Month-End Reporting, Cash-Flow News, and Asset Pricing *

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Abstract

We show that the stock market regularly and systematically receives information about company fundamentals through month-end reporting, even before the quarterly earnings announcement. Such cash-flow news concentrates at the beginning of a month and affects company announcements, analyst revisions, and stock returns. Using this time variation in cash-flow news, we show evidence supporting cash-flow news being more persistent than discount-rate news. Individual stock returns exhibit a post-monthly-announcement drift. Time series market momentum exists only when conditioning on past first-half month return, and is stronger when the past market-wide earnings surprise is bigger.

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1 Introduction

A central issue in finance is to understand the drivers of asset price movements. Prices can move due to revisions in expected cash flows or revisions in discount rates, which are often termed "cash-flow news" or "discount-rate news".[1] To test the asset pricing implications of cash-flow versus discount-rate news requires decomposing price movements into cash-flow news and discount-rate news. However, Chen and Zhao (2009) point out that such decomposition is empirically challenging.

In this paper, we first show that the stock market regularly and systematically receives cash-flow news at the beginning of a month. Such concentrated arrival of cash-flow news in a short time window offers some advantages for identifying the effects of cash-flow versus discount-rate news. We then use this setting to test a key hypothesis regarding cash-flow news—price changes due to cash-flow news are more persistent than price changes due to discount-rate news. We find supportive evidence for the hypothesis and shed new light on the post-announcement price drift and the time-series market momentum.

The cash-flow news we study comes from the month-end reports. There are several reasons why firms produce month-end reports for internal or external uses. First, there is a widely adopted business practice called "month-end closing," which is an accounting procedure undertaken at the month end to close out the posting period. It includes settling work in progress material, reconciling inventory discrepancies, depreciating fixed assets, posting billing documents, and payroll. Many firms perform the month-end closing and usually complete it shortly after month end. Based on the responses by 2,300 firms worldwide in the General Accounting and Reporting Open Standards Benchmarking sur-

[1] For example, asset pricing models in Bansal and Yaron (2004) and Barro and Ursúa (2012) illustrate the importance of long-run cash-flow risk or disaster risk, while Campbell and Cochrane (1999) feature time-varying discount rates due to risk aversion. On the other hand, Shiller (1992) shows that stock-price variations cannot be accounted for by information regarding future dividends, and there appears to be excess volatility. And excess trading and predictable returns can be a consequence of investor behavioral biases, according to Daniel and Hirshleifer (2015). The discount-rate news is sometimes also known as the "expected-return news" in, for example, Callen and Segal (2004) and Hecht and Vuolteenaho (2006).

vey conducted by the American Productivity & Quality Center (APQC), APQC (2018) finds that the median time to complete the monthly consolidated financial statements is 6.4 days. The fastest 25% of firms complete in 4.8 days, while the slowest 25% of firms need ten or more days. The second reason firms produce monthly summary is that the annual budgets of firms often require a monthly update, known as the monthly budget report, to see whether income against spending is in line with the budget. Third, even though monthly reports are not mandatory for all firms, some firms are obligated to disclose monthly performance to selected external institutions. For example, some loans require monthly verification of covenants. The commercial loan agreement guide CGAP (2006, p. 30) states that "Borrowers should note that lenders take financial covenants, including any requirement to provide monthly financial statements and other documentation, very seriously."

We begin by studying firms that publicly disclose their monthly reports, and then extend the analysis to the entire cross-section of stocks and the aggregate market. We identify 5,760 month-end reports issued by 47 firms in the S&P 500 index. The monthly reports are from Bloomberg, and their announcement dates are from the Thomson Reuters Real-Time News database. We confirm that the monthly reports are announced shortly after the month end. 44% of these reports tracked by Bloomberg are announced within the first five calendar days of a month, and 87% are in the first half month.

The monthly reports carry cash-flow news. Those stocks with higher cumulative abnormal returns (CAR) in the three-day $[-1, 1]$ window around the monthly report announcements have higher quarterly earnings surprises and higher analyst revisions, which holds even for months before the quarter end. For example, consider the quarter of October–December (Q4). Our results indicate that the monthly announcements at the beginning of November and December, regarding the firm performance in October and November, are informative about the quarterly earnings.

In addition to quarterly earnings and analyst revision, the monthly announcement also

Problem: we can only separate them to Top/Bottom category when we know the end of the month price.

affects the contemporaneous return dynamics of the announcing firms. Those stocks with high monthly announcement CAR have disproportionately higher returns in the first half (H_1) than the second half (H_2) of the month because the monthly announcements are concentrated in the first half of a month. Surprisingly, the effect remains when we sort by the monthly return instead of the announcement CAR. I.e., when we sort stocks based on their whole-month returns, we find that stocks with high returns in a month have disproportionately higher returns in H_1 than H_2 of the same month. This is surprising because H_1 and H_2 are ex-ante symmetric components of the whole-month return. Further, the effect is substantial. When sorting stocks into quintiles based on their whole-month returns, the H_1 and H_2 return difference in the same month is 0.19% per day higher for the top quintile than the bottom quintile, or equivalently 47.88% annualized. The difference between H_1 and H_2 disappears when we exclude the three-day monthly announcement CAR from the analysis.[2] This shows that the cash-flow news revealed by the monthly announcements is sufficiently large and tilted towards the beginning of a month that it affects the contemporaneous return dynamics within a month. To our knowledge, we are the first to point out this large return dynamics in a month—high (or low) monthly return is disproportionately realized at the beginning of the same month—and we provide evidence that the monthly announcements drive such dynamics.

The monthly announcements exhibit a post-announcement return drift. This resembles the quarterly post-earnings-announcement drift (PEAD) in Ball and Brown (1968) and Chan et al. (1996), where stock returns continue to drift up for "good news" firms and down for "bad news" firms. Daniel et al. (2020) find that earnings surprise is important for capturing the short-horizon mispricings and that a parsimonious three-factor model including the quarterly PEAD explains a broad range of anomalies. To study post monthly

[2]The effect is even larger when we compare a shorter window at the beginning of a month versus the rest of the month, instead of H_1 versus H_2, and similarly disappears when the three-day monthly announcement CAR is excluded.

announcement drift, we rank stocks at the middle of a month by their monthly announcement CAR during the first half of a month and find a positive return drift in the second half of the month. This post-announcement drift uses calendar time instead of event time, which is one of the advantages of the monthly announcement setting. Event time is often used to study quarterly announcements, where the announcements at different times are aligned as if they occur at the same time. Event time has potential drawbacks.[3] However, due to the wide dispersion of quarterly announcement dates, using calendar time for quarterly announcements involves using stale surprise measures from the previous quarter, or using a subset of stocks that have announced the latest quarterly earnings, or a combination hence potentially comparing surprises from different quarters for different stocks. In contrast, because most monthly reports are announced at the beginning of a month, we can use a calendar time approach with the following benefits: (1) the fiscal period is the same across stocks—previous month, which is also the most recent fiscal period, (2) the earnings surprise can be measured for most stocks. Therefore, the monthly announcements provide a cleaner setting for studying the earnings surprise and post-announcement drift.

Next, we examine whether the effects associated with monthly reports extend to all stocks. Firms may not always publicly disclose their monthly reports to all market participants. On the other hand, some notions of market efficiency hypothesize that stock prices reflect all available information, even for information not publicly available to all (Fama 1970). Besides, some firms may not produce monthly reports. Therefore, we test a joint hypothesis that (1) sufficiently many firms produce monthly reports, and (2) prices reflect information in the monthly reports even for reports not publicly disclosed to all. We find evidence supporting this joint hypothesis. First, the number of management guidance and analyst revision spikes at the beginning of a month, which holds for stocks across various

[3]For example, Foster et al. (1984) argue that using event time risks relying on information available only from hindsight—a trading strategy based on the rank of each firm's earnings surprise is not implementable until the last firm in the sample has announced its earnings.

industries. Such spikes suggest that the management and analysts have more information at the beginning of a month, consistent with our hypothesis that many firms produce month-end reports and the information reaches the market at the beginning of the next month. Second, the pricing implications observed for stocks with Bloomberg monthly reports carry over to all stocks. The contemporaneous monthly return is realized disproportionately in H_1 than in H_2 for all stocks. We also find a post-announcement return drift using H_1 return as a proxy for the monthly announcement surprise, consistent with the return persistence following cash-flow news. Also, the variance ratio (half-month return variance to daily return variance) is higher in H_1 than H_2, further confirming that returns in H_1 are more persistent than in H_2.

After finding evidence that the effects of monthly reports extend to a broad spectrum of stocks in the cross-section, we study the implication of month-end reports on the aggregate market. The month-end report information from different firms hits the market at about the same time—the beginning of the next month. The synchronicity predicts a market-wide pulse of cash-flow news at the beginning of a month. The synchronous feature is distinct from the quarterly earnings announcements, which diffuse throughout a quarter.[4] Consistent with the market-wide pulse of cash-flow news at the beginning of a month, we find asset pricing effects for the aggregate market similar to those for individual stocks. First, high (low) monthly market return is realized disproportionately in H_1 than in H_2 of the same month. After sorting monthly market returns into two groups (above and below median), the half-month market return difference between H_1 and H_2 during the sorting month is 1.28% higher for the high group than the low group, or equivalently 30.72% annualized. This is a considerable magnitude for the market return and is consistent with our hypothesis that cash-flow news is concentrated at the beginning of the month.

Cash-flow news at the beginning of a month implies market return continuation after-

[4] Patton and Verardo (2012) and Savor and Wilson (2016) study investor learning of aggregate cash flows from the quarterly earnings announcements of individual firms.

wards. Consistent with this hypothesis, we find that the time series momentum (TSMOM) for the market return is almost entirely driven by conditioning on past market return in H_1. Moskowitz et al. (2012) show that the future market return is positively related to the past market return. If we split the past market return into past H_1 and past H_2 returns, the positive predictability of future market return remains when conditioning on the past H_1 return. Past H_2 return, if anything, negatively predicts the future market return, which resembles the return reversal documented in Shiller (1992), Campbell and Thompson (2008), and Cochrane (2008), among others.

The stark contrast between H_1 and H_2 for TSMOM can be reconciled by the time-varying composition of cash-flow news and discount-rate news within a month. Unlike cash-flow news, discount-rate news is associated with subsequent return reversal.[5] If the composition of information tilts more toward cash-flow news than discount-rate news at the beginning of a month, it can generate a stronger TSMOM conditioning on the past H_1 return than conditioning on the past H_2 return. To further corroborate this explanation based on cash-flow news, we find that the contrast between H_1 and H_2 for TSMOM is bigger when there is a bigger cash-flow surprise (measured by the market-wide quarterly earnings surprise).

To identify possibly causal effects from month-end reporting and rule out alternative hypotheses, we use three approaches. First, we use the three-day monthly announcement CAR. Our findings disappear if excluding the three-day announcement window from the month, thus directly linking the monthly reports and their announcements to the asset pricing implications. Second, we use a difference in difference approach, comparing the beginning of a month to the rest of the month (first difference) separately for months with good or bad cash-flow news (second difference). The difference in difference approach accounts for the stock-month fixed effects because an omitted variable that has little vari-

[5] As Campbell and Vuolteenaho (2004) point out, if the market price declines due to investors raising the discount rate, the expected future return is higher.

ation within a month is eliminated by comparing the beginning of a month to the rest of the month for the same stock. Therefore, our result is not driven by exposure to betas in the widely used factor models at the monthly or coarser frequencies. This approach also accounts for the market-day fixed effects. An omitted day-of-the-month effect for the market return, if any, can be offset by comparing the same day in different months with good or bad cash-flow news. Lastly, we exploit the disruption of month-end reporting by the seven-day Chinese New Year holiday, which typically falls in January or February. When the holiday overlaps with the end of January, it disrupts the end-of-January reporting. Consistently, we do not detect cash-flow news at the beginning of February for the Chinese stocks cross-listed in the United States, even though cash-flow news is detected at the beginning of other months for these stocks. When we create a synthetic February starting from the end of the Chinese New Year holiday, based on the hypothesis that the holiday-interrupted reporting is carried out after people return from holiday, we detect cash-flow news at the beginning of the synthetic February.[6] In contrast, for U.S. stocks, we detect cash-flow news at the beginning of February but not the synthetic February calibrated to the Chinese New Year.

We make five contributions to the literature. First, the concentrated arrival of cash-flow news at the beginning of a month constitutes a new setting for testing asset pricing implications of cash-flow versus discount-rate news. This setting has some advantages relative to existing approaches. The existing approaches measure cash-flow news by (1) modeling cash-flow news and discount-rate news, and then estimating cash-flow news from the model using methods such as vector autoregression (e.g., Campbell and Vuolteenaho 2004); or (2) using proxies such as quarterly earnings, alternative data, Wall Street Journal or other news media. Unlike the first approach, our setting does not require us to explicitly model cash-flow news and discount-rate news hence avoids potential misspeci-

[6]We confirmed with several accountants in China that the month-end reporting, if interrupted by the Chinese New Year holiday, is carried out after the holiday for their firms.

fication. Compared to quarterly earnings announcements, our setting has two advantages. First, the arrival of cash-flow news is synchronous at the beginning of a month for different firms. This allows the use of calendar time as opposed to event time in our studies. Such synchronicity also leads to pronounced cash-flow news for the aggregate market. Second, the monthly cash-flow news is concentrated in a narrow time frame. This alleviates the selection issue seen in quarterly disclosures (e.g., DellaVigna and Pollet 2009). There is a considerable time variation in the amount of cash-flow news from the monthly reports—87% are announced by the end of the first half month and only 13% in the second half month. This is a 7 to 1 ratio. Such large and anticipated variation in cash-flow news is useful for researchers interested in comparing asset pricing implications when there is a lot of cash-flow news versus when there is relatively little cash-flow news. In contrast, quarterly announcements diffuse throughout a quarter. For alternative data such as satellite image (Zhu 2019, Mukherjee et al. 2020) or news articles (Tetlock 2007, Engelberg et al. 2018), it is likely that the satellites provide a similar number of images and newspapers print a similar number of articles every day. Therefore, ex ante, it is easier to identify days with more or less cash-flow news in our setting based on month-end reports.

Second, using the cash-flow news at the beginning of a month, we test and find support for a key implication of cash-flow news—it implies higher persistence for the subsequent returns than discount-rate news. In the cross-section of individual stocks, we find using a calendar time approach a post-announcement drift, which Daniel et al. (2020) show is an important factor in determining the cross-sectional stock returns. For the aggregate market, we find a contrast of time series momentum after H_1 while reversal after H_2. This is consistent with the monthly cash-flow news being concentrated in H_1 instead of H_2. Using trading activities of speculators and hedgers, Moskowitz et al. (2012) show speculators profit from time series momentum at the expense of hedgers. We contribute by pointing out a likely source of information for the speculators. Huang et al. (2019) argue that the evidence on time series momentum is weak. There is also literature documenting market return reversal in Shiller (1992), Campbell and Thompson (2008), and Cochrane (2008), among others. Our finding of time series momentum after H_1 while reversal after H_2 helps reconcile the results in Moskowitz et al. (2012), Huang et al. (2019), and the market return reversal literature. Time series momentum coincides with concentrated cash-flow news at the beginning of a month, while market return reversal dominates at other times. When conditioning on lagged monthly market returns, which mixes momentum following H_1 and reversal following H_2, we find a weaker time series momentum, which is consistent with Huang et al. (2019). Therefore, we contribute to the market return momentum and reversal literature by showing that the time variation in the composition of cash-flow news and discount-rate news can shed light on the mixed evidence of time series momentum and reversal.

Third, we show the cash-flow news concentrated at the beginning of a month leads to a front-loaded realization of contemporaneous returns. Specifically, a high (or low) monthly return is realized disproportionately at the beginning of a month. The effect disappears if we exclude the three-day announcement window of the monthly reports. The market return also exhibits such front-loaded contemporaneous realization. Such front-loaded return realization at the beginning of a month is contrary to the implication from a time-homogeneous Brownian motion, which drives the random shocks in many models of stock price dynamics. Unlike quarterly earnings announcements, the monthly cash-flow news concentrates around a deterministic time—the beginning of a month. The arrival of shocks at a deterministic time, its effect on the modeling choice of stochastic processes, and the pricing implication on derivative assets likely warrant further studies in the future.

Fourth, to the extent that behavioral biases can drive return predictabilities, the post monthly announcement drift we document can be consistent with the hypothesis in Daniel et al. (2020) that "a subset of investors fail to take into account the implications of the latest earnings surprises," which generates the post-announcement drift when the mispricing is subsequently corrected. The announcements of monthly reports are less salient than the quarterly earnings announcements. Therefore, the hypothesis that some investors do not pay sufficient attention is likely more applicable to monthly reports than quarterly reports. Our evidence helps link such behavioral biases to the arrival of cash-flow news.

Lastly, our findings indicate that monthly reports provide a regular preview of quarterly earnings. Yet these internal monthly reports are relatively less studied, and their disclosure attracts less regulatory scrutiny than the quarterly reports. Given our limited scope, we leave the regulatory and additional asset pricing implications for future studies.

The rest of this paper is organized as follows. Section 2 analyzes companies that publicly disclose their monthly reports. Sections 3 and 4 extend the analysis to the full cross-section of individual stocks and the aggregate market, respectively. Section 5 contains some further discussions, and Section 6 concludes.

2 Stocks that Publicly Disclose Monthly Reports

In this section, we analyze firms that publicly disclose their monthly reports. We obtain the monthly report data from Bloomberg. The Bloomberg data do not contain the announcement dates of the reports. The announcement dates are obtained from the Thomson Reuters Real-Time News database by manually reading through the articles to identify an exact match to the month-end report. We restrict to firms in the S&P 500 index when collecting the data on monthly reports. Appendix A details the construction of the sample.

The final sample has 5,760 monthly reports disclosed by 47 firms in the sample period of January 2000–December 2016. Table A1 lists these firms. Figure A1 shows the industry break down of the monthly reports. The top three industries are retail, financial service, and airlines. The monthly report does not have a standardized format. Different firms can report different data items. For example, Costco (a retailer) reports a total of 26 unique data items, including revenue, same-store sales, number of locations, sales per customer growth, EBIT, EBITDA, among others. American Express, a financial service firm, reports 16 unique data items, three of which do not overlap with Costco's data items (total loans, card loans, net charge-off rate). United Airline reports 23 unique data items, ten of which do not overlap with Costco's or American Express's data items (e.g., revenue passenger mile, cargo ton miles, load factor, etc.). The size distribution of firms in the sample tilts more towards large firms compared to the entire stock universe in the Center for Research in Security Prices (CRSP) database, as shown in Figure A2.

Figure 1 shows the distribution of the announcement dates of the monthly reports. Figure 1a shows that the number of monthly announcements spikes at the beginning of each calendar month while there are few announcements towards the end of each month. Figure 1b shows that, on average, the first five days in a month each has more than 8% of the total monthly number of announcements. Combined, 44% of the monthly announcements are in the first five days. By the end of the first half month, 87% of the monthly reports are announced.

The average and the volatility of announcement returns are summarized in Table 1, using the stock return data from the CRSP database. The daily volatility is 2.53% in the three-day $[-1, 1]$ window around announcements and is 2.80% on the announcement day. The announcement volatility is higher than the daily volatility of 2.26% in the rest of the month. The average return is not statistically different between the announcement window and the rest of the month. The point estimate for the average return is higher in the monthly announcement window than the rest of the month, which resembles the higher average return during the quarterly announcements studied in Frazzini and Lamont (2007) and Savor and Wilson (2016), among others.

2.1 Monthly Announcement CAR

Table 2 shows the effect of monthly announcement surprises on the return dynamics around the monthly announcement and the quarterly earnings surprises. The announcement surprise is measured by the three-day CAR around the $[-1, 1]$ announcement window, following the quarterly announcement literature. Table 2 has two panels. Panel A shows the results for months 2 and 3 before the quarter end, and Panel B shows the results for all months. For example, if a stock's fourth quarter includes October to December, panel A includes the announcements and returns in November and December when the monthly reports for October and November are announced, while panel B includes the announcements and returns in November, December, and January. We show months 2 and 3, in addition to all months, to illustrate the extent to which the monthly reports convey information about quarterly firm performance even before the quarter end.

In panel A, the top quintile announcement CAR is 1.76%, while the bottom quintile CAR is -1.73%. The difference in announcement CAR between the top and bottom quintiles is 3.49% per day, or equivalently 10.47% over the three-day announcement window. This magnitude is large. The whole-month return difference is 0.51% per day, or equivalently 10.71% per month, between the top and bottom quintiles of stocks sorted by CAR.[7] Therefore, the whole-month return difference is almost entirely accounted for by the three-day difference in announcement CAR. If we exclude the three-day announcement window, the whole-month return spread between the top and bottom quintiles shrinks to only 0.03% per day, or equivalently 0.63% per month.

Because the announcements are concentrated in the first half of a month, the announcement CAR also leads to a much larger return spread in the first half than the second half of a month. The return spread in H_1 between top and bottom quintiles of stocks sorted by CAR is 0.86% per day, or equivalently 9.03% per half month. In contrast, the return spread

[7] There are 21 trading days in a month, on average.

in H_2 is only 0.16% per day, or equivalently 1.68% per half month. The large difference between H_1 and H_2 disappears when we exclude the three-day announcement windows, as shown by $H1_{ex[-1,1]}$ being almost the same as $H2_{ex[-1,1]}$ in columns (5) and (6).

The monthly announcements are also informative for the quarterly earnings surprises and analyst forecasts of quarterly earnings. Table 3 shows that the stocks in the top CAR quintile have 0.49 higher quarterly standardized unexpected earnings (SUE) than stocks in the bottom CAR quintile when using monthly announcement CAR in months 2 and 3 of a quarter before the quarter end. SUE is the seasonal earnings change (change in rolling annual earnings between adjacent quarters, or equivalently current quarter earnings minus last year same-quarter earnings) scaled by the standard deviation of the previous eight quarters' seasonal earnings change, following Foster et al. (1984) and Hou et al. (2018).[8] The difference in quarterly earnings surprise between the top and bottom CAR quintiles is equivalent to 0.49 standard deviations of seasonal earnings change. Therefore, the monthly reports provide a preview of the quarterly performance even before the quarter end. The result is similar when using the monthly announcement CAR in all months.

Table 3 also shows that the analyst revisions of their forecasts of quarterly earnings tend to be higher during the three-day monthly announcement windows if the announcement returns are higher.[9] Restricting to the months before the quarter end, column (1) shows that the difference in analyst revisions during the announcement window between stocks in the top and the bottom announcement return quintiles is 6.27 basis points (bps) per day, or equivalently 18.81 bps over the three-day announcement window. To see the magnitude, consider a hypothetical stock whose price to earnings ratio is 20, or equivalently, the price to quarterly earnings ratio is 80. Since the analyst revisions in Table 3 are scaled by stock prices, a revision of 18.81 bps over the three-day announcement window amounts to

[8] The accounting data such as earnings are from the Compustat database.

[9] The analyst forecast data are from the IBES database. Following IBES, when computing analyst revisions, we exclude forecasts that are simply the restatement of the last one, as well as those that are more than 180 days old from the previous forecast.

$18.81/10000/(1/80) = 15.05\%$ of the quarterly earnings. This suggests that the monthly announcements contain information that is likely relevant for quarterly earnings forecasts made by analysts, even in months before the quarter end. The result is similar in column (3) using all months.

2.2 Alternative Proxies of Monthly Announcement Surprises

Table 4 compares various proxies for the monthly announcement surprises, in addition to the monthly announcement CAR used in Section 2.1. This serves several purposes. First, when studying the contemporaneous dynamics around monthly announcements such as the analysis in Section 2.3, using only the announcement CAR to measure surprise can sometimes cloud the interpretation of the results. For example, Table 2 finds that when the announcement CAR is higher, the H_1 return is disproportionately higher than the H_2 return. However, it is difficult to interpret this finding because it may just be a mechanical effect of conditioning on the announcement CAR and the announcements tend to be in H_1. To explore the impact of monthly announcements on the return dynamics within a month, Section 2.3 needs a proxy for monthly announcement surprises that does not impose mechanical restrictions on the intra-month return dynamics. Further, Sections 3 and 4.3 study whether the findings extend to the full set of stocks, some of which do not publicly disclose monthly reports, hence require a proxy of monthly announcement surprises other than the monthly announcement CAR.

Table 4 compares the following proxies of monthly announcement surprises: the three-day monthly announcement CAR ($r_{[-1,1]}$), contemporaneous return in the whole month (r_M), the first half month (r_{H1}), and the second half month (r_{H2}) for the month containing the announcement, as well as the quarterly SUE.

Panel A shows that, for months before the quarter end, all the proxies correlate with the three-day monthly announcement CAR. Sorting on the announcement CAR itself leads to a quintile spread of 3.49% per day in announcement CAR. This is followed by a quintile spread in announcement CAR of 1.89% and 1.83%, respectively, if sorting on the contemporaneous H_1 return and the whole-month return. The quintile spread in announcement CAR, though significant, is much smaller if sorting on the contemporaneous H_2 return or the quarterly SUE. Among the proxies, the H_1 return and the whole-month return are the best proxies for the monthly announcement CAR, while the H_2 return and the quarterly SUE are weaker proxies. This is consistent with the monthly announcements being mostly in H_1. The whole-month return, compared to H_1 return, contains more non-announcement days; hence is a slightly weaker proxy for the announcement CAR. The quarterly SUE is informative for the monthly announcement surprise. But it is a weaker proxy, likely because the quarterly SUE also contains surprises for the other months in the quarter.

All the proxies for the monthly announcement surprises are informative for the quarterly earnings surprise SUE. The effects on quarterly SUE are similar when using the announcement CAR, the H_1 return, or the whole-month return. Sorting on either of these monthly proxies is associated with a quintile spread in quarterly SUE of around 0.50, i.e., a quintile spread in quarterly earnings surprise equivalent to 0.50 standard deviations of seasonal earnings change. The H_2 return is a much weaker proxy for the quarterly SUE. To our knowledge, the finding that the H_1 return is more informative about the quarterly SUE than the H_2 return is not documented before and is consistent with monthly announcements being concentrated in H_1 instead of H_2.

Panel B shows the results using all months. The results similarly indicate that the H_1 return and the whole-month return are the best proxies for the announcement CAR, and both are informative for the quarterly earnings surprise.

2.3 Front-loaded Announcements and Front-loaded Returns

We study in Table 5 how monthly announcements affect the contemporaneous return dynamics within the month of announcement. We use the whole-month return as a proxy for the monthly announcement surprise, based on the findings in Section 2.2. Section 2.2 shows that H_1 return is also a good proxy for the monthly announcement surprise. However, we do not use H_1 return because it mechanically affects the intra-month return dynamics. For example, if we sort on H_1 return and H_1 turns out to be high, it automatically implies that the returns at the beginning of the month are likely higher than the rest of the month. We need a conditioning variable that correlates with the monthly surprise but does not by itself impose any restrictions on the return dynamics within the month. The whole-month return qualifies because a high whole-month return does not automatically imply whether the return at the beginning of the month is higher or lower than the return later in the month.

When sorting monthly returns into quintiles, panel A of Table 5 shows that the difference in monthly returns between the top and the bottom quintiles is 1.08% per day. Interestingly, the return spread between the top and the bottom quintiles is much larger on the announcement days (1.83% per day) than the rest of the month (0.94% per day). This is consistent with the finding in Section 2.1 that the announcement return is an important determinant of the monthly return. The spread in H_1 returns between the top and the bottom quintiles is 1.20% per day and is larger than the spread in H_2 returns of 0.97% per day, likely because most monthly announcements are in H_1. The difference between the H_1 return spread and the H_2 return spread is 0.23% per day (t-stat. = 3.39). The difference is large, equivalent to 2.42% in terms of half-month return or 57.96% if annualized. The half-month return difference of 2.42% is almost entirely accounted for by the three-day announcement return in excess of the daily return in the rest of the month ($3 \times (1.83\% - 0.94\%) = 2.67\%$). If we exclude the three-day announcement window, the difference between H_1 and H_2 disappears, as shown by $H1_{ex[-1,1]}$ and $H2_{ex[-1,1]}$ in columns (5) and (6) of panel A.

Similar to Panel A, Panel B finds using all months that the whole-month return is realized disproportionately in the first half month, and the monthly announcements drive this effect. For quintile portfolios sorted by the whole-month return, the top minus bottom quintile spread of H_1 return is higher than the same quintile spread of H_2 return by 0.19% per day, or equivalently 47.88% annualized. This finding is consistent with the return dynamics in Table 2, with the added benefit that the conditioning variable whole-month return in Table 5 does not impose any mechanical restrictions on intra-month return dynamics.

Next, we show in Figure 2 that the front-loaded return realization documented in Table 5 holds not only for the H_1/H_2 split but also for other divisions of early versus late month. In Figure 2, we first sort stocks into quintiles based on their whole-month returns, the same as Table 5. Next, instead of comparing returns in H_1 versus H_2, we compare the returns in the first t days of a month to the average daily returns in the whole month. Specifically, each stock's cumulative return in the first t days of a month is demeaned by its whole-month return interpolated linearly to t days to get its cumulative abnormal return during the first t days. Figure 2 shows the difference between the top and the bottom quintiles in the cumulative abnormal return, which we call the $FRONTLOAD$ measure in this paper.

$$FRONTLOAD_t = (r_{1\to t}^{Top} - \frac{t}{T} r_{1\to T}^{Top}) - (r_{1\to t}^{Bottom} - \frac{t}{T} r_{1\to T}^{Bottom}), \tag{1}$$

where $r_{1\to t}$ is the cumulative return during the first t trading days of a month. T is the total number of trading days in a month. $\frac{t}{T} r_{1\to T}$ is the monthly return linearly interpolated to t days. Subtraction by $\frac{t}{T} r_{1\to T}$ serves to compare the first t days to the rest of the month, which is analogous to comparing H_1 and H_2 in Table 5.

If the whole-month return is realized disproportionately towards the beginning of a month, $r^{Top}_{1\to t} - \frac{t}{T} r^{Top}_{1\to T}$ is likely positive at the beginning of a month for stocks in the top quintile of monthly return, while $r^{Bottom}_{1\to t} - \frac{t}{T} r^{Bottom}_{1\to T}$ is likely negative at the beginning of a month for stocks in the bottom quintile of monthly return. Combined, $FRONTLOAD$ is likely positive at the beginning of a month. On the contrary, if the whole-month return is realized evenly during the month, $FRONTLOAD$ will be zero throughout the month because the actual return in the first t days $r_{1\to t}$ equals the linearly interpolated whole-month return $\frac{t}{T} r_{1\to T}$. By construction, $FRONTLOAD$ is zero at the month end.

Figure 2a shows that $FRONTLOAD$ spikes up early in the month, corroborating the evidence in Table 5 that the whole-month return is realized disproportionately in H_1 than H_2.[10] The spike is more pronounced at the beginning of the month, consistent with the monthly announcements being concentrated at the beginning of a month. At day 15, $FRONTLOAD$ is 1.19%, which is consistent with the magnitude of H_1 and H_2 difference reported in Table 5.[11]

To illustrate the impact of the monthly announcement on $FRONTLOAD$, Figure 2b excludes the three-day monthly announcement window from equation (1). The spike at the beginning of the month disappears. This is consistent with Tables 2 and 5, where the difference between H_1 and H_2 disappears after excluding the three-day monthly announcement window. The evidence indicates that the monthly announcements concentrated at the beginning of a month tilt the realization of the whole-month return disproportionately towards the beginning of a month.

[10]Trading days in equation (1) are mapped to calendar days for Figure 2 to align different months. $FRONTLOAD$ for a non-trading day is set to its last value on a trading day in the same month or zero if there is no earlier trading day in the month.

[11]At middle of the month, $r_{1\to t} - \frac{t}{T} r_{1\to T}$ in equation (1) is approximately $r_{H_1} - \frac{1}{2}(r_{H_1} + r_{H_2})$, where r_{H_1} and r_{H_2} are returns in H_1 and H_2, respectively. This equals $\frac{1}{2}(r_{H_1} - r_{H_2})$, which corresponds to half of the return difference between H_1 and H_2 in Table 5. Table 5 shows that the spread in return difference between H_1 and H_2 is 0.19% per day, or equivalently 2.00% in terms of cumulative half-month return. This predicts a magnitude of 1.00% at mid-month in Figure 2a. The actual number in Figure 2a at mid-month is 1.19%, which is close to the magnitude implied from Table 5. They are not identical because Figure 2a uses cumulative return, which includes return compounding. Table 5 uses a simple average of daily returns to facilitate comparison of returns across windows of different lengths such as the three-day announcement window, rest of the month, first half month, etc.

2.4 Post Monthly Announcement Drift

In Table 6, we test a key implication of cash-flow news—it implies higher persistence for the subsequent returns than discount-rate news. Table 6 uses a calendar time approach—at the end of H_1, it uses all the stocks that have monthly announcements during H_1. It runs Fama-MacBeth regressions of their subsequent stock returns in H_2 on proxies of their announcement surprises in H_1, such as their three-day announcement CAR during H_1 or their H_1 stock returns. All the stock returns in this table are in excess of the contemporaneous market return, and their unit is percent per day.

Table 6 shows that the three-day announcement CAR during H_1 positively forecasts the subsequent H_2 returns with a slope estimate of 0.030 (t-stat. = 2.05). The slope estimate increases to 0.043 (t-stat. = 3.19) when the regression includes additional control variables such as market beta, size, book-to-market ratio, and momentum. To see the magnitude of the predictability, recall from Table 2 that the top and bottom quintile spread of announcement CAR is 3.49% per day. This implies a magnitude of $0.043 \times 3.49\% = 0.15\%$ per day or, equivalently, 1.58% for the cumulative half-month return in H_2.

In contrast, the rest of H_1 return without the three-day announcement return (denoted $H1_{ex[-1,1]}$ in the table) is not statistically significantly related to H_2 return. If anything, the point estimate is negative, which is consistent with the short-term return reversal documented in Jegadeesh (1990) and Lehmann (1990). When we combine the monthly announcement CAR and $H1_{ex[-1,1]}$ to study the ability of H_1 return to forecast H_2 return, the point estimate is positive and equals 0.026. For comparison, this table also examines the ability of H_2 return to forecast the subsequent half-month return (i.e., the return in the first half of the next month, which is denoted $H3$ in columns (9) and (10) in the table), the point estimate is negative and equals -0.045. The negative estimate for H_2 is consistent with the short-term reversal and the lack of monthly announcements in H_2. The difference between the predictability of H_2 return using H_1 return and the predictability of next month's H_1

return using H_2 return is $0.026 - (-0.045) = 0.071$ with t-stat. = 1.79. This is statistically significant at the 90% level, despite the short-term reversal associated with $H1_{ex[-1,1]}$.[12]

Overall, we find a statistically and economically significant return continuation following the three-day monthly announcement CAR. It is sufficiently large to affect the return continuation conditional on half-month returns. Specifically, the return continuation after H_1, where the monthly announcements are concentrated, is more positive than the return continuation after H_2.

3 Full Cross-Section of Stocks

In this section, we test the hypothesis that the asset pricing implications for firms that publicly disclose monthly reports, documented in Section 2, can extend to the full cross-section of individual stocks. In the entire cross-section, some firms may not produce monthly reports. Those firms that produce monthly reports may not always publicly disclose the monthly reports to all market participants. Therefore, we are testing a joint hypothesis that sufficiently many firms produce monthly reports and that prices reflect information in the monthly reports even for reports that are not publicly disclosed to all. A priori, the strong form market efficiency in Fama (1970) predicts that the security prices reflect even undisclosed information. As discussed in Section 1, some loans require monthly verification of covenants, which transmits information specified in the covenants to lenders even if a firm does not formally produce monthly reports or disclose monthly reports publicly.

There is also evidence of insider trading based on monthly reports, which can incorporate information in the monthly reports into prices. As an example, a U.S. Securities and Exchange Commission anti-fraud case SEC (2004) indicates that a member of the Board of

[12]Other than the reversal affecting $H1_{ex[-1,1]}$, the statistical significance of return persistence conditional on the entire H_1 return is also limited by the sample period of 2000–2016 in Table 6, during which even the well known predictors controlled in Table 6 are often only marginally significant. Nonetheless, return persistence conditional on the announcement CAR is statistically significant.

Directors of Interstate Bakeries Corporation ('IBC') on January 29, 2003 received a confidential negative monthly IBC financial report and, on February 3, 2003, sold 16,230 shares of IBC stock. On February 11, 2003, IBC announced a downward revision to its earnings estimate, and IBC's stock price dropped 25% that day. The case refers to a monthly financial report for IBC in January 2003, which is not a fiscal quarter end for IBC.

We begin by providing evidence that many firms produce monthly reports, even though some of these monthly reports may not be publicly disclosed. Figure 3 examines management guidance issued by all U.S. firms. We hypothesize that firms are more likely to issue guidance when they receive new information from the monthly reports, which is consistent with downward earnings revision in the insider trading case of IBC. This predicts that the management guidance occurs more often at the beginning of a month after the month-end reporting. Consistently, Figure 3a shows that the number of management guidance spikes at the beginning of each month in a typical quarter. The management guidance data include managerial forecasts on earnings, capital expenditure, sales, and gross margin.[13] In Figure 3a, we exclude guidance during the three-day $[-1, 1]$ window around the quarterly earnings announcement when the information releases from management are known to be high. Even when including the quarterly earnings announcement days in Figure 3b, the early-month guidance spike is still visible. The amount of guidance outside the quarterly earnings announcements is the gap between the two lines in Figure 3b, and the gap is bigger at the beginning of a month than the previous month end. In Figure 3a, the peak number of guidance early in the month is 1,168, 857, and 1,160 in the first, second, and third month of a quarter, respectively. These sum up to 3,185, which is 68% of the peak number of 4,710 during quarterly earnings announcements in Figure 3b. Therefore, the amount of management information released early in the month is substantial, even

[13]The management guidance data from 1994.1 to 2016.12 are from the Thomson Reuters IBES guidance database, which provides real-time comments directly from management about future expectations. We supplement the IBES data with the First Call guidance data for the years before 2002, as the IBES coverage is small in the early years due to the phase-out of Thomas Reuters guidance from First Call to IBES.

when compared to quarterly earnings announcements.

Next, Figure 4 studies analyst revisions. Similar to management guidance, analyst revisions may be frequent at the beginning of a month if analysts learn the information in the month-end reports and update their beliefs. Consistently, Figure 4 shows that the number of analyst revisions spikes at the beginning of each month in a typical quarter.[14] The peak is roughly twice the number of revisions made near the end of the month.

Figure 5 shows the numbers of management guidance and analyst revisions separately for each of the Fama-French five industries. Every industry exhibits spikes in management guidance and analyst revisions during the early part of a month. To the extent these spikes at the beginning of a month reflect information from the month-end reports, this suggests that the month-end reports are broadly produced across various industries.

In Figure 6, we use only firms whose fiscal quarters end in months 3, 6, 9, or 12 of a year. This helps address a potential concern that the monthly spikes in Figures 3 and 4 may be caused by information from the quarterly reports if fiscal quarter-ends are evenly distributed across different months. The spikes at the beginning of each month remain in Figure 6. In our sample, 83.8% of firms have fiscal quarter-ends in months 3, 6, 9, or 12—March 5.0%, June 6.7%, September 6.0%, and December 66.2%. Therefore, our results are unlikely driven by firms whose fiscal quarters do not end in months 3, 6, 9, or 12, which is confirmed by Figure 6.

Overall, the evidence from management guidance and analyst revisions indicates that the firm management and analysts receive more information at the beginning of a month than the rest of a month, which is consistent with our hypothesis that many firms produce monthly reports.

[14] Figure 4 uses analyst revisions over long-term growth rates from the IBES database during 1983.1–2016.12. The results are similar using analyst revisions over other forecast horizons.

3.1 Front-loaded Returns

Having found evidence that many firms produce monthly reports, we study next whether these monthly reports, some of which may not be publicly disclosed, affect stock prices. Specifically, we study whether the finding of front-loaded returns within a month in Section 2.3 exists for the full cross-section of individual stocks. Because we no longer condition on monthly announcement CAR, the sample includes all individual stocks in the CRSP universe from January 1926 to December 2016 in the rest of the paper unless otherwise noted.

Figure 7 shows the $FRONTLOAD$ measure in equation (1) for all 12 months. In each month, $FRONTLOAD$ is calculated between the top and the bottom deciles of stocks sorted by their whole-month returns. We observe early-month spikes in every month in Figure 7. This is consistent with the finding in Section 2.3 that the monthly reports affect stock prices, and the effect is larger at the beginning of a month. The early-month spike has a large magnitude. The maximum spike is observed in January at 5.16% on day 11. Even if we exclude January due to the known January effect (Keim 1983; Reinganum 1983), the spikes in other months often exceed 1% and sometimes reach almost 2%.

The confidence band in Figure 7 indicates that the spikes are statistically significant. In addition, under the null hypothesis that the time when the monthly reports affect the stock returns is randomly distributed in a month, there is an equal chance of observing positive and negative spikes of the $FRONTLOAD$ measure at the beginning of a month. Under this null hypothesis, the probability of positive spikes at the beginning of all months is only $0.5^{12} = 0.02\%$, assuming independence across all 12 months. This is statistically significant even relative to the significance criterion in Harvey et al. (2016). Therefore, we reject this null hypothesis in favor of our hypothesis that the month-end reports affect stock returns predominantly at the beginning of a month.

Figures 8a and 8b show the $FRONTLOAD$ measure for large stocks separately from small stocks, to control the impact of microcaps pointed out by Fama and French (2008) and Hou et al. (2018). Both large and small stocks exhibit spikes at the beginning of a month.[15] Even for large stocks, $FRONTLOAD$ rises to a peak of 0.69% in less than half a month, which is a large magnitude.

For comparison, Figure 8 also shows the $FRONTLOAD$ measure for quarterly earnings announcements. I.e., equation (1) sorts by the quarterly instead of monthly returns, and $FRONTLOAD_t$ is calculated for $t = 1, 2, \ldots, T$ where T is the total number of trading days in a quarter instead of a month. Figures 8c and 8d show an early-quarter spike similar to the early-month spike observed for monthly announcements in Figures 8a and 8b. This suggests that the monthly reports and the quarterly reports generate similar return dynamics within a month and a quarter, respectively. For small stocks, $FRONTLOAD$ rises substantially in the last few days of the month and the quarter in Figures 8b and 8d. Our hypothesis does not restrict these last few days. Instead, our focus is on the spikes early in the month. Even though the rise in the last few days might be related to information drifting out shortly before the month end, the spike in the early part of a month is larger. Further, for large stocks, the rise in $FRONTLOAD$ is almost entirely concentrated in the early part of a month. These suggest that the information in the monthly reports affects the stock prices predominantly at the beginning of a month.

3.2 Post Monthly Announcement Drift

In Table 7, we study whether the post monthly announcement drift shown in Section 2.4 extends to the full cross-section of individual stocks. Since we do not directly observe all the disclosures of monthly reports in the full cross-section, we use the returns in the first half of a month as a proxy for the surprises associated with the monthly reports. Section 2.2 compares alternative proxies and finds that the H_1 return is the best proxy for the

[15] Stocks with market capitalizations above (below) the New York Stock Exchange median are classified as large (small) stocks.

monthly announcement surprise. Similar to Table 6, Table 7 uses a calendar time approach by running a Fama-MacBeth regression of H_2 returns on H_1 returns and comparing the result to another Fama-MacBeth regression of H_1 returns in the next month (denoted as H_3 in the table) on H_2 returns.

Table 7 shows that the slope using H_1 to forecast H_2 is higher than the slope using H_2 to forecast next month's H_1. The slope difference is 0.012 for all stocks and 0.018 for large stocks. An extra 10% return in H_1 is associated with 0.12% higher return for all stocks and 0.18% higher return for big stocks in H_2, compared to the effect of H_2 on subsequent H_1. The effect remains similar after including additional control variables. This is consistent with Table 6, which finds that the monthly announcement CAR is associated with a return continuation while the other days are associated with a return reversal subsequently.

On the other hand, the slope difference in Table 7 is smaller than that in Table 6. The slope from regressing H_2 on H_1 is negative in Table 7, which is also different from Table 6 where the slope from regressing H_2 on H_1 is statistically insignificantly different from zero. This is likely because the full cross-section of stocks may contain stocks that do not produce monthly reports, while Table 6 uses only stocks that have monthly announcements in H_1 when using H_1 returns to forecast H_2 returns. If there is no announcement, the short-term return reversal known in the literature dominants, as shown in Table 6. This provides an explanation for why the slope from regressing H_2 returns on H_1 returns is lower in Table 7 than in Table 6. It also helps explain why the difference between regressing H_2 returns on H_1 returns and regressing next month's H_1 returns on H_2 returns is smaller in Table 7 than in Table 6—if a stock does not produce monthly reports, there is no difference between H_1 and H_2.

Despite the smaller magnitude, the result in Table 7 is consistent with Table 6 in terms of the positive difference in slope between regressing H_2 returns on H_1 returns and regressing next month's H_1 returns on H_2 returns. Therefore, using the full cross-section of stocks,

Table 7 provides evidence consistent with the hypothesis that the cash-flow news from the monthly reports is associated with a positive continuation of the subsequent returns.

4 Aggregate Market

After showing in the previous section that the monthly reports affect a broad cross-section of stocks, this section studies how the monthly reports affect the aggregate stock market. The monthly reports clustered at the beginning of a month aggregate to market-wide cash-flow news. This section tests the asset pricing implications of the monthly reports for the market, parallel to those for the individual stocks in Sections 2 and 3. Specifically, Section 4.1 studies the effect on the market return dynamics within a month, while Section 4.2 uses the Chinese New Year shock to month-end reporting to study whether month-end reporting causes the intra-month market return dynamics. Section 4.3 tests the implication of cash-flow news on the persistence of market returns, i.e., time series market momentum.

4.1 Front-loaded Market Returns

We first study whether the finding of front-loaded returns within a month in Sections 2.3 and 3.1 extends to the aggregate market. Similar to these sections, we use the whole-month market return as a proxy for the aggregate surprise from the monthly reports.[16] The $FRONTLOAD$ measure is similarly constructed from equation (1), except that the top or bottom sort in equation (1) is from comparing monthly market returns to their time series median.[17]

Figure 9 shows that the $FRONTLOAD$ measure spikes up in the first half of a month. The spike reaches a peak of 0.69% in less than a month, which is a big magnitude for the

[16] We use real returns and real earnings for the market in Section 4 following the literature, such as Campbell and Shiller (1988), although the result is similar using nominal quantities.

[17] As a robustness check against potential look-ahead bias from using the time series median, we have also tried another top (bottom) sort depending on whether the monthly market return is above (below) zero. The result is similar.

market. The evidence is consistent with our hypothesis that the month-end surprises tilt the realization of the whole-month market return towards the beginning of a month.

4.2 Chinese New Year Shock to Month-end Reporting

Next, we use the Chinese New Year (CNY) holiday to study the causal effect of month-end reporting on the market return dynamics. Since the year 2000, the CNY holiday contains seven days. The holiday usually starts on different dates in different years, around late January or early February, as shown in Figure A3.[18]

First, we hypothesize that the interruption of end-of-January reporting due to the holiday weakens the front-loaded return dynamics in February. Figure 10 confirms this. Specifically, we calculate the $FRONTLOAD$ measure in the same way as Figure 9 but use the value-weighted return of Chinese stocks cross-listed in the U.S. We use the cross-listed stocks because the financial market in China closes during the CNY holiday. Figure 10a shows no pronounced spike in early February for the Chinese stocks cross-listed in the U.S., consistent with the disruption of end-of-January reporting due to the CNY holiday. Meanwhile, other U.S. stocks (the non-Chinese stocks) still exhibit the same spike in early February, as illustrated in Figure 10b, consistent with the end-of-January reports still being produced for the U.S. stocks.

Next, we create a synthetic February starting from the end of the CNY holiday, based on the hypothesis that the holiday-interrupted reporting is carried out after people return from holiday. The synthetic February ends before the next month. When the synthetic February has fewer than 29 days, we linearly interpolate the $FRONTLOAD$ measure by spreading out the available days evenly on a scale of 1 to 29 and then linearly interpolating the other days. When we use the synthetic February, the front-loaded spike re-appears for the Chinese cross-listed stocks (Figure 10c), consistent with the end-of-January reporting

[18]The CNY holiday dates are from `https://www.timeanddate.com/calendar/?year=2000&country=41`.

being deferred until after the CNY holiday. The spike in the synthetic February is statistically significant (t-stat. = 2.05 on day 2 of the synthetic February). Meanwhile, the front-loaded pattern disappears for the U.S. stocks during the synthetic February calibrated to the CNY holiday (Figure 10d). For other months of the year, there are similar spikes for both the Chinese cross-listed stocks and the U.S. stocks in the early part of a month (see Figure A4).

To summarize, we find that (i) the Chinese stocks exhibit a stronger $FRONTLOAD$ spike during the synthetic February than the actual February, while the opposite holds for the U.S. stocks; and (ii) both the Chinese and the U.S. stocks exhibit similar spikes for non-February months. With the caveat that the number of Chinese cross-listed stocks and the sample period are limited, this provides additional evidence that the month-end reporting is plausibly causal for the front-loaded return dynamics in a month.

4.3 Time Series Momentum

In this section, we examine whether the market return persistence is consistent with the prediction based on the cash-flow news from monthly reports. Specifically, we analyze whether the time series momentum (TSMOM) of market return in Moskowitz et al. (2012) is stronger when conditioning on the cash-flow news from monthly reports.

First, we split the past market return, which is the predictor variable in the TSMOM regressions, into two components—past return in H_1 and past return in H_2. We then separately use each component to forecast future market returns. We split the predictor into two components because the monthly reports are largely revealed in the first half of a month, and Section 2.2 finds that the H_1 return is the best proxy for the surprise from the monthly report. Under the hypothesis that the cash-flow news from the monthly report is associated with higher return persistence, we expect that the TSMOM is stronger when conditioning on the past H_1 return than conditioning on the past H_2 return.

The difference between using H_1 return versus H_2 return to forecast future market return turns out to be stark. Table 8 shows that higher market returns in H_1 forecast higher market returns, resembling the time series momentum documented in Moskowitz et al. (2012). However, the H_2 market return exhibits reversal—higher returns in H_2 forecast lower market returns. Such contrast holds for almost all the look-back and holding horizons ranging from one month to two years. For example, a one-standard-deviation increase in the past six-month H_1 return predicts a 0.54% increase in market return in the next month, yet the same one-standard-deviation increase in the past six-month H_2 return predicts the opposite—a decline in market return by 0.44% in the next month. For all 49 combinations of look-back and holding horizons, the estimate from H_1 is larger than the estimate from H_2. The estimates from H_2 are all negative except for the combination of the one-month look-back period and the one-month holding period. This single positive estimate after H_2 is consistent with the positive short-term autocorrelation of index returns in Lo and MacKinlay (1990), and also turns negative if we skip one month between the look-back and the holding periods (unreported in the table). The Lo and MacKinlay (1990) effect unlikely drives the positive momentum predicted using the H_1 return because we already skip a half month between the look-back period and the subsequent holding returns.

The stark difference between H_1 and H_2 is consistent with our hypothesis of return persistence from the cash-flow news in the monthly reports, which hit the market predominantly in H_1. Without the monthly reports, reversal dominates the forecast using H_2 returns. Such mixture of continuation and reversal—continuation after the cash-flow news from monthly reports and reversal otherwise—is also consistent with the findings in Table 6 for individual stocks.

In Table 8, an individual estimate for a given combination of the look-back and the holding horizons is not always statistically significant. This is not uncommon in time series predictions of market returns (e.g., Moskowitz et al. 2012, Fig. 1C). However, the fact that all the estimates across 49 combinations of look-back and holding horizons for H_1 are higher than those for H_2 indicates that the t-statistics from individual regressions likely under-estimate the overall statistical significance, which we investigate using a bootstrap. Huang et al. (2019) also use bootstrap to examine the statistical significance of TSMOM. To study the relevance of timing (H_1 vs. H_2), we bootstrap by randomly shuffling daily market returns within each month (but not across months) and then repeating the regressions for each simulated time series of market returns. After the random shuffle, the simulated H_1 and H_2 returns should have no difference for predicting market returns, which allows us to see the distribution of estimates under the null hypothesis that H_1 and H_2 have the same predictability for future market returns. We calculate the p-value using the fraction of simulations where the estimates based on H_1 returns (b_{H_1}) exceed the estimates based on H_2 returns (b_{H_2}) for all 49 combinations of horizons by an amount equal to the minimum of $b_{H_1} - b_{H_2}$ across all horizons in Panels A and B. The p-value is 0.007. Therefore, we reject the null hypothesis that the returns in H_1 and H_2 have the same predictability for future market returns.

Next, to further connect TSMOM with cash-flow news, we interact the magnitude of the monthly surprises in the TSMOM regression. I.e., we test the hypothesis that TSMOM is stronger if there is a bigger cash-flow surprise, particularly for H_1. For example, if there is no surprise from the monthly reports in a given month, the H_1 return is unrelated to cash-flow news from the monthly reports, which weakens the subsequent return continuation. On the other hand, a stronger cash-flow surprise from the monthly reports will strengthen TSMOM and particularly so in H_1. Specifically, we use the absolute value of the quarterly market SUE (denoted ABSUE) to measure the magnitude of cash-flow news. The quarterly earnings surprise is correlated with the proxies of monthly surprises, as shown in Table 4. We use the absolute value because a very negative earnings surprise is still an important piece of cash-flow news, and is likely associated with persistence of returns on the downside. In Table 9, we interact the lagged market return in H_1 and H_2, respectively, with the lagged market ABSUE.[19] Panel A of Table 9 shows that the estimates for the interaction between H_1 return and ABSUE are positive for all look-back and holding horizons while Panel B shows that the estimates for the interaction between H_2 return and ABSUE are mostly negative and are all smaller than the estimates in Panel A. Using a bootstrap similar to the one used for Table 8, the difference between Panels A and B is statistically significant with a p-value of 0.006. The result from the interaction with earnings surprise provides additional evidence for the role of cash-flow news in TSMOM.

The opposite signs from H_1 and H_2 imply that, if one ignores the difference between H_1 and H_2 and combines them in the analysis, the result is weaker. To confirm this, we interact ABSUE with past returns without separating past H_1 and H_2 returns in Table 10. The estimates for the interaction between ABSUE and past returns are still mostly positive, consistent with our hypothesis that cash-flow news drives the TSMOM. However, the economic and statistical magnitudes are much smaller in Table 10 than Panel A of Table 9.[20] All the independent variables are standardized to have a unit standard deviation, so the estimates in Tables 9 and 10 are directly comparable. As shown in Tables 8 and 9, H_1 exhibits a stronger TSMOM effect than H_2. Pinpointing when the cash-flow news hits the market helps sharpen the estimate for the impact of cash-flow news on TSMOM.

Overall, we find that TSMOM is stronger when the past market return coincides with (1) the arrival of cash-flow news, as seen by comparing H_1 and H_2 in Table 8; (2) larger cash-flow shocks, shown in Table 10; and (3) the interaction of (1) and (2), shown in Table 9. The results provide evidence that cash-flow news drives TSMOM.

[19] The quarterly market SUE is computed using the market earnings data from Robert Shiller's website `http://www.econ.yale.edu/~shiller/data/ie_data.xls`.

[20] To get the statistical significance in Table 10, we bootstrap by randomly shuffling the quarterly market earnings over time, computing the earnings surprises using the shuffled earnings, and then running the regressions for each simulated sample. Here, we do not shuffle the returns within a month, as in Table 9, because the analysis in Table 10 does not distinguish H_1 and H_2. As a robustness check, we have also done another bootstrap for Table 9 by randomly shuffling the quarterly market earnings similar to the bootstrap in Table 10 instead of shuffling returns within a month, and Table 9 remains statistically significant at the 1% level.

5 Further Discussions

5.1 Macro Announcements

The average market return is high on days of the Federal Open Market Committee (FOMC) announcement and the macro announcements on inflation and unemployment, as shown in Savor and Wilson (2013), Savor and Wilson (2014), and Lucca and Moench (2015). To study whether the macro announcements drive our findings on the market return, we exclude these macro announcement days in Figure 11 and Table 11. Following Savor and Wilson (2014), we use consumer price index (CPI) announcements before February 1972 and producer price index (PPI) thereafter because PPI numbers are always released a few days earlier, which diminishes the news content of CPI numbers. The inflation and unemployment announcement dates come from the U.S. Bureau of Labor Statistics. The FOMC announcement dates are from the Federal Reserve website.

Even after excluding these macro announcement days, Figure 11 is virtually identical to Figure 9. This is in contrast to Figure 2, where excluding the three days around monthly announcements eliminated the front-loaded return dynamics. Table 11 shows that the results for TSMOM are similar to Table 8 after excluding these macro announcements.[21] After excluding the macro announcements, the H_1 market return still positively forecasts future market returns while the H_2 market return predominantly leads to a reversal in the future. The estimates for H_1 are higher than those for H_2 for all combinations of look-back and holding months. If anything, the result is slightly stronger after excluding macro announcements. For example, the numbers in the lower right corner of panel A corresponding to long look-back and holding horizons are positive, while they are slightly negative in panel A of Table 8. This suggests a slight long-term reversal following a long win-

[21] Table 11 excludes the macro announcement days from the right-hand-side variable to see how the macro announcements affect the ability of the predictor to forecast future returns inclusive of returns on future macro announcement days. We have also tried excluding the macro announcement days from both sides of the TSMOM regressions, and the results remain similar.

ning streak of past macro announcement returns which, if excluded, generates a slightly stronger continuation. These results indicate that the macro announcements studied here are not a key driver of the front-loaded market return dynamics within a month or the TSMOM difference following H_1 vs. H_2.[22]

This section is not trying to rule out macro news as an important driver of the aggregate stock market return. Quite the contrary, the aggregate cash-flow news from the monthly reports can be viewed as a macro indicator. The analysis in this section just illustrates that our findings are not driven by the prominent macro announcements already documented in the literature.

5.2 Turn-of-the-Month and January Effects

Lakonishok and Smidt (1988) show that the average market return is high around the turn of the month, specifically in the four trading days starting from the last trading day of a month to the first three trading days of the next month. Rozeff and Kinney (1976) show that the stock returns in January tend to be higher than in other months. Keim (1983), among others, shows that the high January return is largely confined to small stocks and to the first trading week of January, particularly the first trading day. Ogden (1990) and Etula et al. (2019) point out that the turn-of-the-month effect and the January effects likely are connected and can be explained by the institutional liquidity needs at the turn of the month to pay wages etc.

We focus on the return persistence conditional on cash-flow news. In contrast, the turn-of-the-month and the January effects focus on high average returns instead of the conditional return dynamics. If the cash-flow news is bad, we find it manifests as low return at the beginning of a month instead of the high return predicted by the turn-of-the-

[22] For comparability with Figure 9 and Table 8, Figure 11 and Table 11 use the full sample 1926–2016. Data on the macro announcement days are available starting from 1958. Therefore, no days are excluded before 1958 in Figure 11 and Table 11. We have also compared the results with and without macro announcement days in the sample period of 1958–2016. The results are similar to their counterparts in the full sample.

month and the January effects. For example, Table 2 shows that for stocks in the lowest quintile of monthly announcement CAR, their returns in H_1 are negative and below their returns in H_2. Similarly, our return persistence analysis finds a low return following bad cash-flow news.

Further, our finding is not driven only by the first three or five days of a month (see, for example, Figures 8 and 9). Instead, our effects are mainly driven by the three days around the monthly announcements, as shown in Figure 2 and Table 6. To limit the impact from small stocks in January, we show that the results are robust outside January (e.g., Figure 7) and applicable to large stocks and the value-weighted market (e.g., Figure 8 and Table 8). Therefore, the findings in this paper are distinct from the turn-of-the-month and the January effects.

5.3 Variance Ratio

Next, Table 12 shows the variance ratio (half-month return variance divided by the one-day return variance and the number of trading days in the half-month window) to provide further evidence on the difference in return persistence between H_1 and H_2.

The variance ratio is higher in H_1 than in H_2, confirming that the return persistence is higher in H_1 than H_2.[23] During H_1, the variance ratio for the market return is 1.33. A variance ratio above one indicates a positive autocorrelation between the one-day returns. On the other hand, the variance ratio for the market is 1.00 in H_2, consistent with one-day returns following a random walk in H_2. The difference between H_1 and H_2 is statistically significant (t-stat. = 3.91). The variance ratio is higher in H_1 than H_2 for both large and small stocks, too. For individual stocks, the variance ratio in H_1 is below one, which is likely affected by the short-term reversal in daily returns related to market microstructure (e.g., Roll 1984). Nonetheless, the difference between H_1 and H_2 is positive, consistent with

[23]See Campbell et al. (1997, Chap. 2.4.3) for more information on the variance ratio.

the return persistence being higher in H_1 than H_2.

5.4 Placebo Months

We conduct placebo tests to confirm that the front-loaded return dynamics in Figures 8 and 9 are related to the start of a month. Specifically, we create placebo months by shifting an actual month by $shift = -15, -14, \ldots,$ or 15 days. For example, a shift of -15 days means using the last 15 days of the previous month and excluding the last 15 days of the current month.

We compute the $FRONTLOAD$ measure in equation (1) for placebo months corresponding to different $shift$ and all days within a given placebo month. To show the result in a two-dimensional graph, we plot $FRONTLOAD$ in the middle of a placebo month (day 15) against $shift$. Figure A5 shows that, across all placebo months, the peak is at $shift = 0$ (the actual month). The result holds for both large and small stocks. Figure A6 shows the placebo test results for the market. Across all placebo months, the peak is at $shift = 1$, i.e., when the "month" is from day 2 of a month to day 1 of the next month. This represents a mere one-day delay relative to the actual month. These results confirm that the front-loaded dynamics are the most pronounced at the beginning of an actual calendar month.

6 Conclusion

This paper shows that the month-end reporting constitutes an important information event. Information in the month-end reports provides a preview of the quarterly earnings surprise and substantially affects stock returns, management guidance, and analyst forecasts. The monthly reports, relative to quarterly reports, are less studied and subject to less regulatory scrutiny so far. There is a variety of practices in the production and disclosure of monthly reports. Some companies publicly disclose the monthly reports. Some companies do not publicly disclose the reports, but may revise management guidance based on the monthly information or provide such information to their lenders if required by loan covenants. At the same time, some companies may not formally summarize their performance monthly.

Despite the difference in the disclosure of monthly reports, we find important asset pricing implications that are similar across a broad spectrum of companies. First, the announcement return of a monthly report is a significant determinant of the monthly return. The flip side of the same coin is that the monthly return is realized disproportionately in the early part of a month because the monthly reports are usually announced at that time. Consistent with cash-flow news being persistent, the return persistence is stronger after the announcement of monthly reports or after the first half of a month, compared to the rest of the month. This holds for both individual stocks, large or small, and the aggregate market. The monthly reports across different individual stocks are disclosed almost synchronously at the beginning of a month, which aggregates to cash-flow news for the market. Consistently, we find that the time series momentum arises only by conditioning on the past market return in the first half of a month. The market return in the second half of a month, strikingly, exhibits subsequent return reversal.

The month-end reports and their disclosure provide a useful setting to test implications of cash-flow news versus discount-rate news. Prominent asset pricing theories differ in whether an asset pricing anomaly is best explained by cash-flow surprises, expectation errors about firm fundamentals, or changes in the required discount rate. However, decomposing asset price movements into cash-flow shocks and discount-rate shocks is known to be difficult. Here, the number of monthly announcements in the first half of a month is 7 times the number of monthly announcements in the second half of a month. Such a large variation can help us distinguish hypotheses with versus without cash-flow news, thus better understand the drivers of asset price movements.

References

APQC, 2018. Cycle Time to Perform the Monthly Close.

Ball, R., Brown, P., 1968. Empirical evaluation of accounting income numbers. Journal of Accounting Research 6, 159–178.

Bansal, R., Yaron, A., 2004. Risk for the long run: A potential resolution of asset pricing puzzles. The Journal of Finance 59, 1481–1509.

Barro, R. J., Ursúa, J. F., 2012. Rare macroeconomic disasters. Annu. Rev. Econ. 4, 83–109.

Callen, J. L., Segal, D., 2004. Do accruals drive firm-level stock returns? a variance decomposition analysis. Journal of accounting Research 42, 527–560.

Campbell, J. Y., Cochrane, J. H., 1999. By force of habit: A consumption-based explanation of aggregate stock market behavior. Journal of political Economy 107, 205–251.

Campbell, J. Y., Lo, A., MacKinlay, A. C., 1997. The Econometrics of Financial Markets. Princeton University Press.

Campbell, J. Y., Shiller, R., 1988. Stock prices, earnings, and expected dividends. Journal of Finance 43, 661–76.

Campbell, J. Y., Thompson, S., 2008. Predicting excess stock returns out of sample: Can anything beat the historical average? Review of Financial Studies 21, 1509–1531.

Campbell, J. Y., Vuolteenaho, T., 2004. Bad beta, good beta. The American Economic Review 94, 1249–1275.

CGAP, 2006. Commercial Loan Agreements, A Technical Guide for Microfinance Institutions.

Chan, L. K. C., Jegadeesh, N., Lakonishok, J., 1996. Momentum strategies. Journal of Finance 51, 1681–1713.

Chen, L., Zhao, X., 2009. Return decomposition. The Review of Financial Studies 22, 5213–5249.

Cochrane, J. H., 2008. The dog that did not bark: A defense of return predictability. Review of Financial Studies 21, 1533–1575.

Daniel, K., Hirshleifer, D., 2015. Overconfident investors, predictable returns, and excessive trading. Journal of Economic Perspectives 29, 61–88.

Daniel, K., Hirshleifer, D., Sun, L., 2020. Short-and long-horizon behavioral factors. The Review of Financial Studies 33, 1673–1736.

DellaVigna, S., Pollet, J. M., 2009. Investor inattention and friday earnings announcements. Journal of Finance 64, 709–749.

Engelberg, J., McLean, R. D., Pontiff, J., 2018. Anomalies and news. Journal of Finance 73, 1971–2001.

Etula, E., Rinne, K., Suominen, M., Vaittinen, L., 2019. Dash for Cash: Monthly Market Impact of Institutional Liquidity Needs. Review of Financial Studies .

Fama, E. F., 1970. Efficient capital markets: A review of theory and empirical work. The journal of Finance 25, 383–417.

Fama, E. F., French, K. R., 2008. Dissecting anomalies. The Journal of Finance 63, 1653–1678.

Foster, G., Olsen, C., Shevlin, T., 1984. Earnings releases, anomalies, and the behavior of security returns. The Accounting Review 59, 574–603.

Frazzini, A., Lamont, O. A., 2007. The earnings announcement premium and trading volume. NBER working paper .

Harvey, C. R., Liu, Y., Zhu, H., 2016. ... and the cross-section of expected returns. The Review of Financial Studies 29, 5–68.

Hecht, P., Vuolteenaho, T., 2006. Explaining returns with cash-flow proxies. The Review of Financial Studies 19, 159–194.

Hou, K., Xue, C., Zhang, L., 2018. Replicating Anomalies. Review of Financial Studies .

Huang, D., Li, J., Wang, L., Zhou, G., 2019. Time series momentum: Is it there? Journal of Financial Economics .

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. Journal of Finance 45, 881–98.

Keim, D. B., 1983. Size-related anomalies and stock return seasonality : Further empirical evidence. Journal of Financial Economics 12, 13–32.

Lakonishok, J., Smidt, S., 1988. Are seasonal anomalies real? a ninety-year perspective. The review of financial studies 1, 403–425.

Lehmann, B. N., 1990. Fads, martingales, and market efficiency. The Quarterly Journal of Economics 105, 1–28.

Lo, A. W., MacKinlay, A. C., 1990. When Are Contrarian Profits Due to Stock Market Overreaction? Review of Financial Studies 3, 175–205.

Loh, R. K., Stulz, R. M., 2011. When are analyst recommendation changes influential? Review of Financial Studies 24, 593–627.

Lucca, D. O., Moench, E., 2015. The pre-fomc announcement drift. The Journal of Finance 70, 329–371.

Moskowitz, T. J., Ooi, Y. H., Pedersen, L. H., 2012. Time series momentum. Journal of Financial Economics 104, 228 – 250.

Mukherjee, A., Panayotov, G., Shon, J., 2020. Eye in the sky: private satellites and government macro data. Journal of Financial Economics, forthcoming .

Newey, W. K., West, K. D., 1987. A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica 55, 703–708.

Ogden, J. P., 1990. Turn-of-month evaluations of liquid profits and stock returns: A common explanation for the monthly and january effects. Journal of Finance 45, 1259–72.

Patton, A. J., Verardo, M., 2012. Does beta move with news? firm-specific information flows and learning about profitability. Review of Financial Studies 25, 2789–2839.

Reinganum, M. R., 1983. The anomalous stock market behavior of small firms in january: Empirical tests for tax-loss selling effects. Journal of Financial Economics 12.

Roll, R., 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. The Journal of finance 39, 1127–1139.

Rozeff, M. S., Kinney, W. R., 1976. Capital market seasonality: The case of stock returns. Journal of financial economics 3, 379–402.

Savor, P., Wilson, M., 2013. How much do investors care about macroeconomic risk? evidence from scheduled economic announcements. Journal of Financial and Quantitative Analysis 48, 343–375.

Savor, P., Wilson, M., 2014. Asset pricing: A tale of two days. Journal of Financial Economics 113, 171–201.

Savor, P., Wilson, M., 2016. Earnings announcements and systematic risk. The Journal of Finance 71, 83–138.

SEC, 2004. Securities Exchange Act of 1934 Release No. 49645. Investment Advisers Act of 1940 Release No. 2233. Administrative Proceeding File No. 3-11473.

Shiller, R., 1992. Market Volatility. The MIT Press.

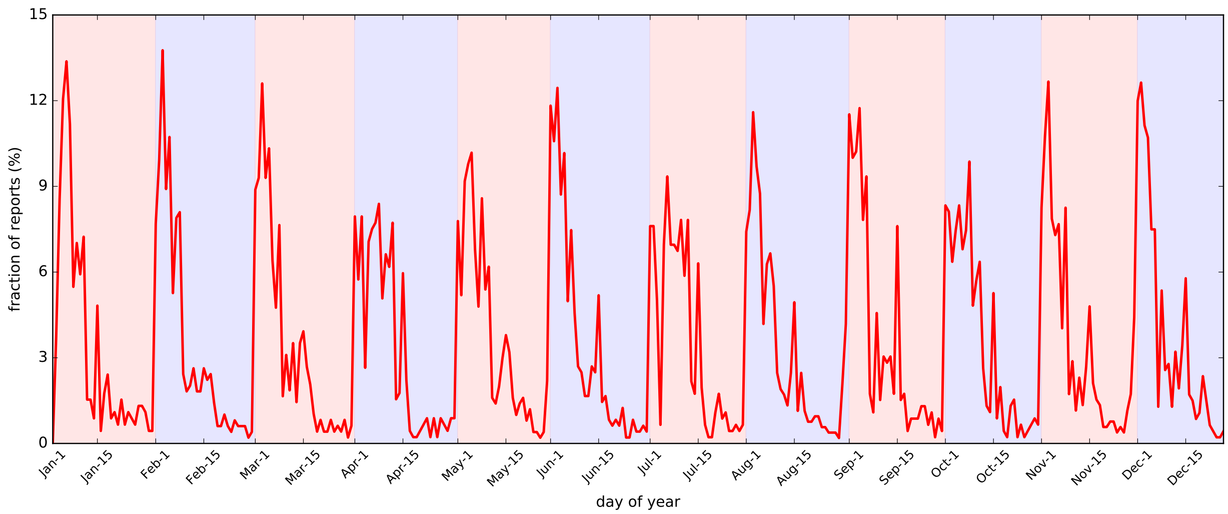
Tetlock, P. C., 2007. Giving content to investor sentiment: The role of media in the stock market. Journal of Finance 62, 1139–1168.

Zhu, C., 2019. Big data as a governance mechanism. The Review of Financial Studies 32, 2021–2061.

Figure 1: Announcement Dates of Monthly Reports

This figure shows the fraction of the daily number of monthly reports relative to the total number of monthly reports in the corresponding calendar month. Plot (a) shows the fraction for each day of the year. Plot (b) shows the fraction and its cumulative version by day of the month.

(a) Distribution within a year



(b) Distribution within a month

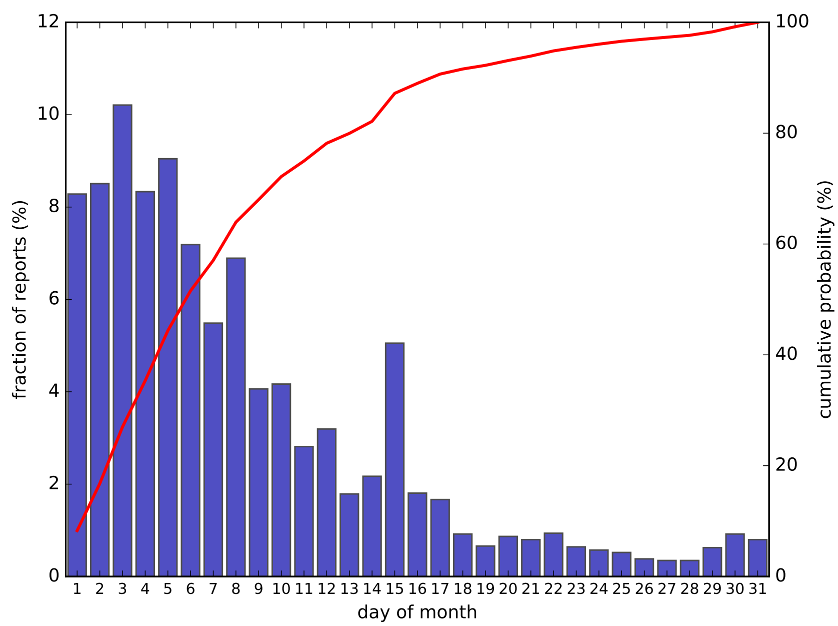
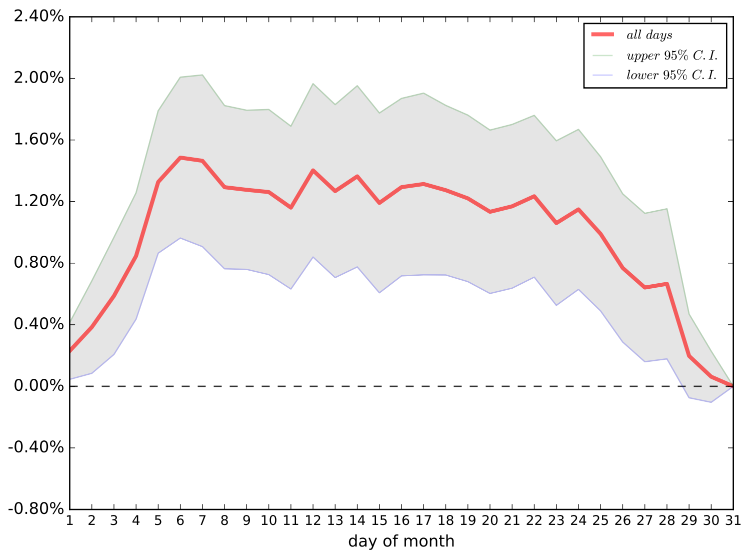


Figure 2: Contemporaneous Return Responses, with/without Monthly Announcement Days

Plot (a) shows the cumulative abnormal return spread between stocks with good and bad news in a month, which is the *FRONTLOAD* measure in equation (1). Plot (b) is the same as (a) except that the returns in the three-day [-1,1] window around monthly reports are excluded. Good (bad) news is measured by contemporaneous monthly returns in the top (bottom) quintile in the cross-section. Each stock's daily return is first demeaned by its average in the month before constructing the cumulative abnormal return spread. Hence the cumulative spread converges to zero at month end.

(a) All days



(b) Exclude 3-day window around the monthly report

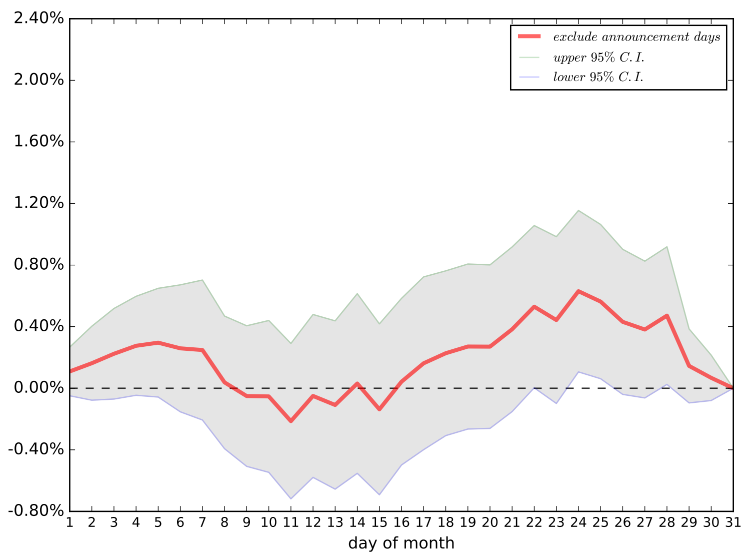
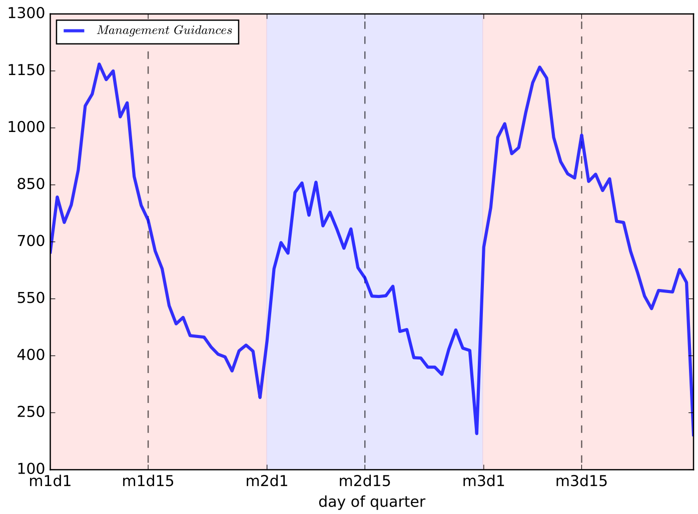


Figure 3: Announcement Dates of Management Guidance

Plot (a) shows the daily number of management guidance from all U.S. firms, excluding guidance in the three-day $[-1, 1]$ window around quarterly earnings announcements. Plot (b) shows the number of guidance in the $[-1, 1]$ window around quarterly earnings announcements and the combined number of all guidance. Multiple guidance observations from the same firm on the same day count as one. "mxdy" in the horizontal axis denotes day y of month x in a quarter. E.g., m1d15 means day 15 in January, April, July, and October.

(a) Guidance outside the quarterly announcement



(b) All guidance

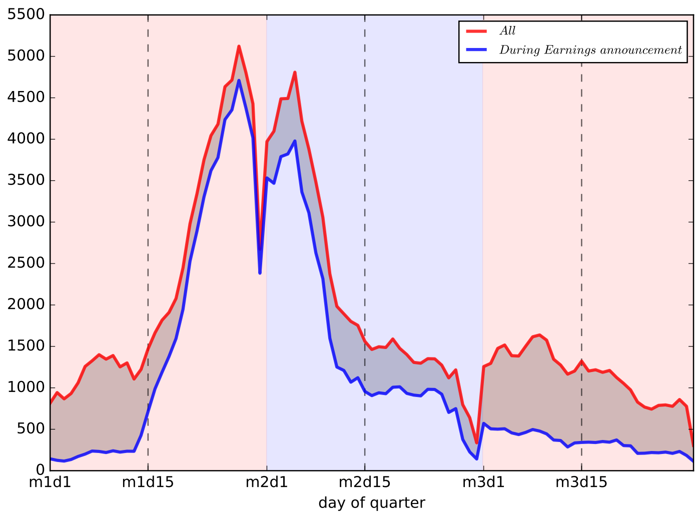


Figure 4: Announcement Dates of Analyst Revision

This figure shows the daily number of analyst revisions for all U.S. stocks. Following Loh and Stulz (2011), we exclude revisions in the trading day [-1, 1] window around quarterly earnings announcements, and multiple revisions by the same analyst on the same day count as one. "mxdy" in the horizontal axis denotes day y of month x in a quarter. E.g., m1d15 means day 15 in January, April, July, and October.

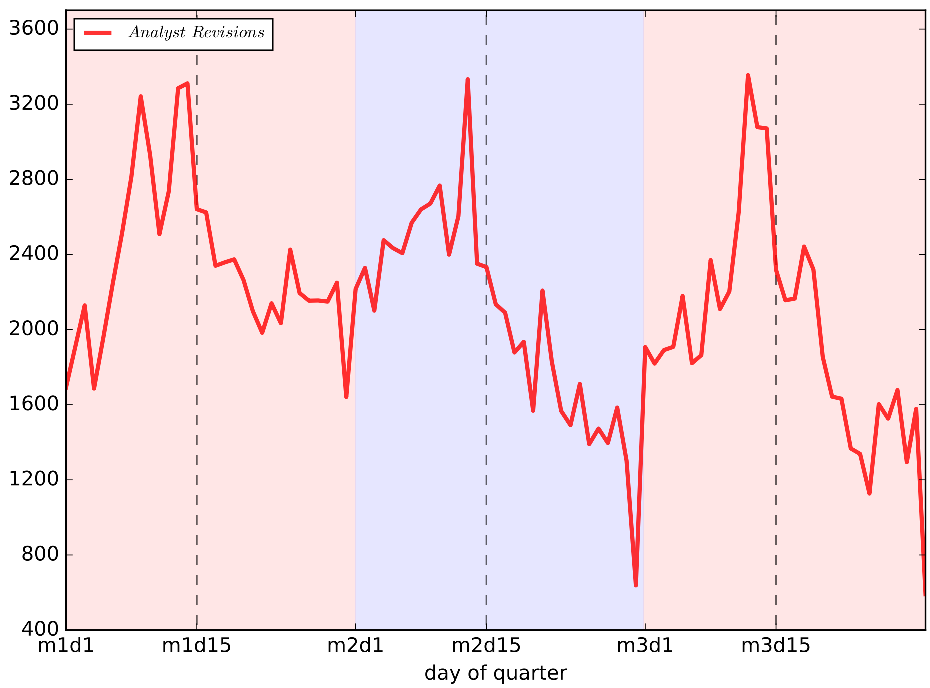
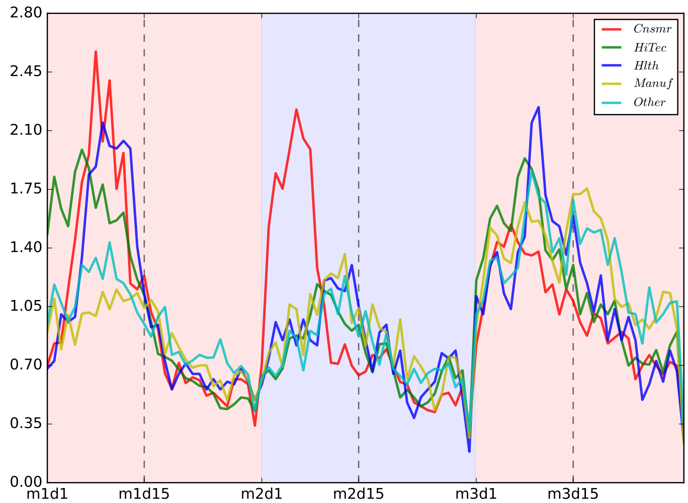


Figure 5: Guidance and Analyst Revision by Industry

This figure shows the daily number of management guidance and analyst revision by industry. We assign each stock to one of the five Fama-French industries (Cnsmr, HiTec, Hlth, Manuf, Other) at the end of June, and then replicate Figures 3a and 4 for each industry. Each industry is normalized to an average of 1 for comparability.

(a) Guidance, by Industry



(b) Analyst Revision, by Industry

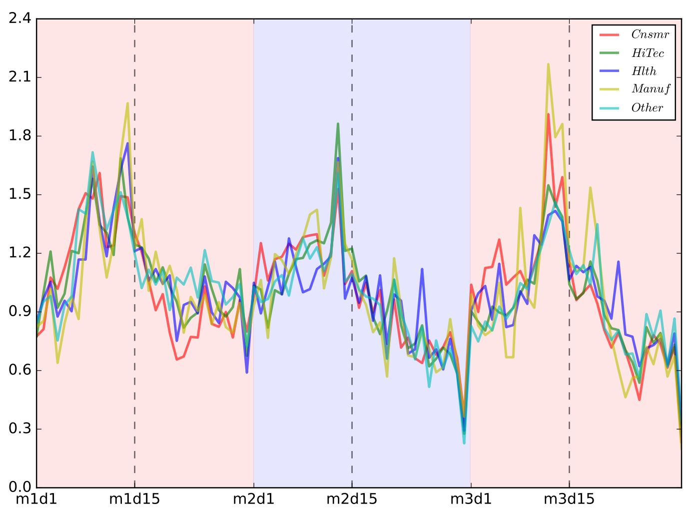


Figure 6: Companies with Fiscal Quarters Ending in March/June/September/December

This figure replicates Figures 3a and 4 using only firms with fiscal quarters ending in March, June, September, or December.

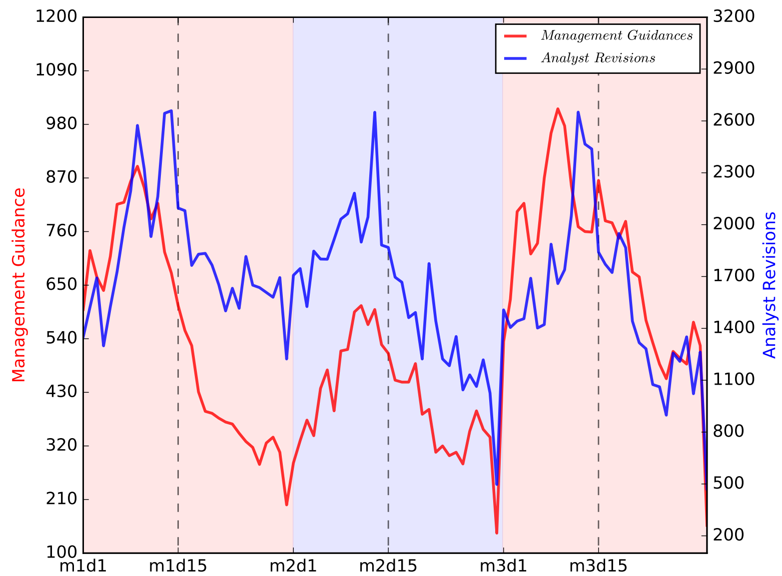


Figure 7: Return Responses, All Individual Stocks

This figure shows the cumulative abnormal return spread between stocks with good and bad news, which is the *FRONTLOAD* measure in equation (1), separately for each of the twelve calendar months. Good (bad) news is measured by contemporaneous monthly returns in the top (bottom) decile in the cross-section. Each stock's daily return is first demeaned by its average in the month before constructing the cumulative abnormal return spread. Hence the cumulative spread converges to zero at month end.

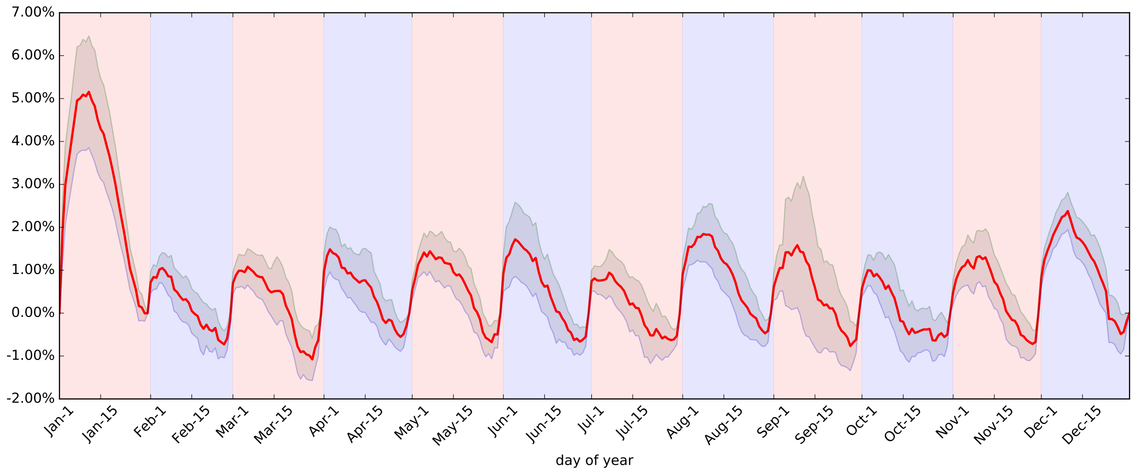
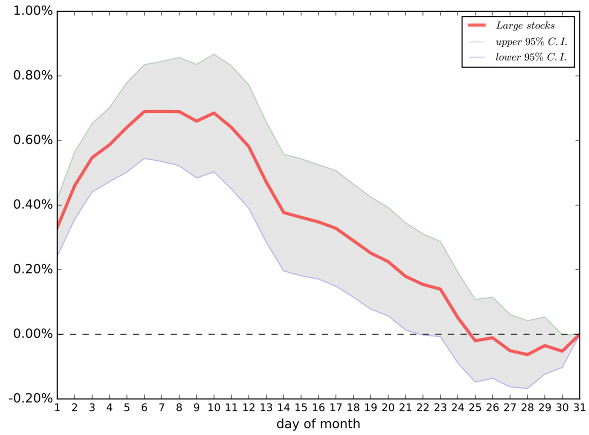


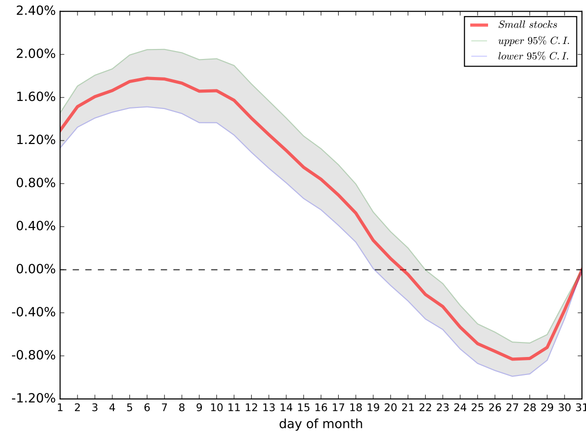
Figure 8: Monthly vs. Quarterly Return Responses

This figure compares the monthly and quarterly cumulative abnormal return spreads in equation (1). The monthly spread is constructed as in Figure 7. The quarterly spread is constructed similarly except that good (bad) news is measured by contemporaneous quarterly returns instead of monthly returns.

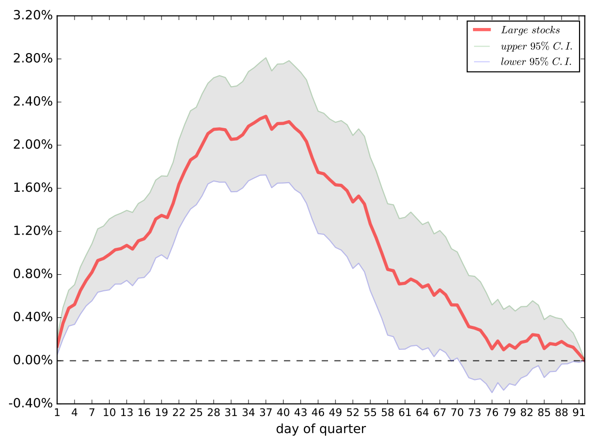
(a) Monthly, large Stocks



(b) Monthly, small Stocks



(c) Quarterly, large Stocks



(d) Quarterly, small Stocks

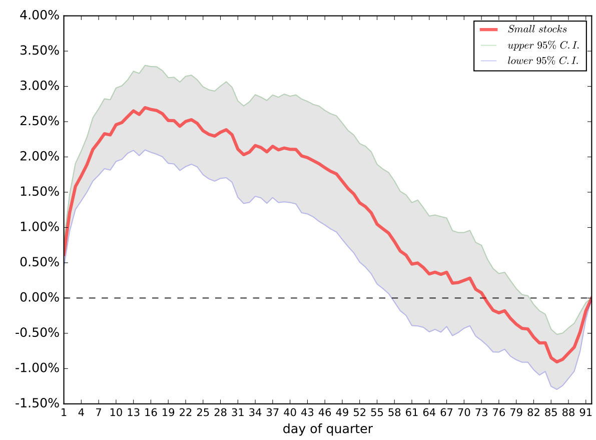


Figure 9: Market Return Responses

This figure shows the cumulative abnormal return spread between good and bad news for the U.S. value-weighted market returns, which is the *FRONTLOAD* measure in equation (1). Good (bad) news is measured by contemporaneous monthly market returns being above (below) its time series median. The daily market return is first demeaned by its average in the month before constructing the cumulative abnormal return spread. Hence the cumulative spread converges to zero at month end.

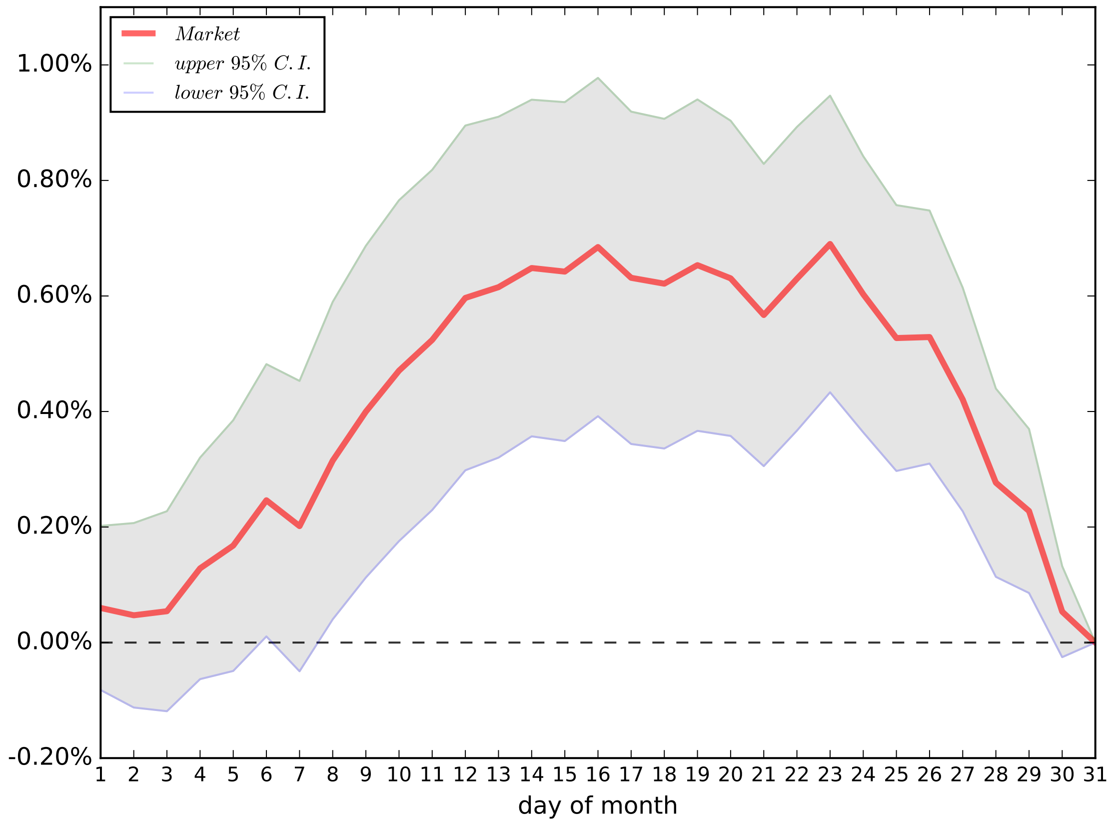
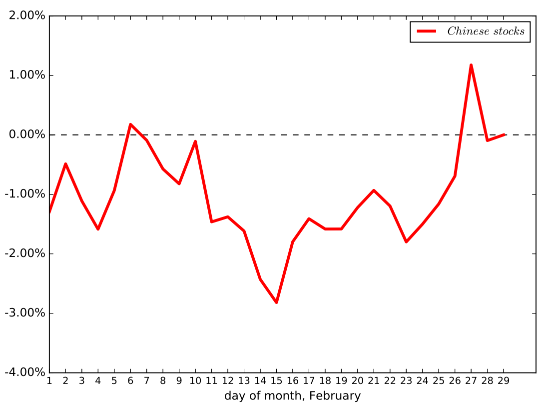


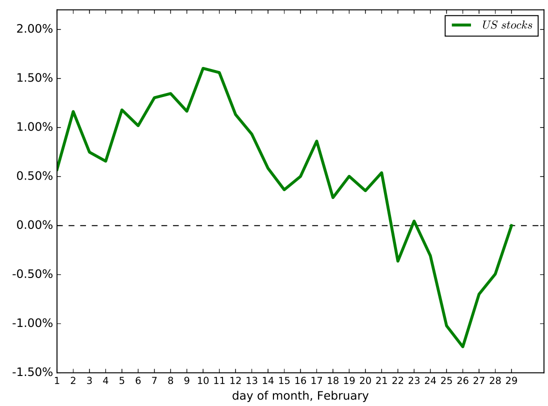
Figure 10: Chinese New Year Holiday and Return Responses

This figure shows the cumulative abnormal return spread between good and bad news, which is the *FRONTLOAD* measure in equation (1), during February and a synthetic February. The synthetic February includes days between the end of the Chinese New Year holiday and the beginning of the next calendar month, which are then linearly interpolated to 29 days. The cumulative abnormal return spread is calculated as in Figure 9, using the value-weighted return of Chinese stocks cross-listed in the U.S. in plots (a) and (c) and non-Chinese stocks in the U.S. in plots (b) and (d), respectively.

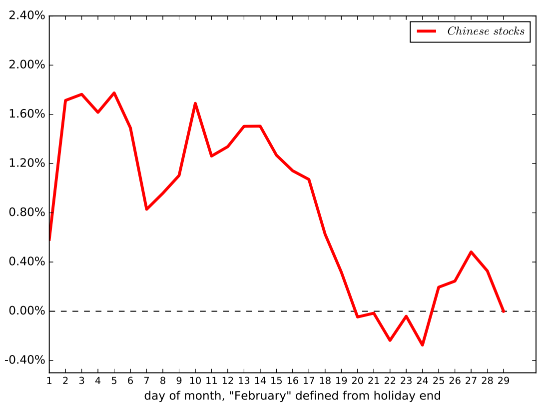
(a) Chinese stocks, Feb



(b) US stocks, Feb



(c) Chinese stocks, synthetic Feb



(d) US stocks, synthetic Feb

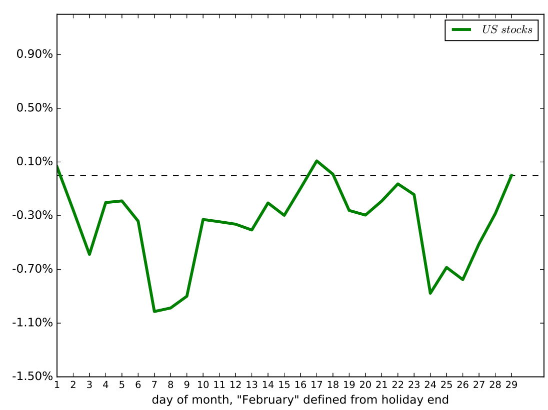


Figure 11: Market Return Responses, Excluding Macro Announcement Days

This figure shows the *FRONTLOAD* measure in Figure 9 for the market return, excluding days containing macro announcements on inflation, unemployment, or the FOMC announcements.

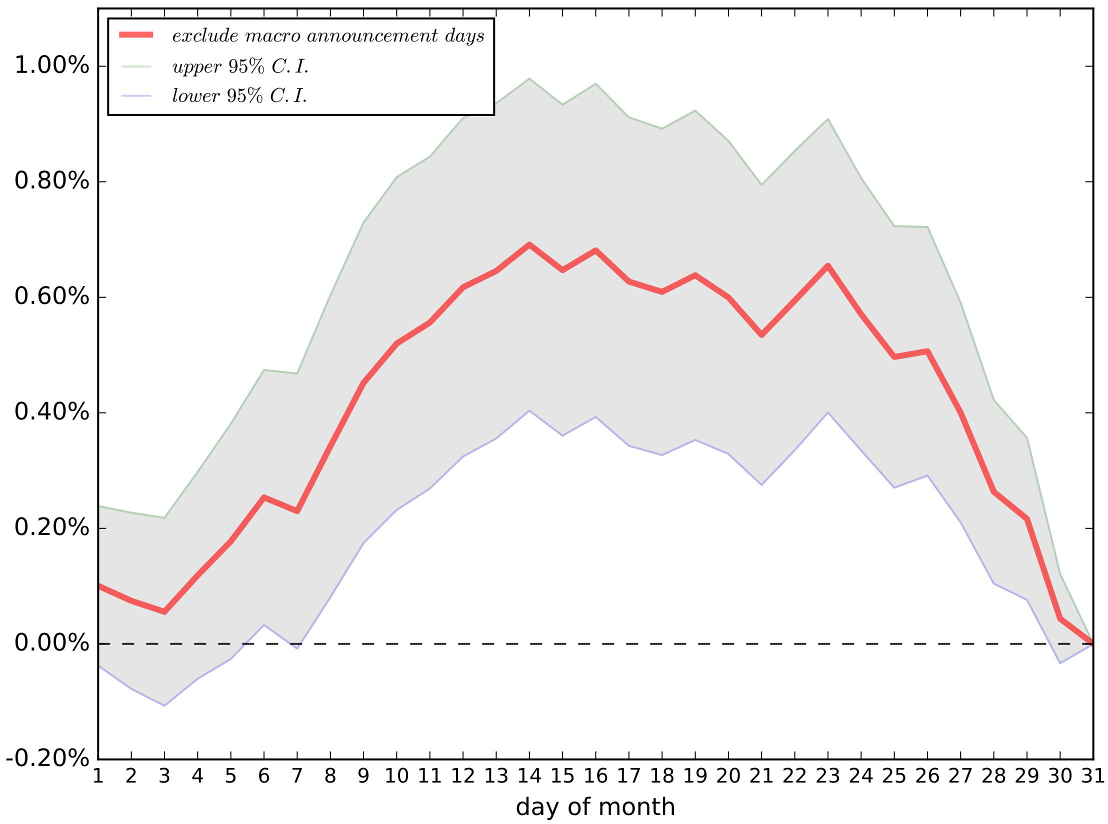


Table 1: Summary Statistics

This table reports the average and volatility of daily stock return during (a) the three-day $[-1, 1]$ window around monthly report announcement, (b) the day of monthly report announcement, and (c) the rest of the month outside the $[-1, 1]$ window. The return, in percent, is in excess of the value-weighted market return. The average return and volatility are first computed for each stock and then averaged across stocks.

		Daily Avg Return (%)	Daily Volatility (%)
(a)	$[-1, 1]$ around announcement	0.05	2.53
(b)	announcement day	0.07	2.80
(c)	rest of month	0.02	2.26
	(a) − (c)	0.03	0.28
	t	(1.43)	(2.39)
	(b) − (c)	0.05	0.55
	t	(1.16)	(2.91)

Table 2: Returns around Monthly Announcements, by Announcement CAR

This table reports the returns around monthly announcements for stock quintiles sorted by the announcement CAR in the three-day window around monthly announcement ($r_{[-1,1]}$). For each quintile, it reports the average daily returns during the following windows: the three-day window around monthly announcement ($[-1,1]$), the month (M), each half months ($H1$ and $H2$), and the month or each half months excluding the three-day window around monthly announcement ($M_{ex[-1,1]}$, $H1_{ex[-1,1]}$, and $H2_{ex[-1,1]}$). The stock return, in percent, is in excess of the value-weighted market return. Panel A shows returns in months 2 and 3 of the quarter before quarter end, while Panel B shows returns in all months containing monthly reports corresponding to the quarter (e.g., for the fourth quarter, panel A includes November and December while panel B includes November, December, and January).

so bad 3-day return means, we should long them?

Panel A: Months 2 and 3 before quarter end

$r_{[-1,1]}$ quintile	(1) $[-1,1]$	(2) $M_{ex[-1,1]}$	(1) - (2)	(3) $H1$	(4) $H2$	(3) - (4)	(5) $H1_{ex[-1,1]}$	(6) $H2_{ex[-1,1]}$	(5) - (6)	M
Low	-1.73	0.01	-1.74	-0.39	-0.08	-0.32	0.04	-0.01	0.05	-0.24
2	-0.55	0.04	-0.59	-0.07	-0.02	-0.05	0.08	0.01	0.07	-0.04
3	0.02	0.05	-0.03	0.06	0.03	0.04	0.07	0.03	0.04	0.05
4	0.59	0.02	0.57	0.17	0.03	0.14	0.03	0.01	0.02	0.10
High	1.76	0.04	1.72	0.47	0.08	0.39	0.04	0.04	0.00	0.28
High - Low	3.49	0.03	3.46	0.86	0.16	0.71	0.00	0.05	-0.05	0.51
t	(26.23)	(0.88)	(24.89)	(16.92)	(3.88)	(11.47)	(0.02)	(1.18)	(0.75)	(15.16)

Panel B: All months

$r_{[-1,1]}$ quintile	(1) $[-1,1]$	(2) $M_{ex[-1,1]}$	(1) - (2)	(3) $H1$	(4) $H2$	(3) - (4)	(5) $H1_{ex[-1,1]}$	(6) $H2_{ex[-1,1]}$	(5) - (6)	M
Low	-1.81	0.00	-1.81	-0.44	-0.06	-0.38	0.03	0.00	0.03	-0.25
2	-0.56	0.03	-0.59	-0.07	-0.03	-0.05	0.07	-0.01	0.08	-0.05
3	0.04	0.04	0.00	0.06	0.02	0.04	0.05	0.02	0.03	0.04
4	0.66	0.02	0.64	0.18	0.04	0.14	0.01	0.02	-0.01	0.11
High	1.88	0.03	1.85	0.50	0.06	0.44	0.02	0.03	0.00	0.28
High - Low	3.69	0.03	3.66	0.94	0.12	0.82	-0.01	0.03	-0.03	0.54
t	(32.30)	(0.84)	(30.93)	(20.67)	(3.57)	(15.23)	(0.13)	(0.79)	(0.58)	(16.30)

Table 3: Monthly Announcement CAR, Quarterly Surprises, and Analyst Revisions

This table reports the average quarterly SUE and the daily average analyst revisions for stock quintiles sorted by the returns in the three-day window around monthly announcement ($r_{[-1,1]}$). It reports the daily average analyst revisions for both the three-day window around monthly announcement ($\text{Rev}_{[-1,1]}$) and the rest of the month ($\text{Rev}_{ex[-1,1]}$). The revision of the current quarter EPS forecast (FPI=6) is scaled by the share price adjusted for splits and then averaged across revisions for the same stock on a given day. Revision=0 when there is no revision for the stock in a day. The revision is in basis points. The daily revisions are winsorized at 1 and 99% and are demeaned by the cross-sectional average revision. This table separately shows the results conditional on monthly announcement CAR in months 2 and 3 of the quarter before quarter end and conditional on monthly announcement CAR in all months containing monthly reports corresponding to the quarter (e.g., for the fourth quarter, months 2 and 3 include November and December while all months include November, December, and January).

	Months 2 and 3 before quarter end				All months			
		(1)	(2)			(3)	(4)	
$r_{[-1,1]}$ quintile	SUE	$\text{Rev}_{[-1,1]}$	$\text{Rev}_{ex[-1,1]}$	(1) - (2)	SUE	$\text{Rev}_{[-1,1]}$	$\text{Rev}_{ex[-1,1]}$	(3) - (4)
Low	-0.16	-4.64	-1.17	-3.48	-0.10	-3.96	-0.48	-3.48
2	0.17	-1.60	-0.37	-1.22	0.16	-1.13	0.23	-1.37
3	0.27	-0.62	-0.63	0.01	0.26	-0.84	-0.35	-0.49
4	0.33	-0.56	-0.45	-0.11	0.31	-1.44	-0.58	-0.86
High	0.34	1.70	-0.11	1.81	0.40	2.26	0.01	2.25
High - Low	0.49	6.27	1.12	5.15	0.49	6.17	0.48	5.69
t	(4.93)	(3.71)	(1.74)	(3.00)	(5.83)	(4.49)	(0.68)	(3.80)

Table 4: Alternative Proxies of Monthly Announcement Surprises

This table reports the average return in the three-day window around monthly announcement ($r_{[-1,1]}$) and quarterly SUE for stock quintiles sorted by various proxies of monthly announcement surprise. These proxies include $r_{[-1,1]}$, contemporaneous return in the month (r_M), in the first half month (r_{H1}), in the second half month (r_{H2}), and the quarterly SUE. The stock return, in percent, is in excess of the value-weighted market return. Panel A shows returns in months 2 and 3 of the quarter before quarter end, while Panel B shows returns in all months containing monthly reports corresponding to the quarter (e.g., for the fourth quarter, panel A includes November and December while panel B includes November, December, and January).

Panel A: Months 2 and 3 before quarter end

	$r_{[-1,1]}$, by X quintile					SUE, by X quintile				
X quintile	$X = r_{[-1,1]}$	$X = r_M$	$X = r_{H1}$	$X = r_{H2}$	$X =$ SUE	$X = r_{[-1,1]}$	$X = r_M$	$X = r_{H1}$	$X = r_{H2}$	$X =$ SUE
Low	-1.73	-0.93	-0.98	-0.33	-0.17	-0.16	-0.11	-0.23	-0.04	-2.13
2	-0.55	-0.23	-0.23	-0.08	-0.11	0.17	0.17	0.27	0.17	-0.24
3	0.02	0.09	0.06	0.09	0.08	0.27	0.23	0.38	0.24	0.33
4	0.59	0.28	0.35	0.26	0.12	0.33	0.32	0.23	0.32	0.89
High	1.76	0.90	0.91	0.19	0.31	0.34	0.36	0.28	0.24	2.03
High - Low	3.49	1.83	1.89	0.52	0.48	0.49	0.47	0.51	0.28	4.16
t	(26.23)	(16.02)	(15.93)	(4.99)	(5.06)	(4.93)	(3.78)	(4.70)	(2.16)	(31.01)

Panel B: All months

	$r_{[-1,1]}$, by X quintile					SUE, by X quintile				
X quintile	$X = r_{[-1,1]}$	$X = r_M$	$X = r_{H1}$	$X = r_{H2}$	$X =$ SUE	$X = r_{[-1,1]}$	$X = r_M$	$X = r_{H1}$	$X = r_{H2}$	$X =$ SUE
Low	-1.81	-0.90	-1.04	-0.24	-0.12	-0.10	-0.08	-0.17	-0.03	-2.05
2	-0.56	-0.25	-0.27	-0.03	-0.04	0.16	0.19	0.23	0.22	-0.24
3	0.04	0.06	0.07	0.07	0.06	0.26	0.22	0.33	0.23	0.33
4	0.66	0.38	0.42	0.27	0.11	0.31	0.32	0.30	0.30	0.88
High	1.88	0.96	1.05	0.20	0.29	0.40	0.38	0.31	0.27	2.01
High - Low	3.69	1.85	2.09	0.44	0.41	0.49	0.46	0.48	0.30	4.07
t	(32.30)	(19.90)	(21.23)	(4.93)	(5.21)	(5.83)	(4.68)	(5.29)	(3.05)	(37.82)

Table 5: Returns around Monthly Announcements, by Contemporaneous Monthly Return

This table reports the returns around monthly announcements for stock quintiles sorted by the contemporaneous monthly return (r_M). For each quintile, it reports the average daily returns during the following windows: the three-day window around monthly announcement ($[-1,1]$), the month (M), each half months ($H1$ and $H2$), and the month or each half months excluding the three-day window around monthly announcement ($M_{ex[-1,1]}$, $H1_{ex[-1,1]}$, and $H2_{ex[-1,1]}$). The stock return, in percent, is in excess of the value-weighted market return. Panel A shows returns in months 2 and 3 of the quarter before quarter end, while Panel B shows returns in all months containing monthly reports corresponding to the quarter (e.g., for the fourth quarter, panel A includes November and December while panel B includes November, December, and January).

Panel A: Months 2 and 3 before quarter end

r_M quintile	(1) $[-1,1]$	(2) $M_{ex[-1,1]}$	(1) - (2)	(3) $H1$	(4) $H2$	(3) - (4)	(5) $H1_{ex[-1,1]}$	(6) $H2_{ex[-1,1]}$	(5) - (6)	M
Low	-0.93	-0.44	-0.49	-0.55	-0.49	-0.06	-0.41	-0.46	0.05	-0.52
2	-0.23	-0.15	-0.08	-0.16	-0.17	0.01	-0.12	-0.16	0.04	-0.16
3	0.09	0.02	0.08	0.05	0.00	0.05	0.03	0.01	0.02	0.03
4	0.28	0.20	0.08	0.24	0.19	0.04	0.22	0.19	0.02	0.22
High	0.90	0.50	0.40	0.65	0.48	0.18	0.53	0.48	0.06	0.57
High - Low	1.83	0.94	0.89	1.20	0.97	0.23	0.94	0.94	0.00	1.08
t	(16.02)	(23.06)	(7.62)	(22.88)	(17.52)	(3.39)	(14.87)	(17.46)	(0.03)	(26.29)

Panel B: All months

r_M quintile	(1) $[-1,1]$	(2) $M_{ex[-1,1]}$	(1) - (2)	(3) $H1$	(4) $H2$	(3) - (4)	(5) $H1_{ex[-1,1]}$	(6) $H2_{ex[-1,1]}$	(5) - (6)	M
Low	-0.90	-0.47	-0.43	-0.56	-0.52	-0.04	-0.44	-0.50	0.06	-0.54
2	-0.25	-0.16	-0.09	-0.17	-0.17	0.00	-0.14	-0.17	0.03	-0.17
3	0.06	0.02	0.03	0.04	0.02	0.02	0.03	0.02	0.01	0.03
4	0.38	0.20	0.18	0.26	0.19	0.08	0.21	0.18	0.03	0.22
High	0.96	0.52	0.44	0.67	0.51	0.16	0.53	0.51	0.02	0.59
High - Low	1.85	0.99	0.87	1.23	1.04	0.19	0.96	1.01	-0.04	1.13
t	(19.90)	(28.81)	(9.31)	(27.52)	(22.93)	(3.47)	(19.41)	(22.66)	(0.70)	(32.17)

Table 6: Post-Monthly-Announcement Drift, Conditional on Announcement Return

This table shows the Fama-MacBeth regression results of stock returns in the second half ($H2$) of a month on the stock returns in the three-day window around monthly announcement ($[-1,1]$), the stock returns in the first half ($H1$), or the stock returns in the first half excluding the three-day window around monthly announcement ($H1_{ex[-1,1]}$) in the same month. It also shows the results of regressing stock returns in the first half of the next month ($H3$) on the stock returns in the second half ($H2$) of a month. It uses only observations where the three-day announcement window ends by the middle of a month. The stock returns in the regressions are daily and in percent. The control variables include market beta (β), market capitalization in log ($LOGSIZE$), book-to-market ratio (BM, winsorized at 1 and 99%), the past one-year return momentum (MOM). β is estimated using monthly returns in five-year windows and requiring at least 24 monthly observations. t-statistics robust to heteroskedasticity are in the parentheses.

	$H2$ (columns 1-8)								$H3$ (columns 9-10)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$[-1,1]$	0.030		0.031		0.043		0.036			
	(2.05)		(1.98)		(3.19)		(3.14)			
$H1_{ex[-1,1]}$		-0.017	-0.015			-0.033	-0.023			
		(0.77)	(0.65)			(1.39)	(0.94)			
$H1$				0.014				0.026		
				(0.60)				(1.02)		
$H2$									0.001	-0.045
									(0.03)	(1.48)
β					-0.061	-0.033	-0.037	-0.009		-0.062
					(1.27)	(0.78)	(0.92)	(0.21)		(1.45)
$LOGSIZE$					-0.010	-0.017	-0.017	-0.012		-0.027
					(1.03)	(1.74)	(1.73)	(1.25)		(2.38)
BM					0.033	0.005	0.027	0.016		-0.022
					(1.06)	(0.15)	(0.83)	(0.49)		(0.64)
MOM					0.013	0.020	-0.002	0.033		0.016
					(0.22)	(0.33)	(0.04)	(0.55)		(0.29)

Table 7: Post-Monthly-Announcement Drift, Full Cross-Section of Stocks

This table shows the results of the Fama-MacBeth regressions:

$$r_{H_2} = a_{H_1} + b_{H_1} \cdot r_{H_1} + \epsilon_{H_2}$$
$$r_{H3} = a_{H_2} + b_{H_2} \cdot r_{H_2} + \epsilon_{H3},$$

which regresses the stock returns in the second half of a month (H_2) on the returns in the first half of the same month (H_1), and regresses the stock returns in the first half of the next month ($H3$) on the stock returns in the second half of a month (H_2). The stock returns in the regressions are cumulative half-month returns and are in percent. The control variables include market beta (β), market capitalization in log ($LOGSIZE$), book-to-market ratio (BM, winsorized at 1 and 99%), the past one-year return momentum (MOM). t-statistics robust to heteroskedasticity are in the parentheses.

	All stocks				Large stocks			
	$H2$	$H3$	$H2$	$H3$	$H2$	$H3$	$H2$	$H3$
$H1$	-0.080		-0.094		-0.044		-0.060	
	(24.48)		(31.33)		(10.28)		(16.97)	
$H2$		-0.093		-0.104		-0.062		-0.077
		(25.16)		(30.18)		(13.39)		(19.23)
β			-0.149	0.124			-0.1686	0.129
			(2.08)	(1.65)			(2.08)	(1.55)
$LOGSIZE$			-0.098	-0.090			-0.037	-0.041
			(5.06)	(4.49)			(2.37)	(2.70)
BM			0.061	0.105			0.034	0.091
			(3.17)	(5.41)			(1.01)	(2.73)
MOM			0.532	0.002			0.008	0.003
			(5.67)	(1.78)			(6.97)	(2.54)
$b_{H_1} - b_{H_2}$	0.012		0.009		0.018		0.017	
	(2.66)		(2.37)		(2.87)		(3.41)	

Table 8: Market TSMOM

This table shows the time series regression results for the value-weighted market return:

$$r_{[t+1,t+F]} = a_{H_1} + b_{H_1} \cdot r_{[t-L+1,t],H_1} + \epsilon$$
$$r_{[t+1,t+F]} = a_{H_2} + b_{H_2} \cdot r_{[t-L+1,t],H_2} + \varepsilon,$$

where $r_{[t+1,t+F]}$ is the future average F-month return. $r_{[t-L+1,t],H_1}$ and $r_{[t-L+1,t],H_2}$ are the lagged L-month average of returns in the first or the second half month, respectively. Panel A and B show the estimates of b_{H_1} and b_{H_2} respectively. For ease of interpretation, all the independent variables are standardized by their respective full-sample standard deviation. So the estimates in Panels A and B are the effect of a one standard deviation change in lag return on future return (in percent per month). Negative estimates are color-coded. Newey and West (1987) t-statistics adjusted for correlation between F months are in the parentheses in the subscript. In Panel C, we bootstrap by randomly re-shuffling daily market returns within each month (but not across months) and then running the same regressions as for Panels A and B. The p-value is the fraction of simulations where, for all look-back and holding horizons, $b_{H_1} - b_{H_2}$ exceeds the minimum of $b_{H_1} - b_{H_2}$ between Panels A and B. There are 1,000 simulations.

Panel A: b_{H_1}, conditional on lagged market return in the first-half month

Look-back	Future holding months F						
months L	1	3	6	9	12	18	24
1	$0.69_{(2.2)}$	$0.23_{(1.4)}$	$0.24_{(2.7)}$	$0.16_{(2.4)}$	$0.14_{(2.1)}$	$0.09_{(2.0)}$	$0.03_{(1.0)}$
3	$0.38_{(1.5)}$	$0.27_{(1.4)}$	$0.24_{(1.9)}$	$0.22_{(2.1)}$	$0.13_{(1.5)}$	$0.08_{(1.3)}$	$0.01_{(0.2)}$
6	$0.54_{(2.1)}$	$0.34_{(2.1)}$	$0.30_{(2.0)}$	$0.21_{(1.4)}$	$0.13_{(1.1)}$	$0.06_{(0.6)}$	$-0.01_{(0.1)}$
9	$0.44_{(1.7)}$	$0.36_{(1.6)}$	$0.24_{(1.3)}$	$0.17_{(1.0)}$	$0.11_{(0.8)}$	$0.01_{(0.1)}$	$-0.03_{(0.3)}$
12	$0.41_{(1.6)}$	$0.24_{(1.2)}$	$0.17_{(1.0)}$	$0.12_{(0.7)}$	$0.04_{(0.3)}$	$-0.04_{(0.3)}$	$-0.05_{(0.6)}$
18	$0.32_{(1.3)}$	$0.18_{(0.9)}$	$0.09_{(0.5)}$	$0.01_{(0.1)}$	$-0.04_{(0.3)}$	$-0.07_{(0.6)}$	$-0.07_{(0.7)}$
24	$0.14_{(0.6)}$	$0.02_{(0.1)}$	$-0.02_{(0.1)}$	$-0.05_{(0.3)}$	$-0.08_{(0.5)}$	$-0.09_{(0.7)}$	$-0.09_{(0.7)}$

Panel B: b_{H_2}, conditional on lagged market return in the second-half month

Look-back	Future holding months F						
months L	1	3	6	9	12	18	24
1	$0.22_{(0.7)}$	$-0.25_{(1.3)}$	$-0.17_{(1.5)}$	$-0.02_{(0.3)}$	$-0.05_{(0.7)}$	$-0.06_{(1.2)}$	$-0.09_{(1.8)}$
3	$-0.41_{(1.3)}$	$-0.45_{(1.7)}$	$-0.24_{(1.4)}$	$-0.09_{(1.1)}$	$-0.12_{(1.1)}$	$-0.12_{(1.3)}$	$-0.15_{(2.2)}$
6	$-0.44_{(1.2)}$	$-0.36_{(1.2)}$	$-0.11_{(0.7)}$	$-0.07_{(0.6)}$	$-0.16_{(1.1)}$	$-0.19_{(1.6)}$	$-0.19_{(2.2)}$
9	$-0.06_{(0.2)}$	$-0.18_{(0.6)}$	$-0.09_{(0.5)}$	$-0.13_{(0.9)}$	$-0.17_{(1.0)}$	$-0.24_{(1.7)}$	$-0.22_{(2.1)}$
12	$-0.16_{(0.4)}$	$-0.25_{(0.8)}$	$-0.22_{(1.1)}$	$-0.19_{(1.1)}$	$-0.28_{(1.5)}$	$-0.29_{(2.1)}$	$-0.27_{(2.6)}$
18	$-0.27_{(0.7)}$	$-0.32_{(1.0)}$	$-0.34_{(1.7)}$	$-0.33_{(1.9)}$	$-0.36_{(2.0)}$	$-0.35_{(2.6)}$	$-0.32_{(2.9)}$
24	$-0.43_{(1.1)}$	$-0.46_{(1.4)}$	$-0.39_{(1.9)}$	$-0.36_{(2.0)}$	$-0.39_{(2.2)}$	$-0.37_{(2.8)}$	$-0.36_{(2.9)}$

Panel C: Bootstrap p-value

p-value	0.007

Table 9: Market TSMOM and Market SUE

This table shows the time series regression results for the value-weighted market return:

$$r_{[t+1,t+F]} = a_{H_1} + b_{H_1} \cdot r_{[t-L+1,t],H_1} + c_{H_1} \cdot ABSUE_{[t-L+1,t]} + d_{H_1} \cdot r_{[t-L+1,t],H_1} \cdot ABSUE_{[t-L+1,t]} + \epsilon$$
$$r_{[t+1,t+F]} = a_{H_2} + b_{H_2} \cdot r_{[t-L+1,t],H_2} + c_{H_2} \cdot ABSUE_{[t-L+1,t]} + d_{H_2} \cdot r_{[t-L+1,t],H_2} \cdot ABSUE_{[t-L+1,t]} + \varepsilon,$$

where $r_{[t+1,t+F]}$ is the future average F-month return. $r_{[t-L+1,t],H_1}$ and $r_{[t-L+1,t],H_2}$ are the lagged L-month average of returns in the first or the second half month, respectively. $ABSUE_{[t-L+1,t]}$ is the lagged L-month average of the absolute value of market SUE. Panel A and B show the estimates of d_{H_1} and d_{H_2}, respectively. For ease of interpretation, all the independent variables are standardized by their respective full-sample standard deviation. So the estimates in Panels A and B are the effect of a one standard deviation change in the independent variable on future return (in percent per month). Negative estimates are color-coded. Newey and West (1987) t-statistics adjusted for correlation between F months are in the parentheses in the subscript. We conduct in Panel C a bootstrap by randomly re-shuffling daily market returns within each month (but not across months) and then run the same regressions as for Panels A and B. The p-value is the fraction of simulations where, for all look-back and holding horizons, $d_{H_1} - d_{H_2}$ exceeds the minimum of $d_{H_1} - d_{H_2}$ between Panels A and B. There are 1,000 simulations.

Panel A: d_{H_1}, conditional on lagged market return in the first-half month

Look-back	Future holding months F						
months L	1	3	6	9	12	18	24
1	$0.24_{(1.7)}$	$0.19_{(2.3)}$	$0.10_{(1.7)}$	$0.11_{(2.1)}$	$0.09_{(2.0)}$	$0.07_{(1.9)}$	$0.02_{(0.7)}$
3	$0.33_{(2.5)}$	$0.20_{(2.5)}$	$0.08_{(1.4)}$	$0.10_{(2.1)}$	$0.09_{(2.1)}$	$0.08_{(2.4)}$	$0.00_{(0.1)}$
6	$0.18_{(1.4)}$	$0.03_{(0.3)}$	$0.03_{(0.5)}$	$0.10_{(2.1)}$	$0.09_{(2.2)}$	$0.09_{(2.6)}$	$0.01_{(0.5)}$
9	$0.04_{(0.3)}$	$0.04_{(0.4)}$	$0.10_{(1.6)}$	$0.16_{(3.0)}$	$0.15_{(3.4)}$	$0.11_{(3.1)}$	$0.04_{(1.5)}$
12	$0.23_{(1.5)}$	$0.21_{(2.3)}$	$0.22_{(3.3)}$	$0.25_{(4.5)}$	$0.21_{(4.6)}$	$0.14_{(3.9)}$	$0.09_{(2.8)}$
18	$0.20_{(1.5)}$	$0.16_{(2.0)}$	$0.14_{(2.4)}$	$0.16_{(3.2)}$	$0.13_{(3.2)}$	$0.09_{(2.8)}$	$0.06_{(2.0)}$
24	$0.13_{(1.0)}$	$0.10_{(1.2)}$	$0.15_{(2.5)}$	$0.09_{(1.9)}$	$0.07_{(1.7)}$	$0.07_{(2.2)}$	$0.07_{(2.5)}$

Panel B: d_{H_2}, conditional on lagged market return in the second-half month

Look-back	Future holding months F						
months L	1	3	6	9	12	18	24
1	$-0.18_{(1.3)}$	$-0.15_{(1.8)}$	$-0.04_{(0.7)}$	$-0.04_{(0.9)}$	$-0.04_{(0.9)}$	$-0.03_{(0.8)}$	$-0.02_{(0.7)}$
3	$-0.34_{(2.5)}$	$-0.23_{(2.8)}$	$-0.07_{(1.2)}$	$-0.06_{(1.3)}$	$-0.05_{(1.1)}$	$-0.00_{(0.1)}$	$-0.03_{(1.1)}$
6	$-0.10_{(0.7)}$	$-0.02_{(0.2)}$	$-0.04_{(0.6)}$	$-0.05_{(0.9)}$	$-0.00_{(0.0)}$	$-0.00_{(0.1)}$	$-0.03_{(1.0)}$
9	$0.01_{(0.0)}$	$-0.01_{(0.1)}$	$-0.04_{(0.6)}$	$-0.01_{(0.1)}$	$0.03_{(0.7)}$	$-0.02_{(0.7)}$	$-0.06_{(2.0)}$
12	$-0.00_{(0.0)}$	$0.01_{(0.1)}$	$-0.01_{(0.1)}$	$0.00_{(0.0)}$	$0.01_{(0.1)}$	$-0.06_{(1.6)}$	$-0.09_{(2.9)}$
18	$-0.08_{(0.6)}$	$-0.03_{(0.3)}$	$-0.07_{(1.2)}$	$-0.09_{(1.7)}$	$-0.09_{(2.1)}$	$-0.12_{(3.3)}$	$-0.10_{(3.5)}$
24	$-0.18_{(1.2)}$	$-0.20_{(2.3)}$	$-0.21_{(3.3)}$	$-0.21_{(4.0)}$	$-0.19_{(4.2)}$	$-0.14_{(3.9)}$	$-0.07_{(2.2)}$

Panel C: Bootstrap p-value

p-value	0.006

Table 10: Market TSMOM and Market SUE, Conditional on Whole-Month Returns

This table shows the time series regression results for the value-weighted market return:

$$r_{[t+1,t+F]} = a + b \cdot r_{[t-L+1,t]} + c \cdot ABSUE_{[t-L+1,t]} + d \cdot r_{[t-L+1,t]} \cdot ABSUE_{[t-L+1,t]} + \epsilon,$$

where $r_{[t+1,t+F]}$ is the future average F-month return. $r_{[t-L+1,t]}$ is the lagged L-month average return. $ABSUE_{[t-L+1,t]}$ is the lagged L-month average of the absolute value of market SUE. Panel A shows the estimates of d. For ease of interpretation, all the independent variables are standardized by their respective full-sample standard deviation. So the estimates in Panel A are the effect of a one standard deviation change in the independent variable on future return (in percent per month). Negative estimates are color-coded. Newey and West (1987) t-statistics adjusted for correlation between F months are in the parentheses in the subscript. In Panel B, we bootstrap by randomly re-shuffling market earnings across quarters and then running the same regressions as for Panel A. The p-value is the fraction of simulations where, for all look-back and holding horizons, d exceeds the minimum of d in Panel A. There are 1,000 simulations.

Panel A: d, conditional on lagged whole-month market return

Look-back	Future holding months F						
months L	1	3	6	9	12	18	24
1	$0.03_{(0.1)}$	$0.02_{(0.2)}$	$0.03_{(0.4)}$	$0.04_{(0.6)}$	$0.03_{(0.6)}$	$0.03_{(0.6)}$	$-0.00_{(0.1)}$
3	$0.06_{(0.4)}$	$0.03_{(0.2)}$	$0.02_{(0.2)}$	$0.04_{(0.4)}$	$0.04_{(0.4)}$	$0.06_{(0.8)}$	$-0.03_{(0.5)}$
6	$0.14_{(0.7)}$	$0.05_{(0.3)}$	$0.01_{(0.1)}$	$0.05_{(0.4)}$	$0.07_{(0.6)}$	$0.06_{(0.8)}$	$-0.02_{(0.3)}$
9	$0.04_{(0.2)}$	$0.03_{(0.2)}$	$0.05_{(0.3)}$	$0.12_{(0.8)}$	$0.13_{(1.0)}$	$0.07_{(0.8)}$	$-0.01_{(0.1)}$
12	$0.17_{(1.0)}$	$0.16_{(1.0)}$	$0.16_{(1.0)}$	$0.18_{(1.2)}$	$0.16_{(1.4)}$	$0.07_{(0.9)}$	$0.00_{(0.1)}$
18	$0.11_{(0.6)}$	$0.11_{(0.7)}$	$0.08_{(0.5)}$	$0.07_{(0.6)}$	$0.05_{(0.5)}$	$0.01_{(0.1)}$	$-0.02_{(0.3)}$
24	$0.02_{(0.1)}$	$-0.01_{(0.1)}$	$0.01_{(0.1)}$	$-0.03_{(0.3)}$	$-0.05_{(0.5)}$	$-0.03_{(0.4)}$	$0.01_{(0.1)}$

Panel B: Bootstrap p-value

p-value	0.042

Table 11: Market TSMOM, Excluding Macro Announcement Days from Predictor

This table shows the results of the same time series regressions as Table 8 for the market return, except that the market returns on days containing macro announcements are excluded from the right-hand-side variable (lagged market return). The macro announcements include announcements on inflation, unemployment, and the FOMC announcements.

Panel A: b_{H_1}, conditional on lagged market return in the first-half month

Look-back months L	Future holding months F: 1	3	6	9	12	18	24
1	$0.73_{(2.3)}$	$0.24_{(1.5)}$	$0.23_{(2.6)}$	$0.15_{(2.3)}$	$0.13_{(2.1)}$	$0.10_{(1.9)}$	$0.05_{(1.3)}$
3	$0.40_{(1.6)}$	$0.24_{(1.2)}$	$0.20_{(1.5)}$	$0.19_{(1.9)}$	$0.12_{(1.2)}$	$0.10_{(1.2)}$	$0.04_{(0.6)}$
6	$0.53_{(2.1)}$	$0.28_{(1.6)}$	$0.25_{(1.6)}$	$0.18_{(1.2)}$	$0.13_{(0.9)}$	$0.08_{(0.7)}$	$0.03_{(0.3)}$
9	$0.41_{(1.6)}$	$0.31_{(1.4)}$	$0.21_{(1.1)}$	$0.16_{(0.9)}$	$0.12_{(0.8)}$	$0.06_{(0.4)}$	$0.03_{(0.2)}$
12	$0.39_{(1.6)}$	$0.20_{(1.0)}$	$0.16_{(0.9)}$	$0.13_{(0.8)}$	$0.08_{(0.5)}$	$0.03_{(0.2)}$	$0.02_{(0.2)}$
18	$0.35_{(1.5)}$	$0.20_{(1.0)}$	$0.13_{(0.7)}$	$0.07_{(0.4)}$	$0.03_{(0.2)}$	$0.02_{(0.1)}$	$0.03_{(0.2)}$
24	$0.21_{(0.9)}$	$0.09_{(0.4)}$	$0.06_{(0.3)}$	$0.04_{(0.2)}$	$0.02_{(0.1)}$	$0.03_{(0.2)}$	$0.02_{(0.1)}$

Panel B: b_{H_2}, conditional on lagged market return in the second-half month

Look-back months L	Future holding months F: 1	3	6	9	12	18	24
1	$0.22_{(0.7)}$	$-0.23_{(1.2)}$	$-0.17_{(1.4)}$	$-0.02_{(0.2)}$	$-0.03_{(0.5)}$	$-0.05_{(0.9)}$	$-0.08_{(1.8)}$
3	$-0.39_{(1.2)}$	$-0.44_{(1.6)}$	$-0.24_{(1.3)}$	$-0.08_{(0.9)}$	$-0.10_{(0.8)}$	$-0.11_{(1.1)}$	$-0.15_{(2.3)}$
6	$-0.44_{(1.1)}$	$-0.36_{(1.1)}$	$-0.11_{(0.6)}$	$-0.05_{(0.4)}$	$-0.12_{(0.9)}$	$-0.17_{(1.4)}$	$-0.18_{(2.3)}$
9	$-0.05_{(0.1)}$	$-0.16_{(0.5)}$	$-0.06_{(0.3)}$	$-0.09_{(0.6)}$	$-0.13_{(0.7)}$	$-0.22_{(1.6)}$	$-0.20_{(2.1)}$
12	$-0.12_{(0.3)}$	$-0.21_{(0.6)}$	$-0.18_{(0.8)}$	$-0.15_{(0.8)}$	$-0.23_{(1.2)}$	$-0.27_{(1.9)}$	$-0.26_{(2.6)}$
18	$-0.22_{(0.5)}$	$-0.28_{(0.8)}$	$-0.30_{(1.3)}$	$-0.30_{(1.5)}$	$-0.33_{(1.7)}$	$-0.33_{(2.4)}$	$-0.31_{(3.0)}$
24	$-0.40_{(0.9)}$	$-0.43_{(1.2)}$	$-0.36_{(1.6)}$	$-0.32_{(1.6)}$	$-0.36_{(1.9)}$	$-0.36_{(2.8)}$	$-0.35_{(3.0)}$

Panel C: Bootstrap p-value

p-value	0.003

Table 12: Variance Ratio

We estimate the variance ratio (the half-month return variance divided by the one-day return variance and the number of trading days in the half-month window) during the first half (H_1) and the second half (H_2) of a month. We divide the whole sample into three-year windows (1926-1928, 1929-1931, ..., 2013-2016), where the last window has four years. For each window, we use time series observations of half-month and one-day returns to compute the half-month and one-day variances and their ratio in H_1 and H_2, respectively. The resulting variance ratio is averaged across time for the market, and averaged first cross-sectionally and then across time for individual stocks.

	H_1	H_2	$H_1 - H_2$	t-stat
Market	1.33	1.00	0.32	(3.91)
Large stocks	0.96	0.90	0.06	(2.88)
Small stocks	0.92	0.85	0.07	(4.02)

Appendix

A Construction of Monthly Reports Data

We download all the historical data items in Bloomberg, known as the Bloomberg bulk data fields, for all S&P 500 firms. There are a total of 1,050 Bloomberg bulk data fields, although most monthly reports contain only a small subset of the data fields. We include a firm even if it subsequently drops out of the S&P 500 index. Overall we searched Bloomberg bulk data fields for 1,177 firms. To comply with the Bloomberg data download limit, we use a two-step download procedure. First, we conduct an initial download of all 1,050 bulk data fields and all 1,177 firms for two years (2005 and 2015) to narrow down the list of firms disclosing monthly reports and the available bulk data fields in the monthly reports of each firm. Then, we download all years for those firms with monthly reports and their available bulk data fields based on the information in the initial download. We use the "BDS" function of the Bloomberg Excel interface for the download and specify "FUND_PER=M" to request monthly reports in the "BDS" function.

Bloomberg does not provide the announcement date of the monthly reports. We use the Thomson Reuters Real-Time News database to obtain the announcement dates. We manually read through the news articles to identify the matching month-end report and its announcement date. To narrow down the number of news articles, we impose three filters based on keywords in the news headline. First, we require the headline to contain at least one keyword related to a month, including "month," "month-end," "the retail month of," "weeks ended," "January," "February," "March," "April," "May," "June," "July," "August," "September," "October," "December," and their abbreviated versions. Second, we require the headline to contain at least one keyword related to firm fundamentals, including "performance," "order," "sales," "operation," "asset," "revenue," "statistic," "activity," "traffic," "user," "member," "deliver," "volume," "delinquencies rate," "charge-off."

Finally, we require the headline to contain the firm name or ticker to exclude industry or market-wise general news.

After reading the news articles, if there are multiple repeated coverage on the same month-end news, we use the earliest one to get the announcement date. If an announcement of monthly data coincides with a quarterly earnings announcement, we treat it as part of the quarterly earnings announcement and exclude it from our sample to construct a sample of monthly announcements distinct from the quarterly earnings announcements.

Figure A1: Industry Distribution of Bloomberg Monthly Reports

This figure shows the number of Bloomberg monthly reports by industry, based on the Bloomberg industry classification.

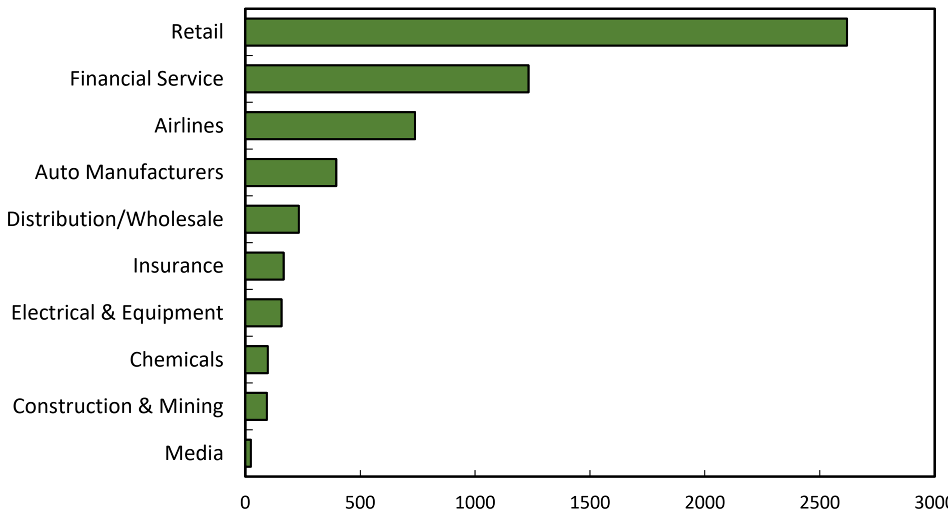


Figure A2: Size Distribution of Stocks with Bloomberg Monthly Reports

This figure shows the size distribution of stocks with Bloomberg monthly reports and the size distribution of all common stocks in the CRSP universe. The snapshot of size distribution is for December 2010.

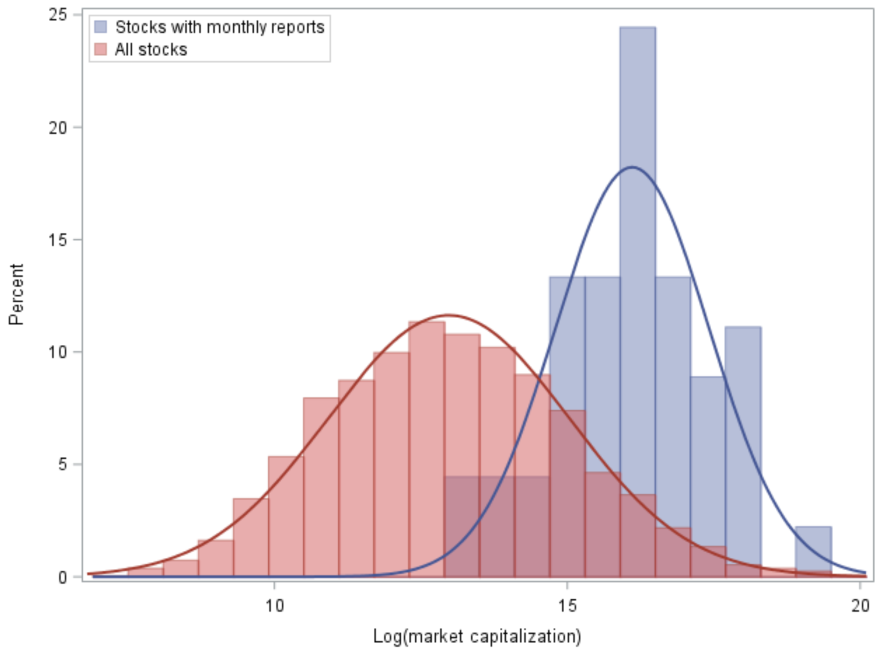


Figure A3: Distribution of the Chinese New Year Holiday Dates

This figure shows the distribution of the starting dates of the Chinese New Year holiday between 2000 and 2016.

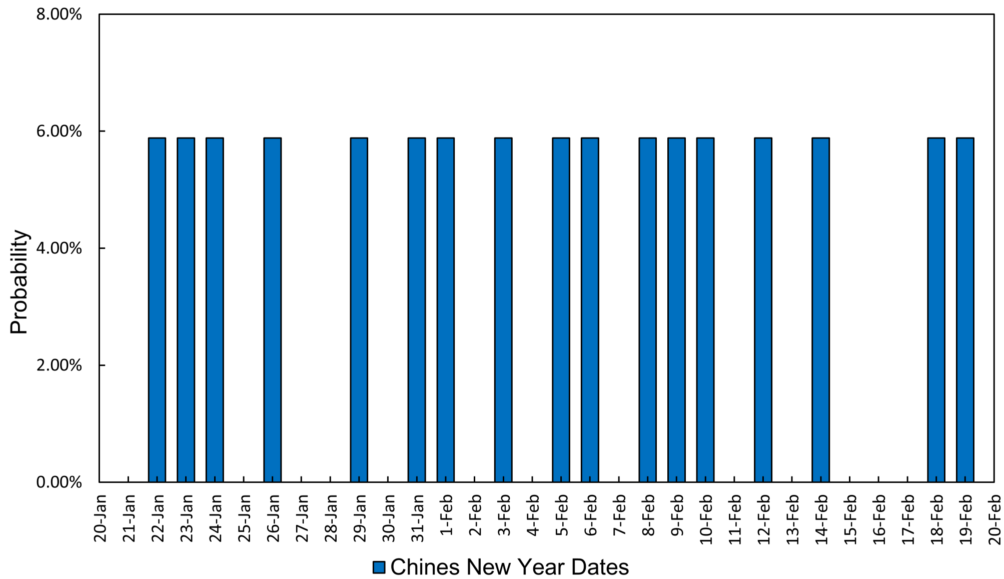
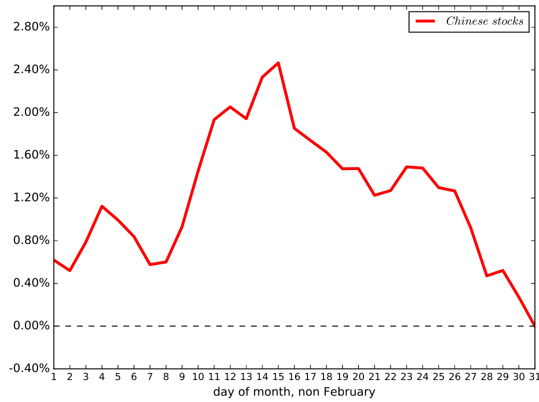


Figure A4: Return Responses for Chinese/U.S. Stocks outside February

This figure shows the cumulative abnormal return spread between good and bad news, which is the *FRONTLOAD* measure in equation (1), during non-February months. The cumulative abnormal return spread is calculated as in Figure 9, using the value-weighted return of Chinese stocks cross-listed in the U.S. in plot (a) and non-Chinese stocks in the U.S. in plot (b), respectively.

(a) Chinese stocks



(b) US stocks

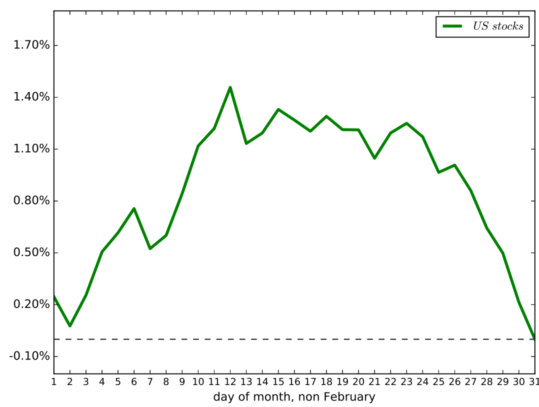
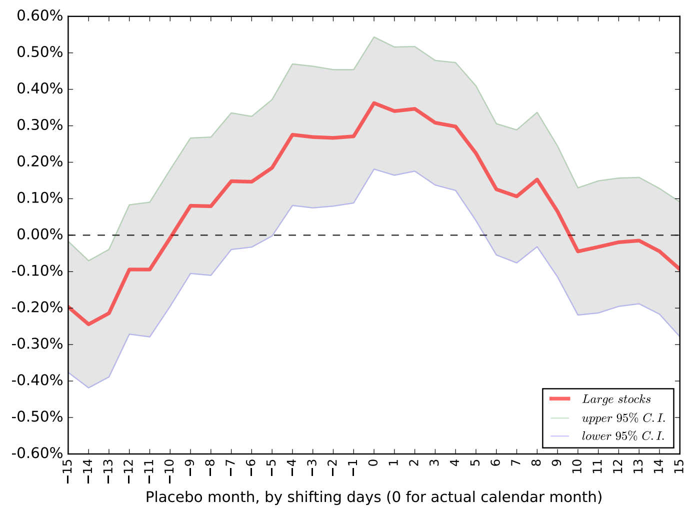


Figure A5: Placebo Months for Individual Stocks

This figure calculates the monthly cumulative abnormal return spreads between good and bad news in Figure 8 for individual stocks using placebo months, which are created by shifting calendar months by −15, −14, . . . , or 15 days. For example, −15 day shift means using the last 15 days of the previous month and excluding the last 15 days of the current month as the placebo month. This figure plots the cumulative abnormal return spreads in the middle (day 15) of a placebo month against the number of days shifted when creating the placebo month.

(a) Large Stocks



(b) Small Stocks

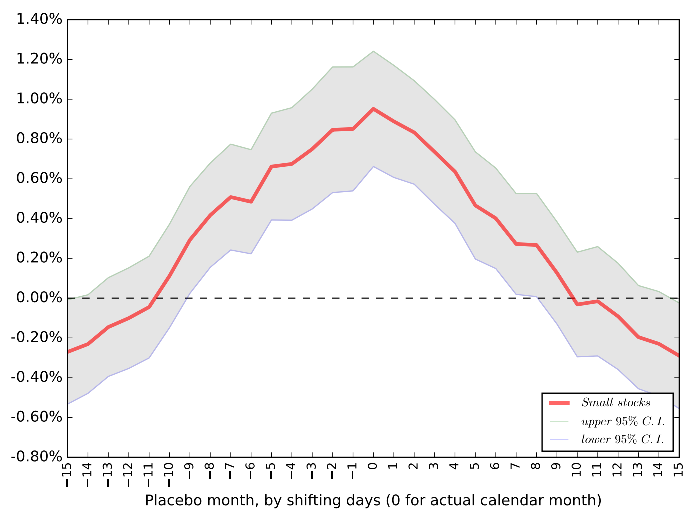


Figure A6: Placebo Months for the Market

This figure calculates the monthly cumulative abnormal return spreads between good and bad news in Figure 9 for the market return using placebo months, which are created by shifting calendar months by -15, -14, ..., or 15 days. For example, -15 day shift means using the last 15 days of the previous month and excluding the last 15 days of the current month as the placebo month. This figure plots the cumulative abnormal return spreads in the middle (day 15) of a placebo month against the number of days shifted when creating the placebo month.

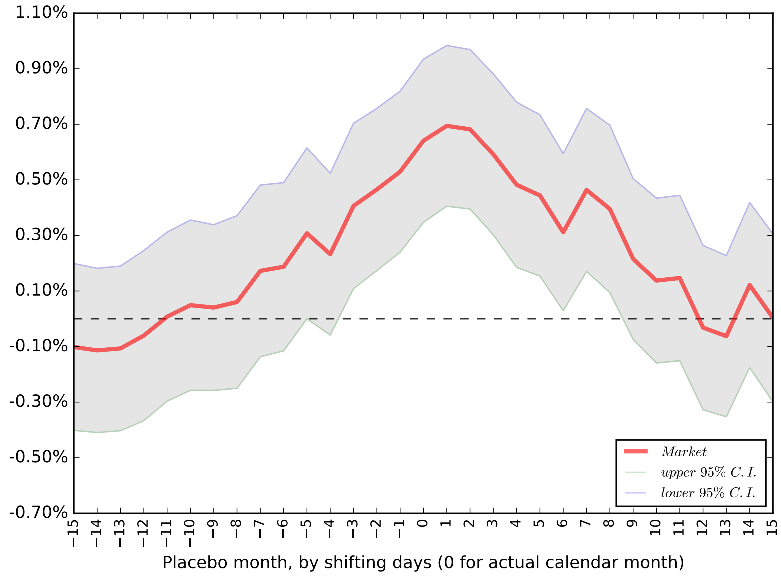


Table A1: List of Companies with Bloomberg Monthly Reports

Delta, General Motor, and United Airline changed their permno during the sample period; hence each is shown with two permnos.

ticker	permno	Name
AAL	21020	American Airline
ADS	89002	Alliance Data
ALK	28804	Alaska Airlines
AN	76282	AUTONATION INC
ANF	83976	Abercrombie & Fitch
ASH	24272	ASHLAND INC.
AXP	59176	American Express
BEN	37584	Franklin Resources
CAL	10866	Continental airline
CAT	18542	Caterpillar
CBOE	93429	CBOE
CME	89626	CME
COF	81055	Capital One
COST	87055	COSTCO
DAL	91926, 26112	Delta
DDS	49429	Dillard
DFS	92121	Discover financial
DG	30382	Dollar General
DRI	81655	Darden Restaurants
EMR	22103	Emerson Electric
ETFC	83862	Etrade
F	25785	Ford Motors
FAST	11618	Fastenal
GM	12079, 12369	General Motor
GPS	59010	Gap
GWW	52695	WW Grainger
ICE	90993	Intercontinental Exchange
JCP	18403	JC PENNEY
JWN	57817	Nordstrom
KSS	77606	Kohls
LB	64282	Ibands
LDG	53612	Long Drugs
LM	65330	Legg Mason
LUV	58683	Southwest
M	77462	Macy
MCD	43449	McDonald
NDAQ	90601	Nasdaq
PGR	64390	Progressive
RAD	46922	Rite Aid
ROST	91556	Ross Store
SCHW	75186	Charles Schwab
SSP	84176	E W SCRIPPS COMPANY
TGT	49154	Target
TJX	40539	TJX
UAL	91103, 19596	United Airline
WBA	19502	Walgreens Boots All
WMT	55976	Walmart