negative. For example, bankruptcy rumors will have a negative impact on the firm's customers, suppliers, and providers of capital but a positive impact on its 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 the resolution of a patent infringement lawsuit.[3]

These examples illustrate that a firm at the center of a valuation-relevant news development can lead the returns of other firms that are similar on the relevant dimension of valuation. We provide several results in support of this underlying reason for return leadership. In particular, we show that stocks can lead the returns of stocks that are larger and operate in a different industry. We show that the lead-lag relation can be short-lived. And, as a more direct evidence for this mechanism of leadership, we also show that the number of followers that a stock has is positively related to the newsworthiness of its firm-level developments. For this purpose, we use the Thomson-Reuters News Analytics dataset that covers the period from April 1996 to December 2011. We find that when stocks experience an increase

[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 suggested in previous literature reviewed later in this section.

[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 sell the item at a price lower than 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.

in the number of news stories written about them, which, we argue, should be indicative of important news developments at the firm level, the number of stocks whose returns they lead increases as well. These findings are consistent with the notion that stocks may lead other stocks not only because they are quicker to react to common market or industry news but also because the firm itself may be at the origin of important news relevant for other firms.

There is ample evidence in the finance literature that prices react slowly to a firm's own news (e.g., the post-earnings announcement drift). Prices may react slower still when the relevant news is announced by another firm, especially when that news is of non-routine nature, which makes it difficult to immediately assess its effect on the firm 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) document that, in total, about 218 valuation-relevant news are announced by firms each day. Only about 20% of these news items contain 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 overlook relevant news announcements by other firms due to limited attention or the inability to quickly assess the degree of relevance of other firms' news due to slow processing of complex information.

We show that news indeed travels slowly across stocks and that trading strategies can be devised to exploit delays in stock price reactions at monthly and weekly frequencies. We do not attempt to identify return leaders using ex-ante firm characteristics. Rather, we rely on the statistical ability of leader stocks to Granger-cause their followers' returns, which 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. This approach, therefore, could help uncover new channels of information flow.

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 of at least one year. 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 returns 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 for each follower, we first multiply the estimated regression coefficient on a leader's lagged return by the leader's current-month's return to obtain that leader's signal and then compute the weighted average signal across all leaders of a particular follower stock. We confirm that this methodology is indeed able to identify lead-lag relationships that persist out-of-sample by showing 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.

The leaders' ability to predict their followers' returns is unlikely to be explained by data snooping. To illustrate this, we scramble our panel data along the time dimension while preserving each cross section. The leaders that we identify using this scrambled 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. In addition, we find that the return differential between the highest- and lowest-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.

Our methodology relates this paper to the literature on the lead-lag effect in stock returns. In that literature, stock prices of certain firms (followers) are shown to react with a delay to price innovations of other firms (leaders). Lo and MacKinlay (1990) document that leaders are large firms and followers are small firms by showing that large stocks predict returns of small stocks, 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.[4] 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)). Taken together, this evidence suggests that the lead-lag effect can be ascribed largely to slow diffusion of common information from stocks that have high levels of investor attention to those that do not.

One important point of difference from the lead-lag literature is that smaller stocks can lead returns of larger stocks. A long-short trading strategy based on the leader signal works better when leaders are composed of small rather than large stocks: Equal-weighting signals across leader stocks yields stronger predictive power for 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

[4] 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 stocks that traded on the last day of the previous period, thus largely eliminating the concern about non-synchronous trading. In addition, in 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 leader signal survives skipping one month before portfolio formation for equal-weighted portfolios, and the weekly leader signal survives skipping up to three weeks for equal-weighted and up to two weeks for value-weighted portfolios.

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.

Another important distinction from the lead-lag literature 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, when we limit the set of leaders to stocks belonging to a different industry than the follower, the strategy still works. From an investor's perspective, an advantage of intra-industry long-short bets is that these result in industry-neutral long-short portfolios that are hedged against industry-wide shocks. Such portfolios have less volatile returns relative to portfolios sorted over the entire stock sample, since those will likely contain uneven industry loadings.

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. Albuquerque, Ramadorai, and Watugala (2015) show that information can flow slowly across countries by showing that firms with high trade credit located in producer countries have stock returns that are strongly predictable based on the returns of their associated customer countries. 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

[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.

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. An important advantage of the Granger causality methodology used in this paper is its ability to identify not only stable (long-term) leaders, such as those determined by supply-chain links, but also transitory (short-term) leaders, whose leadership for a given firm will disappear once the relevant news development is resolved, and which are, therefore, not identifiable through traditional data sources.[7] Our paper is similar in spirit to Gatev, Goetzmann, and Rouwenhorst (2006) in that both papers rely on a statistical technique to identify firm interconnections. Gatev, Goetzmann, and Rouwenhorst (2006) investigate the performance of a pairs trading strategy and, like us, document the strategy is profitable even after accounting for trading costs.

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 firms with a larger number of news stories written about them tend to have more stock followers. Section V concludes.

[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 ownership and analyst coverage, we believe that our results are independent of these phenomena.

[7] Another advantage is not being limited by data availability (for example, firms are required by the SEC to report the identity of the customer only if that customer comprises more than 10% of a firm's consolidated sales revenues, and hence less prominent customers will be missing from the dataset, which would make it impossible to identify all customer-supplier pairs).

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 τ, we run the following monthly regression for each combination of stocks i and j:[8]

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

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.[9]

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.

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

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

[9]We were able to verify 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 to calculate abnormal returns. For these reasons and for the simplicity of exposition and replication, we report the results based on leader signals calculated with raw returns.

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. Hence, leaders are drawn from a somewhat larger set of stocks than followers.[11] The table shows that 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 of firm-month observations have at least one leader.

Insert Table 1 about here.

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. 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 lower turnover, and to be younger than its average leader stock.

[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. We choose to allow foreign stocks in the set of possible leaders because U.S. firms may be economically linked to firms in other countries (see, e.g., Albuquerque, Ramadorai, and Watugala (2015)).

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 market- or industry-wide news. Of note, market capitalizations in that table appear small because they are averaged over the entire sample period from 1929 to 2011. Finally, while leader-follower relations exhibit some persistence over time, the probability that a leader-follower pair existed as such in the past declines smoothly when moving further back in time, which is likely reflective of the fact that the leader and the follower had fewer similarities further in the past (for more details, see Table A1 and Section A1 in the Online Appendix).

III. Return Predictability

Having obtained a set of J_τ^i leaders for each stock i in month τ, if such leaders exist, we proceed to calculate the aggregate leader signal as the weighted average of the products of the leaders' returns in month τ and the corresponding coefficient estimate $\hat{b}_3$:

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

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 ($w_j = 1/J_\tau^i$). The inset box in Figure 1 illustrates how the aggregate equal-weighted leader signal is computed.[12]

[12]The advantage of the equal- or value-weighted signal aggregation methods is their 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

In the following, we present results based on portfolio sorts and cross-sectional return regressions. The data used in the paper are described in Section A2 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. We compute signals for each follower stock in month τ and we sort followers into deciles based on the aggregate leader signal 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 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 window and portfolio formation.

Insert Figure 1 about here.

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 highest- and lowest-signal portfolios.[13] 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 for both return-weighting methods. Moreover, 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,

Insert Table 2 about here.

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.

[13] 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 cube root of the number of observations in the time series.

but not when value-weighted. The lack of significance of the value-weighted alpha on the highest-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 the extreme decile 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 raw return differentials are 0.61% with a t-statistic of 6.20, and 0.45% with a t-statistic of 3.39 for equal- and value-weighted portfolios, respectively.[14] 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. The return differentials between highest and lowest leader-signal portfolios have positive loadings on size and book-to-market factors (see Panels A and B of Table A6 in the Online Appendix). Therefore, the three- and four-factor alphas of the return differentials are lower than the raw return differentials. The monthly four-factor alphas on the return differentials are equal to 0.53% with a t-statistic of 5.12, and 0.38% with a t-statistic of 2.67, for equal- and value-weighted portfolios, respectively. The result that value-weighted portfolios generate lower return differentials than equal-weighted portfolios is consistent with the results of the lead-lag literature that large stocks, by virtue of receiving more attention from sophisticated investors who tend to hold large stocks, react faster to new information.

With regard to month-to-month portfolio transition probabilities, we find that there is some persistence in portfolio assignments in the next two months, with somewhat U-shaped transition probabilities, which indicates that the stocks in the high- and low-signal portfolios have a higher chance of remaining in their respective deciles than those with other portfolio

[14] Panel A of Figure A1 in the Online Appendix 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 for both equal- and value-weighted portfolios, which would have turned into $291.60 and $42.95, respectively.

assignments. However, this stickiness in the portfolio assignments disappears 12 months into the future. (These results are presented in Panel C of Table A6 in the Online Appendix.)

Finally, in Panel C, we check how long it takes for the leader signals to be fully 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, forming portfolios in month $\tau+2$ as per Figure 1. The four-factor alphas of the return differentials are no longer significant, either with a 12-month or with a 36-month rolling regression window. This result suggests that leader signals tend to be fully incorporated into followers' prices within one month.[15]

Panel D of Table 2 presents monthly portfolio returns for the specification in which leaders are identified using 36-month rolling regression windows. With a longer regression window, regression coefficients can be estimated more precisely, but there is a smaller chance of identifying short-lived leaders. As can be seen in the table, this methodology, on net, produces very similar returns to the baseline specification. Some differences in results between these two methods will be revealed in the robustness checks and the Fama-MacBeth cross-sectional regressions presented later in the paper.

We have already removed stocks priced at less than $5 per share, but we further check whether our results are sensitive to the exclusion of smaller stocks. In Table A3 in the Online Appendix, we remove stocks in the bottom two and the bottom five NYSE size deciles. The return differentials decrease somewhat but remain statistically significant.

In sum, the results show that leader signals have the power to predict their followers returns in the next month. Moreover, the predictive ability of leaders works *within* industries, which is a result distinct from the lead-lag literature (e.g., Hou (2007)). We next show that the predictive ability of leaders is robust to various methods of aggregating leader signals.

[15] To check whether there is a long-term return reversal, we calculate portfolio returns in the six months subsequent to month $\tau + 2$ and find no significant return differentials: for equal-weighted portfolios, the monthly alpha is -0.02% (t-statistic=-0.41) and for value-weighted portfolios, it is -0.04% (t-statistic=-0.60).

2. Alternative methods for aggregating leader signals

Next, we 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: $Signal_\tau^i = \sum_{j=1}^{J_\tau^i} w_j \text{sign}(\hat{b}_3^{ij}) Ret_\tau^j$. 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 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 3. A comparison with the results in Panels A and B of Table 2 shows that, for value-weighted portfolios, the original specification produces slightly larger return differentials than any of the four alternative methods, while, for equal-weighted portfolios, weighting by the absolute value of the t-statistics of $\hat{b}_3$ produces the largest return differentials. Value-weighting leader returns produces the lowest return differentials, which suggests that signals from large leaders, which are overweighted in this weighting scheme, are incorporated by the followers faster than signals from small leaders, likely because large leaders are more visible.

Insert Table 3 about here.

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 Panel D of Table 2. With the exception of the leader-return aggregation methodology in which leader returns are value-weighted, the ability of leaders to predict their followers returns two months later can be observed for equal-weighted portfolios; for value-weighted portfolios, we do not observe leaders' predictive ability for any of the leader-return aggregation methods. However, when two months are skipped before portfolio construction, none of the return differentials are significant (results not shown).

The results in this subsection show that the predictive ability of leaders is robust to various methods of aggregating leader returns. Assigning larger weights to larger and, thus, more visible, leaders produces the worst return predictability. This result suggests that investor inattention may be contributing to the slow information diffusion from leaders to followers.

3. Smaller leaders and leaders from other industries

In this section, we assess the sensitivity of the results when various restrictions on the set of leader stocks are imposed. First, we restrict leaders to stocks that are smaller than their followers in order to show that information may flow from smaller to larger stocks and otherwise proceed as in the baseline specification. The results are reported in Panel A of Table 4. The return differentials between the highest- and lowest-leader signal portfolios are statistically significant. The raw monthly return differential is 0.48% with a t-statistic of 4.63 and 0.35% with a t-statistic of 2.81 for equal- and value-weighted portfolios, respectively. Their respective four-factor alphas are 0.43% with a t-statistic of 3.89 and 0.28% with a t-statistic of 2.02. The significantly positive return differentials indicate that smaller leaders can indeed lead returns of larger followers. This result, which is new to the lead-lag literature, suggests that a stock may lead another stock perhaps not by the virtue of reacting first to common news but, perhaps, by being at the center of a relevant news.

Insert Table 4 about here.

Second, we restrict leaders to stocks that belong to a different industry than the follower stock and, as before, sort stocks on thus-computed leader signals within each industry. The results, presented in Panel B of Table 4, show that leaders need not belong to the same industry as their followers and that followers within the same industry can still have different leader signals. The return differentials between the highest- and lowest-leader-signal portfolios are statistically significant and even somewhat higher than the return differentials in Panel A. The monthly raw return differentials are 0.55% with a t-statistic of 5.30 and 0.41% with a t-statistic of 3.42 for equal- and value-weighted portfolios, respectively. Their respective four-factor alphas are 0.49% with a t-statistic of 4.47 and 0.40% with a t-statistic of 2.99. Even though Menzly and Ozbas (2010) show that leaders could belong to a different industry than the followers, our results are different from theirs in that, while, in their paper, the stocks in the same industry get the same signal, we sort on leader signals *within* each industry.

We conduct a number of additional robustness checks that are described in detail in Section A3 in the Online Appendix. Among other results, we show that both negative and positive leaders have predictive ability for followers' returns[16]; that both new and recurring leaders can forecast followers' returns; and that leaders' predictive ability for followers' returns in month $t + 1$ is independent of whether they announce quarterly earnings in month t.

4. Placebo test

One may become concerned that the return predictability documented here may be driven not by a lead-lag effect in stock returns, as we claim, but rather by some stock characteristic, such as idiosyncratic volatility, with stocks at the extremes of this characteristic behaving as though they have extreme leader signals.[17] To address this concern, we argue that if 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 identified but, in this case, definitely false leaders will stop predicting their followers' returns.

Specifically, we preserve cross sections but scramble the data along the time dimension by assigning each time period a random number and then sorting the cross sections by this random number. We apply this algorithm to the monthly-frequency sample from January 1980 to December 2011; the sample is kept relatively short to ensure that the stocks exist for most of the considered time period. Since we require that both stocks in every potential leader-follower pair have returns in the prior 12 months, a relatively short sample helps ensure the maximum number of possible leader-follower pairs. Using the scrambled sample, we re-run

[16]The ability of negative return leaders to predict their followers' returns is consistent with Anton and Polk (2014), who argue that stocks with common institutional ownership may be simultaneously pushed away from equilibrium prices by fund-flow-induced trading; the negative cross-predictability in returns will ensue as prices revert back to the fundamentals.

[17]Later in the paper, we run a set of cross-sectional regressions and include all relevant stock characteristics to further mitigate this concern.

regression (1) for all pairs of stocks that have return observations for the previous 12 months. As before, we select as leader-follower pairs those stocks for which $| t\text{-statistic}(b_3) | \geq 2.00$.

In 8.62% of the regressions, a leader is identified. This number is higher than the 4.55% p-value corresponding to a t-statistic of 2.00 that one would observe when the distribution of the estimated coefficients is normal, implying that the actual distribution is fat-tailed. In 4.23% of the regressions, a positive leader is identified, and in 4.39%, a negative leader.

Next, we calculate equal-weighted leader signals according to equation (2) in each month τ and use them to predict followers' returns in month $\tau + 1$ (note that we use followers' returns in the *actual* month $\tau + 1$ and not the scrambled month $\tau + 1$ in order to show that it is not the cross-sectional variation in some omitted stock characteristic observed in month τ that forecasts the cross section of the next month's returns). We form decile portfolios in month τ based on leader signals in that month and check portfolio returns in month $\tau + 1$.

We obtain the following results. The average leader signal is equal to -2.87% for the lowest-signal decile and 3.13% for the highest-signal decile when signals are equal-weighted; these numbers are -2.24% and 2.80%, respectively, when signals are value-weighted. The raw return differentials between the extreme leader-signal deciles is 0.12% (t-statistic=0.71) for equal-weighted portfolios and 0.31% (t-statistic=1.24) for value-weighted portfolios. The corresponding four-factor alphas are 0.18% (t-statistic=0.98) and 0.33% (t-statistic=1.27) for equal- and value-weighted portfolios, respectively. Thus, our methodology does not produce any return predicability on the scrambled data.

When 36-month rolling windows are used to identify leaders, the results are similar. A leader is found in 5.55% of the regressions run (in this case, the distribution of the estimated coefficients $\hat{b}_3$ is less fat-tailed than when using 12-month regression windows). In 2.95% of the regressions run, a positive leader is found, and in 2.60%, a negative leader is found. The average leader signal is -1.95% and 2.28% for the bottom- and top-decile portfolios, respectively, when signals are equal-weighted, and -1.67% and 1.90%, respectively, when value-weighted. The average raw return differential between the highest- and lowest-signal portfolios is -0.17% (t-statistic= -1.08) for equal-weighted portfolios and -0.05% (t-statistic=-0.19) for value-weighted portfolios. The corresponding four-factor alphas are -0.20% (t-statistic=-1.21) and -0.04% (t-statistic=-0.14), respectively. Again, we do not find any evidence of return predictability on the scrambled data.

Our inability to generate return predictability on the scrambled data is in contrast to leaders' significant ability to predict returns on the actual data for the same time period (see the results for equal-weighted portfolios over the same sample period reported in Table A4, Panels C and D, which correspond to 12-month and 36-month estimation windows, respectively).[18] These results confirm that the success of the strategy hinges on identifying leaders that truly exhibit return leadership for their followers and on this leadership being, to some extent, preserved out of sample.

B. Weekly portfolio returns

As information technology gets cheaper, markets become more efficient. Consistently, the results reported in the Online Appendix show that the profitability of the monthly-frequency strategy of trading on leader signals has declined over time. As the market becomes more efficient in incorporating new information, switching to higher trading frequencies may be warranted. In this section, we explore the profitability of a weekly-frequency strategy of trading on leader signals, which should work well if the information from leader stocks is incorporated more quickly than with a one-month delay but more slowly than with a one-week delay. (Tellingly, the lead-lag literature uses weekly return frequencies to document the delayed price reaction of small stocks.) 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 even shorter, starting only in July 2006).

[18] We repeated the data scrambling exercise and again did not find any evidence of return predictability. We refrained from repeating the exercise multiple times because each run is very computationally intensive.

The weekly portfolio construction methodology is similar to the monthly methodology. We run regression (1) with weekly returns using a 52-week rolling regression window. 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. 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. Portfolios are formed within each of the 36 industries, thus ensuring equal industry loadings in the long-short portfolios.

Panels A and B of Table 5 present weekly 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. The weekly four-factor alpha is 0.47% with a t-statistic of 12.21 for equal-weighted return differentials and 0.28% with a t-statistic of 6.14 for value-weighted return differentials. The four factors have little explanatory power for the return differentials, and the resulting alphas are close in magnitude to the raw return differential; the factor loadings on the weekly-frequency factors are reported in Panels A and B of Table A7 in the Online Appendix. These numbers are economically large, amounting to roughly 24% and 15% annualized returns, respectively.[19] While week-to-week portfolio assignments show some persistence in the short term, this persistence disappears 52 weeks into the future. (Panel C of Table A7 in the Online Appendix presents portfolio transition probabilities).

Insert Table 5 about here.

The weekly trading strategy, though more profitable in recent years than the monthly trading strategy, entails significantly higher trading costs as portfolios need to be turned over frequently. Moreover, portfolios need to be assembled quickly; the inability to spread out trades over long periods of time leads to large price impacts of trade. Of course, one could

[19]Panel B of Figure A1 in the Online Appendix 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 for both equal- and value-weighted portfolios, which would have turned into $2,127.59 and $63.64, respectively.

lower trading costs by holding stocks in a portfolio for longer than one week or by holding relatively liquid large stocks; however, we have already shown that both modifications reduce the strategy's raw returns.

Here, we estimate break-even trading costs that would set the post-trading-cost return of the one-week holding strategy to zero. For this estimation, we assume that trading costs are identical across stocks and independent of the amount traded (obviously, in reality, trading costs are lower for more liquid stocks and for smaller trade amounts). Because leader signals are somewhat persistent, the weekly portfolio turnover is lower than 100%, which gives a slight advantage to value-weighted portfolios as they are unaffected by rebalancing costs.

We estimate break-even trading costs for the weekly-frequency trading strategy previously considered in the paper. (Trading costs are expressed in units of return, i.e., as the percentage cost per dollar of a stock traded.) For the simple high-minus-low leader-signal-deciles in Table 5, the break-even trading costs are equal to 0.13% for equal-weighted portfolios and 0.08% for value-weighted portfolios.

By way of comparison, using the TAQ dataset for the time period from January 1983 to August 2001, Sadka and Scherbina (2007) estimate the average effective spread for a typical stock and a typical trade to be 0.25%. Hedge funds are more skilled at minimizing trading costs than an average trader in the TAQ dataset, and their trading costs may easily fall below our estimated break-even values.

The relatively low values of the estimated break-even trading costs for the simple trading strategy imply that the strategies trading on leader signals can support only small investment amounts since large amounts would entail large price impacts. Therefore, the dollar profitability of trading on slow information diffusion that we document here is not very high. These results suggest that the market, though not perfectly efficient, is competitive in the sense that the arbitrage profits are small.

1. Alternative signal aggregation and the speed of information diffusion

Next, as we did for monthly-frequency 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.2. Table 6 reports the results. The first row of the table shows that, as in the case of monthly-frequency signals, the baseline method works slightly better for value-weighted portfolios than the alternative methods. For equal-weighted portfolios, weighting leader returns by the absolute value of the t-statistics of $\hat{b}_3$ works best; as before, value-weighting leader returns produces signals with the worst return predicability. In the next four rows of the table, we form portfolios based on leader signals lagged by one, two, three, and four weeks. This 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.

Insert Table 6 about here.

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

In this section, we test whether conditioning on the correlation between the leader signal and the follower's contemporaneous return improves the leader signals' predictive ability. We expect the predictive ability of the leader signal to be strongest among followers whose prices have not yet co-moved with a signal as the efficacy of the signal depends on delays in the price responses of the followers. In fact, 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 due to the return reversal effect, which is strongly present at both monthly and weekly frequencies. In this case, conditioning future returns on the past leader signal may even become counterproductive.

Every week, within each of the 36 industries, 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. The four-factor alphas of the subsequent week's portfolio returns, presented in Table 7, show that the leader-signal strategy works within each reversal quintile.[20] 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 alpha of the return differential between portfolios 51 and 15 is 1.48% per week (t-statistic=20.57) for equal-weighted portfolios and 0.96% per week (t-statistic=13.42) for value-weighted portfolios.[21] These results show that the performance of the leader-signal strategy can be substantially improved by conditioning on whether or not the followers' prices likely have already reacted to the leader signal.

Insert Table 7 about here.

These return magnitudes are economically large, amounting to annualized returns of 76.96% and 49.92% for equal- and value-weighted portfolios, respectively. However, since frequent trading is required to achieve these returns, the after-trading-cost returns will be substantially lower. Break-even trading costs, calculated as before, for the differential between the corner portfolios based on leader signals and return reversals in Table 7 (portfolio 51 - portfolio 15) are 0.39% for equal-weighted portfolios and 0.025% for value-weighted portfolios. As such, the break-even trading costs are below the average trading costs incurred by a typical investor. Sophisticated traders skilled at minimizing trading costs could achieve economic profits when trading on a weekly strategy that overlays leader signals with reversals. Indeed, in Section A4 in the Online Appendix, we show that short sellers, who are thought to be sophisticated, change their short positions in response to leader signals. The profits achieved on this strategy can be thought of as compensation for ensuring market efficiency.

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

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

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 8.

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, as well as 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 in the following month will 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.

Insert Table 8 about here.

In all regression specifications and in all subsamples, the coefficient on the aggregate leader signal is highly statistically significant; it ranges in magnitude from 0.080 to 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 given that the high-low spread in the average leader signal is smaller when leaders are identified with 36-month rolling regressions relative to when leaders are identified with 12-month rolling regressions. 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, 10 percentage points, then their next month's returns would differ by between 0.8 to 2.4 percentage points. As 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 statistically significant across all specifications. Consistent with the results in Panels E and F of Table A4 in the Online Appendix 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 for the coefficient estimates on the signals when using 36-month rolling regressions are almost twice as high as those when using 12-month rolling regressions.[22]

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. In all regression models, the coefficient on the weekly leader signal is highly statistically significant, and its range of estimates implies that a difference of 10 percentage

[22]In unreported results, we included a quarterly earnings announcement dummy, which equals one if the follower made a quarterly earnings announcement in the previous week and zero otherwise, 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. These results are available upon request.

points in the weekly leader signal would produce a difference in otherwise identical followers' returns of between 3 and 7 percentage points 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 a follower's prior-week return is negative and significant. Specification (5) includes the interaction with a 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 also negative but not significant.

In specifications (7)-(10), we add 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 a 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 strong 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 10 percentage points in the monthly signal generates an average difference in next week's return of almost 0.2 percentage points.

All these results confirm that the aggregate leader signal has independent predictive ability for followers' returns at both monthly and weekly frequencies. 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 independent predictive ability at weekly return horizons.

IV. Leadership and News Originating at the Firm

Thus far, we have established that leaders identified with Granger causality regressions can predict their followers' returns. In this section, we provide evidence that leaders may emerge not only because they are first to react to common market or industry news but also because important valuation-relevant news may originate at the level of the firm. Specifically, we show that a stock's return leadership is associated with newsworthy developments at the firm level. For that purpose, we again use the TRNA dataset, which is geared towards traders and investment professionals. The portion of the dataset made available to us by Thompson-Reuters includes only firm-specific English-language news about U.S.-based firms. This dataset is described in more detail in Section A5 of the Online Appendix. Since this dataset covers only US firms, for the purposes of the analysis in this section, we limit the set of potential leaders to common stocks with share codes 10 or 11. 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.

A. Regression specifications

We argue that return leadership arises, at least in part, because of news developments at leader firms and assume that the more important a news development experienced by a firm is, the more news stories about the firm will appear in the TRNA dataset. Of course, it is important to control for firm characteristics that affect news coverage. Incidentally, because the primary users of the TRNA dataset are investment professionals, the stock characteristics that lead to more detailed news coverage are also associated with sophisticated investor attention. In turn, as we know from prior literature, investor attention is associated with return leadership because it ensures that firms react to common market or industry news ahead of firms with lower levels of sophisticated investor attention. TRNA users will presumably demand more detailed coverage for large firms, firms with high turnover, and, perhaps, firms belonging to certain industries. Therefore, we include these and other firm characteristics that are associated with attention as well as industry or firm dummies in our regressions explaining the number of followers with the number of news stories. Although the TRNA dataset itself is primarily focused on firm-level news, we take additional care to count only news stories about firms when forming news counts (more detailed descriptions are provided in the next subsection).

In order to assess whether the number of a firm's followers is related to its news developments, we regress the number of followers that a firm has on the number of stories written about the firm's own news developments and a set of firm characteristics that are associated with the sophisticated investor attention (e.g., institutional ownership, size, analyst coverage, turnover, industry assignment, past stock performance, book/market). 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 that window. We include year dummies because both the number of publicly traded stocks (and, hence, the number of followers) and news coverage change over the years.

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 of the Online Appendix. In Panel A, the monthly leadership specification with a 12-month rolling regression window is used, and in Panel B, the weekly leadership specification with a 52-week rolling regression window 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. As a result, the average and median numbers of followers in Panel A (357.2 and 329, respectively) are greater than those in Panel B (299.9 and 269, respectively).

We use three regression specifications. In the first specification, we estimate our regressions using quasi-maximum likelihood, which is an appropriate methodology for explaining a count variable (in our case, the number of followers of a stock). This estimation method produces consistent and asymptotically normal coefficient estimates even if the underlying distribution is not Poisson (Wooldridge (2002)).[23] In the second regression specification, we also use the Poisson regression specification but include firm fixed effects (excluding industry dummies). This specification should mitigate concerns regarding omitted firm characteristics that may influence the number of followers and may be correlated with the control variables. In the third regression specification, we run Tobit regressions that treat the number of followers as a continuous variable but recognize that the number of followers cannot fall below zero. Regressions are run at weekly (monthly) frequencies for weekly- (monthly-) frequency leaders, and standard errors are clustered by firm in all regression specifications.

[23] We experimented with assuming that the underlying distribution is a negative gamma rather than Poisson and obtained qualitatively similar results.

B. News counts

News stories often start with a sequence of alerts informing readers in the headline about the topic of the forthcoming article while the article is being written. Once the article is posted, it may get updated, appended, overwritten, or corrected. Consequently, news items posted in TRNA are classified as either "Alert," "Article," "Append," or "Overwrite." All news items are further tagged with a news topic code.

A distinct news story for a given firm is assigned a unique identifier, the primary news access code (PNAC). This identifier allows the reader to keep track of a particular story unfolding with a series of alerts and follow-up reports. Arguably, the more complex or significant a news development, the more items would appear under its assigned PNAC.

Since we like to show that news originating at the firm can give rise to information leadership, in the main regression specification, we make an effort to use a count that only considers news originating at a firm. Therefore, for our primary news count, we consider only stories about specific corporate developments, such as corporate insolvencies and bankruptcies, decisions to raise or return capital, mergers, acquisitions, financial results, legal developments, various strategic decisions, product news, management changes, compensation news, and labor and infrastructure news.[24]

Some of the news stories in the TRNA dataset may not cover new events but instead contain analysis of events that already happened (for example, a news story may report an expert opinion on some recent news, such as a merger announcement). Therefore, our primary news count considers only news that is accompanied by an abnormal trading volume on the day of the news story. We rely on abnormal trading volume instead of abnormal returns to assess the impactfulness of the news because some impactful news may increase investor

[24]Specifically, for this count we consider only news tagged with the following topic codes: 'AAA', 'ALLCE', 'BACT', 'BKRT', 'BOSS1', 'BUYB', 'CASE1', 'CLASS', 'COVB', 'CM1', 'DEAL1', 'DIV', 'DVST', 'FIND1', 'FINE1', 'INDX', 'IPO', 'ISU', 'JOB', 'LIST1', 'MEET1', 'MNGISS', 'MONOP', 'MGR', 'NG1', 'NT1', 'PS1', 'RCH', 'REGS', 'RES', 'RESF', 'SL1', 'STAT', 'STK', 'ENV', 'FAKE1', 'ACB', 'CORPD', 'DBT', 'FUND', 'PVE', 'USC', 'INVB', 'INVD', 'INVI', 'INVM', 'INVS', 'INVT', 'ABS', 'LOA', 'BNK', 'CMPNY', 'INV', 'TAX', 'LAW', 'JUDIC', 'FIN', 'FINS', 'FRAUD1', 'DAT', 'CIV', 'CLJ', 'EQB', 'CDM', 'CDV', 'CORPD', and 'DBT'.

disagreement and, thus, have a large effect on trading volume but potentially a smaller effect on stock returns. Specifically, we assume that a news story is impactful if, on the day of the news story, the share turnover in a stock is abnormally high. We define a particular trading day as a day with an abnormally high turnover for a given stock if on that day the differential between the stock's share turnover and the average share turnover for all publicly traded common stocks in the CRSP dataset falls above the 90th percentile of the differential's distribution calculated over a trailing 250-trading-day window. In rare instances, more than one news story is announced on the day with an abnormal share turnover. In these cases, we count all news announcements because all news could be contributing to the abnormal turnover. In sum, our main news count measure can be described as "impactful firm-level news" as it cumulates the news that specifically mentions firm-level developments and that is accompanied by abnormal turnover.

As a robustness check, we consider five alternative news counts:

1. **"Highly relevant corporate news"**: count only firm-centered news stories as described in footnote 24 that have a relevance score of 1 (as described in the Online Appendix, a relevance score of 1 indicates that a firm is at the center of an event, as opposed to simply being co-mentioned in a news story about an event pertaining to another firm);
2. **"All impactful news"**: count all news stories (excluding stories about trade order imbalances) that fall on abnormal turnover days;
3. **"All highly relevant news"**: count all highly relevant news stories (e.g., news stories with a relevance score of 1);
4. **"All news"**: count all news stories written about a firm;
5. **"Only new news"**: count only unique PNACs, thereby ignoring possible multiple Alerts, Appends, Overwrites, and Articles that possibly are contained within one PNAC.

For firms with no news stories identified over a trailing one-year period when using a particular news count methodology and for firms not present in the TRNA dataset, we set the news count to zero (we chose to include the latter set of firms in the dataset because these firms are potentially on Reuters' radar screen). Because of the extreme right-skewness of the news count variables, we winsorize them at the 99th percentile. Summary statistics for the news count variables are reported in Panel D of Table 9.

C. Regression results

The regression results are reported in Table 9. Pairwise correlations between the control variables are shown in Table A8 of the Online Appendix. Given that weekly-frequency leaders work best in forecasting their followers' returns over the time period of the news sample, we begin by reporting in Panel A the regression results explaining the number of followers at the weekly frequency. We use our primary news count, "impactful firm-level news." The results show that the number of followers that a firm has is positively related to proxies for sophisticated investor attention, such as institutional ownership, analysts coverage, and, in one specification, share turnover; firm size is positively related to the number of followers only when other proxies for investor attention are not included. These findings are consistent with the findings of the lead-lag literature that stocks with higher levels of attention react faster to common shocks and therefore would appear to have more followers. Both analysts and institutional investors, who are sophisticated and react to new common information faster than retail investors, help uncover news developments relevant to a firm, thereby ensuring a quick price reaction to common news shocks. The negative regression coefficient on *Momentum* indicates that stocks that have experienced low returns tend to have more followers, consistent with the view that negative news travels slower across firms than good news.

Insert Table 9 about here.

Importantly, regression coefficients on the news count variables are significantly positive at the 1% level in all regression specifications. Poisson regression coefficients range from 0.0195×10^{-2} to 0.0432×10^{-2}. The economic interpretation is as follows: when a stock's news count increases from the 10th to the 95th percentile in the news count distribution, or from 0 to 117 news stories in the previous 12 months, (Panel D), its number of followers increases by between 2.28% and 5.05% ($0.0195 \times 10^{-2} \times 117$ and $0.0432 \times 10^{-2} \times 117$, respectively).

The median stock has 269 weekly-frequency followers (see the inset box in Figure A2 in the Online Appendix); thus, the Poisson regression specification suggests that the median stock would gain between 6 and 14 new followers. Tobit regression coefficients range from 4.6856×10^{-2} to 12.1579×10^{-2}. These numbers suggest that the same increase in the news count is associated with an increase in the number of weekly-frequency followers between 5 and 14 ($4.6856 \times 10^{-2} \times 117$ and $12.1579 \times 10^{-2} \times 117$, respectively), which is close to the estimates produced by the Poisson regressions.

When the regressions are re-run to explain the number of monthly-frequency followers in Panel B, using, as before, our primary news count, the results are qualitatively similar. The Poisson regression coefficients in specifications (1)-(2) and (4)-(5) range from 0.0149×10^{-2} to 0.0374×10^{-2}. These estimates imply that an increase in the number of news stories that would move the stock from 10th to the 95th percentile in the news distribution is associated with a 1.75% - 4.37% increase in the number of followers. The median stock has 329 monthly-frequency followers (Figure A2 in the Online Appendix). Thus, these numbers would translate into 6 - 14 additional followers for a median stock. The Tobit regression coefficients range from 5.5819×10^{-2} to 13.8233×10^{-2}, which suggests that the same increase in the news count is associated with between 7 and 16 additional followers.

When the variable $News^2$ is included in the regression, the coefficient on that variable is negative, and significantly so in the regression explaining the number of monthly-frequency followers. This nonlinearity in the relation between the number of followers and the news count suggests that very intensive news coverage of a firm increases investor awareness of that leader's relevant news and, as a result, leads to shorter delays in followers' price reactions.

We substitute our primary news count with each of the five alternative news counts in Panel C, using regression specifications (4)-(6) of Panel A. (To conserve space, the Panel only reports the regression coefficients on the news counts.) The regression coefficients on all five alternative news counts are significantly positive in all regression specifications. As before, we compute how many additional followers are associated with a stock moving from the 10th to the 95th percentile of the distribution for each of the news counts that we have created, for both weekly- and monthly-frequency leaders. For the count of only "highly relevant corporate news," these numbers are 7 and 11, respectively; for "all impactful news," these numbers are 5 and 8; for "all highly relevant news," these numbers are 3 and 7; for both "all news" and "only new news," these numbers are 6 and 9. These results show that the relation between news and the number of followers is robust to various news counts. The question of what types of corporate news generate the largest increase in the number of followers is left to future research.

The results in this section show that important firm-specific developments are associated with a larger number of follower stocks. We take this to mean that being at the center of important news is associated with leadership. There could be alternative interpretations for this association. For example, one could argue that news coverage is another proxy for attention, and, as we discussed, stocks with higher levels of attention are faster to react to common news; by this logic, such stocks will lead the returns of more followers who happen to react to the same news with a longer delay. However, this interpretation is unlikely because, firstly, the TRNA dataset itself focuses on firm-level news and, secondly, because we take additional efforts to ensure that we consider only firm-level news. Relatedly, one could argue that there might be an omitted variable that influences both leadership and coverage. News media dedicates more coverage to firms with a higher demand for coverage, that is, firms with higher institutional ownership and firms that trade more often. However, our results are still present when we control for stock characteristics that might be associated with a higher demand for coverage that influences both leadership and news coverage, and our results also hold in regressions with firm fixed effects. Still another alternative explanation for our findings is reverse causality: journalists pay more attention to firms that lead the returns of other firms. We consider this interpretation highly unlikely as it is not clear that Thompson-Reuters corporation keeps track of the statistical ability of stocks to Granger cause returns of other stocks and that this knowledge, in turn, influences the decision of how much coverage to allocate to a given firm.

To sum up, we believe the results presented in this section support our hypothesis that firm's leadership is, to some extent, driven by news originating at the firm. Such news may have ramifications for other firms, but these firms' investors may initially overlook the relevant news, resulting in lead-lag return relations between the firms at the center of the news and other firms also affected by these news developments.

V. Conclusion

We use Granger causality tests to identify leader-follower pairs among individual stocks and show that the returns of leaders have a robust out-of-sample forecasting ability for their followers' returns that works within industries. Analyzing the uncovered leader-follower pairs, we find that information can flow in unexpected directions. In particular, we discover that leaders can be smaller stocks. 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 themselves be at the center of important news developments that have ramifications for other firms. We find support for this conjecture by showing that when stocks experience an increase in the news coverage of their firm-specific developments, the number of stocks whose returns they lead also increases. It is left to future research to investigate what types of firm-level news are most likely to affect other firms.

Our results suggest that individual stocks are highly interconnected by permanent or temporary business ties, similar legal liabilities, and similar exposure to product safety concerns, cross-investments, labor force regulations, consumer tastes, 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.[25] Our results suggest that the difference in R^2s 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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[25] 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^2s. The R^2s computed for the subsample of non-news days are only slightly higher than the R^2s 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^2s on news days, and model R^2s to be 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*.

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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:

$$Illiq_{i,t} = \text{Avg}_t \left[\frac{|R_{i,d}|}{Volume_{i,d}} \right], \tag{3}$$

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):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i^1 \left(R_{m,t} - R_{f,t}\right) + \beta_i^2 \left(R_{m,t-1} - R_{f,t-1}\right) + \epsilon_{i,t}, \tag{4}$$

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, each month, stock i's idiosyncratic volatility 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:

$$R_{i,d} - R_{f,d} = \alpha_i + \beta_i(R_{m,d} - R_{f,d}) + \eta_i \mathrm{SMB}_d + \delta_i \mathrm{HML}_d + \epsilon_{i,d}, \tag{5}$$

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

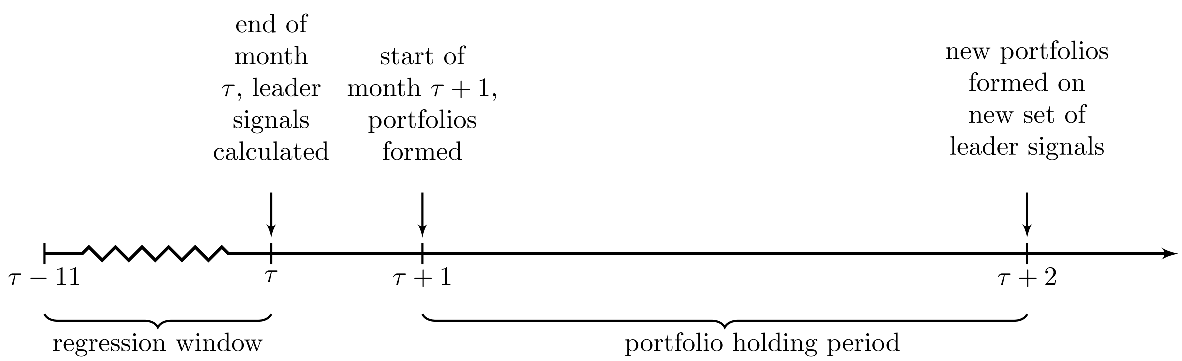


Figure 1. Timeline. This figure presents the timeline for our computations and an example for how an aggregate leader signal is computed.

Table 1
Descriptive statistics for leaders and followers

This table presents characteristics of leader and 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. The statistics are calculated as of January 31 of each year. The sample period is 1929-2011.

Full sample

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

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.

	Quintiles based on number of leaders				
	1 (low)	2	3	4	5 (high)
Avg. number of leaders	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 previous month, were priced above $5 per share, and 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 highest- and lowest-signal portfolios (deciles 10 and 1). Panel C presents the raw return differential and their four-factor alphas for portfolios formed on leader signals that are lagged by one month. Panel D reports analogous raw returns and four-factor alphas for portfolios constructed with 36-month rolling regressions. 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	-3.30%	0.46%	-0.30%	-0.42%	-0.40%
		(1.74)	(-2.68)	(-5.58)	(-5.01)
2	-1.88%	0.69%	0.00%	-0.11%	-0.09%
		(2.98)	(0.02)	(-2.01)	(-1.42)
3	-1.20%	0.72%	0.06%	-0.06%	-0.02%
		(3.20)	(0.73)	(-1.21)	(-0.36)
4	-0.70%	0.79%	0.14%	0.03%	0.06%
		(3.61)	(1.78)	(0.59)	(1.20)
5	-0.28%	0.79%	0.15%	0.03%	0.05%
		(3.58)	(1.90)	(0.60)	(0.97)
6	0.12%	0.90%	0.26%	0.14%	0.17%
		(4.13)	(3.18)	(2.99)	(3.56)
7	0.57%	0.92%	0.27%	0.14%	0.16%
		(4.18)	(3.45)	(3.35)	(3.96)
8	1.06%	0.95%	0.27%	0.13%	0.14%
		(3.97)	(3.23)	(2.65)	(2.89)
9	1.75%	1.00%	0.30%	0.14%	0.16%
		(4.01)	(3.27)	(2.75)	(3.28)
10	3.21%	1.07%	0.32%	0.16%	0.13%
		(4.01)	(2.87)	(2.68)	(2.35)
10-1		0.61%	0.62%	0.57%	0.53%
		(6.20)	(6.10)	(5.75)	(5.12)

Panel B: Value-weighted portfolios

Decile	Leader signal	Excess return	Market alpha	3-factor alpha	4-factor alpha
1	-2.73%	0.34%	-0.35%	-0.35%	-0.34%
		(1.52)	(-4.61)	(-4.72)	(-3.94)
2	-1.66%	0.52%	-0.09%	-0.09%	-0.09%
		(2.61)	(-1.48)	(-1.51)	(-1.38)
3	-1.05%	0.56%	-0.01%	-0.01%	0.02%
		(2.99)	(-0.14)	(-0.14)	(0.30)
4	-0.63%	0.56%	0.01%	0.02%	0.00%
		(3.08)	(0.15)	(0.52)	(0.01)
5	-0.27%	0.56%	-0.01%	-0.01%	0.02%
		(2.96)	(-0.10)	(-0.17)	(0.27)
6	0.01%	0.59%	0.05%	0.05%	0.05%
		(3.41)	(1.26)	(1.30)	(1.09)
7	0.48%	0.65%	0.07%	0.07%	0.08%
		(3.43)	(1.48)	(1.55)	(1.55)
8	0.93%	0.66%	0.07%	0.05%	0.04%
		(3.17)	(1.39)	(0.94)	(0.64)
9	1.51%	0.72%	0.10%	0.07%	0.07%
		(3.47)	(1.76)	(1.21)	(1.14)
10	2.63%	0.79%	0.12%	0.06%	0.05%
		(3.41)	(1.19)	(0.64)	(0.52)
10-1		0.45%	0.46%	0.41%	0.38%
		(3.39)	(3.42)	(3.02)	(2.67)

Panel C: Portfolios formed on leader signals lagged by one month

Return Differentials (Portfolio 10−Portfolio 1)

	EW portfolios		VW portfolios	
Decile	Excess return	4-factor alpha	Excess return	4-factor alpha
10-1	0.15%	0.09%	0.04%	-0.01%
	(1.58)	(0.96)	(0.45)	(-0.08)

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

	EW portfolios		VW portfolios	
Decile	Excess return	4-factor alpha	Excess return	4-factor alpha
1	0.54%	-0.36%	0.42%	-0.27%
	(2.11)	(-4.46)	(1.90)	(-3.18)
2	0.71%	-0.11%	0.51%	-0.18%
	(3.08)	(-1.62)	(2.50)	(-2.99)
3	0.76%	-0.04%	0.53%	-0.06%
	(3.34)	(-0.65)	(2.68)	(-1.05)
4	0.83%	0.04%	0.56%	-0.02%
	(3.76)	(0.82)	(3.02)	(-0.47)
5	0.86%	0.08%	0.57%	-0.02%
	(3.88)	(1.31)	(2.89)	(-0.28)
6	0.82%	0.03%	0.61%	-0.02%
	(3.78)	(0.64)	(3.12)	(-0.41)
7	0.94%	0.13%	0.53%	-0.07%
	(4.27)	(3.07)	(2.72)	(-1.22)
8	1.04%	0.18%	0.74%	0.09%
	(4.41)	(3.41)	(3.72)	(1.68)
9	1.14%	0.26%	0.83%	0.15%
	(4.71)	(4.93)	(4.17)	(2.68)
10	1.15%	0.16%	0.85%	0.05%
	(4.24)	(2.69)	(3.75)	(0.57)
10-1	0.61%	0.52%	0.43%	0.32%
	(7.01)	(5.55)	(3.68)	(2.36)

Table 3

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 previous month, were priced above \$5 per share, and had leaders. Leader signals are computed "non-parametrically," by multiplying the previous 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 portfolios 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 Panels A and B in 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			
0.60%	0.51%	0.31%	0.21%
(8.36)	(6.84)	(2.81)	(1.98)
Non-parametric signals are value-weighted			
0.26%	0.21%	0.25%	0.20%
(4.38)	(3.52)	(2.92)	(2.36)
Non-parametric signals are weighted by $\lvert t\text{-stat}(\hat{b}_3)\rvert$			
0.62%	0.54%	0.32%	0.24%
(8.08)	(6.63)	(2.65)	(2.03)
Non-parametric signals are weighted by $\lvert\hat{b}_3\rvert$			
0.61%	0.51%	0.28%	0.21%
(7.76)	(6.67)	(2.39)	(1.90)

Panel B: Portfolios are formed based on month $t-2$ leader signals, corresponding to Panel D in 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			
0.22%	0.18%	0.04%	0.00%
(3.20)	(2.40)	(0.39)	(0.00)
Non-parametric signals are value-weighted			
-0.00%	-0.06%	-0.05%	-0.09%
(-0.02)	(-1.13)	(-0.55)	(-1.01)
Non-parametric signals are weighted by $\lvert t\text{-stat}(\hat{b}_3)\rvert$			
0.21%	0.17%	0.11%	0.06%
(2.94)	(2.16)	(0.93)	(0.43)
Non-parametric signals are weighted by $\lvert\hat{b}_3\rvert$			
0.17%	0.14%	0.04%	0.01%
(2.39)	(1.81)	(0.40)	(0.04)

Table 4

Signals computed from smaller leaders and leaders in a different industry

This table presents monthly abnormal returns of leader-signal-sorted portfolios. The sample consists of stocks that traded on the last day of the previous month, were priced above $5 per share and had leaders. Leaders are identified with 12-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 highest- and lowest-signal portfolios. In Panel A, leaders are limited to the set of stocks that are smaller than their followers. In Panel B, leaders are limited to the set of stocks that are in a different industry than their followers. Newey-West-adjusted t-statistics are reported in parentheses.

Panel A: Signal is computed only from smaller leaders

	EW portfolios		VW portfolios	
Decile	Excess return	4-factor alpha	Excess return	4-factor alpha
1	0.59%	-0.30%	0.43%	-0.26%
	(2.21)	(-3.63)	(1.95)	(-3.02)
. . .				
10	1.06%	0.13%	0.78%	0.02%
	(4.03)	(2.05)	(3.40)	(0.22)
10-1	0.48%	0.43%	0.35%	0.28%
	(4.63)	(3.89)	(2.81)	(2.02)

Panel B: Signal is computed only from leaders in a different industry

	EW portfolios		VW portfolios	
Decile	Excess return	4-factor alpha	Excess return	4-factor alpha
1	0.53%	-0.35%	0.41%	-0.29%
	(2.01)	(-4.22)	(1.84)	(-3.27)
. . .				
10	1.09%	0.14%	0.83%	0.11%
	(4.02)	(2.34)	(3.55)	(1.22)
10-1	0.55%	0.49%	0.41%	0.40%
	(5.30)	(4.47)	(3.42)	(2.99)

Table 5

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 previous week, were priced above $5 per share, and 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 highest- and lowest-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	-0.11%	-0.25%	-0.28%	-0.25%
	(-1.40)	(-6.61)	(-12.1)	(-11.1)
2	0.03%	-0.09%	-0.12%	-0.10%
	(0.49)	(-3.03)	(-7.02)	(-6.15)
3	0.10%	-0.01%	-0.04%	-0.02%
	(1.51)	(-0.48)	(-2.77)	(-1.59)
4	0.15%	0.04%	0.01%	0.03%
	(2.40)	(1.61)	(0.96)	(2.11)
5	0.17%	0.06%	0.03%	0.05%
	(2.59)	(2.15)	(1.92)	(3.00)
6	0.21%	0.10%	0.07%	0.08%
	(3.18)	(3.51)	(4.49)	(5.29)
7	0.25%	0.14%	0.11%	0.12%
	(3.69)	(4.59)	(6.77)	(7.63)
8	0.27%	0.16%	0.14%	0.15%
	(4.02)	(5.44)	(9.30)	(9.45)
9	0.31%	0.19%	0.17%	0.18%
	(4.23)	(5.63)	(9.48)	(10.40)
10	0.35%	0.23%	0.21%	0.22%
	(4.28)	(5.45)	(8.87)	(9.40)
10-1	0.47%	0.48%	0.49%	0.47%
	(12.35)	(12.54)	(12.58)	(12.21)

Panel B: Value-weighted portfolios

Decile	Excess return	Market alpha	3-factor alpha	4-factor alpha
1	-0.04%	-0.19%	-0.22%	-0.18%
	(-0.54)	(-6.14)	(-7.09)	(-6.00)
2	0.02%	-0.11%	-0.12%	-0.11%
	(0.37)	(-5.50)	(-5.75)	(-5.45)
3	0.10%	-0.03%	-0.03%	-0.03%
	(1.68)	(-1.47)	(-1.78)	(-1.40)
4	0.12%	0.00%	-0.00%	-0.00%
	(2.18)	(0.01)	(-0.11)	(-0.14)
5	0.10%	-0.01%	-0.01%	-0.01%
	(1.83)	(-0.85)	(-0.54)	(-0.82)
6	0.16%	0.04%	0.05%	0.05%
	(2.80)	(2.53)	(2.98)	(2.77)
7	0.14%	0.02%	0.02%	0.01%
	(2.51)	(1.03)	(1.10)	(0.50)
8	0.21%	0.09%	0.10%	0.09%
	(3.48)	(4.65)	(4.89)	(4.60)
9	0.24%	0.11%	0.11%	0.11%
	(3.71)	(5.12)	(4.96)	(4.86)
10	0.23%	0.09%	0.09%	0.10%
	(2.97)	(2.78)	(2.86)	(3.02)
10-1	0.27%	0.28%	0.31%	0.28%
	(6.03)	(6.24)	(6.84)	(6.14)

Table 6
Alternative methods for aggregating weekly leader signals, various weekly lags

This table presents weekly four-factor alphas of the return differentials between the top- and bottom-decile portfolios formed based on leader signals in month $t - Lag$ within each of the 36 industries. In the first two columns, the leader signal is aggregated as in Table 5. In the remaining columns, the leader signals is aggregated "non-parametrically" by multiplying the previous week's leader returns by the sign($\hat{b}_3$) from weekly leader regressions and weighting them as described above each set of results, corresponding to Table 3. The number of weeks skipped before portfolios are formed is indicated in each row heading. The set of stocks is limited to those that traded on the last day of the previous week, were priced above \$5 per share, and had leaders. Newey-West-adjusted t-statistics are reported in parentheses.

Four-factor alphas of the return differential (Portfolio 10−Portfolio 1)

Method for computing the leader signal									
Parametric		Non-parametric							
equal-weighted		equal-weighted		value-weighted		$\|t$-stat$\|$-weighted		$\|\hat{b}_3\|$-weighted	
Weighting method for portfolio returns									
EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
$Lag = 0$ weeks									
0.47%	0.28%	0.50%	0.23%	0.20%	0.15%	0.51%	0.25%	0.45%	0.22%
(12.21)	(6.14)	(14.70)	(6.53)	(8.99)	(4.18)	(14.81)	(6.85)	(13.25)	(6.20)
$Lag = 1$ week									
0.20%	0.09%	0.21%	0.14%	0.10%	0.12%	0.21%	0.15%	0.20%	0.12%
(6.88)	(1.92)	(8.38)	(3.74)	(5.40)	(3.31)	(8.54)	(4.25)	(7.92)	(3.21)
$Lag = 2$ weeks									
0.11%	0.08%	0.12%	0.06%	0.05%	0.02%	0.12%	0.04%	0.12%	0.06%
(4.52)	(1.64)	(6.01)	(1.70)	(1.40)	(0.64)	(5.82)	(1.06)	(6.15)	(1.73)
$Lag = 3$ weeks									
0.06%	0.06%	0.07%	0.05%	0.04%	0.03%	0.07%	0.04%	0.05%	0.05%
(2.13)	(1.17)	(3.10)	(1.50)	(2.16)	(1.08)	(3.37)	(1.06)	(2.24)	(1.33)
$Lag = 4$ weeks									
0.02%	-0.00%	0.02%	0.01%	-0.02%	0.00%	0.02%	0.03%	0.03%	0.01%
(0.57)	(-0.05)	(0.71)	(0.14)	(-1.25)	(0.03)	(0.90)	(0.71)	(0.99)	(0.33)

Table 7

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 traded on the last day of the previous week, were priced above \$5 per share, and had leaders. Portfolio returns are equal-weighted in Panel A and value-weighted in Panel B. The last column reports four-factor alphas of the 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). Newey-West-adjusted t-statistics are reported in parentheses.

Panel A: Equal-weighted portfolios

Signal	Previous week's return quintile						
quintile	1	2	3	4	5	5-1	
1	0.35%	-0.04%	-0.16%	-0.30%	**-0.68%**	-1.02%	
	(10.37)	(-1.58)	(-7.69)	(-12.72)	(-17.80)	(-17.76)	
2	0.46%	0.10%	-0.01%	-0.13%	-0.38%	-0.84%	
	(18.48)	(4.87)	(-0.37)	(-6.26)	(-14.13)	(-20.43)	
3	0.50%	0.16%	0.06%	-0.05%	-0.31%	-0.80%	
	(17.84)	(7.16)	(3.03)	(-2.90)	(-13.88)	(-19.47)	
5	0.59%	0.24%	0.11%	0.03%	-0.26%	-0.84%	
	(20.22)	(11.67)	(5.89)	(1.63)	(-12.42)	(-21.22)	
5	**0.80%**	0.34%	0.17%	0.04%	-0.30%	-1.10%	
	(19.12)	(13.29)	(7.21)	(2.00)	(-11.05)	(-20.72)	51-15
5-1	0.45%	0.37%	0.33%	0.35%	0.38%		**1.48%**
	(10.81)	(11.11)	(10.12)	(11.04)	(10.04)		(20.57)

Panel B: Value-weighted portfolios

Signal	Previous week's return quintile						
quintile	1	2	3	4	5	5-1	
1	0.22%	0.01%	-0.12%	-0.25%	**-0.51%**	-0.73%	
	(5.24)	(0.19)	(-3.91)	(-7.44)	(-10.94)	(-11.30)	
2	0.35%	0.09%	-0.01%	-0.13%	-0.33%	-0.67%	
	(10.05)	(3.58)	(-0.32)	(-5.17)	(-9.97)	(-12.67)	
3	0.40%	0.14%	0.04%	-0.14%	-0.30%	-0.70%	
	(10.11)	(5.67)	(1.60)	(-5.22)	(-9.60)	(-12.43)	
4	0.39%	0.18%	0.06%	-0.10%	-0.25%	-0.64%	
	(10.50)	(7.05)	(2.08)	(-4.53)	(-8.26)	(-12.63)	
5	**0.45%**	0.26%	0.11%	-0.01%	-0.27%	-0.72%	
	(10.09)	(7.75)	(3.35)	(-0.34)	(-6.82)	(-12.12)	51-15
5-1	0.23%	0.26%	0.23%	0.24%	0.24%		**0.96%**
	(3.92)	(5.29)	(4.70)	(5.09)	(4.13)		(13.42)

Table 8
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: Monthly returns; 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
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Leader Signal (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. 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 (EW)$_{t-1}$			-15.555^c					
× Ret_{t-1}			(-1.67)					

*The sample period for this regression is two years shorter than that indicated in the panel header.
^{a}, ^{b}, and ^{c} indicate the 1%, 5% and 10% significance levels, respectively.

Panel B: Monthly returns, sample period: August 1963 - December 2011

			Leaders from 36-mo. rolling windows*	
×100	Ret_t	Ret_t	Ret_t	Ret_t
Model	(1)	(2)	(3)	(4)
Leader Signal $(\mathrm{EW})_{t-1}$	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 than that indicated in the panel header. ^{a}, ^{b}, and ^{c} indicate the 1%, 5% and 10% significance levels, respectively.

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

×100	Ret_t^w	Ret_t^w	Ret_t^w	Ret_t^w	Ret_t^w	$Ret_t^{w\S}$	Ret_t^w	$Ret_t^{w\P}$	Ret_t^w	Ret_t^w	Ret_t^w	Ret_t^w
Model	(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)
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. 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:												
$\times$ 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 9
Determinants of leadership

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 the appendix. The sample consists of all common shares of U.S.-incorporated firms. Panel A reports results for weekly-frequency leaders identified using 52-week rolling regressions and Panel B for monthly-frequency leaders identified using 12-month rolling regressions. In Panels A and B news counts are the number of impactful news stories on firm-centered events reported over a trailing 12-month period (impactful news are considered to be news accompanied by increased share turnover). The values of all explanatory variables are averaged over the trailing 12-month window. Panel C reports regression results for alternative news counts. Panel D reports the distribution of various news counts. For Poisson regressions, z-statistics, and for Tobit regressions, t-statistics are reported in parentheses; all standard errors are clustered by firm. The sample period is April 1997 - December 2011.

Panel A: Weekly leadership

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
News count ($\times$100)	0.0432^a	0.0297^a	12.1579^a	0.0207^a	0.0195^a	4.6856^a	0.0354^a	
	(9.12)	(4.62)	(9.19)	(3.78)	(2.99)	(3.06)	(2.91)	
News count^2($\times$100)							-0.0001	
							(-1.23)	
Inst. Ownership				0.0473^a	0.0562^a	13.9498^a	0.0459^a	
				(7.60)	(4.50)	(7.55)	(7.34)	
Analyst Coverage				0.0016^a	0.0012	0.5351^a	0.0015^a	
				(4.94)	(1.61)	(5.16)	(4.41)	
Turnover				0.0009	0.0020^c	0.2498	0.0008	
				(1.21)	(2.18)	(1.17)	(1.11)	
Momentum($\times$100)				-0.0107^a	-0.0108^a	-2.9867^a	-0.0108^a	
				(-4.56)	(-4.24)	(-4.30)	(-4.60)	
Size ($\times 10^4$)				-0.0421	0.0101	-11.5600	-0.0385	0.0293^c
				(-3.00)	(0.33)	(-2.97)	(-2.80)	(2.24)
Book/Market ($\times$100)				-0.1094	-0.2006	-24.2372	-0.1075	
				(-1.14)	(-0.99)	(-1.03)	(-1.13)	
Firm Dummies	No	Yes	No	No	Yes	No	No	No
Industry Dummies	Yes	No	Yes	Yes	No	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regression Spec.	Poisson	Poisson	Tobit	Poisson	Poisson	Tobit	Poisson	Poisson

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

Panel B: Monthly leadership

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
News count (×100)	0.0374^a	0.0205^a	13.8233^a	0.0181^a	0.0149^a	5.5819^a	0.0449^a
	(11.64)	(3.88)	(12.81)	(4.41)	(2.76)	(3.93)	(4.92)
News count^2(×100)							-0.0001^a
							(-3.28)
Firm Controls	No	No	No	Yes	Yes	Yes	Yes
Firm Dummies	No	Yes	No	No	Yes	No	No
Industry Dummies	Yes	No	Yes	Yes	No	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regression Spec.	Poisson	Poisson	Tobit	Poisson	Poisson	Tobit	Poisson

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

Panel C: Alternative news counts (all coeff ×100)

	Weekly leadership			Monthly leadership		
Model	(4)	(5)	(6)	(4)	(5)	(6)
Highly relevant corporate news	0.0143	0.0131^a	3.3850^a	0.0176^a	0.0159^a	5.7761^a
	(3.62)	(2.66)	(3.08)	(6.61)	(4.37)	(6.32)
All impactful news	0.0116^a	0.0150^a	2.7090^a	0.0147^a	0.0169^a	5.0113^a
	(3.01)	(2.96)	(2.44)	(4.90)	(4.11)	(4.70)
All highly relevant news	0.0077^a	0.0087^b	1.8527^b	0.01346^a	0.01807^a	4.8001^a
	(2.82)	(2.19)	(2.38)	(6.80)	(6.24)	(6.80)
All news	0.0041^a	0.0077^a	1.0371^b	0.0061^a	0.0083^a	2.1451^a
	(2.82)	(3.42)	(2.43)	(5.63)	(5.08)	(5.50)
Only new news	0.0061^a	0.0111^a	1.5300^a	0.0087^a	0.0119^a	3.0006^a
	(2.98)	(3.68)	(2.59)	(5.96)	(5.43)	(5.80)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Dummies	No	Yes	No	No	Yes	No
Industry Dummies	Yes	No	Yes	Yes	No	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Regression Spec.	Poisson	Poisson	Tobit	Poisson	Poisson	Tobit

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

Panel D: Summary statistics for the news count variables

	mean	std. dev.	10th pct.	median	95th pct.	99th pct.
Impactful corporate news	23.46	49.23	0	3	117	304
Highly relevant corporate news	41.88	82.78	0	9	191	488
All impactful news	31.68	66.49	0	5	152	424
All highly relevant news	56.60	108.49	0	15	147	639
All news	87.64	202.64	0	18	411	1,290
Only new news	61.82	148.18	0	13	291	951

Online Appendix
"Cross-Firm Information Flows and the Predictability of Stock Returns"

A1. Calculating the persistence of leader-follower pairs

Table A1 in the Online Appendix reports the persistence of leader-follower pairs over time. The results for 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 time—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 for all leaders, independent of the leadership sign in year t, and for positive and negative leaders, requiring that their respective leadership signs be preserved in year $t - \tau$. We use as a baseline the probability that a leader-follower pair also existed 10 years back in time and report, for every year $t - \tau$, the "excess" probability relative to this baseline (probability in $t - \tau$ minus probability in $t - 10$).

The table shows that the probability of a leader-follower relation also existing up to five years back in time 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.[26]

A2. Data

The data used in this paper are obtained from CRSP monthly and daily files and include all NYSE-, Amex-, and Nasdaq-traded stocks from the CRSP dataset, covering the period from January 1926 to December 2011. We adjust stock returns for delisting in order to avoid survivorship bias (Shumway (1997)).[27]

We do not impose any restrictions on the sample of stocks that are eligible to be identified as leaders. Over the January 1929 to December 2011 period (the initial years are used to estimate leadership regressions), our sample of potential leaders, on average, consists of about 3,305 stocks per month. However, we require that the set of follower stocks consists of common shares of U.S.-incorporated firms, that is, stocks with share codes 10 or 11. Moreover, we require that these stocks have a trade on the last day of the previous month for the monthly-frequency analysis and on the last day of the previous week for the weekly-frequency analysis. For the portfolio results, we further require that followers be priced above $5 per share. These restrictions leave us with an average of about 2,175 stocks per month that are eligible to be identified as followers. For the 1929-1960 subsample, this number is 694, and for the 1961-2011 subsample, it is 3,104.

Accounting variables are obtained from the Merged CRSP/Compustat dataset. The tables and figures presented throughout the paper generally cover the period January 1929 to December 2011. However, some variables, such as accounting variables or those calculated using daily return data, are not available for the early part of the sample. Data on analyst coverage are obtained from the I/B/E/S dataset and data on institutional holdings from the Thompson-Reuters Institutional Holdings dataset. The news coverage data are available

[26]Years $t-6$ through $t-9$ are omitted for space considerations but are available upon request.

[27]Specifically, when a stock is delisted, we use the delisting return from CRSP, if available. Otherwise, we assume the delisting return to be -100%, unless the reason for delisting is coded as 500 (reason unavailable), 520 (went to OTC), 551-573, 580 (various reasons), 574 (bankruptcy), or 584 (does not meet exchange financial guidelines). For these observations, we assume that the delisting return is -30%.

from the Thompson-Reuters News Analytics (TRNA) dataset for the period April 1996 to December 2011.

Monthly and weekly factor returns and industry classifications are obtained from Kenneth French's web site.[28] The results presented in the paper use 38 industry classifications, but the results are almost unchanged when 12 industry classifications are used instead. The monthly average percentages of firms in our sample in each industry are provided in Table A2 in the Online Appendix. The industry classified as "Irrigation Systems" drops out of our sample after the data restrictions are imposed, reducing the number of industries to 37. Additionally, in the results in which portfolio sorts are performed within industries or in which leaders are required to belong to a different industry than their followers, we drop stocks in the industry identified as "Other" because of the implied heterogeneity (moreover, this industry classification has few stocks).

A3. Alternative specifications and robustness tests

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 A4.

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 (Table 2); however, 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 a long-short portfolio that is not industry-neutral.

[28] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html.

Panels B and C present results for the 1980-2011 subperiod, which corresponds to the time period over which weekly returns are computed, for both 12- and 36-month rolling regression windows. Leaders identified with 36-month rolling regressions have more significant predictive power during that time period than leaders identified with 12-month rolling regressions. However, neither method produces significant four-factor alphas for value-weighted portfolios. Similar to many other return anomalies, this return anomaly diminishes over time, especially for large stocks.

The remainder of the robustness tests are presented only for leaders identified with 12-month rolling regressions. In Panel E, signals exclusively from positive leaders are used in portfolio formation, and in Panel F, signals exclusively from negative leaders are used. In Panel E, both equal- and value-weighted portfolio return differentials are significant, suggesting that positive leaders lead returns for both small and large stocks. In Panel F, the return differentials are significant only for equal-weighted portfolios and insignificant for value-weighted portfolios. This evidence suggests that, while both positive and negative leaders contribute to the return predictability of the followers, the contribution of positive leaders is larger.

In Panels G and H, 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 cutoff of 2.57, which corresponds to a two-tailed significance level of 1%. In Panel G, portfolios are formed within industries, and in Panel H, over the entire sample. It can be seen that the return differentials are very close to, or slightly lower than, those that are constructed with a t-statistic cutoff of 2.00 (see Panels A and B of Table 2 and Panel A of Table A4, respectively).

Next, we study the predictive ability of recurring and non-recurring leaders. In Panel I, 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 J, 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 previous three years. Signals from recurring leaders have 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; that is, non-leaders are mistakenly identified as leaders.

Finally, 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 K, only leaders that are *not* announcing earnings in the current month. Hence, the information in the leaders' current returns is likely unrelated to any 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 K are based on the more recent sample period). In Panel L, 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 K and are insignificant for value-weighted portfolios, probably because firms announcing earnings typically attract news coverage, which would result in follower stocks reacting to leaders' news with a shorter delay.

Overall, the results in this section indicate that our findings are robust to various alternative leader specifications and various portfolio construction methodologies.

A4. Do sophisticated investors trade on leader signals?

If sophisticated investors trade on leader signals, one will 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 the 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 sample provided by Markit.

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 information 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 employ 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 short sellers and lenders that report to Markit.

The average utilization over time is plotted in Figure A3. 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.[29] 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 exits 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

[29]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`).)

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:

$$\begin{aligned}\Delta utilization_{it} = \alpha &+ \beta_1 \cdot \mathbb{1}_{it}\{\text{Enters bottom signal decile}\} + \beta_2 \cdot \mathbb{1}_{it}\{\text{Exits bottom signal decile}\} \\ &+ \gamma_1 \cdot \mathbb{1}_{it}\{\text{Enters bottom ind. ret. decile}\} + \gamma_2 \cdot \mathbb{1}_{it}\{\text{Exits bottom ind. ret. decile}\} \\ &+ \mu_1 \cdot \mathbb{1}_{it}\{\text{Enters top return decile}\} + \mu_2 \cdot \mathbb{1}_{it}\{\text{Exits top return decile}\} + \epsilon_{it}. \qquad (6)\end{aligned}$$

Since the weekly leader signal is calculated 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 SEC's T+3 rule, which requires that all security transactions must be settled within three business days after the transaction day, shares sold short on Monday must be borrowed and delivered to the buyers by the close of business on Thursday.[30] 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."[31] Since short sellers may want to avoid stocks that are on special we remove, in one regression specification, stocks with high lending fees. 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 100 basis points per annum. 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

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

[31] 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.

5 the most expensive to borrow.[32] As would be expected, since lending fees are determined by supply and demand for loanable shares, we observe that 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 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 portfolio results, we drop all stocks priced at less than \$5 per share. 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 earnings 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 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 is slightly lower than for the overall sample and equal to 17.60%.

The regression results, reported in Table A5, 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, the number of shares sold short decreases by between

[32] 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.

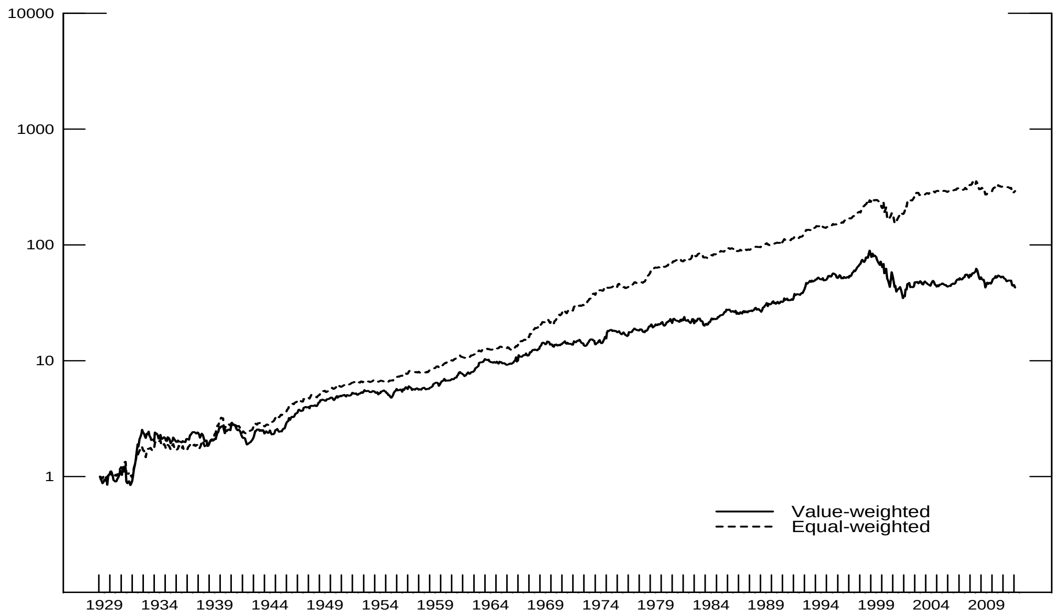
0.075% and 0.084% (depending on the sample restrictions) of the supply of shares available for shorting. Though these magnitudes may be economically small, they are statistically significant. Short-selling demand, however, does not significantly decrease following a stock exiting the bottom signal decile. 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.

A5. The Thomson-Reuters News Analytics dataset

The Thomson-Reuters News Analytics dataset (TRNA) is a machine-readable news feed from Thomson Reuters that includes news items from 41 news media outlets and covers the period from April 1996 to December 2011. We use the portion of the TRNA dataset that covers firms-specific news. Each firm-specific news story is tagged with a Reuters firm identifier which is mapped to its permno. The TRNA dataset provides news stories' headlines, as well as the take date and time. For all take dates that fall on holidays or weekends, we assume that the story date is the next trading day. For all take times after 15:30:00, we assume the story date to be the following trading day.

TRNA also provides a number of quantitative scores for the news computed by Thomson-Reuters, including sentiment scores (indicating whether a story is positive, negative, or neutral), relevance (measuring how relevant a story is to a firm), and uniqueness scores (specifying how new or repetitive a story is). In this paper, we use only the relevance score, which ranges from 0 to 1. The relevance score is calculated by comparing the number of occurrences of the firm name with the number of occurrences of other firm names within the text of the news story. For stories with multiple firms mentioned, the firm with the most mentions will have the highest relevance. A firm with a smaller number of mentions will have a lower relevance score. If the firm is mentioned in the headline, the relevance is set to 1. In news specifications stating "highly relevant news," we only consider firm-specific news stories in which the firm has a relevance score of 1.

Panel A: Monthly portfolios



Panel B: Weekly portfolios

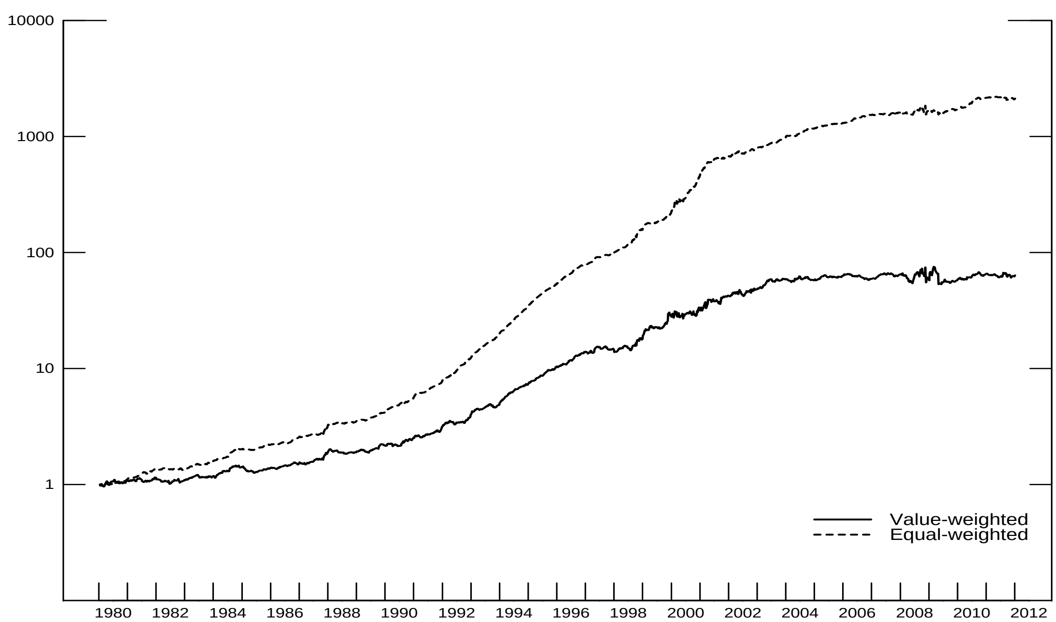


Figure A1. Cumulative returns. The charts plot, for equal- and value-weighted portfolios, the value of $1 invested in the beginning of the period at the return earned on a zero-investment strategy of buying stocks in the top and selling short stocks in the bottom leader signal deciles. In Panel A, leaders 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.

Panel A: Monthly-frequency leaders

Panel B: Weekly-frequency leaders

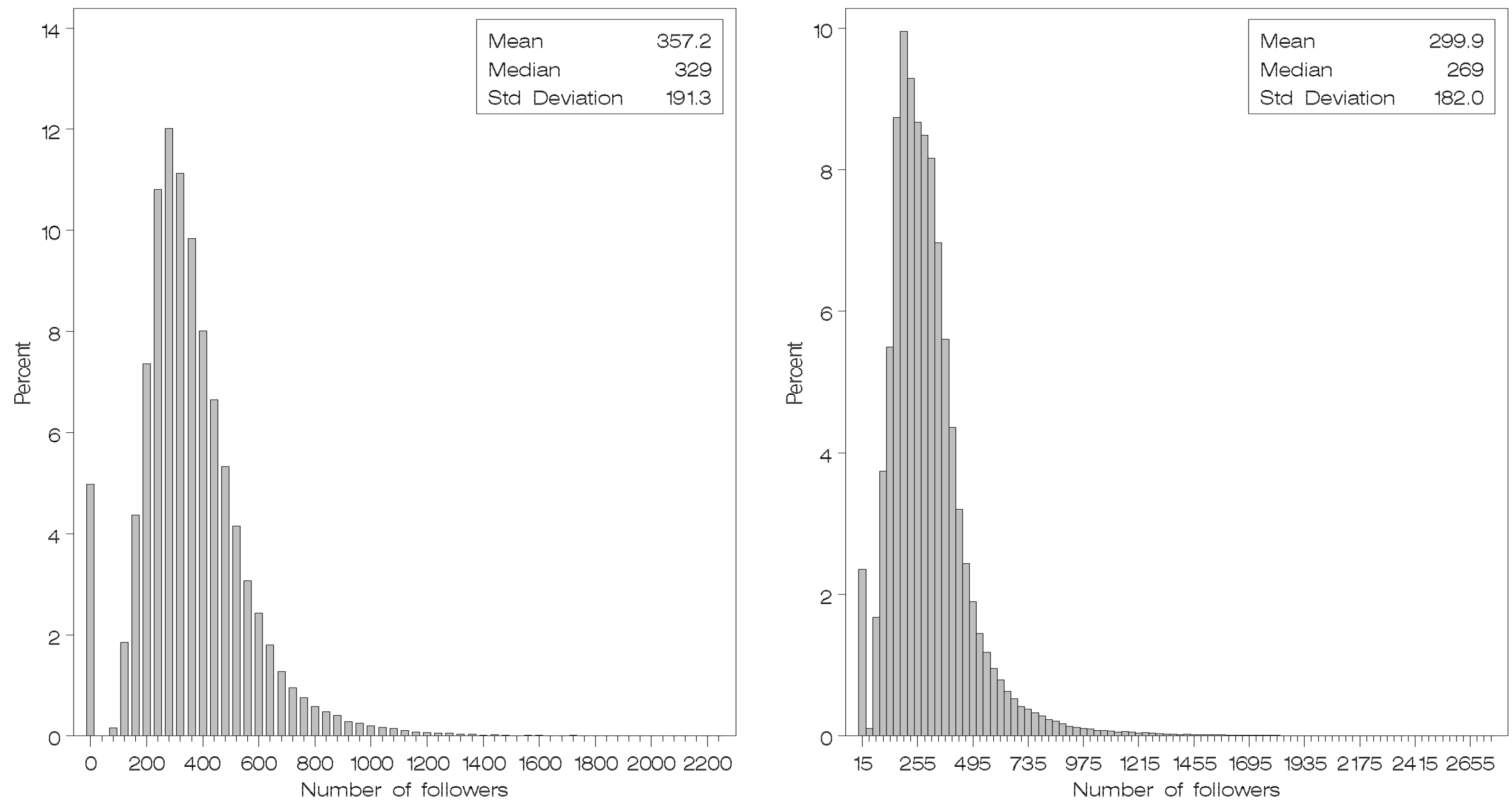


Figure A2. Distribution of the number of followers. The charts plot the distributions of the number of followers computed across all common shares of U.S.-incorporated firms (CRSP stocks with share codes 10 or 11). Leaders are the stocks that are found to Granger-cause monthly (weekly) returns of their followers in one-year rolling regressions. The numbers of followers are sampled at the end of January of each year. The sample period for both plots is April 1997 to December 2011, corresponding to the sample period of Table 9.

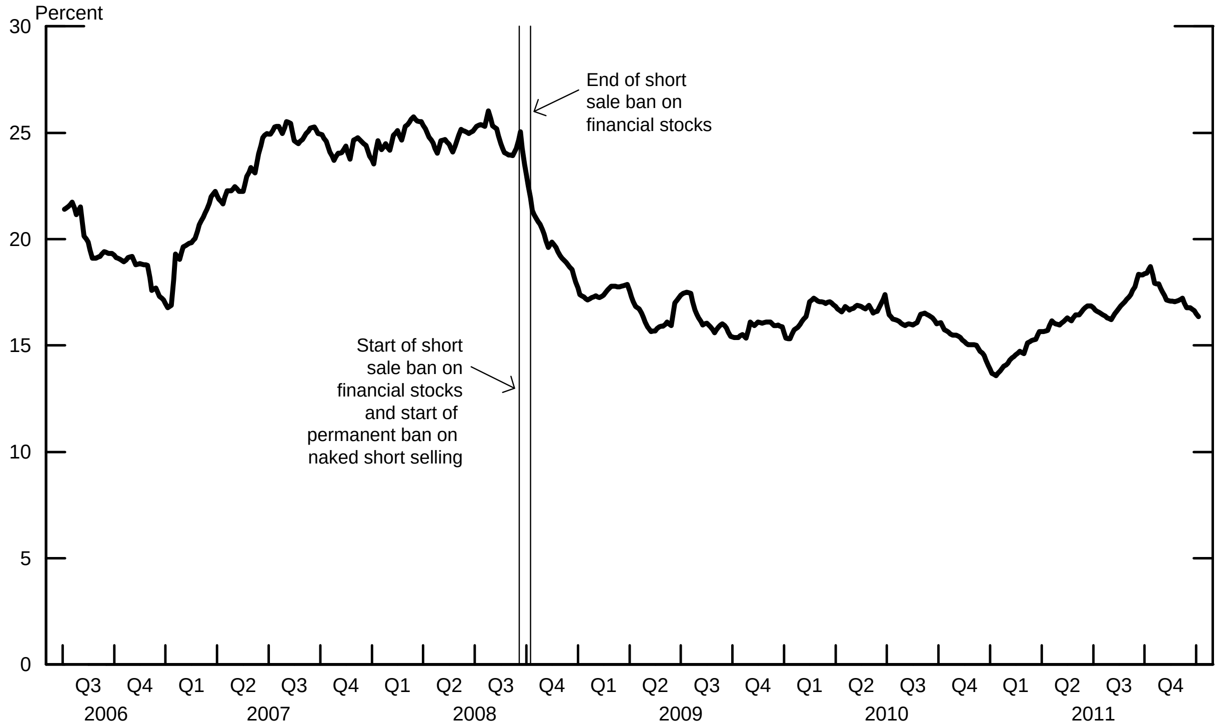


Figure A3. Short-selling activity over time: The average utilization. The figure plots the average utilization across all stocks in the Markit universe. Utilization is defined as the number of shares on loan to short sellers divided by the number of shares available to be loaned out. The sample period is July 3, 2006, to December 31, 2011.

Table A1
Persistence of leadership

This table presents probabilities, as well as excess probabilities relative to year $t-10$ along with the corresponding standard errors, of a leader-follower pair existing in January of year t that was also identified as a leader-follower pair of the same sign in January of year $t-\tau$, $\tau \in \{1, ..., 10\}$, provided that both stocks were present in the CRSP dataset for 12 months (Panel A) or 36 months (Panel B) prior to January 31 of year $t-\tau$. Panels A and B present the results for leaders identified using 12-month and 36-month rolling regression windows, respectively.

Panel A: Leaders are identified using 12-month rolling regression windows

	All leaders			Positive leaders			Negative leaders		
Number of years prior (τ)	prob.	excess prob. relative to $\tau = 10$	std. err. of excess prob.	prob.	excess prob. relative to $\tau = 10$	std. err. of excess prob.	prob.	excess prob. relative to $\tau = 10$	std. err. of excess prob.
1	5.982%	2.565%	0.006%	3.526%	1.578%	0.004%	2.457%	0.986%	0.004%
2	3.538%	0.120%	0.005%	2.051%	0.104%	0.004%	1.487%	0.017%	0.004%
3	3.468%	0.051%	0.005%	2.017%	0.070%	0.004%	1.451%	-0.019%	0.004%
4	3.461%	0.044%	0.006%	2.010%	0.063%	0.004%	1.451%	-0.019%	0.004%
5	3.416%	-0.001%	0.006%	1.984%	0.037%	0.004%	1.432%	-0.038%	0.004%
...									
10	3.417%	0.000%	-	1.947%	0.000%	-	1.470%	0.000%	-

Panel B: Leaders are identified using 36-month rolling regression windows

	All leaders			Positive leaders			Negative leaders		
Number of years prior (τ)	prob.	excess prob. relative to $\tau = 10$	std. err. of excess prob.	prob.	excess prob. relative to $\tau = 10$	std. err. of excess prob.	prob.	excess prob. relative to $\tau = 10$	std. err. of excess prob.
1	30.244%	27.366%	0.009%	18.321%	16.461%	0.007%	11.923%	10.904%	0.006%
2	12.654%	9.776%	0.008%	7.936%	6.076%	0.006%	4.717%	3.698%	0.005%
3	4.416%	1.538%	0.006%	2.878%	1.018%	0.005%	1.538%	0.519%	0.004%
4	2.944%	0.066%	0.006%	1.922%	0.062%	0.005%	1.022%	0.003%	0.004%
5	2.912%	0.034%	0.006%	1.897%	0.037%	0.005%	1.015%	-0.004%	0.004%
...									
10	2.878%	0.000%	-	1.860%	0.000%	-	1.019%	0.000%	-

Table A2
Industries

This table presents the monthly average percentages of stocks in the industries in our sample. The sample consists of common shares of U.S.-incorporated firms (stocks with share codes 10 or 11) that traded on the last day of the previous month and were priced above $5 per share. The averages are computed using only months that have at least one stock observation in a given industry. The sample period is 1929-2011.

Industry	% of stocks
Steam Supply	0.04%
Nonmetalic Minerals, Except Fuels	0.26%
Agriculture, Forestry, and Fishing	0.26%
Other	0.29%
Sanitary Services	0.31%
Public Administration	0.37%
Furniture and Fixtures	0.44%
Lumber and Wood Products	0.55%
Leather and Leader Products	0.64%
Radio and Television Broadcasting	0.76%
Telephone and Telegraph Communication	0.81%
Construction	0.85%
Tobacco Products	1.00%
Miscellaneous Manufacturing Industries	1.11%
Apparel and other Textile Products	1.19%
Printing and Publishing	1.25%
Rubber and Miscellaneous Plastics Products	1.28%
Paper and Allied Products	1.67%
Textile Mill Products	1.68%
Stone, Clay and Glass Products	1.74%
Mining	1.86%
Oil and Gas Extraction	2.18%
Wholesale	2.26%
Petroleum and Coal Products	2.71%
Fabricated Metal Products	2.81%
Instruments and Related Products	2.91%
Primary Metal Industries	4.84%
Food and Kindred Products	5.20%
Transportation	5.40%
Electric, Gas, and Water Supply	5.43%
Transportation Equipment	5.73%
Electrical and Electronic Equipment	5.87%
Chemicals and Allied Products	6.13%
Machinery, Except Electrical	6.38%
Services	6.88%
Retail Stores	7.09%
Finance, Insurance, and Real Estate	10.42%

Table A3
Removing stocks in small NYSE size deciles

This table presents monthly abnormal returns of leader-signal-sorted portfolios, corresponding to Table 2 of the main text. The sample consists of stocks that traded on the last day of the prior month, that were priced above $5 per share, and that had leaders. The set of stocks is further restricted based on their NYSE size decile computed as of the end of the previous June, as indicated in each subtable. Leaders are identified with 12-month rolling regressions in Panel A and 36-months rolling regressions in Panel B, and portfolios are formed within 36 industries based on equal-weighted leader signals 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, return differentials between the highest- and lowest-signal portfolios. Newey-West-adjusted t-statistics are reported in parentheses.

Panel A: Leaders are identified with 12-month regressions

	EW portfolios		VW portfolios	
Decile	Excess return	4-factor alpha	Excess return	4-factor alpha
	NYSE deciles 3 through 10			
1	0.43%	-0.40%	0.35%	-0.33%
	(1.67)	(-5.18)	(1.59)	(-3.84)
...				
10	0.90%	-0.01%	0.68%	-0.04%
	(3.47)	(-0.16)	(3.02)	(-0.51)
10-1	0.47%	0.39%	0.33%	0.29%
	(4.91)	(3.70)	(2.61)	(2.07)
	NYSE deciles 6 through 10			
1	0.41%	-0.34%	0.37%	-0.28%
	(1.68)	(-4.43)	(1.75)	(-3.40)
...				
10	0.80%	-0.02%	0.64%	-0.04%
	(3.19)	(-0.30)	(2.85)	(-0.52)
10-1	0.39%	0.32%	0.27%	0.25%
	(4.37)	(3.03)	(2.44)	(2.07)

Panel B: Leaders are identified with 36-month regressions

	EW portfolios		VW portfolios	
Decile	Excess return	4-factor alpha	Excess return	4-factor alpha
	NYSE deciles 3 through 10			
1	0.51%	-0.35%	0.35%	-0.32%
	(2.05)	(-4.56)	(1.62)	(-3.90)
...				
10	0.97%	0.03%	0.76%	-0.01%
	(3.82)	(0.53)	(3.42)	(-0.13)
10-1	0.46%	0.38%	0.41%	0.31%
	(5.19)	(3.80)	(3.52)	(2.46)
	NYSE deciles 6 through 10			
1	0.47%	-0.29%	0.42%	-0.23%
	(2.02)	(-3.96)	(1.99)	(-2.71)
...				
10	0.83%	-0.02%	0.72%	-0.00%
	(3.41)	(-0.37)	(3.31)	(-0.07)
10-1	0.36%	0.27%	0.31%	0.23%
	(3.81)	(2.59)	(2.72)	(1.91)

Table A4

Alternative specifications and robustness tests

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, 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 equal-weighted leader signals 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, return differentials between the highest- and lowest-signal portfolios. Newey-West-adjusted t-statistics are reported in parentheses.

Portfolios are sorted over the entire sample and *not* within each industry

Panel A: Leaders are identified with 12-month regressions

	EW portfolios		VW portfolios	
Decile	Excess return	4-factor alpha	Excess return	4-factor alpha
1	0.45%	-0.41%	0.31%	-0.42%
	(1.62)	(-4.50)	(1.25)	(-3.95)
...				
10	1.04%	0.05%	0.86%	-0.00%
	(3.62)	(0.81)	(3.24)	(-0.03)
10-1	0.59%	0.46%	0.55%	0.42%
	(5.30)	(4.06)	(3.78)	(2.66)

Panel B: Leaders are identified with 36-month regressions

	EW portfolios		VW portfolios	
Decile	Excess return	4-factor alpha	Excess return	4-factor alpha
1	0.49%	-0.41%	0.37%	-0.35%
	(1.88)	(-4.92)	(1.52)	(-3.44)
...				
10	1.22%	0.21%	0.90%	0.05%
	(4.38)	(3.09)	(3.57)	(0.54)
10-1	0.72%	0.62%	0.53%	0.39%
	(6.69)	(5.95)	(3.70)	(2.55)

1980-2011 time period

Panel C: Leaders are identified with 12-month regressions

	EW portfolios		VW portfolios	
Decile	Excess return	4-factor alpha	Excess return	4-factor alpha
1	0.35%	-0.33%	0.29%	-0.29%
	(1.06)	(-3.51)	(0.99)	(-2.39)
...				
10	0.78%	0.02%	0.55%	-0.17%
	(2.36)	(0.30)	(1.67)	(-1.33)
10-1	0.44%	0.36%	0.26%	0.12%
	(2.93)	(2.58)	(1.39)	(0.64)

Panel D: Leaders are identified with 36-month regressions

	EW portfolios		VW portfolios	
Decile	Excess return	4-factor alpha	Excess return	4-factor alpha
1	0.36%	-0.33%	0.49%	-0.11%
	(1.14)	(-4.21)	(1.64)	(-0.87)
...				
10	1.00%	0.25%	0.91%	0.15%
	(3.03)	(2.80)	(2.77)	(0.94)
10-1	0.64%	0.57%	0.41%	0.26%
	(5.03)	(4.47)	(2.23)	(1.18)

Condition on the sign of leadership

Panel E: Only signals from positive leaders are used

	EW portfolios		VW portfolios	
Decile	Excess return	4-factor alpha	Excess return	4-factor alpha
1	0.53%	-0.30%	0.30%	-0.39%
	(2.21)	(-3.22)	(1.43)	(-4.36)
...				
10	0.94%	0.07%	0.80%	0.11%
	(3.55)	(0.83)	(3.23)	(0.98)
10-1	0.42%	0.36%	0.49%	0.50%
	(2.99)	(2.40)	(3.23)	(2.99)

Panel F: Only signals from negative leaders are used

	EW portfolios		VW portfolios	
Decile	Excess return	4-factor alpha	Excess return	4-factor alpha
1	0.55%	-0.32%	0.47%	-0.22%
	(2.05)	(-3.70)	(1.92)	(-2.36)
...				
10	0.89%	0.01%	0.55%	-0.17%
	(3.51)	(0.12)	(2.40)	(-1.87)
10-1	0.34%	0.33%	0.08%	0.06%
	(2.53)	(2.09)	(0.57)	(0.36)

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

Panel G: Within-industry sorts

	EW portfolios		VW portfolios	
Decile	Excess return	4-factor alpha	Excess return	4-factor alpha
1	0.56%	-0.33%	0.33%	-0.33%
	(2.03)	(-4.39)	(1.50)	(-3.86)
...				
10	1.04%	0.10%	0.75%	0.02%
	(3.85)	(1.78)	(3.30)	(0.18)
10-1	0.48%	0.42%	0.42%	0.35%
	(5.26)	(4.56)	(3.65)	(2.63)

Panel H: Stocks are sorted over the entire sample

	EW portfolios		VW portfolios	
Decile	Excess return	4-factor alpha	Excess return	4-factor alpha
1	0.51%	-0.36%	0.32%	-0.40%
	(1.83)	(-4.41)	(1.25)	(-4.24)
...				
10	1.02%	0.05%	0.81%	-0.00%
	(3.52)	(0.88)	(3.06)	(-0.01)
10-1	0.51%	0.41%	0.49%	0.40%
	(4.84)	(3.96)	(3.40)	(2.66)

First-time vs. recurring leaders

Panel I: 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	0.65%	-0.22%	0.52%	-0.12%
	(2.44)	(-2.88)	(2.45)	(-1.60)
...				
10	0.97%	0.07%	0.72%	0.03%
	(3.65)	(1.24)	(3.05)	(0.43)
10-1	0.32%	0.29%	0.20%	0.15%
	(3.77)	(3.27)	(1.82)	(1.33)

Panel J: 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	0.48%	-0.40%	0.34%	-0.30%
	(1.82)	(-5.20)	(1.61)	(-3.23)
...				
10	1.07%	0.12%	0.78%	0.05%
	(3.93)	(2.28)	(3.34)	(0.57)
10-1	0.59%	0.52%	0.43%	0.36%
	(6.46)	(5.35)	(3.38)	(2.49)

Condition on whether leaders are announcing quarterly earnings (sample period 1972-2011)

Panel K: Only signals from leaders that are *not* announcing quarterly earnings in the current month are used

	EW portfolios		VW portfolios	
Decile	Excess return	4-factor alpha	Excess return	4-factor alpha
1	0.30%	-0.35%	0.16%	-0.28%
	(1.11)	(-4.54)	(0.69)	(-3.41)
...				
10	0.85%	0.08%	0.59%	-0.03%
	(3.01)	(1.12)	(2.35)	(-0.25)
10-1	0.54%	0.43%	0.44%	0.25%
	(4.86)	(3.67)	(3.35)	(1.64)

Panel L: Only signals from leaders that *are* announcing quarterly earnings in the current month are used

	EW portfolios		VW portfolios	
Decile	Excess return	4-factor alpha	Excess return	4-factor alpha
1	0.42%	-0.24%	0.43%	-0.16%
	(1.36)	(-3.36)	(1.59)	(-1.83)
...				
10	0.78%	0.06%	0.52%	-0.05%
	(2.60)	(0.92)	(1.92)	(-0.59)
10-1	0.36%	0.30%	0.09%	0.10%
	(3.48)	(3.08)	(0.62)	(0.83)

Table A5
Short selling in response to the leader signal

This table presents the results of Fama-MacBeth regressions 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 of the previous week):

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

Assuming that short sellers would set up short positions on the following Monday, utilization changes are calculated between 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 per share 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)
α	-0.025	-0.026	-0.023
	(-0.85)	(-0.88)	(-0.82)
β_1	0.075^b	0.076^b	0.084^b
	(2.05)	(2.06)	(2.49)
β_2	-0.033	-0.032	0.020
	(-0.97)	(-0.95)	(0.56)
γ_1	-0.021	-0.021	-0.014
	(-0.68)	(-0.66)	(-0.45)
γ_2	0.051	0.052	0.078^a
	(1.60)	(1.63)	(2.95)
μ_1	0.464	0.465	0.544
	(1.18)	(1.18)	(1.37)
μ_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.
^{a}, ^{b}, and ^{c} indicate the 1%, 5% and 10% significance levels, respectively.

Table A6

Portfolios sorted on the equal-weighted leader signal within 36 industries, 1929-2011: factor loadings and portfolio transition probabilities

This table presents portfolio factor loadings and portfolio transition probabilities for the monthly leader-signal-sorted portfolios presented in Table 2 of the main text. 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, and that had leader stocks are sorted into decile portfolios within each of the 36 industries based on equal-weighted leader signals computed at the end of the previous month, as described in the text. Panels A and B report the four-factor model factor loadings for equal- and value-weighted portfolios, respectively. Newey-West-adjusted t-statistics are reported in parentheses. Panel C reports portfolio transition probabilities.

Panel A: Factor loadings for equal-weighted portfolios

Decile	alpha	MKT	SMB	HML	UMD	R^2
1	-0.40%	1.18	0.65	0.09	-0.017	92.10%
	(-5.01)	(43.40)	(10.04)	(2.74)	(-0.46)	
2	-0.09%	1.08	0.47	0.15	-0.018	93.24%
	(-1.42)	(49.38)	(6.42)	(4.78)	(-0.52)	
3	-0.02%	1.02	0.49	0.14	-0.040	95.70%
	(-0.36)	(60.32)	(8.86)	(4.79)	(-1.65)	
4	0.06%	1.02	0.40	0.17	-0.033	94.81%
	(1.20)	(48.30)	(5.49)	(5.30)	(-1.40)	
5	0.05%	0.99	0.45	0.17	-0.024	95.22%
	(0.97)	(52.67)	(11.61)	(4.87)	(-0.93)	
6	0.17%	1.00	0.42	0.18	-0.027	95.70%
	(3.56)	(55.79)	(7.99)	(5.90)	(-1.17)	
7	0.16%	1.02	0.45	0.20	-0.018	95.67%
	(3.96)	(49.32)	(9.30)	(6.00)	(-0.67)	
8	0.14%	1.04	0.53	0.22	-0.010	95.56%
	(2.89)	(42.04)	(13.44)	(5.29)	(-0.39)	
9	0.16%	1.07	0.62	0.22	-0.023	95.37%
	(3.28)	(41.12)	(12.68)	(6.57)	(-0.75)	
10	0.13%	1.14	0.76	0.19	0.025	94.06%
	(2.35)	(55.09)	(11.65)	(6.65)	(1.05)	
10-1	0.53%	-0.03	0.12	0.10	0.042	2.68%
	(5.12)	(-0.88)	(2.30)	(2.98)	(1.36)	

Panel B: Factor loadings for value-weighted portfolios

Decile	alpha	MKT	SMB	HML	UMD	R^2
1	-0.34%	1.18	0.08	-0.05	-0.010	87.00%
	(-3.94)	(47.36)	(1.76)	(-1.22)	(-0.25)	
2	-0.09%	1.07	-0.03	0.02	0.001	91.03%
	(-1.38)	(66.34)	(-0.82)	(0.85)	(0.06)	
3	0.02%	0.99	-0.03	0.00	-0.024	91.86%
	(0.30)	(51.03)	(-1.16)	(0.13)	(-1.48)	
4	0.00%	1.00	-0.11	0.00	0.024	92.78%
	(0.01)	(75.59)	(-4.62)	(0.09)	(1.31)	
5	0.02%	0.99	-0.06	0.03	-0.026	92.88%
	(0.27)	(56.93)	(-2.07)	(1.17)	(-1.00)	
6	0.05%	0.94	-0.03	0.01	0.004	93.66%
	(1.09)	(67.57)	(-1.09)	(0.32)	(0.26)	
7	0.08%	1.03	-0.11	0.04	-0.007	93.26%
	(1.55)	(45.72)	(-4.98)	(1.46)	(-0.35)	
8	0.04%	1.01	0.02	0.07	0.012	90.76%
	(0.64)	(50.28)	(0.55)	(1.71)	(0.37)	
9	0.07%	1.06	0.03	0.09	-0.005	91.37%
	(1.14)	(68.70)	(0.77)	(3.21)	(-0.21)	
10	0.05%	1.12	0.22	0.09	0.013	87.16%
	(0.52)	(41.11)	(4.81)	(2.35)	(0.41)	
10-1	0.38%	-0.06	0.14	0.13	0.023	2.40%
	(2.67)	(-1.56)	(2.19)	(2.65)	(0.52)	

Panel C: Portfolio transition probabilities

Between month t and month $t+1$

Portfolio in	Portfolio in month $t+1$									
month t	1	2	3	4	5	6	7	8	9	10
1 (low signal)	0.24	0.13	0.09	0.07	0.06	0.06	0.06	0.07	0.08	0.13
2	0.12	0.15	0.12	0.10	0.09	0.08	0.08	0.08	0.09	0.08
3	0.08	0.12	0.13	0.12	0.11	0.10	0.10	0.09	0.08	0.06
4	0.07	0.10	0.12	0.13	0.12	0.12	0.11	0.10	0.08	0.05
5	0.06	0.09	0.11	0.12	0.13	0.13	0.12	0.10	0.08	0.05
6	0.05	0.08	0.10	0.12	0.13	0.14	0.13	0.11	0.09	0.06
7	0.05	0.08	0.10	0.11	0.11	0.13	0.13	0.12	0.10	0.06
8	0.06	0.08	0.09	0.10	0.10	0.11	0.12	0.13	0.12	0.08
9	0.08	0.09	0.09	0.08	0.08	0.09	0.10	0.12	0.15	0.12
10 (high signal)	0.12	0.08	0.07	0.06	0.06	0.06	0.07	0.09	0.13	0.25

Between month t and month $t+2$

Portfolio in	Portfolio in month $t+2$									
month t	1	2	3	4	5	6	7	8	9	10
1 (low signal)	0.18	0.12	0.09	0.07	0.07	0.07	0.07	0.08	0.10	0.16
...										
10 (high signal)	0.15	0.10	0.08	0.07	0.06	0.07	0.07	0.09	0.12	0.19

Between month t and month $t+12$

Portfolio in	Portfolio in month $t+12$									
month t	1	2	3	4	5	6	7	8	9	10
1 (low signal)	0.12	0.11	0.10	0.09	0.09	0.09	0.09	0.09	0.10	0.11
...										
10 (high signal)	0.12	0.11	0.10	0.09	0.09	0.09	0.09	0.10	0.11	0.12

Table A7

Weekly portfolios sorted on the equal-weighted leader signal within 36 industries, 1980-2011: factor loadings and portfolio transition probabilities

This table presents portfolio factor loadings and portfolio transition probabilities for weekly leader-signal-sorted portfolios presented in Table 5 of the main text. 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, and that had leader stocks are sorted into decile portfolios within each of the 36 industries based on equal-weighted leader signals computed at the end of the previous month, as described in the text. Panels A and B report the four-factor model factor loadings for equal- and value-weighted portfolios, respectively. Newey-West-adjusted t-statistics are reported in parentheses. Panel C presents transition probabilities.

Panel A: Factor loadings for equal-weighted portfolios

Decile	alpha	MKT	SMB	HML	UMD	R^2
1	-0.25%	1.10	0.85	0.13	-0.141	92.43%
	(-11.1)	(41.55)	(23.39)	(3.00)	(-5.08)	
2	-0.10%	1.01	0.67	0.19	-0.102	94.46%
	(-6.15)	(50.69)	(18.04)	(6.34)	(-4.54)	
3	-0.02%	0.96	0.61	0.20	-0.091	94.69%
	(-1.59)	(56.35)	(14.40)	(7.10)	(-3.77)	
4	0.03%	0.92	0.56	0.18	-0.088	95.09%
	(2.11)	(63.35)	(14.73)	(6.75)	(-3.71)	
5	0.05%	0.91	0.56	0.20	-0.084	95.30%
	(3.00)	(61.41)	(15.21)	(7.40)	(-3.54)	
6	0.08%	0.91	0.57	0.20	-0.074	95.55%
	(5.29)	(67.39)	(18.52)	(7.72)	(-3.53)	
7	0.12%	0.91	0.60	0.20	-0.077	95.04%
	(7.63)	(57.69)	(20.30)	(6.37)	(-3.30)	
8	0.15%	0.91	0.62	0.17	-0.070	95.02%
	(9.45)	(57.98)	(23.06)	(5.88)	(-3.22)	
9	0.18%	0.95	0.71	0.15	-0.074	94.46%
	(10.40)	(59.22)	(31.81)	(4.77)	(-3.82)	
10	0.22%	1.02	0.87	0.06	-0.083	92.41%
	(9.40)	(51.13)	(39.02)	(1.86)	(-4.52)	
10-1	0.47%	-0.08	0.02	-0.07	0.059	3.78%
	(12.21)	(-1.81)	(0.39)	(-0.98)	(1.50)	

Panel B: Factor loadings for value-weighted portfolios

Decile	alpha	MKT	SMB	HML	UMD	R^2
1	-0.18%	1.22	0.25	0.20	-0.197	83.61%
	(-6.00)	(27.44)	(7.46)	(2.44)	(-4.40)	
2	-0.11%	1.09	0.06	0.09	-0.050	90.10%
	(-5.45)	(49.52)	(2.28)	(2.28)	(-2.13)	
3	-0.03%	1.00	-0.07	0.04	-0.021	91.14%
	(-1.40)	(69.24)	(-2.48)	(1.72)	(-1.15)	
4	-0.00%	1.00	-0.07	0.03	0.003	92.41%
	(-0.14)	(76.61)	(-3.08)	(1.59)	(0.20)	
5	-0.01%	0.96	-0.08	-0.04	0.020	91.95%
	(-0.82)	(102.9)	(-4.05)	(-1.57)	(1.35)	
6	0.05%	0.96	-0.09	-0.04	0.013	91.93%
	(2.77)	(116.3)	(-5.14)	(-2.24)	(1.12)	
7	0.01%	0.97	-0.05	0.02	0.049	91.23%
	(0.50)	(89.92)	(-3.09)	(0.90)	(3.90)	
8	0.09%	0.96	0.00	-0.02	0.025	89.51%
	(4.60)	(56.71)	(0.19)	(-0.69)	(1.50)	
9	0.11%	1.04	0.05	0.00	0.009	88.18%
	(4.86)	(45.30)	(2.27)	(0.02)	(0.48)	
10	0.10%	1.13	0.27	-0.06	-0.042	82.61%
	(3.02)	(49.04)	(6.40)	(-1.19)	(-1.48)	
10-1	0.28%	-0.09	0.03	-0.26	0.155	6.93%
	(6.14)	(-1.47)	(0.42)	(-2.28)	(2.53)	

Panel C: Portfolio transition probabilities

Between week t and week $t+1$

Portfolio in	Portfolio in week $t+1$									
week t	1	2	3	4	5	6	7	8	9	10
1 (low signal)	0.21	0.12	0.08	0.06	0.06	0.06	0.06	0.07	0.10	0.18
2	0.11	0.13	0.11	0.09	0.09	0.09	0.09	0.09	0.11	0.09
3	0.08	0.11	0.12	0.11	0.10	0.11	0.10	0.10	0.10	0.07
4	0.06	0.09	0.11	0.12	0.12	0.12	0.11	0.10	0.09	0.06
5	0.06	0.09	0.11	0.12	0.13	0.13	0.12	0.10	0.08	0.05
6	0.05	0.08	0.11	0.12	0.13	0.14	0.13	0.11	0.09	0.05
7	0.06	0.09	0.10	0.11	0.12	0.13	0.12	0.11	0.09	0.06
8	0.07	0.10	0.10	0.11	0.10	0.11	0.11	0.12	0.11	0.08
9	0.09	0.11	0.10	0.09	0.08	0.09	0.10	0.11	0.13	0.11
10 (high signal)	0.17	0.10	0.07	0.06	0.06	0.06	0.07	0.08	0.12	0.22

Between week t and week $t+2$

Portfolio in	Portfolio in week $t+2$									
week t	1	2	3	4	5	6	7	8	9	10
1 (low signal)	0.20	0.12	0.08	0.07	0.06	0.06	0.06	0.07	0.10	0.17
...										
10 (high signal)	0.17	0.10	0.08	0.06	0.06	0.06	0.07	0.08	0.11	0.21

Between week t and week $t+52$

Portfolio in	Portfolio in week $t+52$									
week t	1	2	3	4	5	6	7	8	9	10
1 (low signal)	0.11	0.11	0.10	0.09	0.09	0.09	0.09	0.10	0.11	0.11
...										
10 (high signal)	0.11	0.11	0.10	0.09	0.09	0.09	0.09	0.10	0.11	0.11

Table A8
Correlations between control variables in Table 9

This table presents correlations between the control variables in Table 9. *News count* is the number of impactful firm-specific news stories appearing in the TRNA dataset over a trailing 12-month window, corresponding to the news counts used in Panels A and B of Table 9. Control variables are described in the appendix. p-values for the significance of the correlation coefficients are presented in parentheses. The sample period is April 1997 - December 2011.

	News Count	Inst. Own.	An. Cov.	Turnover	Momentum	Size	Book/Market
News Count	1.000	0.2246	0.3462	0.1951	-0.0080	0.4175	-0.0234
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Inst. Own.		1.0000	0.47560	0.2590	0.0317	0.1069	-0.0640
			(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
An. Cov.			1.0000	0.2826	0.0131	0.4320	-0.1113
				(<.0001)	(<.0001)	(<.0001)	(<.0001)
Turnover				1.0000	0.2282	0.0179	-0.0746
					(<.0001)	(<.0001)	(<.0001)
Momentum					1.0000	0.0156	-0.0517
						(<.0001)	(<.0001)
Size						1.0000	-0.0401
							(<.0001)