The earnings announcement premium and trading volume

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ABSTRACT

On average, stock prices rise around scheduled earnings announcement dates. We show that this earnings announcement premium is large, robust, and strongly related to the fact that volume surges around announcement dates. Stocks with high past announcement period volume earn the highest announcement premium, suggesting some common underlying cause for both volume and the premium. We show that high premium stocks experience the highest levels of imputed small investor buying, suggesting that the premium is driven by buying by small investors when the announcement catches their attention.

The relation between trading volume and prices in asset markets is not well understood. In the purest neoclassical model with homogenous agents, prices adjust with no trading at all. Risk-based rational asset pricing models attempt to explain expected returns without attempting to explain volume. In this paper, we study the connection between volume and prices by studying regularly scheduled quarterly earnings announcements made by firms. As is well known, these announcements cause both substantial price volatility and substantial increases in volume. In addition, stock prices on average rise in the days around earnings announcements. This earnings announcement premium has been known at least since Beaver (1968) and has since been studied by Chari et al (1988), Ball and Kothari (1991), and Cohen et al (2005).

In this paper, we make two contributions. First, we provide evidence on the magnitude and robustness of the earnings announcement premium. We show that the premium is a substantial anomaly: we find monthly strategies earning excess returns of between 7% and 18% per year, with Sharpe ratios larger than other popular anomalies. The premium is strong in large capitalization stocks, is not only confined to the three-day window around the announcement, and appears consistently since 1927. Second, we provide an explanation for the premium. We hypothesize that the predictable rise in stock price is driven by the predictable rise in volume around earnings announcements. We test this volume hypothesis and show that the premium is strongly related to the concentration of past trading activity around earnings announcement dates. In particular, stocks with high volume around earnings announcements have subsequently both high premiums and high imputed buying by individual investors. This finding suggests that for some stocks, prices are pushed higher around announcement dates by buying pressure from individuals.

On average, as noted in Karpoff (1987) among others, stock returns and trading volume tend to be positively correlated. Stocks tend to rise on high volume and decline on low volume. One can see the earnings announcement premium as a special case of this pattern: when volume is (predictably) high, returns are (predictably) high. There are now many theories to explain why high volume should lead to high prices. Many of these theories involve short-sale constraints (although often these models are static and cannot address time-varying levels of volume). Under short sale constraints, differences of opinion lead to overpricing (see Miller (1977) and Harrison and Kreps (1978)). To the extent that greater differences of opinion lead to more trading volume, higher volume indicates greater overpricing (Scheinkman and Xiong (2003), Mei, Scheinkman, and Xiong (2005)). One explanation for the high volume around earnings announcements is differences of opinion about the meaning of the announcements (see Kandel and Pearson (1995)). Thus one possible story for the earnings announcement premium is that differences of opinion increase around earnings announcements, leading to a rise in price. One could imagine building a model to explain the premium using rational investors with time-varying disagreement.

Another strand of explanations for the correlation of volume and returns involves irrational or random traders. In Baker and Stein (2004), high trading volume indicates the presence of irrational traders who push up prices (their model also involves short sale constraints). In Hong and Yu (2006), high volume indicates the presence of noise traders, and risk-averse rational traders demand a risk premium to compensate for the sentiment risk. Our paper is related to Hong and Yu (2006) in that they study aggregate seasonal patterns in stock market volume and returns, while we study stock-specific seasonal patterns due to earnings announcements. Heston and Sadka (2005) also look at stock-specific seasonals in prices and volume, although they show their results are not driven by earnings announcements.

A specific story involving irrational or cognitively constrained investors is the "attention-grabbing" hypothesis of Lee (1992) and Barber and Odean (2004). According to this hypothesis, individual investors both have limited attention, and rarely sell short. When a stock which they currently do not own grabs their attention, these individual investors are more likely to buy the stock (compared to a stock which does not grab their attention). Institutional investors are less attention constrained. Thus the attention-grabbing hypothesis predicts that individual investors are likely to be net buyers of any stock in the news, whether the news is good or bad. Barber and Odean (2004) show that stocks in the news have both high volume and high net buying by individuals. Further, they show that these stocks subsequently underperform, suggesting that individual investors pushed up prices too high (or prevented prices from falling sufficiently) in response to the news (see also Seasholes and Wu (2005)). The attention-grabbing hypothesis explains why high volume is associated with high returns. Gervais et al (2001) have a similar explanation for the relation between high volume today and high returns over the near future.

Thus there are many theories, not mutually exclusive, explaining why volume and returns might be contemporaneously correlated. The benefit of using earnings announcements is that they are frequent events, exogenously occurring, generating substantial volume, and scheduled at known intervals. Thus they provide a good laboratory for testing whether volume drives returns, and specifically whether predictable volume generates predictable returns.

We focus on testing the attention-grabbing hypothesis. Consistent with the hypothesis, Lee (1992), Hirshleifer et al. (2004), and Dey and Radhakrishna (2006) show that individual investors trade heavily and are net buyers on earnings announcements, no matter whether the news is good or bad. Similarly, Kandel and Pearson (1995) show that volume rises on earnings announcements for good news, bad news, and also in cases where prices don't move much (no news). The attention-grabbing hypothesis predicts that around earnings announcements, prices rise too much (or fall too little) in response to information released, due to buying by individual investors.

When presented with any anomaly, there are two questions one should ask. First, what is causing the anomaly? Second, why haven't arbitrageurs eliminated the anomaly? In this paper, we attempt to answer the first question, but not the second (see Cohen et al. (2005) for an investigation of the second question). We can however make two comments on this issue. First, there are some obvious limits to arbitrage. Frequent trading is required, thus incurring substantial trading costs. There is high idiosyncratic volatility around earnings announcements, which could deter traders who for some reason are unable to sufficiently diversify. As we will show, one type of explanation we certainly can rule out is systematic risk as traditionally defined. If idiosyncratic risk is somehow preventing arbitrage activity, then in this limited sense one can say the premium is reward for bearing risk.

Second, we present evidence suggesting that arbitrageurs *are* trading to eliminate the premium. We show that prior to the announcement there are high imputed buys from large investors. One interpretation is that arbitrageurs are aware of the anomaly, are trading on it, but have not yet completely eliminated it (see also Baker, Litov, and Wurgler (2004) for evidence of sophisticated investor trading around earnings announcements).

This paper is organized as follows. In section I, we provide a description of earnings announcements and data. In section , we show the magnitude and robustness of the earnings announcement premium. In section III, we document the connection between volume and the premium. In section IV, we examine in more detail the attention-grabbing hypothesis and look at variables measuring retail investor trading. Section V presents conclusions.

I. Earnings announcements

A. Announcement dates

Publicly traded US firms are required to file quarterly earnings reports at legally specified intervals. Filing deadlines depend on the fiscal year-end of the company. Our source for earnings announcements dates is Compustat, which claims to report the date that the earnings report appears in the Wall Street Journal or newswire services. The first earnings announcement available on Compustat is December 1970. Since coverage is incomplete in the early years, we start in 1972. Our final sample includes all common stocks traded in CRSP between January 1972 and December 2004. In what follows, we will usually require a previous year of announcements in order to predict the announcement date for this year. Thus we will look at returns in the period 1973 to 2004 (and for NASDAQ firms, we will start in 1974 since 1973 is the first full year of NASDAQ in CRSP/Compustat merged database).

Compustat's data on earnings announcement is incomplete, especially for small firms in the early part of the sample. Panel A of Table I shows the coverage for 1973 (our first year), 1974 (the first year including NASDAQ), 2004 (our last year), and the entire sample. Over the full sample, only 68% of all firm-years contain the required four announcements. The coverage of earnings announcement rises from 50% in 1974 to 95% in the final year. In the last three columns we show coverage of earnings announcements for smaller and larger firms as well as the percentage of market capitalization of firms with exactly four announcements in the calendar year.

The coverage is often incomplete for small stocks, especially in the early years. We conjecture that this is due the fact that news sources are more likely to report earnings announcements for big stocks. In most of the empirical analysis we require stocks to have at least 4 announcements in the previous year, hence after this filter is applied our basic sample includes 68% of CRSP common stocks or 96% in terms of market capitalization.

Panel B shows the distribution of announcements and fiscal year-ends by calendar month. Most firms (62%) have December fiscal year-ends, and many others have March, June, and September year ends. These seasonalities in fiscal years produce seasonalities in earnings announcements, since announcement deadlines are linked to fiscal year-ends. Most of the announcing activity is concentrated in the months of January, February, April, July and October (these months account for about 66% of announcements). Nevertheless each month has a sufficiently large number of earnings announcements such that when we later form portfolios based on scheduled announcements, we will have sufficiently diversified portfolios in each month.

B. Actual dates versus expected dates

In order to test whether firms earn a predictable premium around their announcement dates, it is necessary to use only public information known in real time. Although precise scheduled announcement dates are often known in advance by market participants, sometimes announcements are early, late, or cancelled. This timing can contain information (for example, a delayed announcement date might convey bad news). Thus one cannot use actual announcement dates, but rather must construct a proxy for expected announcements dates (a point emphasized by Cohen et al (2005)).

Prior accounting literature has used various models for forecasting earnings announcement dates focusing mainly on a three-day widow around the announcement (Givoly and Palmon (1982), Chambers and Penman (1984), Begley and Fisher (1998), Cohen et al. (2005)). For the purpose of our analysis we are not interested in generating high frequency expected announcement dates; instead, we use monthly data and expected announcement months (we explain our focus on monthly, not daily, portfolios in the next section).

We use two simple algorithms to forecast announcement months. The first method is based on historical announcement months: we simply use the previous year's announcement month. For example, if firm XYZ had an announcement in March 1997, we expect it to have an announcement in March 1998.

The second algorithm is based on the firm’s fiscal year end. As seen in Table I, there are obvious seasonalities in the timing of the announcement related to a firm’s fiscal year end. We use the historical distribution of announcement months and fiscal year-ends to construct expected announcement months based on the firm’s fiscal year end. For example, firms with fiscal year ending in October tend to announce in February, May, June and December: therefore, if firm ZYX has a fiscal year ending in October, we expected it to announce its earnings in February, May, June and December. We report a detailed explanation of the algorithm in the appendix. This second approach has the methodological advantage that one can construct reasonably accurate proxies for announcement months by looking just at the month end of the fiscal year of the company. This variable changes rarely and is thus much easier to collect than precise announcement dates, which are only available in COMPUSTAT over the period 1971-2004. Thus using this algorithm allows us to make inference based a longer sample period, producing more reliable estimates.

In Table II we summarize the performance of the two forecasting algorithms by reporting the fraction of earnings announcements that are released on expected months. We require firms to have at least 12 months of prior return data from CRSP to be included in the table. In the top panel we report results for the full sample while in the bottom panel we show results by firm size.[1] Overall, the results show that we can predict with a high degree of accuracy the announcement month. In our entire sample, using last year's announcement months as a proxy, 80% of the announcements are in the expected announcement month; looking at the universe of firms with at least 4 earnings announcements in the previous calendar year raises the accuracy of the algorithm to 93%. For the fiscal year method, this number is 73%, lower but still respectable. Panel B shows that the accuracy of predicted announcements months increases in firm size.

To summarize, a highly accurate way of predicting announcement months is to use last year's announcement month and restrict the sample to firms with four announcements in the previous year. Less accurate, but still informative, is simply using the firm's fiscal year end to predict announcement months.

II. The earnings announcement premium

In this paper we focus on portfolio returns in calendar months. Thus the strategy we explore is as follows. On the last trading day of month t-1, buy every stock expected to announce earnings in month t, and short every stock not expected to announce. Hold this portfolio until the last day of month t, then form a new portfolio for the next month.

We focus on monthly returns for four reasons. First, since our interest is in expected announcement returns, it is convenient to have a wide window around the specific day to increase the chance that we are buying before the announcement and selling after the announcement. This wide window also helps avoid the inaccuracies of Compustat data. Since the Compustat date sometimes comes from the Wall Street Journal (appearing the day after the announcement) and sometimes from newswires (appearing the day of the announcement), and since announcements can occur before, during, or after trading hours, pinning down the precise date is difficult. Second, we wish to calculate returns that do not reflect short-term asymmetric information and changes in liquidity around announcement dates. By using monthly returns, we are using a strategy that on average buys two weeks before the expected announcement and sells two weeks after, thus avoiding issues of liquidity on the exact announcement day. Third, monthly returns are a familiar unit for financial economists and allow easy comparison to existing patterns. Fourth, as we show later, looking at a 3-day window around the announcement date misses much of the premium. Prior to the announcement day, there is a substantial pre-event run-up, as well as a positive drift after the announcement. Thus a 20-day window is more informative than a 3-day window.

A. Average premium, 1973-2004

Table III summarize the earnings premium. We form calendar time portfolios based on whether or not a firm is expected to have an announcement this month, using last year's announcement month as the method for forecasting announcement dates. We examine monthly returns of the value weighted portfolio of firms expected to announce as well as returns on the value weighted portfolio on firms not expected to announce. Thus we are testing for the existence of an unconditional announcement effect: we are asking whether all firms tend to go up in expected announcement months. We also form a long-short portfolio, where every firm in the sample goes into the long portfolio four months out of the year and into the short portfolio eight months out of the year. We restrict the sample to firms which have had exactly 4 earnings announcements in the previous 12 calendar months. For comparison, we also show the value weighted market portfolio for this sample of firms.

Table III shows that there is large and significant announcement premium. In months in which stocks are expected to announce earnings, stock returns are higher than in months in which no announcement is scheduled. The long-short portfolio generates returns of 61 basis points per month (or about 7% per year) with a t-statistic over 5. One can immediately see from Table III that the CAPM cannot explain the announcement premium (see also Ball and Kothari (1991)). The CAPM predicts the market portfolio has the highest possible Sharpe ratio. Table III shows that a portfolio of expected announcers has a Sharpe ratio 60% higher than the market and 170% higher than a portfolio of expected non-announcers. The long-short portfolio (which hedges out market risk) has a Sharpe ratio 136% higher than the market. The portfolio of expected announcers has a much higher mean than the market, but only slightly higher variance. Announcement month volatility is largely idiosyncratic and diversifies away in portfolios holding many stocks (the portfolio of expected announcers always contains at least 161 firms in each month up to a maximum of 2945 firms). Table III also shows that the portfolio of expected announcers does not look especially risky measured by skewness or kurtosis.

Table IV further examines systematic risk factors. Since every firm is going in and out of the long portfolio every four months, risks that are associated with characteristics of stocks are unlikely to explain the premium. For example, it is unlikely that the long portfolio overweights value stocks or high beta stocks, since every stock rotates in and out of the portfolio every quarter. Thus, not surprisingly, Table IV shows the earnings announcement return is essentially unrelated to market risk or to any of the other factors commonly used in asset pricing. We regress the calendar time portfolio return on the earnings announcement strategy on the market, the value factor, the size factor, and the momentum factor (all from Ken French's web page); none have any effect on the abnormal returns.

Comparing the earnings announcement premium to these other factors, the earnings announcement strategy has an annual Sharpe ratio of 0.94, while for value, size, momentum, and the market, the highest Sharpe ratio over the same period is 0.70 for momentum (not shown in the table). Thus the earnings announcement premium is statistically stronger and (before considering trading costs) economically more attractive than any other individual factor.

Panel A of Table IV also shows other ways of classifying announcement months. Using our simple algorithm based on fiscal year end over the period 1973– 2004, expected announcers earn a premium of 72 basis points. The third row of Panel A shows the premium using actual (as opposed to expected) announcers. This row is not an implementable strategy, and we show it simply for comparison. It turns out that the results are very similar using actual announcement dates.

Panel B looks across subperiods in the 1973-2004 period. The premium is large and highly statistically significant across the entire sample period, delivering between 40 and 92 basis points a month. Despite the fact each sub-sample contains only 10 year worth of monthly data, we are able to safely reject the null hypothesis of a zero premium in each of the sub-periods between 1973 and 2004.

In summary, using various different methods to predict announcement months produces large and statistically strong earnings announcement premia. The premium is associated with a sizeable Sharpe ratio and is stable over different periods.

B. Premium using only fiscal year end

In panel C of Table IV, we perform a test over the period 1926 – 1973. As noted above, it is possible to construct a reasonable proxy of expected announcement months by only looking at fiscal year ends. This allows us to extend the sample to the period before earnings announcement dates are available on Compustat. Fiscal year end dates are available on Compustat starting in 1950. To compute fiscal year end date for the period 1927–1949 we use the firm's first non missing fiscal year as a proxy. For example, if firm XYZ started trading in 1927 and reported a December fiscal year end in 1950, we assume it had a December fiscal year end between 1927 and 1949. Although firms very rarely change their fiscal year, this assumption obviously introduces an additional source of forecast error.

Is it reasonable to assume that firms the seasonal patterns observed subsequent to 1973 is a reliable proxy for the pattern of announcement month over the period 1927-1972? Obviously there are many factors influencing the distribution of announcing months that are likely to vary over time. Leftwich, Watts, and Zimmerman (1981) report that in 1931, 63% percent of NYSE firms were publishing quarterly earnings. By 1939, the NYSE required firms to report quarterly earnings, with some exceptions allowed. The SEC imposed semiannual reporting requirements in 1955 and quarterly requirements in 1970. Thus it appears that the patterns of reporting frequency observed post-1970 are likely to be noisy indicators of pre-1970 behavior, because of regulatory changes. As a result, we view our expected announcement dates pre-1970 as informative but imperfect. The various sources of forecast error will reduce the accuracy of our predictions and presumably make it more difficult to reject the null hypothesis.

Panel B of Table IV shows monthly returns on the earnings announcement strategy. Despite the fact that we are using a noisy proxy for expected announcement months, there is clear evidence of a large premium. Over the period 1926-1972, expected announcers have returns that are 38 basis points per month higher than expected non-announcers. Figure 1 plots the annual returns of the long-short portfolio over the complete sample period from 1927 to 2004. Although, like everything else, the announcement strategy was quite volatile in the 1930's, it has consistently earned positive returns over the whole period.

C. The premium and firm size

In Table V we report the announcement premium by firm size. Every month we sort stocks using the market value of equity at the end of the previous month and assign them to ten deciles portfolios using NYSE breakpoints, restricting the sample to firms with exactly four announcements in the previous year (thus discarding many small firms). We report returns on the announcement strategy for these size deciles. The results show that the earnings premium is not concentrated in small stocks. Using the fiscal year method, it appears uniformly spread across size classes. Using the previous year method, it is stronger in larger stocks. In either case, it is clear that large cap stocks earn a large and significant premium.

This fact that the premium does not appear larger for small firms is surprising for several reasons. It is contrary to the explanation that higher trading costs allow a higher premium, and also contrary to the idea that earnings announcement generate larger volatility for small firms than for large firms due to lesser information about small firms. This result contrasts with previous findings that the earnings premium is larger for small firms, although some of these results come from studies using actual (instead of expected) dates and narrow daily windows instead of wide monthly windows (Chari et al. (1988) and Ball and Kothari (1991)).

It is unclear precisely what the attention-grabbing hypothesis would predict about small vs. large firms. On the one hand, if there is less news in general about small stocks, than those rare days when news does occur should attract more attention. On the other hand, many of these small stocks have earnings announcements that never get mentioned in the Wall Street Journal at all (thus leading to Compustat's low coverage of these announcements). It is hard to grab the attention of an individual investor if your announcement is not reported.

Due the erratic coverage of small firm announcement dates in Compustat, it is difficult to draw any strong inferences about the difference between large and small firms, so we don't want to overemphasize our results on size. It could be our results reflect poor data quality for small firms. What we can say for sure is that for large firms, where data quality is high, and where our algorithms to forecast earnings announcement dates perform well, there is a sizeable earnings announcement premium.

D. The persistence of the premium

So far we have shown that all firms tend to go up around announcement dates. We now turn to the question of whether one can identify firms with a higher ex ante premium. We start by sorting firms based on their past premium, and asking whether past premia predict future premia. For every stock, we compute the average monthly return in announcement months minus the average monthly returns in non-announcements month over the previous four years. To be included in the portfolio, we require stocks to have a complete history of 16 announcements over the past 48 months. At the beginning of every calendar month stocks are ranked in order of their average announcement premium over the previous four years. We assign stocks to one of five value weighted portfolios every month. Within each portfolio, we report the returns of the (value weighted) strategy that is long stocks expected to announce and short stocks not expected to announce

The results in Table VI show that stocks with high past premia tend to have high subsequent premia. The first row shows that this month's premium is 0.44 percent per month for low past premium stocks, but a whopping 1.37 percent for high past premium stocks. The forecastable difference in premium between these two groups is about 93 basis points per month. The rest of the rows in Panel A show that this predictability is very persistent. While the first row shows returns in month t based on the past premium as of month t-1, the rows below use information as of month t-j for various values of j. Even if we discard all information from the past three years when sorting firms into quintiles (so that we are using past premia calculated from four to six years ago) we still get a sizable difference between the top and bottom quintile. Thus, whatever is causing differences in the premium is a slowly changing phenomenon.

One possible complicating issue is the stock-specific seasonal of Heston and Sadka (2005). They show that stocks that go up this month tend to go up twelve months later. So, for example, some stocks tend to have high returns in June and some tend to have low returns in June. Like us, they find a highly persistent seasonal lasting many years. To ensure that this particular effect is not driving our results, in Panel B of Table VI we calculate the premium for month t by discarding all information from prior years from that same calendar month. Thus our calculation of the premium uses 44 prior months of data (instead of 48 as in Panel A). Panel B shows this adjustment produces little change in the results.

To summarize, the earnings announcement premium varies across stocks. Some stocks have a very high premium in expected announcement months, and it is easy to identify these stocks based on their past announcement premium. This cross-sectional difference in premium is very persistent and it lasts many years.

III. The volume hypothesis

We now turn to test the hypothesis that the predictable rise in stock price is driven by the predictable rise in trading activity around earnings announcements. According to the volume hypothesis, some variable - disagreement, sentiment, or net buying pressure from attention-constrained individuals - causes both volume and prices to rise around earnings announcements. In this section we start by looking at the average pattern of volume and returns. We then turn to differences across different stocks in these patterns. Last, we consider alternative explanations.

A. Returns and volume around announcements

Figure 2 gives a graphical depiction of the monthly patterns of returns and volume. We show the average return and average abnormal volume in month t+k of a portfolio that is long month t announcers and short month t non-announcers. Our measure of trading activity is scaled volume (SV), defined as the ratio of share volume for firm j today to firm j's average monthly share volume over the previous 12 months:

$$SV_t^j = \frac{VOL_t^j}{\frac{1}{12}\sum_{s=-13}^{-1} VOL_{t+s}^l} \tag{1.1}$$

Abnormal volume (AV) is defined as scaled volume minus the equal weight average of scaled volume that month:

$$AV_t^j = SV_t^j - \frac{1}{n}\sum_{j=1}^{n} SV_t^j \tag{1.2}$$

Thus, under the null hypothesis of no announcement effect, both abnormal volume and abnormal returns should be on average zero. Looking at prices and trading activity subsequent to an earning announcement, it is clear that both return and volume exhibit a strong seasonal component. In the initial announcement month (month 0), announcing stocks earn a premium of 60 basis points and abnormal volume of announcing firms, expressed a percent of average monthly volume, is 6.5% higher than abnormal volume of non announcers. Subsequent to initial announcement, prices rise on higher than average volume on announcing months and revert back on lower than average volume in non-announcing months, generating seasonal variation in expected returns.

We now turn from monthly calendar time to daily event time. Figure 3 and Table VII show event time volume and stock returns in the 20 trading day window around announcement dates.

To analyze high frequency trading activity around announcement dates, we use the actual announcement day recorded by Compustat. Since Compustat announcement dates are based on press reports, the trading day in which the news is released to investors could be anywhere from day -1 to day +1.[2] Since announcement coverage is erratic for smaller firms, we restrict the sample to stocks with market capitalization above CRSP median. We calculate abnormal returns as the firm's stock return today minus the return on an equal weighted portfolio of non-announcing stocks

$$AR_t^j = RET_t^j - \frac{1}{n^{no\,ann}} \sum_{i \in no\,ann} RET_t^i \tag{1.3}$$

To get abnormal volume, we calculate daily (instead of monthly) versions of equations (1.1) and (1.2). For these calculations, non-announcers are defined as firms not announcing within a 20 day window around the announcement. We cumulate returns and volume by trading days. Note that since Figure 3 is drawn in event time and uses the actual announcement date, it does not reflect a tradable strategy.

The cumulative abnormal return in Figure 3 and Table VII show the timing of the earnings announcement premium. Most of the premium is not earned in the three-day window surrounding the announcement. Instead, there is a pre-announcement run-up of about 25 basis points in the 10 trading days prior to the announcement, then another 21 basis points earned in the three days around the announcement, and finally an additional 30 basis points earned in the days subsequent the announcement (as shown in Table VII, these three mean estimates all separately have t-statistics above 7). This pattern helps motivate our use of monthly, rather than daily, returns in the previous analysis.

Cumulative abnormal volume displays slightly a different pattern from cumulative abnormal returns. Rather than rising prior to the announcement, volume is below average before announcements (as noted in Chae (2005)). Volume dramatically surges right at the announcement, and remains above average for the next 10 trading days. As one can see from the figure and from table VIII, volume on day 0 is more than 50% higher than average. Thus increases in volume around announcements are quite substantial. Since volume and returns move together during and after the announcement, the volume hypothesis can explain both the event-day returns and the post-event drift in returns. It has a harder time explaining the pre-event price run-up, a subject we return to later.

B. Cross-sectional differences in volume and return

Looking at Figure 3 it is clear that on average, volume and returns are both quite elevated on announcement dates. A different question is whether those firms with predictably high announcement period volume also tend to have high announcement period returns. Table VIII directly tests this cross-sectional volume hypothesis. In order to test for return predictability around scheduled announcements induced by volume predictability, we sort stocks in different classes for which scheduled announcement are more likely to induce the largest increase in trading activity, and construct a long-short portfolio as before. The volume hypothesis predicts that a cross-sectional variable that forecasts differences in trading volume in announcement months should forecast differences in subsequent announcement premia.

Our sorting variable is, for each stock, the *volume concentration ratio* defined as the percent of total share volume over the previous four years that occurred in (actual) announcement months. Thus we are not sorting on generic high turnover; rather we are sorting on whether trading activity tends to be concentrated in a specific four month period out of the year. For example: suppose that the total share volume of stock XYZ in the past 4 years was 10,000 shares and the total number of shares traded over the past 16 announcement months was 7,500 shares, then the volume concentration ratio is given by 7,500 / 10,000 = 75%. To avoid the price dynamics associated with high frequency changes in volume (as in Gervais et al. (2001)), we lag the volume concentration ratio by 3 months when forming portfolios based on this measure.

We sort stocks based on past increases in volume in earnings announcement months, and test whether portfolios with predictably higher volume around earning announcements have predictably higher returns. According to the volume hypothesis, firms whose volume is concentrated in specific dates should also have returns concentrated in those dates. Panel A of Table VIII shows first that past volume concentration in announcement months does a good job forecasting subsequent abnormal volume in expected announcement months. We use equation (1.1) to calculate abnormal volume, measured in units of this month's volume as a fraction of prior average monthly volume.

Looking at the difference between high volume concentration and low volume concentration stocks, it is striking that high volume concentration today predicts higher subsequent abnormal volume on announcing months and lower subsequent volume in non-announcing months. For stocks whose past volume is mostly concentrated in announcement months (high volume concentration ratio stocks), volume is about 9% higher than average in expected announcement months. For stocks whose past volume is not concentrated in earnings announcement months (low volume concentration ratio stocks), there is no statistically significant increase in volume in expected announcement months. Thus some firms have trading activity concentrated around earnings releases; these stocks have persistently high announcement-related volume, and other stocks do not.

Panels C and D show that the predictable increase in volume does indeed lead to predictable return. For the high volume concentration stocks, the monthly strategy of going long expected announcers and short a portfolio of expected non-announcers earns 153 basis points per month with a t-statistic of 6. For the low volume concentration stocks, the announcement premium is 39 basis points per month and statistically indistinguishable from zero. Thus, consistent with the volume hypothesis, high volume concentration ratio stocks experience predictably high volume and high returns in expected announcement months, generating an announcement premium around 18% per year.

In expected non-announcement months, low volume concentration stocks earn excess returns of 74 basis points while high volume concentration stocks earn only 39 basis points. This statistically significant difference of 35 basis points suggests that the high returns on announcement months tend to reverse in subsequent months. High premium stocks tend to "give back" their premium in non-announcement months. Thus the high returns generated by high announcement volume seem to have no permanent effect. Instead, at least in this specific context, high volume creates temporary components in stock prices.

Figure 4 shows the timing of the earnings announcement premium for the two different groups of stocks. As for Figure 3, we use actual announcements and restrict the sample to firms above the CRSP median to produce daily plots in event time. The daily pattern in Figure 4 confirms that the monthly pattern in Table VIII is not concentrated on a small window around announcement dates. Figure 4 shows that stocks with high past volume concentration have a surge in volume right around the announcement date, while the low volume concentration group has a much smaller increase in volume. Stocks with high prior volume concentration also have a much higher cumulative abnormal returns, starting (as in Figure 3) several days before the announcement (around 60 basis points) and continuing after (earning an additional 60 basis points). The surge in volume in high concentration stocks persists for the two week period subsequent to the announcement, inducing the large post announcement drift. Conversely, subsequent to the announcement low concentration stocks show a smaller increase in volume and post event premium.

To summarize, the evidence is consistent with high volume causing high returns, or at least some third variable causing both volume and returns. Stocks without predictably high announcement volume have a small earnings announcement premium that is insignificantly different from zero. Stocks with predictably high announcement volume have a premium of 1.5% per month, allowing us to construct a long/short portfolio generating 18% per year.

C. Idiosyncratic volatility

As discussed already, standard measures of systematic risk do not explain the premium. Another hypothesis is that the earnings announcement premium reflects compensation for idiosyncratic risk. In Table VIII, we display one measure of idiosyncratic risk in the different months. For each portfolio and month, we calculate the cross-sectional standard deviation of raw returns for the stocks in that portfolio in that month. We then average across all months, 1973-2004, and report the time-series average of this cross-sectional number as our measure of idiosyncratic risk.

Idiosyncratic risk is indeed higher in announcement months. Across all stocks with exactly four earnings announcements in the prior calendar year, the monthly standard deviation of returns rises from about 13.7% in expected non-announcement months to about 14.7% in expected announcement months (not reported in the table). Panel B in Table VIII shows that high volume concentration stocks have higher idiosyncratic volatility increases in announcement months than low volume concentration stocks. Thus there is some evidence that higher premium stocks have higher earnings-related idiosyncratic risk.

However, it seems unlikely that a story where all types of idiosyncratic risk earn a premium can explain the magnitudes observed in Tables VIII. The high volume group has excess returns that are 1.9% on expected announcement months and 0.4% per month on other months. Volatility is 14.5% in expected announcement months and 12.6% in other months. It seems unlikely that such large differences in return could be explained by such small differences in volatility.

One possible theory is that announcement period returns reflect fundamental/permanent innovations in prices, while non-announcement returns reflect sentiment/noise/temporary innovations in prices. In the framework of Campbell and Shiller (1988) and Campbell and Vuolteenaho (2004), perhaps earnings announcement returns reflect cash flow news while non-announcement returns reflect future return news. If fundamental idiosyncratic risk earns a premium while non-fundamental idiosyncratic risk does not, then that would explain high average returns around expected announcement dates (of course, one would need to develop models where idiosyncratic risk is priced). While this explanation is appealing and may well contain some truth, it fails to generate predictions about volume, and as we have shown, volume is a key element of the story.

A different story about idiosyncratic risk is that it is a limit to arbitrage that prevents sophisticated investors from eliminating the earnings premium. If for some reason arbitrageurs are unable to sufficiently diversify, then the high risk around announcements would deter attempts to eliminate the anomaly. While this explanation is undoubtedly true, it fails to explain the sign of the premium: it explain why rational arbitragers may fail to smooth prices but it does not explain why the premium arises in the first place.

D. Other explanations for the premium

We here consider other non-volume explanations for the earnings announcement premium. One explanation for the premium is based on analyst forecast bias. There is evidence that firms and analysts cooperate to produce analyst earnings forecasts for the upcoming quarters that are biased downward (Richardson et al. (2004)). Analyst set earnings forecasts such that the firm rarely falls short and frequently exceeds consensus earnings estimates. If naive investors fail to realize this downward bias in forecasts, then these naive investors will tend to be consistently positively surprised by the actual earnings announcement. If these investors affect market prices, they will consistently push up prices on earnings announcements because they perceive most announcements to be good news.

A related explanation reflects naive anchoring. Perhaps investors compare this quarters earnings to historical earnings. In an economy with nominal profits growing due to either inflation or real growth, on average, investors using these naive benchmarks will constantly be surprised by this quarter's high earnings and will send prices higher.

These explanations based on naive investor surprise, while appealing, fail to predict the cross-sectional relation between volume and the premium. Two other pieces of evidence cast doubt on this class of explanations. First, as detailed in Barber and Odean (2004) and Hirshleifer et al. (2004) individual investors are net buyers in response to either positive surprises (such as extremely high earnings growth) or negative surprises (such as extremely low earnings growth). Buying by the least sophisticated investors in response to bad news seems inconsistent with the naive anchoring story. Second, as shown in Table IV, the earnings announcement premium appears in many different subperiods. Analyst forecasts and consensus earnings estimates are a relatively recent development and are unlikely to explain return patterns prior to the 1970s.

Inflation varied widely over this period, yet the premium shows up in low inflation periods (such as 1927-1949) as well as high inflation periods (such as 1973-1983). So the stability of the premium suggests a more general explanation.

Another possible explanation is liquidity. If announcement dates involve high levels of asymmetric information or low liquidity, then investors will demand a premium to hold stocks during this period. While this explanation seems feasible for the day or two right before the announcement, it is not a plausible explanation for a strategy that buys two weeks before the announcement and sells two weeks after. Lee, Mucklow, and Ready (1993), for example, show bid/ask spreads widening in the hours surrounding the announcement but quickly reverting to normal within a day or two.

IV. Order imbalances around announcement days

In this section we examine daily order flow and returns around actual announcement days in event time. According to the attention-grabbing hypothesis, individual investor buying is triggered by the announcement. We investigate this hypothesis by calculating imputed order flow from large and small investors. We view the evidence in this section as primarily suggestive since it relies on a number of assumptions.

To compute trading imbalances around earnings announcements we use the NYSE Trades and Quotations (TAQ) database. We split trades based on the dollar value of the trade and compute a measure of trade-initiation which captures which side of the trade demands immediate execution. We identify each trade on the TAQ tape as buyer or seller initiated using the procedure detailed in Lee and Ready (1991) and Odders and White (2000). A trade is classified as buyer initiated if the trade price is above the quote midpoint of the most recent bid ask spread, or if the trade price is above the last executed trade price.

Our goal is to identify trading activity by individual investors. To identify retail investors, we use the standard assumption that individuals use small trade sizes and institutional investors use larger trade sizes. We use trades less than $5,000 (small trades) as a proxy for individual investors' trades and trades over $50,000 (big trades) as a proxy for institutional trades.[3] As confirmed by Barber et al. (2005) and Hvidkjaer (2005), this assumption produces fairly accurate classifications of trader types prior to the year 2000. Subsequent to 2000, changes in market environment (such as decimalization and algorithmic trading) cause this classification to be less reliable. Thus we restrict our analysis to the period 1993-2000.

One of the earliest applications of this approach is the Lee (1992) study of individual investor trading in the hours and minutes around earnings announcements (see also Bhattacharya (2001), Hirshleifer et al. (2004) and Battalio and Mendenhall (2005)). Instead, we perform a daily analysis and use the intraday data only in order to calculate daily-level aggregates. For every stock and for the two size categories (small and big) we compute order imbalances (*Net Buy*) as the ratio of buyer initiated volume minus seller initiated volume for firm j today to firm j average daily volume over the previous 250 trading days

$$\begin{aligned} Net\ Buy_{BIG} &= \frac{BUY_{BIG} - SELL_{BIG}}{\overline{VOL}} \\ Net\ Buy_{SMALL} &= \frac{BUY_{SMALL} - SELL_{SMALL}}{\overline{VOL}} \\ \overline{VOL} &= \frac{1}{250}\sum_{s=-250}^{-1} VOL_s \end{aligned} \tag{1.4}$$

Where *BUY* is total buyer initiated volume in day t, *SELL* is total seller initiated volume, and VOL is daily volume (all measured as number of shares). We calculate *Abnormal Net Buy* as the normalized trade imbalances by subtracting from *Net Buy* the equal weighted average of it for all non-announcing firms that day.

$$Abnormal\ \ Net\ \ Buy_t = Net\ \ Buy_t - \frac{1}{n^{no\ ann}} \sum_{non\ ann} Net\ \ Buy_t \qquad (1.5)$$

Non-announcers are defined as firms not announcing within a 20 day window around the announcement. Thus, under the null hypothesis of no announcement effect, *Abnormal Net Buy* should be on average zero.

Figure 5 shows *Abnormal Net Buy* in event time. Consistent with the attention-grabbing hypothesis (and with Lee (1992), Barber et al. (2005) and Hirshleifer et al. (2004)), small investor buying soars on the announcement day. Compared to net buying by institutions, which seem to fluctuate somewhat, the peak in small buying is quite pronounced. When interpreting Figure 5, it is important to keep in mind that our method of imputing orders and the identity of the traders (though standard) produces noisy measures of true individual behavior. Other studies confirm that our method is sufficiently accurate to uncover the important properties of the data, so the shape of the small buy curve is probably a good guide to reality.[4] On the other hand, the precise quantities shown on the axis of Figure 5 might not be reliable. For example, Figure 5 shows that the magnitude of institutional trading is far larger than the magnitude of individual trading, which is not surprising given the mechanical definitions based on trade side. Thus we view Figure 5 as suggestive but not conclusive evidence.

Looking at the pattern of net buying by institutions shows an intriguing pattern over time. According to our measure, large investors buy in the days preceding earnings announcements. In particular, large imputed buy orders appear to peak the day before small imputed buy orders. Large investors' buying activity drops on the announcement day and on the two trading days subsequent to the announcement, when individual buying is most intense. Thus large investors appear to be front-running small investors buy initiating purchases of announcement stocks in the weeks prior to an earnings announcement.

One interpretation of this evidence is that the "smart money" appropriately anticipates net buying by the "dumb money": large investors tend to purchase announcing stocks prior to the announcement. This process is precisely what should be happening in an efficient market: sophisticated traders should be accommodating uninformed demand shocks and smoothing prices, thus eliminating predictable returns. However, while large traders appear to be arbitraging away the anomaly, apparently they are not arbitraging enough, for the small traders are still affecting prices.

This pattern of trading by large investors is our explanation for the pre-announcement run-up in prices. Large traders, anticipating uninformed buying, buy stocks in the days and weeks ahead of the scheduled announcement. In the absence of these large traders, the spike in cumulative abnormal returns at day 0 shown in figure 3 would be much more pronounced. So the large traders help smooth out the spike in prices, although something prevents them from smoothing it all the way down to a flat line. Of course, if these large traders cause a rise in prices from date t-10 to t-1, one might ask why some third class of traders do not front-run them and buy at date t-11. A possible answer is idiosyncratic risk or holding costs. If sophisticated traders are unable to fully diversify or face a high daily cost of holding shares, then they will trade off price appreciation against length of holding period.

Figure 6 connects imputed buying with the volume-related measure shown in Table VIII. We separately examine stocks with high and low concentration of trading activity around previous announcements. For the two groups of stocks, we cumulate the small net order flow of the type shown in Figure 5. Table VIII shows that the lagged volume concentration ratio forecasts both high returns and high volume around announcement dates. Figure 6 shows that this variable may capturing buying from small investors: high past announcement-related volume predicts buying by small investors. Firms with high past announcement volume have high small buys surging on the announcement, while firms with low past announcement volume have no discernable announcement effect.

Thus three common features characterize the behavior of security prices around scheduled earning announcements for this set of firms: high returns around announcements, high trading volume around announcements, and high small investor buying pressure around announcements. Our interpretation of this evidence is that there are some firms who have more attention-grabbing earnings announcements or who have an investor base that is more attention-constrained. It may be that these firms have more media coverage devoted to their earnings, or have more variable earnings, or appeal differently to inattentive investors. For whatever reason, year after year, these firms garner small investor attention around earnings announcements dates. Consistent with the attention-grabbing hypothesis, these firms earn predictable higher returns around earnings announcements.

V. Conclusion

In this paper we test whether predicable increases in volume lead to predictable increases in prices. Quarterly earnings announcements, frequent events that are scheduled at known intervals, exogenously occurring, and that generate substantial volume, provide a natural setting to test the hypothesis that predictable volume generates predictable returns. We focus on monthly data using expected announcement months based on stale information, hence issues related to timing of the announcement or changes in liquidity around the announcement dates are unlikely to be an issue.

We show that the strategy of buying every stock expected to announce over the subsequent month and shorting every stock not expected to announce yields a return of over 60 basis points per month. We show that announcement premium is quantitatively substantial, especially among large cap securities, lasts about 20 days, and is evident in samples going back to 1927.

Consistent with the volume hypothesis, stocks with the largest predicted volume increases in announcement months (as forecasted by a high concentration of past trading activity around earnings announcements) tend to have higher subsequent premia. These stocks also tend to have the highest imputed buying by small investors around announcement dates.

Mounting evidence shows individuals investors appear to make uninformed trading decisions.[5] Consistent with the attention-grabbing hypothesis, according to which individual investors are more likely to initiated purchases on stocks that grab their attention via an earnings announcement, small investors buys (as proxied by small buyer initiated trades) soar on announcement day, especially for securities where most of the past trading activity in concentrated around announcements. One coherent explanation of these facts is that some securities attract small attention constrained investors around earnings announcement dates. Since these investors rarely sell short, the predictable rise in volume pushes prices higher around announcement dates, generating a seasonal component in the stock's expected return.

These results fit into the broader research effort to connect trading activity to prices. Concepts such as liquidity, information flow, heterogeneous beliefs, and short sale constraints are all potentially important in understanding this connection. The evidence here imposes an additional requirement on any theory attempting to connect volume and prices. Any theory now must explain why highly predictable volume leads to highly predictable return. One potential explanation is uninformed demand by individuals, coupled with imperfect arbitrage by informed traders.

ENDNOTES

[1] If the forecasting algorithm was completely accurate, 100% of the announcements would fall in predicted months. If the algorithm was completely random, only 33% of the announcements would (for firms with four announcements per year).

[2] For announcements reported on days where the market is closed, we use the next available business day as the announcement date.

[3] Several papers rely on similar dollar cutoff to separate trading imbalances of individual and institutional investors. See for example, Lee (1992), Lee and Radhakrishna (2000) and more recently Hvidkjaer (2005) and Barber et al. (2005).

[4] Barber and at. (2005), who have access to actual individual trade data and use the same dollar cutoffs, show that order imbalances of buyer and seller initiated small trades on TAQ are highly correlated which purchases and sales by individual investors at a large discount brokerage house (1991–1996) and at a large retail brokerage house (1997-1999)/

[5] See Odean (1999), Barber and Odean (1999) and Frazzini and Lamont (2006).

Table I: Coverage of earnings announcement dates, 1973 – 2004

Panel A shows coverage of earnings announcement dates for CRSP/COMPUSTAT stocks. The earnings announcement represents the date in which quarterly earnings and earnings per share figures are first publicly reported in the various news media. "At least one (four) ann." is the fraction of Compustat firms with at least one announcement that calendar year. "Exactly four ann" is the fraction of Compustat firms with exactly four announcements that calendar year. "Larger firms" are all firms with market capitalization above the median of the CRSP/COMPUSTAT universe that year, "smaller firms" are below median. "Market value" is the total market capitalization of firms with exactly four announcements in that calendar year divided by the total market value of the CRSP/COMPUSTAT stock universe.

Panel A: coverage of earnings announcement dates

		Exactly 4 ann			
year	At least one ann	All firms	smaller firms	larger firms	market value
1973	0.79	0.70	0.66	0.73	0.84
1974	0.55	0.50	0.33	0.66	0.88
2004	0.98	0.95	0.94	0.97	0.98
1973-2004	0.77	0.68	0.54	0.82	0.96

Panel B shows distribution of earnings announcement dates for CRSP/COMPUSTAT stocks. Column one reports the fraction of firms with fiscal year ending in each calendar month. Column two reports the fraction of earnings announcements occurring in each calendar month. Column three reports the fraction of fourth fiscal quarter earnings announcements occurring in each calendar month. Column four reports the fraction of first, second or third fiscal quarter earnings announcements occurring in each calendar month. Column five and six report the distribution of earnings announcements for firm with fiscal year ending in December.

Panel B: distribution of earnings announcement dates

			all firms		Dec fiscal year	
	Fiscal yr end	Ann	Q4	Q1-Q3	Q4	Q1-Q3
Jan	4.32	9.73	23.96	5.15	36.49	0.00
Feb	1.76	9.79	29.22	3.52	45.89	0.00
Mar	4.82	4.71	12.38	2.24	15.32	0.01
Apr	1.94	15.21	4.08	18.80	2.27	23.97
May	2.04	7.59	3.44	8.93	0.01	8.53
Jun	8.29	2.41	2.77	2.29	0.00	0.09
Jul	2.07	15.01	3.44	18.74	0.00	25.12
Aug	1.96	7.51	5.31	8.22	0.00	8.01
Sep	7.02	2.46	3.18	2.22	0.00	0.14
Oct	2.75	15.69	4.02	19.45	0.00	25.85
Nov	1.51	7.38	4.71	8.24	0.00	8.26
Dec	61.52	2.52	3.50	2.20	0.01	0.03

Table II: Accuracy of announcement date prediction, 1973-2004

This table shows the accuracy of announcement date prediction. We report the fraction of announcements that occur on expected date and the fraction of announcements that do not occur on expected dates. This table includes all available stocks. The top part of panel A reports results for announcements predicted based on fiscal year end. At the beginning of each calendar month t, we compute the frequency of announcements in table A1 using data available up to month t. We assign each firms to one of two portfolios: if calendar month t+1 matches any of four calendar months with the highest number of announcements corresponding to the firms' fiscal year end month, we classify the firms as expected announcer in month t+1, provided that the firm did not have an announcement in month t. If calendar month t+1 does not match any of the four calendar months with the highest number of announcements corresponding to the firms' fiscal year end month, or the firms has an announcement in month t, we classify the firm as expected non-announcer in month t+1. The bottom part of panel A reports results for announcements predicted based on the previous year. We set the expected announcement month equal to the firm's previous year announcement month, provided that the firm did not have an announcement in the last calendar month. Panel B report the accuracy of announcement date prediction by firms size. We assign firms to size deciles at the beginning of each calendar month using NYSE breakpoints.

	All firms	Four announcements in the previous year			
	1973 - 2004	1973-2004	1973-1983	1984-1993	1994-2004
Ann predicted based on fiscal year end					
% Announcement	0.54	0.73	0.72	0.70	0.72
% No announcement	0.46	0.27	0.28	0.30	0.28
Ann predicted based on previous year					
% Announcement	0.80	0.93	0.92	0.92	0.93
% No announcement	0.20	0.07	0.08	0.08	0.07

Size Decile	1 (small)	2	3	4	5	6	7	8	9	10 (large)
Ann predicted based on fiscal year end										
% Announcement	0.31	0.58	0.64	0.68	0.73	0.78	0.83	0.86	0.86	0.91
% No announcement	0.69	0.42	0.36	0.32	0.27	0.22	0.17	0.14	0.14	0.09
Ann predicted based on previous year										
% Announcement	0.75	0.82	0.84	0.86	0.87	0.87	0.88	0.90	0.92	0.94
% No announcement	0.25	0.18	0.16	0.14	0.13	0.13	0.12	0.10	0.08	0.06

Table III: Excess returns on expected announcement months vs other months, 1973-2004

This table shows calendar time portfolio excess returns. At the beginning of every calendar month stocks are assigned to one of two portfolios (expected announcers and expected non-announcers) using announcements predicted based on the previous year. All stocks are value weighted within a given portfolio, and the portfolios are rebalanced every calendar month to maintain value weights. This table includes all available stocks with four announcements in the previous twelve months at portfolio formation. We report average portfolio returns minus Treasury bill returns in the period 1973 to 2004. Returns are in monthly percent, t-statistics are shown below the coefficient estimates. L/S is monthly average return of a zero cost portfolio that holds the portfolio of expected announcers and sells short the portfolio of expected non-announcers.

	All stocks	Expected non-announcers	Expected announcers	L/S
Mean	**0.529**	0.329	**0.942**	**0.613**
t-statistic	[2.28]	[1.34]	[3.60]	[5.30]
Std deviation	4.598	4.802	5.117	2.264
Skewness	-0.438	-0.535	-0.032	1.366
kurtosis	4.749	5.436	4.882	11.095
Sharpe ratio	0.115	0.069	0.184	0.271

Table IV: The earnings announcement premium

This table shows calendar time portfolio abnormal returns. At the beginning of every calendar month stocks are assigned to one of two portfolios (expected announcers and expected non-announcers) using either announcement predicted based on fiscal year end, or announcement predicted based on the previous year. All stocks are value weighted within a given portfolio, and the portfolios are rebalanced every calendar month to maintain value weights. This table includes all available stocks with four announcements in the previous twelve months at portfolio formation. We report the monthly return of a zero cost portfolio that hold the portfolio of expected announcers and sell short the portfolio of expected non-announcers. Alpha is the intercept on a regression of return from the rolling strategy. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios and Carhart (1997) momentum factor. # of stocks is the average number of stocks in the portfolio. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates.

	xret	Alpha	MKT	SMB	HML	UMD	R2
Panel A: Full sample 1973-2004, different methods, 4 prior announcements required							
previous year	**0.613**	**0.613**	-0.037	0.031	**-0.135**	0.087	0.07
	[5.30]	[5.13]	[-1.33]	[0.87]	[-3.24]	[3.32]	
fiscal year end	**0.723**	**0.77**	0.005	-0.037	-0.082	-0.001	0.009
	[5.09]	[5.08]	[0.14]	[-0.83]	[-1.55]	[-0.03]	
Actual dates	**0.603**	**0.599**	-0.012	-0.013	**-0.094**	**0.063**	0.038
	[5.82]	[5.51]	[-0.47]	[-0.40]	[-2.47]	[2.60]	
Panel B: Subsamples, 1973-2004, using previous year method, 4 prior ann required							
1973 – 1983	**0.396**	**0.438**	-0.023	-0.087	-0.029	0.034	0.035
	[2.21]	[2.22]	[-0.51]	[-1.34]	[-0.42]	[0.73]	
1984- 1993	**0.521**	**0.592**	-0.025	-0.064	-0.114	-0.029	0.034
	[3.79]	[4.00]	[-0.70]	[-1.03]	[-1.81]	[-0.62]	
1994 – 2004	**0.915**	**0.811**	0.029	0.081	-0.135	0.149	0.171
	[3.58]	[3.21]	[0.44]	[1.22]	[-1.58]	[3.28]	
Panel C: Fiscal year-end method, testing back to 1927, no prior ann required							
1927 – 1972	**0.384**	**0.390**	-0.004	0.03	0.022	-0.025	0.007
	[3.41]	[3.33]	[-0.19]	[0.84]	[0.59]	[-0.89]	
1927 – 1949	**0.510**	**0.526**	-0.010	0.005	0.023	-0.04	0.009
	[2.53]	[2.55]	[-0.28]	[0.09]	[0.41]	[-0.99]	
1950- 1972	**0.259**	0.210	0.001	**0.102**	0.038	0.034	0.021
	[2.56]	[1.91]	[0.04]	[2.23]	[0.78]	[0.87]	
1973-2004	**0.727**	**0.774**	0.002	-0.039	-0.081	0.001	0.009
	[5.16]	[5.15]	[0.07]	[-0.87]	[-1.55]	[0.02]	
Full sample 1927 – 2004	**0.523**	**0.528**	0.013	0.011	-0.007	-0.018	0.003
	[5.91]	[5.71]	[0.72]	[0.41]	[-0.24]	[-0.84]	

Table V: Robustness checks: size, 1973–2004

This table shows calendar time portfolio abnormal returns. At the beginning of every calendar month stocks are assigned to one of two portfolios (expected announcers and expected non-announcers) using either announcement predicted based on fiscal year end, or announcement predicted based on the previous year. All stocks are value weighted within a given portfolio, and the portfolios are rebalanced every calendar month to maintain value weights. This table includes all available stocks in the period 1973 to 2004 with four announcements in the previous twelve months at portfolio formation. We report the monthly return of a zero cost portfolio that hold the portfolio of expected announcers and sell short the portfolio of expected non-announcers. # of stocks is the average number of stocks in the portfolio. We assign firms to size deciles at the beginning of each calendar month using NYSE breakpoints. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates.

Size decile	1(small)	2	3	4	5	6	7	8	9	10 (large)
Ann based on previous year	0.021	**0.300**	**0.300**	**0.413**	**0.351**	**0.548**	**0.749**	**0.724**	**0.693**	**0.621**
	[0.27]	[2.97]	[2.63]	[3.26]	[2.43]	[4.25]	[5.32]	[5.10]	[4.48]	[3.48]
Ann based on fiscal year end	**0.705**	**0.615**	**0.589**	**0.408**	**0.663**	**0.605**	**0.459**	**0.952**	**0.688**	**0.719**
	[8.16]	[5.64]	[4.70]	[2.96]	[4.09]	[3.75]	[2.91]	[5.51]	[3.52]	[3.61]

Table VI: The persistence of the announcement premium, 1973-2004

This table shows calendar time portfolio returns. At the beginning of every calendar month stocks are ranked in ascending order on the basis of the previous announcement premium (PREMIUM). The ranked stocks are assigned to one of 5 quintile portfolios. We use four year premium, defined as average return on the previous 16 announcement months minus by the average return on non-announcement months in the previous 48 months. We lag PREMIUM from one month to five years. Within each quintile, we assign stocks to one of two portfolios (expected announcers and expected non-announcers) using announcement predicted based on the previous year. All stocks are value weighted within a given portfolio, and the portfolios are rebalanced every calendar month to maintain value weights. This table includes all available stocks in the period 1973 to 2004 with 16 announcements in the previous 48 months at portfolio formation. L/S is the return of a zero cost portfolio that holds the portfolio of expected announcers and sell short the portfolio of expected non-announcers. Average # of stocks per month is the average number of announcers and non announcers per calendar month. Returns are in monthly percent, t-statistics are shown below the coefficient estimates.

Panel A: sort on lagged announcement premium								
	Average # of stocks per month	# of months	1(low)	2	3	4	5(high)	5-1
Expected non-announcers	1323	335	1.103	0.598	0.278	0.479	1.010	-0.094
Expected announcers	590		1.549	0.950	0.948	1.278	2.379	0.834
L/S	1913		0.441	0.412	**0.649**	**0.788**	**1.369**	**0.928**
			[1.60]	[1.93]	[3.38]	[4.64]	[6.06]	[2.68]
Skip 1 year, L/S	1680	324	0.192	**0.607**	**0.590**	**0.972**	**1.230**	**1.038**
			[0.70]	[2.39]	[2.90]	[4.52]	[5.99]	[2.89]
Skip 3 years, L/S	1400	300	0.146	**0.763**	**0.479**	**0.754**	**0.961**	**0.816**
			[0.55]	[3.22]	[2.19]	[2.92]	[4.44]	[2.44]
Skip 5 years, L/S	1192	240	**0.799**	0.196	**0.659**	**0.780**	**0.780**	-0.020
			[2.93]	[0.91]	[2.69]	[3.54]	[3.58]	[-0.06]
Panel B: lagged announcement premium, skip announcement in t-12, t-24, t-36, t-48								
Expected non-announcers	1323	335	0.911	0.375	0.339	0.371	0.803	-0.108
Expected announcers	590		1.115	0.965	0.798	1.080	2.287	1.172
L/S	1913		0.204	**0.565**	**0.475**	**0.691**	**1.484**	**1.280**
			[0.86]	[2.55]	[3.02]	[4.88]	[6.87]	[4.04]

Table VII: Event time returns and volume around announcements, 1973–2004

This table shows event time average abnormal returns and average abnormal volume around earnings announcements dates. Abnormal return (AR) is defined as daily return minus the return of an equally weighted portfolio of all non-announcing firms that day. Abnormal volume AV is defined as daily scaled volume minus the average scaled volume of a portfolio of all non-announcing firms that day

$$AR_t^j = RET_t^j - (1/n^{no\,ann})\sum_{no\,ann} RET_t^j \qquad AV_t^j = SV_t^j - (1/n^{no\,ann})\sum_{no\,ann} SV_t^j$$

where SV (scaled volume) is the ratio of daily share volume for firm j to firm j's average daily volume over the previous 250 trading days

$$SV_t^j = VOL_t^j / \left(\frac{1}{250} \sum_{s=-250}^{-1} VOL_{t+s}^j \right).$$

We exclude a window of ± 10 trading days around the announcement to compute non-event averages. We cumulate by trading days to obtain cumulative average abnormal returns (CAARs). This table includes all available stocks in the period 1973 to 2004 with exactly four earnings announcement during the previous calendar year and market capitalization above the median of the CRSP/COMPUSTAT universe that day. T-statistics are calculated using the standard error of the mean, clustered by calendar quarter, and are in parenthesis.

Trading day	AR	t-stat	CAARs	t-stat	AV	t-stat	CAAVs	t-stat
-10	0.020%	(2.21)	0.020%	(2.21)	-2.26%	(-1.69)	-2.26%	(-1.69)
-9	0.013%	(1.60)	0.034%	(2.71)	-2.33%	(-1.81)	-4.59%	(-2.47)
-8	0.015%	(2.44)	0.049%	(3.52)	-2.84%	(-2.11)	-7.43%	(-3.24)
-7	0.014%	(1.51)	0.063%	(3.76)	-3.95%	(-2.98)	-11.37%	(-4.29)
-6	0.026%	(2.49)	0.089%	(4.51)	-4.36%	(-3.46)	-15.74%	(-5.36)
-5	0.023%	(2.06)	0.113%	(4.94)	-4.17%	(-4.04)	-19.91%	(-6.40)
-4	0.027%	(2.96)	0.139%	(5.68)	-4.49%	(-3.62)	-24.40%	(-7.29)
-3	0.050%	(4.55)	0.189%	(7.04)	-3.79%	(-3.51)	-28.19%	(-8.01)
-2	0.060%	(4.21)	0.249%	(8.19)	-1.66%	(-1.35)	-29.86%	(-8.01)
-1	0.089%	(4.23)	0.338%	(9.15)	17.70%	(7.04)	-12.15%	(-2.70)
0	0.089%	(5.11)	0.428%	(10.45)	52.47%	(20.76)	40.31%	(7.82)
1	0.032%	(2.89)	0.460%	(10.84)	52.52%	(9.89)	92.83%	(12.54)
2	0.041%	(3.86)	0.501%	(11.46)	20.12%	(11.89)	112.95%	(14.87)
3	0.010%	(1.34)	0.511%	(11.52)	11.52%	(9.57)	124.47%	(16.19)
4	0.040%	(5.30)	0.551%	(12.24)	6.92%	(7.86)	131.39%	(16.98)
5	0.045%	(4.25)	0.596%	(12.89)	4.41%	(4.73)	135.80%	(17.42)
6	0.045%	(5.43)	0.641%	(13.64)	3.35%	(3.00)	139.16%	(17.67)
7	0.029%	(3.57)	0.670%	(14.05)	1.96%	(2.00)	141.11%	(17.78)
8	0.035%	(3.66)	0.705%	(14.50)	1.45%	(1.34)	142.57%	(17.80)
8	0.029%	(4.28)	0.733%	(14.94)	0.86%	(0.79)	143.43%	(17.74)
10	0.023%	(3.42)	0.756%	(15.27)	0.66%	(0.62)	144.09%	(17.67)
[-10,-2]	0.249%	(8.19)			-29.86%	-(8.01)		
[-1 , 1]	0.210%	(7.13)			122.69%	(19.18)		
[2 ,+10]	0.296%	(11.58)			51.26%	(15.00)		

Table VIII: The Volume Hypothesis, 1973 – 2004

This table shows calendar time portfolio abnormal returns, abnormal volume and volatility. At the beginning of every calendar month stocks are ranked in ascending order on the basis of the volume concentration ratio defined as volume on the previous 16 announcements months divided by the total volume in the previous 48 months.

$$Volume\ Concentration\ Ratio_t^j = \sum_{s=-48}^{0}\left(VOL_{t+s}^j \times ANN\right) / \left(\sum_{s=-48}^{0} VOL_{t+s}^j\right)$$

where VOL is monthly volume and ANN is a dummy equal to 1 on announcement months and zero otherwise. The ratio is lagged 3 months. The ranked stocks are assigned to one of 5 quintile portfolios. Within each quintile, we assign stocks to one of two portfolios (expected announcers and expected non-announcers) using announcement predicted based on the previous year. All stocks are value weighted within a given portfolio, and the portfolios are rebalanced every calendar month to maintain value weights. This table includes all available stocks in the period 1973 to 2004 with 16 announcements in the previous 48 months at portfolio formation. We report average portfolio returns minus Treasury bill returns, alpha, abnormal volume and volatility. L/S is a zero cost portfolio that holds the portfolio of expected announcers and sells short the portfolio of expected non-announcers. Scaled volume (SV) is defined as the ratio of share volume for firm j today to firm j's average monthly volume over the previous 12 months. We market-adjust this measure by subtracting from it the equal weight average of scaled volume for all firms that month

$$AV_t^j = SV_t^j - \frac{1}{n}\sum_{j=1}^{n} SV_t^j \qquad\qquad SV_t^j = VOL_t^j / \left(\frac{1}{12}\sum_{s=-13}^{-1} VOL_{t+s}^l\right)$$

Volatility is defined as follows: for each portfolio and month, we calculate the cross-sectional standard deviation of raw returns for the stocks in that portfolio in that month. We then average across all months, 1973-2004, and report the time-series average .Alpha is the intercept on a regression of return from the rolling strategy. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios and Carhart (1997) momentum factor. Returns, alphas, volatility and volume are in monthly percent, t-statistics are shown below the coefficient estimates.

Table VIII (continued): The volume hypothesis, 1973 – 2004

	All months	Expected announcers	Expected non-announcers	L/S	All months	Expected announcers	Expected non-announcers	L/S
	Panel A: Abnormal volume (%)				Panel B: idiosyncratic volatility (%)			
Low volume concentration	0.288	2.070	-0.104	2.174	**13.212**	**13.634**	**12.887**	**0.746**
	[0.35]	[1.94]	[-0.15]	[1.82]	[54.09]	[48.61]	[51.47]	[3.24]
High volume concentration	0.461	**8.727**	**-1.936**	**10.663**	**13.258**	**14.532**	**12.648**	**1.884**
	[0.74]	[8.24]	[-2.27]	[7.72]	[53.87]	[46.74]	[53.11]	[7.32]
High minus low	0.175	**6.656**	**-1.832**	**8.488**	0.083	**0.898**	-0.240	**1.138**
	[0.16]	[4.46]	[-2.66]	[4.54]	[0.52]	[3.43]	[-1.37]	[3.69]
	Panel C: excess returns (%)				Panel D: 4-factor Alpha (%)			
Low volume concentration	**0.711**	**1.125**	**0.740**	0.385	-0.008	0.329	-0.016	0.344
	[3.10]	[3.90]	[3.12]	[1.79]	[-0.08]	[1.68]	[-0.15]	[1.52]
High volume concentration	**0.624**	**1.916**	0.387	**1.530**	0.052	**1.149**	**-0.247**	**1.396**
	[2.16]	[5.39]	[1.32]	[6.34]	[0.53]	[4.89]	[-2.24]	[5.41]
High minus low	-0.093	**0.792**	**-0.353**	**1.144**	0.034	**0.820**	-0.231	**1.051**
	[-0.65]	[2.73]	[-2.14]	[3.52]	[0.26]	[2.73]	[-1.52]	[3.04]

Table A1: Distribution of earnings announcement dates by fiscal year, 1973-2004

This table shows the distribution of earnings announcement dates for CRSP/COMPUSTAT stocks by fiscal year end month. The earnings announcement represents the date in which quarterly earnings and earnings per share figures are first publicly reported in the various news media. For every firm with a fiscal year ending in calendar month t, we report the fraction of announcements occurring in every calendar month in the period 1973 to 2004. For each fiscal year end month, we report in bold the four calendar months with the highest number of announcements.

	Fiscal year end month											
% of ann	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan	0.05	11.57	**16.29**	0.21	10.22	**16.07**	0.05	13.18	**16.96**	4.70	**14.96**	8.63
Feb	3.61	0.13	8.97	**12.63**	0.08	9.54	11.58	0.09	8.64	**14.62**	6.54	**10.87**
Mar	**14.82**	3.33	0.02	12.29	**16.25**	0.09	**14.08**	**14.61**	0.17	11.10	**16.34**	3.65
Apr	4.48	**13.24**	4.42	0.03	8.75	**16.33**	0.03	10.70	**16.93**	0.10	9.78	**18.98**
May	**18.18**	6.24	**12.53**	3.21	0.01	9.48	12.38	0.35	8.50	**15.28**	0.11	6.61
Jun	7.60	**17.14**	5.64	**13.87**	4.86	0.03	**13.35**	**14.68**	0.12	10.01	**16.52**	0.08
Jul	0.04	8.47	**17.15**	6.30	**12.64**	4.62	0.04	10.22	**17.36**	0.13	8.56	**19.17**
Aug	**18.06**	0.44	8.88	**15.60**	5.41	**12.81**	2.16	0.04	8.20	**15.75**	0.02	6.12
Sep	7.57	**15.32**	0.10	10.00	**17.31**	4.95	12.33	2.52	0.05	9.39	**15.52**	0.12
Oct	0.09	9.71	**17.11**	0.08	8.98	**17.35**	7.77	**14.85**	5.92	0.01	9.96	**19.50**
Nov	**17.33**	0.62	8.87	**13.79**	0.06	8.64	**12.85**	5.51	**12.51**	3.11	0.12	6.22
Dec	8.17	**13.79**	0.02	11.99	**15.41**	0.08	**13.39**	**13.24**	4.65	**15.80**	1.58	0.04

Figure 1: The earnings announcement premium, 1927-2004

This figure shows returns of the earnings premium portfolio. At the beginning of every calendar month stocks are assigned to one of two portfolios (expected announcers and expected non-announcers) using announcement predicted based on fiscal year end. All stocks are value weighted within a given portfolio, and the portfolios are rebalanced every calendar month to maintain value weights. The portfolios include all available stocks with four announcements in the previous twelve months at portfolio formation. We plot the annual return of the long/short portfolio.

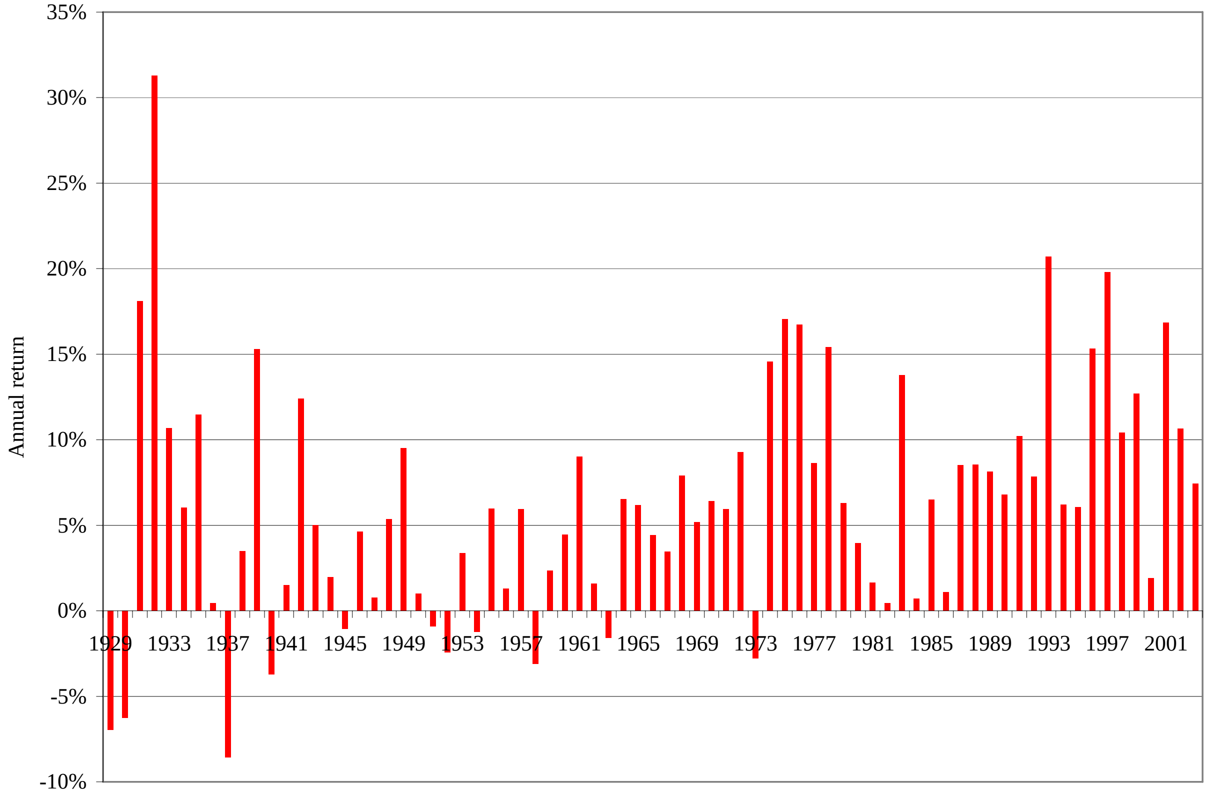


Figure 2: excess returns and abnormal volume subsequent to announcement month, 1973–2004

This figure shows average abnormal return and average abnormal volume in month t+k of a portfolio of announcing stocks in month t. Abnormal return is defined as monthly return minus the average return of a portfolio of non announcers. We report average monthly abnormal volume (return) of a portfolio of announcers minus volume (return) of a portfolio of non-announcers. Scaled volume (SV) is defined as the ratio of share volume for firm j today to firm j's average monthly volume over the previous 12 months. Abnormal volume (AV) is defined as scaled volume minus the equal weight average of scaled volume that month. This table includes all available stocks in the period 1973 to 2004.

$$AV_t^j = SV_t^j - \frac{1}{n}\sum_{j=1}^{n} SV_t^j \qquad\qquad SV_t^j = VOL_t^j \Big/ \left(\frac{1}{12} \sum_{s=-13}^{-1} VOL_{t+s}^l \right)$$

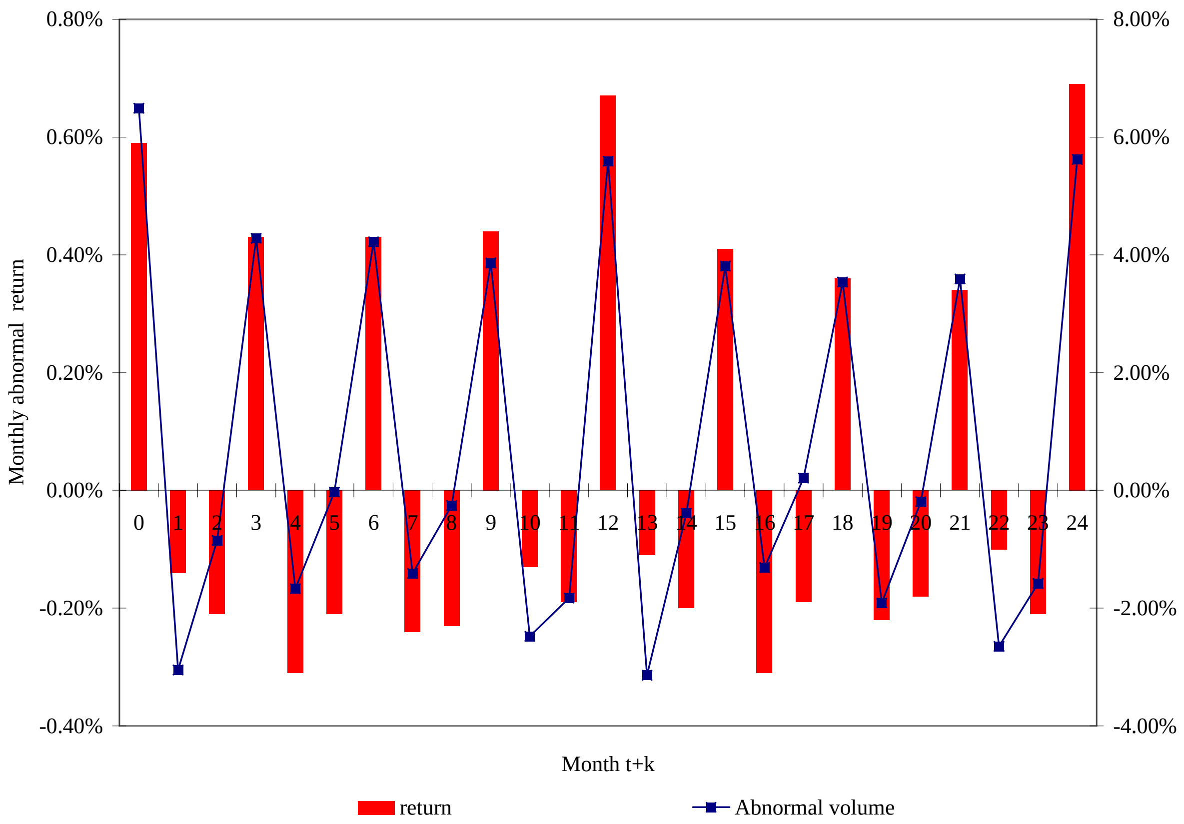


Figure 3: CAR and volume around earnings announcements, 1973–2004

This figure shows event–time daily cumulative abnormal return and cumulative turnover in trading day t+k for firms announcing earnings at date t. Abnormal return is defined as daily return minus an equally weighted portfolio of non-announcing firms. Scaled volume is defined as share volume in month t divided by average volume in the previous 250 trading days. Abnormal volume is defined as scaled volume minus the equal weight average of scaled volume for all firms on that day. This figure includes firms in the period 1973 – 2004 with market capitalization (as of the previous month) above the median market capitalization of CRSP firms. Volume and return are in percent.

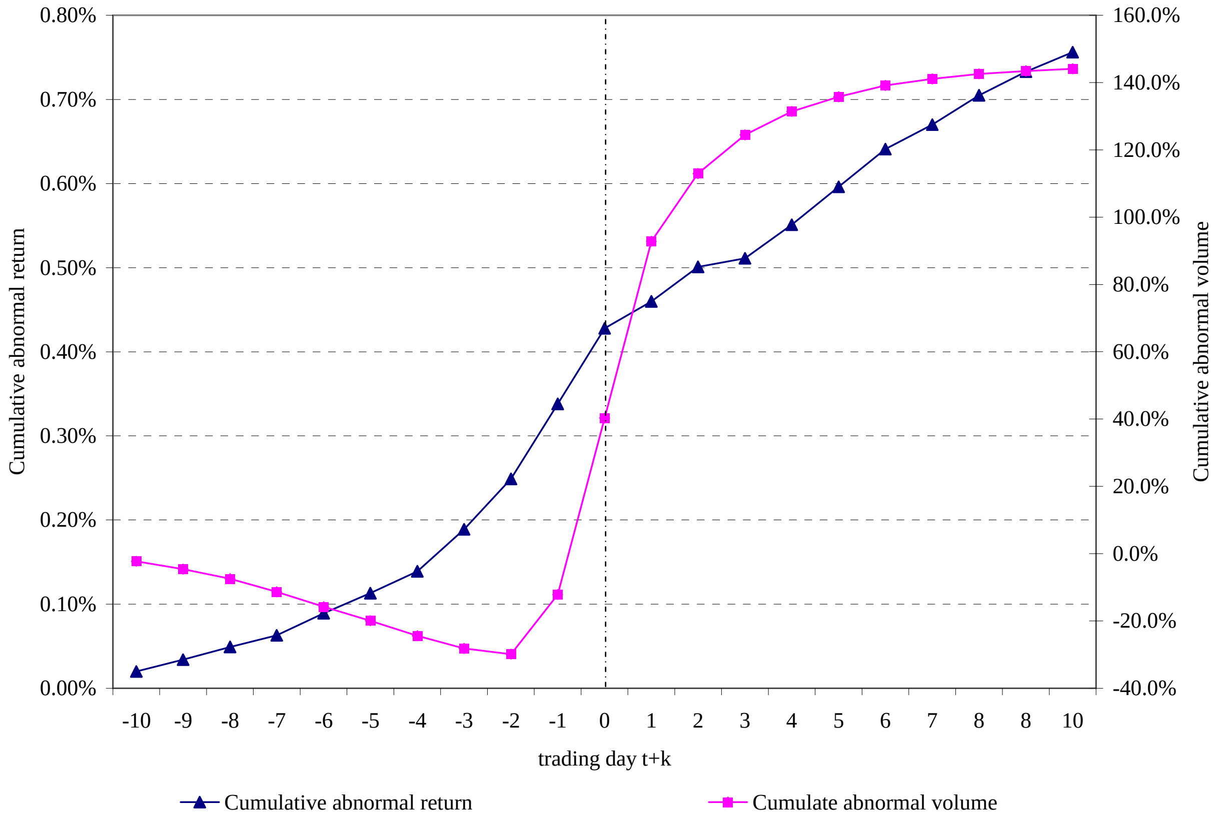


Figure 4: Returns and volume sorted by prior volume concentration ratio.

This figure shows event–time daily cumulative abnormal return and cumulative turnover in trading day t+k for firms announcing earnings at date t. Abnormal return is defined as daily return minus an equally weighted portfolio of non (expected) announcing firms. Abnormal return is defined as daily return minus an equally weighted portfolio of non-announcing firms. Scaled volume is defined as share volume in month t divided by average volume in the previous 250 trading days. Abnormal volume is defined as scaled volume minus the equal weight average of scaled volume for all firms on that day. We cumulate by trading days to obtain cumulative average abnormal returns (CAARs) and cumulative average abnormal volume (CAAVs). At the beginning of every calendar month stocks are ranked in ascending order on the basis of the volume concentration ratio defined as volume on the previous 16 announcements months divided by the total volume in the previous 48 months. We lagged volume concentration 3 months. This figure includes firms with market capitalization (as of the previous month) above the median market capitalization of CRSP firms. We plot returns and volume for the top 20% high volume concentration ratio stocks and the bottom 20% low volume concentration ratio stocks.

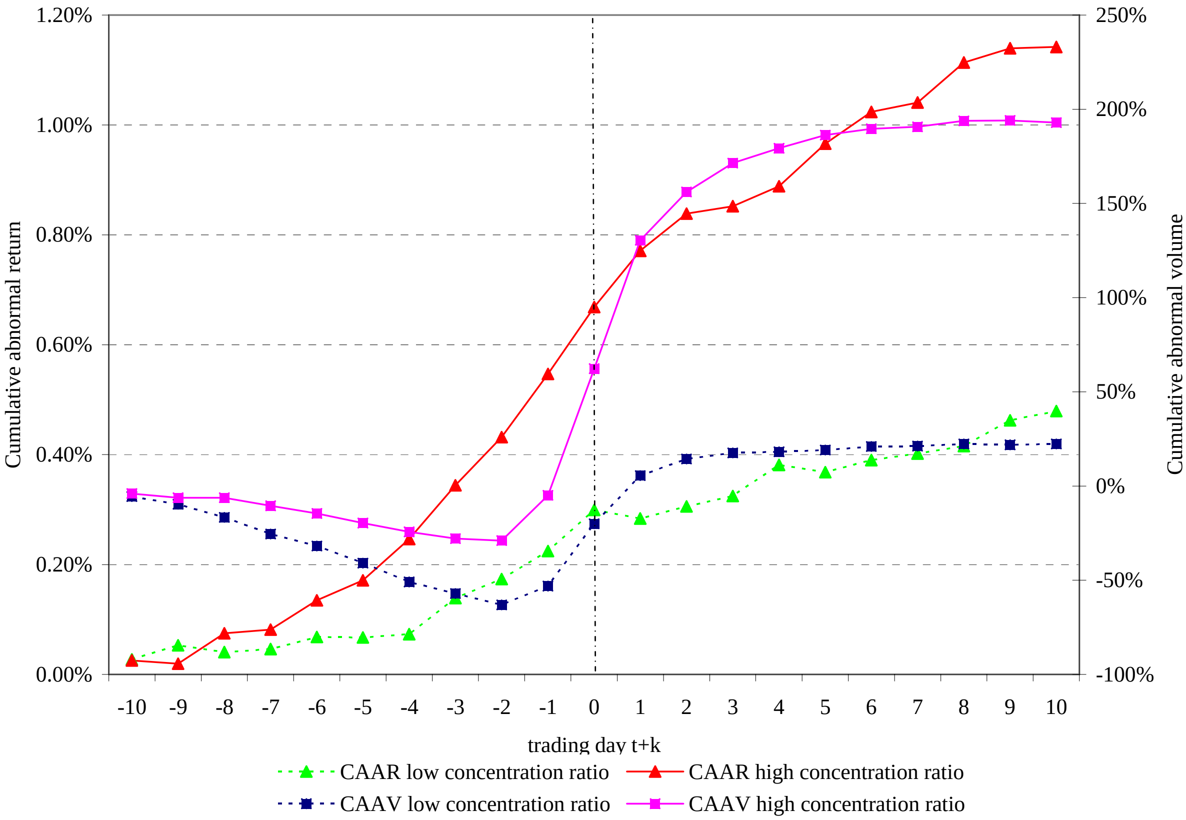


Figure 5: Order flow around announcements, 1993-2000

This figure shows event–time daily abnormal order flow in trading day t+k for firms announcing earnings at date t. We split trades based on dollar value of the trade and compute a measure of trade-initiation which captures which side of the trade demands immediate execution. Each trade on the TAQ tape as buyer or seller initiated using a procedure detailed in Lee and Ready (1991): a trade is classified as buyer initiated or seller initiated, respectively, if the trade price is above or below the quote midpoint of the most recent bid ask spread, or if the trade price is above or below the last executed trade price. Small (large) trades are defines a trades less than \$5,000 (\$50,000). For every stock and for each trade size bin we compute order imbalances (*Net Buy*) as the ratio buyer initiated volume minus seller initiated volume for firm j today to firm j average daily volume over the previous 250 trading days

$$Net\ \ Buy_{BIG} = \frac{BUY_{BIG} - SELL_{BIG}}{\overline{VOL}} \qquad Net\ \ Buy_{SMALL} = \frac{BUY_{SMALL} - SELL_{SMALL}}{\overline{VOL}} \qquad \overline{VOL} = \frac{1}{250}\sum_{s=-250}^{-1} VOL_s$$

where BUY is total buyer initiated volume in day t (number of shares), SELL is total seller initiated volume, and VOL is daily volume. We normalize *Net Buy* by subtracting from it the equal weighted average of *Net Buy* for all non-announcing firms that day. This figure includes firms in the period 1993 to 2000 with market capitalization (as of the previous month) above the median market capitalization of CRSP firms.

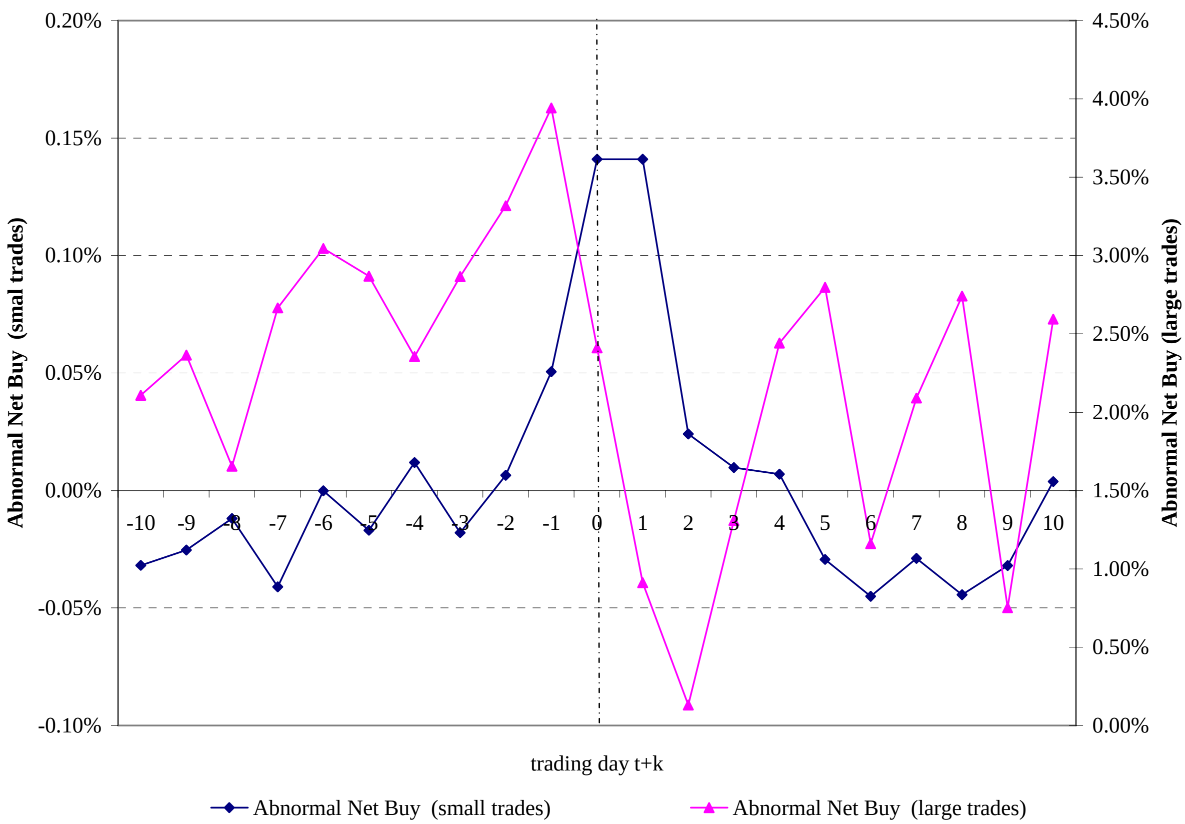
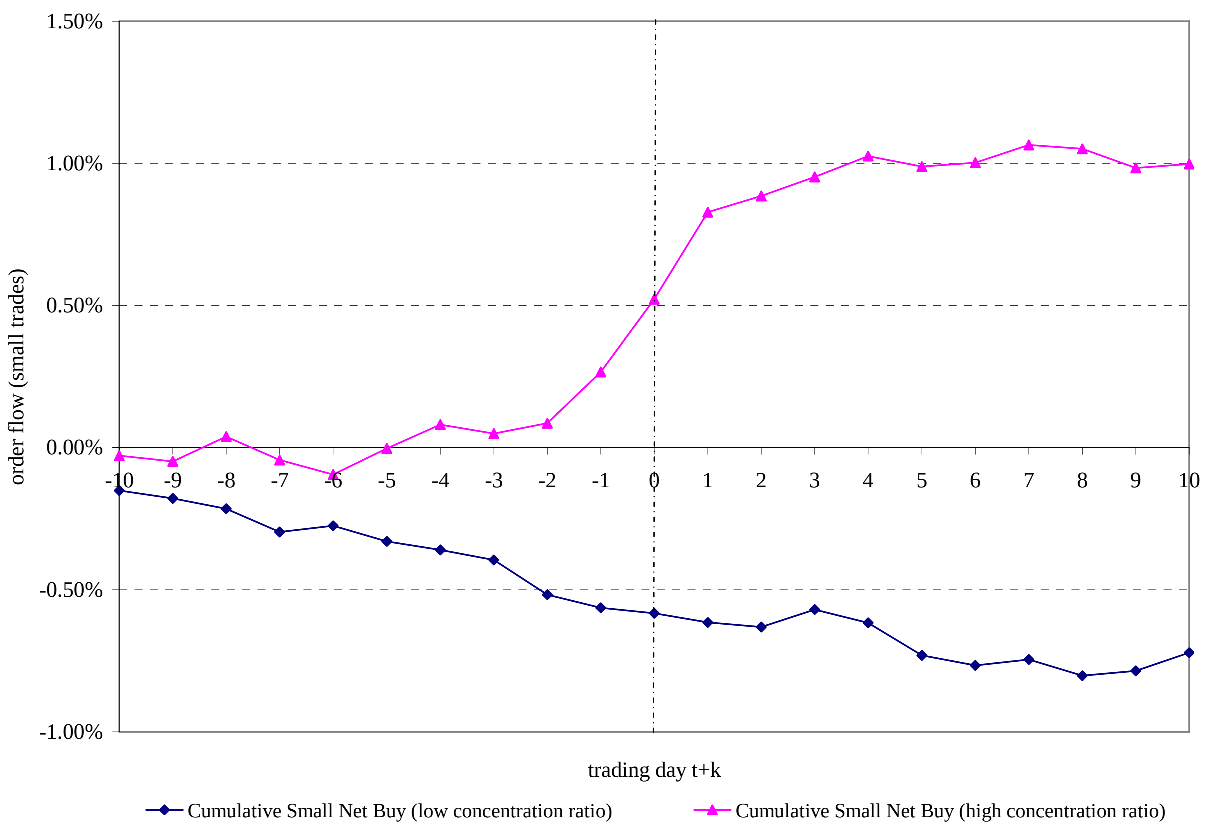


Figure 6: Order flow sorted by prior volume concentration ratio, 1993–2000

This figure shows event–time daily abnormal order flow in trading day t+k for firms announcing earnings at date t. We split trades based on dollar value of the trade and compute a measure of trade-initiation which captures which side of the trade demands immediate execution. Each trade on the TAQ tape as buyer or seller initiated using a procedure detailed in Lee and Ready (1991): a trade is classified as buyer initiated or seller initiated, respectively, if the trade price is above or below the quote midpoint of the most recent bid ask spread, or if the trade price is above or below the last executed trade price. Small (large) trades are defines a trades less than $5,000 ($50,000). For every stock and for each trade size we compute order imbalances (*Net Buy*) as the ratio buyer initiated volume minus seller initiated volume for firm j today to firm j average daily volume over the previous 250 trading days

$$Net\ \ Buy_{BIG} = \frac{BUY_{BIG} - SELL_{BIG}}{\overline{VOL}} \qquad Net\ \ Buy_{SMALL} = \frac{BUY_{SMALL} - SELL_{SMALL}}{\overline{VOL}} \qquad \overline{VOL} = \frac{1}{250}\sum_{s=-250}^{-1} VOL_s$$

where BUY is total buyer initiated volume in day t (number of shares), SELL is total seller initiated volume, and VOL is daily volume. We normalize *Net Buy* by subtracting from it the equal weighted average of *Net Buy* for all non-announcing firms that day. This figure includes firms with market capitalization (as of the previous month) above the median market capitalization of CRSP firms. We cumulate by trading days to obtain cumulative net buy. At the beginning of every calendar month stocks are ranked in ascending order on the basis of the volume concentration ratio defined as volume on the previous 16 announcements months divided by the total volume in the previous 48 months. We lagged volume concentration 3 months. This figure includes firms in the period 1993 to 2000 with market capitalization (as of the previous month) above the median market capitalization of CRSP firms. We plot small order flow for the top 20% high volume concentration ratio stocks and the bottom 20% low volume concentration ratio stocks.



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Appendix: fiscal year end method to predict announcements

In this section we describe the algorithm used to forecast announcement months based on fiscal year end. Table A1 shows the distribution of earnings announcement dates for CRSP/COMPUSTAT stocks by fiscal year end for the period 1973-2004. For every firm with a fiscal year ending in calendar month t, we report the fraction of earning announcements occurring in every calendar month. For each fiscal year end month, we highlight the four calendar months with the highest number of announcements. For example: firm with a fiscal year ending in December tend to announce in February (10.87% of the total number of announcements), April (18.98%), July (19.17%) and October (19.5%). Firms with a fiscal year ending in December tend to announce in March May, August and November, and so on.

We compute expected announcement month as follows. At the beginning of each calendar month t, we compute the frequency of announcements in table A1 using data available up to month t. We assign each firms to one two portfolios: if calendar month t+1 matches any of four calendar months with the highest number of announcements corresponding to the firms' fiscal year end month and we classify the firms as expected announcer in month t+1, provided that the firm did not have an announcement in month t. If calendar month t+1 does not match any of the four calendar months with the highest number of announcements corresponding to the firms' fiscal year end month, or the firms has an announcement in month t, we classify the firm as expected non-announcer in month t+1. For example, based on the second row of table A1, on the last trading day of January 2005 we would classify firms with fiscal year end ending April, October and December that did not have an announcement in January 2005, as expected announcers in February 2005.