The Evolution of Market Price Efficiency Around Earnings News

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ABSTRACT

This paper studies the speed of price discovery following earnings announcements over 40 years. I use earnings surprises and the idiosyncratic volatility on announcement days to examine the responsiveness of stock prices to earnings news. The main contribution of this paper is to show that, for all stocks, financial markets have become more efficient at incorporating earnings news rapidly into stock prices over time. In recent years, after conditioning on earnings surprises, post-earnings announcement drift is almost extinct. The growth in newswire coverage and significant changes in financial regulations coincide with significant improvements in market price efficiency around earnings announcements.

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The efficient market hypothesis lies at the heart of financial economics. If the efficient market hypothesis holds, then prices fluctuate unpredictably. However, several empirical studies challenge the efficient market hypothesis, especially around the release of public information.[1] For example, the post-earnings announcement drift (PEAD) anomaly that is the tendency of stock prices to drift in the same direction as earnings surprises, is densely documented (e.g., Ball and Brown, 1968, Bernard and Thomas, 1989).[2]

The financial market landscape has changed dramatically since the efficient market hypothesis was brought forward more than 50 years ago by Fama (1965) and Samuelson (1965). In light of the recent technological revolution in trading and data analysis and the rise in information production, how market price efficiency has evolved around the release of public information remains little understood.

In this paper, I ask: Have financial markets become more efficient at incorporating earnings news into stock prices? By more efficient, I mean whether stock prices reflect earnings news more rapidly following announcements, which relates to price discovery - one of the essential roles of financial markets (O'Hara, 2003). I focus on earnings announcements because it is one of the most anticipated firm-level news and the PEAD is perceived as strong empirical evidence against the efficient market hypothesis.

To answer this question is important in light of the recent body of work by Andrew Lo on the adaptive market hypothesis (see Lo, 2017). Contrary to the efficient market hypothesis, a central premise of the adaptive market hypothesis is that market efficiency is dynamic and not static. The dynamics are related to how market participants adapt to changes impacting the environment of financial markets, for instance, the rise in information production and

[1] Fama, Fisher, Jensen, and Roll (1969) present early evidence of market price efficiency around stock splits at the monthly frequency. Other important papers challenge the efficient market hypothesis without conditioning on public information. For instance, Lo and MacKinlay (1988) provide evidence that stocks prices do not follow random walks using variance estimators.

[2] Other significant papers on the implication of PEAD to market price efficiency includes Chan, Jegadeesh, and Lakonishok (1996), Sadka (2006), Hirshleifer, Lim, and Teoh (2009) and DellaVigna and Pollet (2009).

algorithmic trading.[3] If market participants have adapted to these changes, then financial markets should have become more efficient at rapidly incorporating earnings news into stock prices, in part, because these changes led to more news dissemination and facilitated the ability of investors to trade immediately to new information. What is not clear, however, is how the speed of price discovery has changed over time and what are some of the key events that have influenced the speed of price discovery. This paper sheds light on these issues.

The analysis undertaken in this paper is divided into three parts. First, I examine the evolution of PEAD after conditioning on earnings surprises (i.e., the difference between actual and expected earnings) and the evolution in the responsiveness of stock prices to earnings surprises on announcement days over time. Second, I examine the change in stocks' abnormal idiosyncratic volatility on announcement days as an alternative measure of stock price responsiveness to earnings news over time. Idiosyncratic volatility is commonly used as a measure of firm-specific information flow (see, Engelberg, Gao, and Jagannathan, 2008, Griffin, Hirschey, and Kelly, 2011). The benefits of using idiosyncratic volatility are that it can reflect other information content not captured by earnings surprises and it increases the number of earnings announcements in my analysis (relative to solely using earnings surprises). Lastly, I examine the potential sources underlying the evolution of market price efficiency around earnings announcements.

The first set of results presents the evolution of PEAD for the full sample and for large (S&P 1500) and small (non-S&P 1500) stocks separately.[4] I begin by plotting price drifts, which are buy-and-hold abnormal returns (BHAR) after conditioning on earnings surprises, -10 to +61 trading days around earnings announcements. For the full sample, I find that price drifts following announcements gradually disappear over time. Since 2011, I find no signifi-

[3]Previous research finds that recent changes in financial markets such as the rise of algorithmic trading and market fragmentation to be beneficial to market quality (see, Hendershott, Jones, and Menkveld, 2011, O'Hara and Ye, 2011, Conrad, Wahal, and Xiang, 2015).

[4]It is well known that PEAD are more persistent for small stocks (e.g., Bhushan, 1994, Chordia, Goyal, Sadka, Sadka, and Shivakumar, 2009). Therefore, it is important to also examine the change in PEAD only for the smallest U.S. stocks (e.g., non-S&P 1500 stocks).

cant price drifts following earnings announcements. The only evidence of price drifts occurs in the top and bottom deciles of earnings surprises for non-S&P 1500 stocks. Nonetheless, these drifts have become less persistent over the years.

If indeed, price drifts have become less persistent following earnings announcements, then stock prices should reflect more of the earnings surprise on the announcement day. To examine this premise, I use 5-year rolling OLS regressions to estimate the impact of earnings surprises on announcement day returns (BHAR on days[0,1]). I find a positive and significant trend over time in the estimated coefficients. Stock prices of S&P 1500 stocks and non-S&P 1500 stocks are eight and four times more responsive to earnings surprises on announcement days in 2010-2015 than in the first five years of the sample (1984-1989), respectively. Consistent with prices reflecting earnings surprises more rapidly on earnings announcement days, I find that the impact of earnings surprises on price drifts (BHAR on days[2,61]) is not statistically significant since 2008 for S&P 1500 stocks. For non-S&P 1500 stocks, however, coefficients remain statistically significant and positive over the years. However, I observe a modest downward trend in the estimated coefficients.

The second set of results consists of an analysis of the evolution in abnormal idiosyncratic volatility (AIVOL) on earnings announcement days.[5] I measure AIVOL as the difference between idiosyncratic volatility on announcement days relative to non-announcement days. If stock prices become more responsive to earnings news, then there should be a significant increase in AIVOL. It is only after the year 2000 that I begin to observe a significant increase in AIVOL. In 2015, idiosyncratic volatility on announcement days relative to non-announcement days is 150% and 50% greater for S&P 1500 and non-S&P 1500 stocks, respectively. This increase in idiosyncratic volatility has significant repercussion on the calculation of stocks' idiosyncratic volatility at the monthly frequency. I find that in recent years, the cross-sectional average in monthly idiosyncratic volatility for months with earnings announcements

[5] Other papers that study idiosyncratic volatility around earnings announcements include Bailey, Li, Mao, and Zhong (2003) and Jiang, Xu, and Yao (2009).

increased by more than 30 percent relative to non-announcement months.

To my knowledge, this is the first paper that presents evidence of less persistent PEAD over time and that markets have become more efficient at incorporating earnings news rapidly into stock prices. The path towards more efficient prices following earnings announcements appears in time to be gradual. However, it is at the turn of the century that I begin to see a significant and positive trend in stock prices responsiveness to earnings surprises and in AIVOL on announcement days. Moreover, I observe a significant structural break (positive jump) in AIVOL on July of 2002.

To uncover which factors are the primary sources underlying the improvement in the speed of price discovery appears like a daunting task. I begin answering this question by focusing on an important factor influencing the incorporation of news into stock prices documented in the finance and accounting literature, that is, investor attention (see, Peress, 2008, DellaVigna and Pollet, 2009, Hirshleifer, Lim, and Teoh, 2009, 2011, Boulland, Degeorge, and Ginglinger, 2017, Boulland and Dessaint, 2017). This literature finds less persistent PEAD when investors pay more attention to earnings announcements.

I investigate how investor attention to earnings announcements has changed over time using two proxies of attention: the number of analysts forecasts from I/B/E/S and the amount of media coverage surrounding firms' earnings announcements from the Dow Jones (DJ) Newswire database.[6] A firm with more analysts and media coverage will have more news dissemination around its earnings announcement, therefore, it will capture the attention of more investors.[7]

I highlight the change in investor attention through the evolution in news dissemination for S&P 500 and non-S&P 500 stocks. I emphasize the difference between S&P 500 and

[6] I choose these two proxies because Hong, Lim, and Stein (2000) argues that analysts coverage is a good measure of the amount of firm news propagated by analysts and Tetlock, Saar-Tsechansky, and Macskassy (2008), Tetlock (2011) and Boulland, Degeorge, and Ginglinger (2017) use DJ to capture investor attention to earnings news.

[7] I further argue that the number of analysts following a firm and the number of news articles written about a firm reflects the demand from investors to learn more about the particular firm. Hence, it reflects the willingness of investors to pay more attention to earnings news.

non-S&P 500 stocks because recent research shows that changes in information technology in data processing benefited more the largest firms for the reason that large firms have a longer history of data to process (see, Begenau, Farboodi, and Veldkamp, 2017, Farboodi, Matray, and Veldkamp, 2017). In turn, large firms grow even larger because of a lower cost of capital. Because analysts and newswire coverage consists of information production, it is important to differentiate how both proxies of investor attention change over time for both S&P 500 and non-S&P 500 stocks to make sure that the largest stocks do not solely drive my findings.

I find that the median number of analysts following a S&P 500 stock has increased significantly, from five analysts in 1984 to 14 in 2015. For a non-S&P 500 stock, I observe a modest increase, from two analysts in 1984 to four in 2015. The DJ newswire data shows that the total number of newswire articles on U.S. stocks increased from approximately 10,000 articles in 1980 to 100,000 articles in 1995, to staggering new heights of approximately 400,000 articles in 2000. Similarly to analysts coverage, newswire coverage (in the number of articles) is largely dominated by large stocks. In general, firms in the S&P 500 receive ten times more news coverage than non-S&P 500 firms.[8] On earnings announcement days, all firms receive significantly more news coverage over time, and on average, a S&P 500 firm earns twice as much coverage than a non-S&P 500 firm on announcement days. Consistent with the previous literature on investor attention around earnings announcements, the increase in analysts and newswire coverage can explain why earnings news incorporate prices more rapidly over time.

I then examine how analyst and newswire coverage influence stock prices responsiveness around earnings announcement to confirm whether more coverage does benefit the speed at which earnings surprises incorporate prices. I find that, for all stocks, more newswire coverage benefit the speed at which earnings news is reflected in stock prices. First, more abnormal

[8]However, the fraction of newswire coverage for non-S&P 500 stocks increases over time relative to S&P 500 stocks.

newswire coverage before the announcement makes stock prices *less* responsive to earnings surprises on announcement days.[9] This result conveys that more newswire coverage leads to more information dissemination about the firm (e.g., updates on firm performance) before the announcement day. Consequently, prices adjust to this information and are less responsive to earnings surprises on announcement days because earnings surprises contain some stale information.[10] Second, more abnormal newswire coverage on the announcement day increases the responsiveness stocks' prices to earnings surprises, which implies that newswire coverage facilitates earnings news dissemination. These results are robust to different time periods in my sample. In contrasts to newswire coverage, I find no robust findings regarding the role of having more analyst coverage to the price responsiveness to earnings surprises.[11]

Besides investor attention, what other factors may have influenced the speed of price discovery? Visualizing AIVOL on announcement days shows discrete positive changes and trends over time. I examine whether these are a result of new financial regulations and changes in the market architecture (e.g., fragmentation of stock exchanges). I find that significant positive increases in AIVOL on earnings announcement days coincides with important financial regulations, precisely, the Sarbanes-Oxley Act (SOX) and Regulation National Market System (Reg NMS). The objective of SOX was to improved the transparency and disclosure of earnings, which may have facilitated the ability of investors to process and understand the implication of an earnings news on firms' fundamentals. The structural break (positive jump) that I observe in AIVOL on July 2002 occurs precisely at the passage of SOX. As for Reg NMS, it led to the proliferation of algorithmic trading because it provided strong incentives for trading venues to automate (Jones, 2013). Consequently, traders can trade

[9] I define in Section IV the definition of abnormal analysts and abnormal newswire coverage. It is related to the work of Hong, Lim, and Stein (2000), and it has for objective to control for firm fixed-effects.

[10] An earnings surprise contains stale information because expected earnings are from analysts estimates that are released at different periods before the earnings announcement. Therefore, older analysts estimates relative to the announcement date will contain more stale information.

[11] However, I do not rule out the implication of analysts coverage to price formation because in the newswire dataset, a large fraction of news reports analysts forecasts and opinions.

or adjust prices at the time of an earnings announcement more rapidly. If indeed these regulations are the main reasons underlying the improvement in the speed of price discovery, though causally proving this remains difficult, it suggests that both greater transparency and technological progress led to an improvement in market price efficiency.

The findings of this paper contribute to recent research on market price efficiency. Bai, Philippon, and Savov (2016) show significant improvement in the efficiency of stock prices at reflecting future earnings in the medium and long horizons, but only for S&P 500 stocks. Their findings provide evidence of an improvement in price informativeness related to the revelatory price efficiency, which is, the market-based component of price informativeness that contributes to the efficiency of capital allocation (see Bond, Edmans, and Goldstein, 2012). Farboodi, Matray, and Veldkamp (2017) show that the rise in price informativeness documented in Bai, Philippon, and Savov (2016) comes from a composition effect because S&P 500 firms are getting older and larger. Begenau, Farboodi, and Veldkamp (2017) provide a model to demonstrate that large firms, with more economic activity and a longer firm history, offer more data to process to investors, and consequently, reduce the firms cost of capital because the data can better forecast firm value and reduce the risk of equity investment. Other important papers that cast doubt on the benefit of data abundance (i.e., big data) now available to price informativeness include Dugast and Foucault (2017) and Grennan and Michaely (2017). Contrary to this recent research development, this paper focuses on price informativeness around the release of firm-specific news and analyzes the evolution in the speed at which news incorporates into stock prices.

I. Earnings Announcement Samples

I use two earnings announcement samples to study price discovery around earnings announcements. The first sample consist of firms with reported earnings and earnings announcement dates from Compustat. The second sample consists of firms from Compustat but with at least one earnings forecast in I/B/E/S. For the construction of both samples, I impose the following selection criteria for each earnings announcement i for firm-quarter q:

1. The earnings announcement date is reported in Compustat.
2. The price per share is available from Compustat as of the end of quarter q and is greater than \$1 and the stock market capitalization is greater than \$5 million.
3. The firm's shares are traded on the New York Stock Exchange (NYSE), American stock Exchange, or NASDAQ.
4. Accounting data are available to assign the stock to one of the 25 size and book-to-market Fama-French portfolios using the NYSE breakpoints.

The sample period for the Compustat sample and the I/B/E/S sample begins in 1973 and 1984, respectively, and both samples end on December 31, 2015.[12] The total number of earnings announcements is 611,681 for the Compustat sample and 274,107 for the I/B/E/S sample. Figure 1 shows the total number of earnings announcements and the number of unique firms per year for both samples. Both figures capture the rise and fall in the number of U.S. publicly-listing firms (see, Doidge, Karolyi, and Stulz, 2017).

Figure 2 shows the median and the 10th-90th percentile range in stock market capitalization in Panel A and stock price at the end of quarter q of the respective quarterly earnings announcement in Panel B for the I/B/E/S sample firms for S&P 1500 and non-S&P 1500 stocks. It is important to differentiate between S&P 1500 and non-S&P 1500 stocks because the smallest market capitalization stocks are expected to have more persistent PEAD following earnings announcements (e.g., Bhushan, 1994, Chordia, Goyal, Sadka, Sadka, and Shivakumar, 2009). Therefore, my also examines price drifts only for small stocks.[13] Consistent with the findings of Farboodi, Matray, and Veldkamp (2017), the figure shows that the

[12]The sample coverage in I/B/E/S starts in 1983, but just a limited number of firms are covered in I/B/E/S, and that meet the selection criteria.

[13]S&P 1500 firms represent about 90% of the total U.S. market capitalization.

largest firms in the tail distribution among S&P 1500 stocks have become larger over time.

A. Estimating earnings surprises

I use earnings surprises as a measure of unexpected news about fundamentals on earnings announcement days. I define the earnings surprise as:

$$Surprise_{i,t} = \frac{\text{EPS}_{i,t} - E_{t-1}[\text{EPS}_{i,t}]}{P_{i,t-5}}, \tag{1}$$

where $\text{EPS}_{i,t}$ is the earnings per share of earnings announcement i for a firm announcing on day t, and $E_{t-1}[\text{EPS}_{i,t}]$ is the expectation of earnings per share, measured by the consensus analyst forecast. I define the consensus analyst forecast as the median of all analyst forecasts issued over 90 days before the earnings announcement date. If analysts revise their forecasts during this interval, I use only their most recent forecasts. I further scale the surprise by the firm's stock price five trading days before the announcement. Moreover, I winsorized earnings surprises at the 1st and 99th percentile. I choose this measure of surprise over the simple random-walk approach because past research shows that price drifts are more persistent following earnings announcements when surprises are calculated using analysts forecasts (see, Livnat and Mendenhall, 2006).

Table I reports the summary statistics for earnings surprises, in percent, for S&P 1500 and non-S&P 1500 stocks at different time intervals from 1984. The table shows that the average earnings surprise is negative, but the median is positive. In the earlier part of the sample, the distribution of earnings surprises is more negatively skewed and becomes less skewed in recent years. This change in skewness is more evident in Figure 3, Panel A. This figure shows the median and the 10th-90th percentile range of earnings surprises. After 1995, the distribution of earnings surprises remains stable, except during the financial crisis of 2008 where the distribution of earnings surprises widens significantly.

I plot in Panel B, the median and the 10th-90th percentile range of analyst dispersion in analyst forecasts since 1984. Analyst dispersion is commonly used as a measure of investor disagreement about future earnings. I measure analyst dispersion in expected earnings as:

$$dispersion_{i,t} = \frac{\sqrt{V_{t-1}[EPS_{i,t}]}}{|E_{t-1}[EPS_{i,t}]|}, \tag{2}$$

where V_{t-1} is the variance of all earnings forecasts that analysts issue for firm-announcement i within ninety days before the announcement date t. I calculate this measure for earnings announcements with at least four analysts forecasts. The median dispersion remains stable since the 1980s. But, the distribution significantly widens during the financial crisis of 2008. High dispersion in analysts forecasts can influence the relationship between stock returns and earnings surprises (see, Kinney, Burgstahler, and Martin, 2002) and, as some of my results show, the responsiveness of stock prices to earnings surprises weakens during the financial crisis.

II. The Evolution of Price Discovery Following Earnings Surprises

How do stock prices respond to earnings surprises? How did it change over time? In this section, I first visualize price drifts after conditioning on earnings surprises followed by a regression analysis of the impact of earnings surprises on stock returns on the announcement and subsequent days.

A. Visualizing price drifts

To visualize price drifts, I follow Hirshleifer, Lim, and Teoh (2009) and calculate abnormal daily returns to account for return premium associated with size and book-to-market. I deduct from stock returns the return on the size and book-to-market benchmark portfolios obtained from Ken French's website.[14] Stocks are matched to one of 25 portfolios at the end of June of every year based on their market capitalization at the end of June and their book-to-market ratio, calculated as the book equity of the last fiscal year end in the prior calendar year divided by the market value of equity at the end of December of the previous

[14]Data source: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

year. I define buy-and-hold abnormal returns (BHAR) for stock-earnings announcement i from day τ to T ($\tau < T$) as:

$$BHAR[\tau, T]_i = \prod_{k=\tau}^{T}(1 + R_{i,k}) - \prod_{k=\tau}^{T}(1 + R_{p,k}), \tag{3}$$

where $R_{i,k}$ is the daily return of the stock-earnings announcement i and $R_{p,k}$ is the return on the size and book-to-market matching Fama-French portfolio on day k.

Figure 4 shows BHAR from ten trading days before the earnings announcement (τ=-10) to 61 trading days following the announcement (T=61) for each earnings surprise quintiles at different periods since 1984 for the I/B/E/S sample. The shaded area corresponds to the pointwise 95% confidence intervals around BHAR.

Because I do not know the precise timestamp of the earnings announcement release, day 0 corresponds to the date of the earnings announcement and the following trading day. I must combine both trading days because if a firm announces its earnings after 4 p.m., then such announcement is impounded in the stock price only on the following trading day. Precise earnings announcement time for recent earnings announcements can be retrieved using intraday newswires. Since 1996, I/B/E/S provide earnings announcement timestamps, but when I compare timestamps from I/B/E/S and to those from an intraday newswire database like Dow Jones, I find several mismatches across timestamps. Intraday newswire timestamps are more accurate (see, Santosh, 2016, Li, 2016, Grégoire and Martineau, 2018).

Figure 4 shows a clear demarcation in price drifts across earnings surprises quintiles following earnings announcements for all periods and highlights the evolution in price drifts since 1984. Between 1984 to 1990 I observe slow and continuous price drifts following earnings announcements. From 1991 to 2010, price drifts gradually become less persistent over time. In the latter part of the sample, from 2006 to 2010, I observe price drifts only for the top and bottom earnings surprises. Top earnings surprise quintiles have more pronounced drifts than bottom earnings surprise quintiles, consistent with the findings of Doyle, Lundholm, and Soliman (2006). But from 2011 to 2015, I find no pronounced price drifts following earnings announcements. Altogether, the evolution in price drifts shows that markets have become more efficient at quickly incorporating earnings surprises into stock prices, and that price discovery mainly occurs on the announcement day.

Figure 4 also shows a trend in pre-drifts, i.e., price drifts leading to the earnings announcement on day 0. To explain this phenomenon is beyond the scope of this paper, but one potential factor contributing to the disappearance of pre-drifts can be attributed to Regulation Fair Disclosure (Reg FD). This regulation restricts firms to release all information pertinent to a earnings result at the scheduled earnings announcement day. This regulation aimed at reducing information leakage and to make sure that all investors have access to the same information at the same time (Bailey, Li, Mao, and Zhong, 2003, Michaely, Rubin, and Vedrashko, 2014).

It is expected, however, that PEAD is more pronounced for small stocks than for large stocks (e.g., Bhushan, 1994, Chordia, Goyal, Sadka, Sadka, and Shivakumar, 2009). For the period of 2011 to 2015, I plot in Figure 5, BHAR for S&P 1500 and non-S&P 1500 stocks. The figure shows that price drifts following earnings announcements for S&P 1500 stocks are nonexistent. But for non-S&P 1500 stocks, moderate price drifts are present at long horizon following earnings announcements in the top and bottom earnings surprise quintiles.

Similarly, in Figure 6, I plot BHAR for the top and bottom earnings surprise deciles for the period of 2010 to 2015. There are no price drifts for S&P 1500 stock, but there are price drifts for non-S&P 1500 stocks. What this figure suggest is that the apparent price drifts in Figure 5 Panel B are driven by big surprises of small stocks (non-S&P 1500).

I then examine more closely the persistence of price drifts in the top and bottom earnings surprise deciles. Table II, reports the mean BHAR for various trading day intervals following earnings announcements since 1984. Numbers in bold are the mean BHAR that are statistically different from zero at the 5% statistical significance. Standard errors are clustered by firm and announcement date for BHAR[0,1] and by firm and calendar quarter of the announcement date for the remaining BHAR.

Two important findings emerge from this table. First, mean BHAR vary considerably over the years and remain statistically significant other than the recent period of 2011-2015 for S&P 1500 stocks. Second, the persistence in price drifts has changed over the years. Despite that non-S&P 1500 stocks still have some statistically significant price drifts in recent years, price drifts are less persistent over the course of 60 trading days following the announcement. I find significant drifts in the first trading week following earnings announcements and closer to the 60th trading day, which often coincides with the following announcement.

I next study the evolution of price drifts following big earnings surprises from another angle. In Figure 7, I plot the mean difference in BHAR[5,61], 5 to 61 trading days following earnings announcements, between big positive surprises (Surprise $\geq$ 0.5%) and big negative surprises (Surprise $\leq$ -0.5%) for every year since 1984. Keeping the earnings surprise cutoff fix helps to mitigate fluctuations in earnings surprises shown in Figure 3. |0.5%| correspond to earnings surprises outside the 10th-90th percentile range, to approximately 2,035 stock-earnings observations, and about 23% of the total number of stock-earnings observations in a given year. Moreover, the chosen cutoff puts more weight on the number of observations to small stocks (non-S&P 1500) because small stocks are more likely to have large surprises as shown in Table I. I choose BHAR[5,61] because I am interested in long-horizon price drifts and not short horizon drifts (less than a week) that follow earnings announcements.

Figure 7 shows that the mean difference in BHAR[5,61] is statistically different from zero at the 5% confidence level before 2008 with standard errors clustered by calendar quarter. However, around 2000, the mean difference of BHAR[5,61] begins to gradually decay. In recent years, the mean difference is not statistically different from zero. Therefore, long horizon price drifts for large earnings surprises gradually become less persistent. What this figure further conveys is that a momentum strategy conditioned on earnings surprises, e.g., go long on large positive earnings surprises stocks and short, large negative surprises, generate lower returns over the years.

Overall, results of this section paint a clear picture that markets have become more efficient at incorporating earnings surprises into stock prices following earnings announcements. The only evidence of price drifts following announcements in recent years occurs for small stocks (non-S&P 1500 stocks) following large surprises. Nonetheless, these price drifts have become less persistent over time.

B. Quantifying the impact of earnings surprises on BHAR

If price drifts become less persistent over the years, then stock prices should reflect more of the earnings surprise on announcement days. Therefore, stock prices must have become more responsive to earnings surprises on the announcement day. I examine this hypothesis in this section.

Table III reports coefficient estimates of the following regression model

$$BHAR[\tau, T]_i = \alpha + \beta Surprise_i + e_i, \tag{4}$$

where $BHAR[\tau, T]_i$ is either BHAR[0,1] or BHAR[2,61] for stock-earnings announcement i, and $Surprise_i$ is the earnings surprise defined in Equation (1). Panel A to C report the coefficients estimates for BHAR[0,1] and Panel D to F for BHAR[2,61] as dependent variable broken down by different sample groups: full sample, S&P 1500 stocks, and non-S&P 1500 stocks.

Results of Panel A to C in Table III show that the impact of earnings surprises on BHAR[0,1] (β coefficients) gradually increases from 1984 to 2015. The impact of earnings surprises on BHAR[0,1] is always greater for S&P 1500 than for non-S&P 1500 stocks. The R^2 also increases, from 1% to 6% for the full sample, from 1% to 8% for S&P 1500 stocks, and from 2% to 6% for non-S&P 1500 stocks.

Panel D to F of Table III show a decrease in the response of BHAR[2,61] to earnings surprises in the last 20 years. Moreover, between 2010 and 2015, earnings surprise coefficients for S&P 1500 stocks are not statistically significant.

I then analyze time trends in the price response to earnings surprises. I estimate the following 5-year rolling regressions

$$BHAR[0,1]_i = \alpha + \beta Surprise_i + \epsilon_i, \tag{5}$$

$$BHAR[2,61]_i = \alpha + \beta Surprise_i + \epsilon_i, \tag{6}$$

for S&P 1500 and non-S&P 1500 stocks separately. Figure 8 shows the estimated β and estimated trend lines of β. Panel A and B show positive trends in the estimated β coefficients and the trend is more steep for S&P 1500 stocks, close to a 45 degree angle, than for non-S&P 1500 stocks. These results indicate that, over time, stock prices reflect more of the earnings surprise on announcement days.

For the impact of earnings surprises on long-run returns (BHAR[2,61]), the estimated coefficients β of Equation (6) for S&P 1500 stocks show no trends since 1984. However, from 2000, there is a clear downward trend in the estimated β coefficients. After 2007, I observe no statistical significance in the estimated β. For non-S&P 1500 stocks, I find no negative and statistically significant trends, but the β have been decreasing slightly since 2000.

Altogether, the main findings of this section suggest that stock prices on earnings announcement days have become more responsive to earnings surprises and that earnings surprises lose predictable power to explain stock returns at long-horizon following earnings announcements. These results indicate that financial markets have become more efficient at incorporating earnings surprises into stock prices on announcement days.

III. Idiosyncratic Volatility Around Earnings Announcements

One concern with the previous analysis is that the measure of earnings surprises reflects only one component of the earnings news. A second matter is that earnings surprises restrict the sample of earnings announcements because not all stocks have analysts' earnings forecasts.

To partially overcome these concerns, I study the change in stocks' abnormal idiosyncratic volatility around earnings announcement at the daily and monthly frequency using the Compustat sample. Idiosyncratic volatility (IVOL) is commonly used as a measure of stock price response to firm-specific news (e.g., Ross, 1989, Landsman and Maydew, 2002, Tetlock, 2011). IVOL can capture other unexpected news components not reflected in earnings surprises. Also, the Compustat sample begins in 1973 and increases the number of announcements by about 120% relative to the I/B/E/S sample, which starts in 1984.

A. Daily idiosyncratic volatility

I follow Ang, Hodrick, Xing, and Zhang (2006) and calculate for stock i its idiosyncratic volatility relative to the Fama-French three-factor model as:

$$r_t^i = \alpha_i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \epsilon_t^i. \tag{7}$$

The above equation is estimated using 250 trading days in a rolling OLS regression. I follow Barber, De George, Lehavy, and Trueman (2013) and calculate the abnormal idiosyncratic volatility (AIVOL) for each stock as:

$$AIVOL_{i,t} = \sqrt{\frac{(\epsilon_t^i)^2}{(\bar{\epsilon}_{non}^i)^2}}, \tag{8}$$

where $(\epsilon_t^i)^2$ is the squared residual from Equation (7) for earnings announcement on day t and $(\bar{\epsilon}_{non}^i)^2$ is the average of the daily squared residuals over the non-announcement period for stock i. I define the non-announcement period as trading days outside the [-3, 3] trading day window around the announcement. The AIVOL measure can be interpreted as the percentage by which idiosyncratic volatility on the earnings announcement day exceeds the average volatility on non-announcement days.

In Figure 9, I plot the average AIVOL on two consecutive trading days across all stocks around earnings announcements for days[-2,-1], [0,1] (the announcement), and [2,3].[15] From

[15]For example, the AIVOL on days[0,1] is (AIVOL $_t$+ AIVOL $_{t+1}$)/2, where t is day 0, the earnings announcement day, and $t + 1$ is the following trading day.

1970 to 2000, there is a slight increase in AIVOL on earnings announcement days[0,1] and before 2000, AIVOL is approximately zero. However, post-2000, there is a significant increase in AIVOL. In the recent years, abnormal idiosyncratic volatility is approximately 80% greater than non-announcement days.

In Figure 10, I plot from 1974 to 2015 the cross-sectional average of AIVOL on days[0,1] for S&P 1500 and non-S&P 1500 stocks at the quarterly and monthly frequencies. The figure shows a significant and sudden increase in AIVOL after 2000. By 2015, idiosyncratic volatility is 150% and 60% greater than non-announcing days for S&P 1500 and non-S&P 1500 stocks, respectively. What led to this sudden increase in AIVOL after 2000 and especially the jump in AIVOL on July 2002 are issues that I will investigate in Section IV.

B. Monthly idiosyncratic volatility

A direct implication of the significant increase in idiosyncratic volatility on earnings announcement days is that the idiosyncratic volatility at the monthly frequency may have increased as well relative to non-announcing months. Since 2003, Brandt, Brav, Graham, and Kumar (2009) document a downward trend in idiosyncratic volatility following an upward trend from 1962 to 1997, as shown in Campbell, Lettau, Malkiel, and Xu (2001).

I follow Ang, Hodrick, Xing, and Zhang (2006) and calculate the monthly frequency idiosyncratic volatility as:

$$IVOL_m^i = \sqrt{var(\epsilon_t^i)} \cdot \sqrt{N}, \tag{9}$$

where $\epsilon_{i,t}$ is the estimated residual from Equation (7) and N is the number of trading days in month m for stock i. I exclude stocks with less than 15 trading days in a month.

Figure 11 Panel A shows the average change in monthly IVOL, from month $m-1$ to m, where month m is the earnings month, for S&P 1500 and non-S&P 1500 stocks from 1974 to 2015. The figure paints a clear picture of an increase in IVOL on announcement months. But, similarly to Figure 10, the increase in the monthly IVOL occurs after 2000, and the increase is more pronounced for S&P 1500 stocks.

Panel B shows a significant downward trend in the change of IVOL, from month m to $m+1$, where month $m+1$ is the month following the earnings announcement month. Therefore, the increase in IVOL on earnings announcement days has a significant impact on IVOL at the monthly frequency only in the month of the earnings announcement.

Figure 12 shows the cross-sectional average of IVOL on earnings announcement months over IVOL of non-announcing months. The figure shows a similar trend as previous figures, and in 2015, IVOL for earnings announcement months are approximately 30% greater than non-earnings announcement months.

Overall, the results of this section confirm that stock prices have become more responsive to earnings news on announcement days but only after 2000. In the next section, I investigate some of the potential causes for the improvement in the speed at which stock prices reflect earnings surprises and to the increase in AIVOL.

IV. Possible Explanations for the Improvement in the Speed of Price Discovery

What are the key drivers underlying the significant improvement in the speed of price discovery following earnings announcements? Several factors come to mind, ranging from the spur in trading volume and increase in market liquidity to the growing presence of information technology (e.g., algorithmic and high-frequency trading) in financial markets. Nonetheless, causally answering this question remains difficult.

To partially address this question, in this section, I first investigate how a key determinant previously documented in the finance and accounting literature that is known to influence price response to earnings news changes over time, that is, investor attention. Several empirical research shows that more investor attention to earnings news leads to less persistent price drifts following earnings announcements (see, Peress, 2008, DellaVigna and

Pollet, 2009, Hirshleifer, Lim, and Teoh, 2009, Boulland and Dessaint, 2017). I then analyze whether there are important events in financial markets that coincide with the jump and positive trends in abnormal idiosyncratic volatility (AIVOL) on earnings announcement days as shown in Figure 10.

A. The evolution in news dissemination

To examine changes in investor attention around earnings announcements I use two standard proxies of investor attention: analysts coverage in I/B/E/S and media coverage from the Dow Jones (DJ) Newswire. The number of analysts following a firm may influence the speed of price discovery. For example, Hong, Lim, and Stein (2000) argue that firms that sit on bad news (e.g., lower than expected earnings) will have less incentive to bring investors up to date quickly. Thus, analysts play an important role in getting the news out about current and future expected earnings. Firms' media coverage also plays an essential role in how prices respond to earnings news. Boulland, Degeorge, and Ginglinger (2017) find that when European firms adopt modern news dissemination technology, i.e., newswire services, less persistent are price drifts following earnings announcements.

I begin with a descriptive analysis of how analysts and newswire coverage changes for S&P 500 and non-S&P 500 stocks over time. Recent works by Begenau, Farboodi, and Veldkamp (2017) and Farboodi, Matray, and Veldkamp (2017) argue that changes in information technology in data processing benefited more the largest firms (S&P 500) because large firms have a longer history of data to process. Because analysts and newswire coverage consists of information production, it is essential to understand how both proxies of investor attention change over time and how it affected price discovery separately for S&P 500 and non-S&P 500 stocks to make sure that the largest U.S. stocks do not solely drive my findings.

Figure 13 shows the median number of analyst forecasts for S&P 500 and non-S&P 500 stocks. The median number of analyst following a S&P 500 stock has almost triple, from five in 1984 to approximately 14 in 2015 whereas the number of analysts following a non-S&P

500 stock has doubled, from two to four.

I then examine the evolution in newswire coverage. The left plot in Figure 14 Panel A shows the number of DJ newswire articles for S&P 500 and non-S&P 500 stocks. I observe a sudden growth in the number of newswire articles for U.S. firms at the turn of the century and the growth continued for another ten years, for all stocks.

The second and third plots of Panel A show the fraction of the total newswire coverage and the average number of newswires per stock for S&P and non-S&P 500 stocks, respectively. I find that the fraction of the total number of newswire articles about non-S&P 500 (S&P 500) stocks grows (decreases) by approximately 10%. By 2015, 70% of all newswire articles on U.S. stocks concern non-S&P 500 stocks. The third plot shows that before 2005, the average number of newswire articles for S&P 500 stocks is about four times higher than non-S&P 500 stocks. After 2005, this number decreases to approximately two in 2015. Therefore, the overall decrease in newswire coverage shown in the left figure of Panel A impacted S&P 500 stocks more than non-S&P 500 stocks.

Figure 14 Panel B shows the number of news articles at different time periods around earnings announcements. Over the years, both S&P 500 and non-S&P 500 stocks receive more newswire coverage on earnings announcement days (days[0,1]). Panel C shows the fraction of earnings announcements with at least one news articles on earnings announcement days. Before 1997, for approximately 40% (20%) of earnings announcements for S&P 500 stocks (non-S&P 500 stocks) generates at least one newswire article. These numbers increased to approximately 100% in 2000. One explanation as to why there is a sudden increase in media coverage around earnings announcements in 2000 can be attributed to Regulation Fair Disclosure (Reg FD) that require firms to disclose earnings information as soon as available through press releases to all investors at the same time (Dyck and Zingales, 2003, Michaely, Rubin, and Vedrashko, 2014, Boulland, Degeorge, and Ginglinger, 2017).

A.1. The role of news dissemination for price response to earnings surprises

Despite a significant increase in analysts and newswire coverage, it is still not clear whether more coverage influence stock prices' responsiveness to earnings surprises on announcement days. Moreover, it is possible that only the largest firms benefited from this substantial increase in coverage. I examine these issues next.

Similarly to Hong, Lim, and Stein (2000), I calculate the "residual" media and analysts coverage to control for various firm-specific and time-varying characteristics that can influence the amount of coverage a firm receives. I first winsorize the number of analyst forecasts, the total number of newswire articles on earnings announcement days[0,1], and the total number of newswire articles from [-60,-2] tradings days before the earnings announcement at the 1st and 99th percentiles. I then regress the number of analyst forecasts, the total number of news articles on earnings announcement day, and the total number of news articles 60 trading days before the earnings announcement on the firm log market capitalization and on industry and time fixed-effects for S&P 500 and non-S&P 500 stocks separately.[16] I further include the signed earnings surprise and its absolute value in the regression when the dependent variable is the total number of news articles on the earnings announcement day. I use the residual of each regression as measures of abnormal analysts and newswire coverage.

To examine the role of analysts and newswire coverage to stock price responsiveness to earnings surprises, I estimate the following regression:

$$\begin{aligned} BHAR[0,1]_i = &\alpha + Surprise_i + Surprise_i \cdot Analyst_i + Surprise_i \cdot News_i^{EA} + \\ &Surprise_i \cdot News_i^{Before} + Analyst_i + News_i^{EA} + News_i^{Before} + \epsilon_i, \end{aligned} \tag{10}$$

where *Analyst* is a dummy equal to one if a stock has higher than the median abnormal number of analyst forecasts before its announcement, zero otherwise. $News^{EA}$ is a dummy equal to one if a stock followings its earnings announcement on days[0,1] has higher than the

[16] I use the ten Global Industry Classification Standard sector codes as industry dummy variables.

median abnormal number of newswire articles, zero otherwise. Similarly, $News^{Before}$ is a dummy equal to one if a stock before its earnings announcement on trading days[-60,-2] has higher than the median abnormal number of newswire articles, zero otherwise. I estimate this regression separately for S&P and non-S&P 500 stocks, at different periods. The median is calculated from the respective sample of S&P 500 and non-S&P 500 stocks and the chosen period.

Table IV reports the regression results and omits from the table the non-interacted variables and the intercept. The main result is that when a firm receives more newswire coverage (i.e., higher than the median number of abnormal newswire coverage among S&P 500 or non-S&P 500 stocks) following its earnings announcement, its stock price is more responsive to earnings surprises across all periods, for both S&P 500 and non-S&P 500 stocks. This result holds for all time periods. The estimated coefficients $Surprise \times News^{EA}$ indicate that stock prices are more responsive to earnings surprise by approximately 41% and 32% for S&P 500 and non-S&P 500, respectively when a firm has higher than abnormal newswire coverage.

Newswire coverage also plays a role before the announcement. The estimated coefficients for $Surprise \times News^{Before}$ indicate that firms with higher than the median abnormal newswire coverage before earnings announcements are less responsive to earnings surprises. One explanation for this finding is that more news dissemination about a firm (e.g., firm performance) before the announcement gets incorporated into stock prices. Therefore, the measure of earnings surprises becomes a more "stale" measure of surprises because it contains earnings estimates from analysts that have not updated their earnings forecasts for new information.

I find no robust results on the implication of abnormal analyst coverage to stock price responsiveness to earnings surprises. However, I do not rule out the impact of analysts coverage to price formation because, in the newswire dataset, I observe a significant fraction of news articles that discuss analysts forecasts and opinions on firms' performance.

Altogether, these results imply that the observed growth in newswire coverage has contributed to price efficiency around earnings announcements. Despite that large stocks dominate the media landscape, all stocks benefit from the growing presence of newswire coverage.

B. Changes in financial regulations and market architecture

I next investigate key events in financial regulations and changes in the industrial organization of financial markets that may have coincided with the discrete jump and upward trends in AIVOL on announcement days.

To choose the set of events, I follow Conrad and Wahal (2016). In a similar spirit to this paper, Conrad and Wahal (2016) study the evolution of the term structure of liquidity provision (i.e., realized spread), which is a measure of profitability for liquidity providers since 2000. The authors document important changes in financial regulations and in market architecture that coincide with a significant decrease in realized spreads. The authors argue that lower realized spreads forced liquidity providers to invest in speed to make liquidity provision viable. In turn, this increases the speed at which prices reflect new information. I choose similar events as in Conrad and Wahal (2016) and also include two important regulations that impacted how earnings are reported and disclosed, that is, Regulation Fair Disclosure (Reg FD) and the Sarbanes-Oxley Act (SOX).

Table V presents the results of OLS regressions of AIVOL on earnings announcement day[0,1] on a dummy Post-Event equal to one if the earnings announcement occurs after a particular event. I also control for market volatility (excess market return squared) and its interaction with the Post-Event dummy (not reported). For each event, I define a pre-event period from days -90 to -1 of the first instance of the change and a post-event period as days +1 to +90 after the full implementation of the change.[17] I choose the window length of 90 days (one calendar quarter) to take into account that the majority of stocks announce their earnings in the first month of each calendar quarter.

[17] See Appendix Section A for event dates.

Panel A of Table V presents the results of the change in AIVOL around financial regulatory events, which are, Reg FD, Decimalization, SOX, Autoquote, and Regulation National Market System (Reg NMS).[18] Panel B presents the results around changes in market architecture, which consists of mergers and acquisition among different U.S. stock exchanges.

Panel A shows positive and statistically significant increases in AIVOL around Reg FD, SOX, and Reg NMS and a decrease around Decimalization. As emphasized by Bailey, Li, Mao, and Zhong (2003), to understand the implication of Reg FD to IVOL is difficult because the effective date of Reg FD (October 23, 2000) occurs just before the full implementation of Decimalization for the NYSE and AMEX (January 19, 2001) and NASDAQ (April 9, 2011). Though AIVOL increases following Reg FD, I observe a decrease in AIVOL following the full implementation of Decimalization. Figure 10 shows no definitive sign of a permanent increase in AIVOL around 2000 and 2001. This contrast with the permanent increase (jump) in AIVOL that I observe on July 2002, which coincide with the implementation of SOX.[19]

Before the passage of SOX, AIVOL was not statistically different from zero, but following its passage on July 30, 2002, AIVOL increased to 21% (statistically significant at the 5% level). SOX was passed as an "act to protect investors by improving the accuracy and reliability of corporate disclosures made pursuant to the securities laws, and for other purposes." Though the effects of disclosure and its overall desirability is still an ongoing debate in academic research, better disclosure can increase market efficiency (see, Goldstein and Yang, 2017). The findings of Cohen, Dey, and Lys (2008) attribute, in part, the passage of SOX to a decrease in earnings management. Consequently, SOX may have improved the trust of investors towards reported earnings and facilitated their ability to process the news

[18] Decimalization is a system where stock prices are quoted using a decimal format rather than fractions. The SEC ordered all U.S. stock markets to change to decimalization by April 9, 2001. Because of decimalization, the depth at the inside quote decreases significantly. The NYSE proposed a liquidity quote to be displayed to market participants for each stock along with the best bid and ask price and was designed to provide a firm bid and ask for substantial size available immediately (Hendershott, Jones, and Menkveld, 2011).

[19] Figure B1 zooms-in on the cross-sectional average of AIVOL around the passage of SOX and shows a clear and permanent jump in AIVOL on July 2002 when SOX was signed by the President George W. Bush.

and understand its implication to firm fundamentals. In turn, price discovery occurs more rapidly.

Reg NMS was designed to modernize and strengthen the National Market System for equity securities but is often perceived as a determinant to the exacerbation of market fragmentation, which led to the rise of technology in financial markets and the proliferation of high-frequency trading. I find that AIVOL increases from an average of 56.7% before the adoption of Reg NMS by the SEC on June 29, 2005, to 89.5% following the full implementation of Reg NMS on October 8, 2007. We have to be careful not to attribute Reg NMS as the potential leading cause of the increase in AIVOL around that period. Reg NMS came in part as a response to new trends in financial markets (e.g., technological advancement in algorithmic trading). But Reg NMS provided strong incentives for stock exchanges to automate, especially the NYSE, and encouraged competition among trading venues (Jones, 2013). This increase in competition led to technological upgrades in financial markets and reductions in latency (i.e., the delay or lapse of time between a request and a response). Moreover, commentary from Friedman (2016) argues that the year 2007 marked the passage of significant technological progress in cloud computing and processing power to process big data.

As for other financial regulations, I find no significant changes in AIVOL around the period of Autoquote. The results of Panel B further show no substantial changes in abnormal IVOL around any of the critical acquisitions among stock exchanges that changed the market architecture landscape. However, this does not imply that changes in market architecture did not play a role. On the contrary, Reg NMS is in part responsible for significant changes in the market architecture landscape (e.g., fragmentation). Moreover,

To demonstrate the role of SOX and Reg NMS, causally, to market price efficiency around earnings announcements remains difficult. Nonetheless, the overall result conveys that more disclosure and transparency of reported earnings and the increasing role of technology in financial markets to be beneficial to price discovery.

V. Conclusion

In this paper, I document the evolution of price discovery following earnings announcements. The main finding of this paper is that financial markets have become more efficient at rapidly incorporating earnings news into stock prices. I use earnings surprises and idiosyncratic volatility as measures of earnings news and show that over the last 40 years stock prices become more responsive to earnings news on announcement days. In recent years, I find no evidence of post-earnings announcement drift following earnings surprises except for small (non-S&P 1500) stocks. However, the persistence of price drifts for small stocks has weakened over the years. I further show that the growth in newswire coverage corresponds to greater market price efficiency around earnings announcements. Moreover, the implementation of SOX and RegNMS coincide with significant and permanent increases in abnormal idiosyncratic volatility on earnings announcement days.

In recent years, markets appear to incorporate all earnings surprises on the day of the announcement. Building on the results of this paper, Grégoire and Martineau (2018) show that, between 2011 to 2015 for S&P 1500 stocks, earnings surprises are fully incorporated into stock prices generally by 10 a.m.

Despite the fact that markets have become more efficient at incorporating earnings surprises, one must be careful to interpret these results as "markets becoming more efficient at incorporating *all* news content of an earnings announcement." Earnings announcements are elaborate and contain more information than just unexpected earnings per share. Therefore, another aspect of the earnings announcement may take more than a few days to process and to incorporated into stock prices. With the advancement of technology and data processing, we should expect markets to rapidly process and incorporate information that is easily quantifiable such as earnings surprises into stock prices. However, how other critical details of an earnings announcement that is not as readily measurable incorporate into stock prices is yet well understood. I leave this challenging empirical task to future research.

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Figure 1. The Number of Earnings Announcements and Unique Firms

This figure shows the total number of earnings announcements and the number of unique firms per year for the Compustat sample in Panel A and for the I/B/E/S sample in Panel B. The sample period is from January 1, 1973, to December 31, 2015 for the Compustat sample and from January 1, 1984, to December 31, 2015 for the I/B/E/S sample.

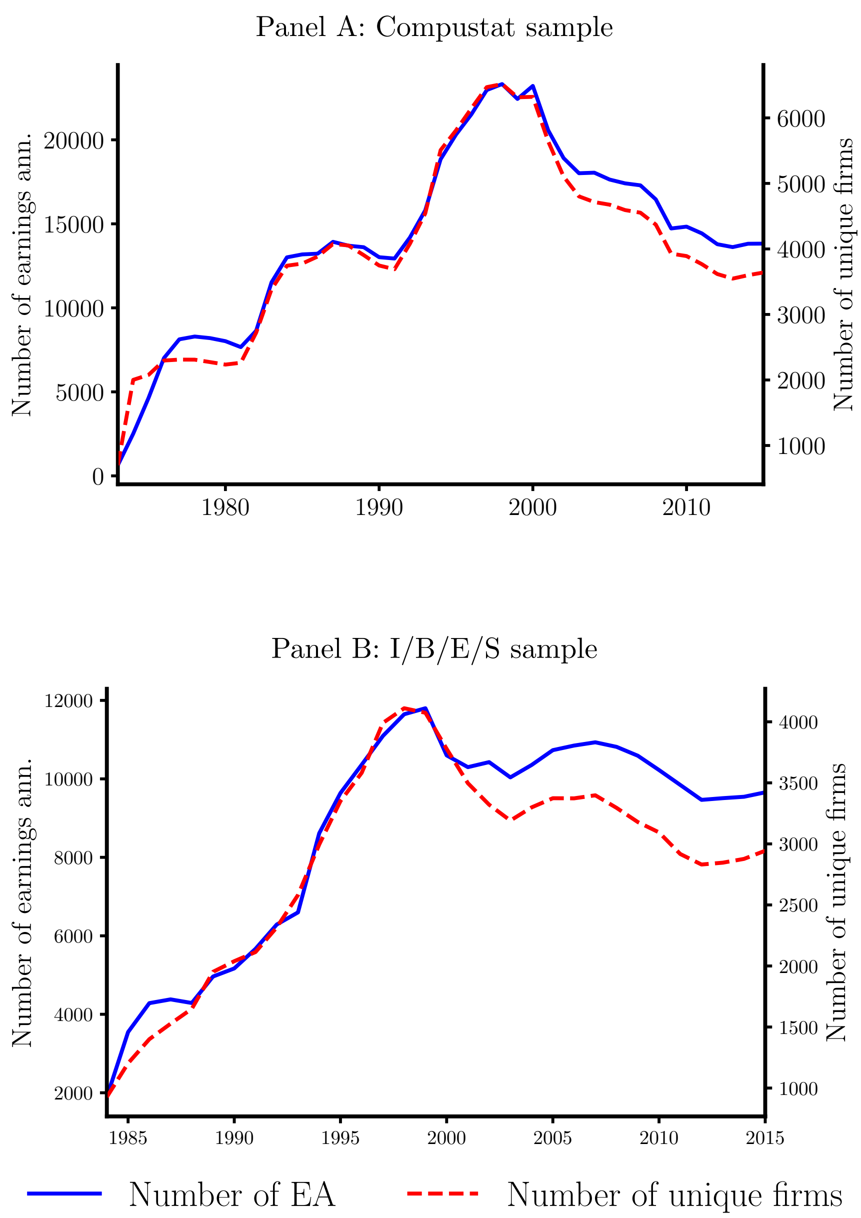


Figure 2. Sample Firm Size and Stock Price

This figure shows the median (solid back line) and the 10th-90th percentile range (shaded area) in firm size measured by stock market capitalization and in stock price from 1984 to 2015 for S&P 1500 and non-S&P 1500 firms. The sample consists of U.S.-based firms with at least one earnings forecast in I/B/E/S with accounting data in Compustat, precisely, total assets and market capitalization, at the end of December of the previous calendar year.

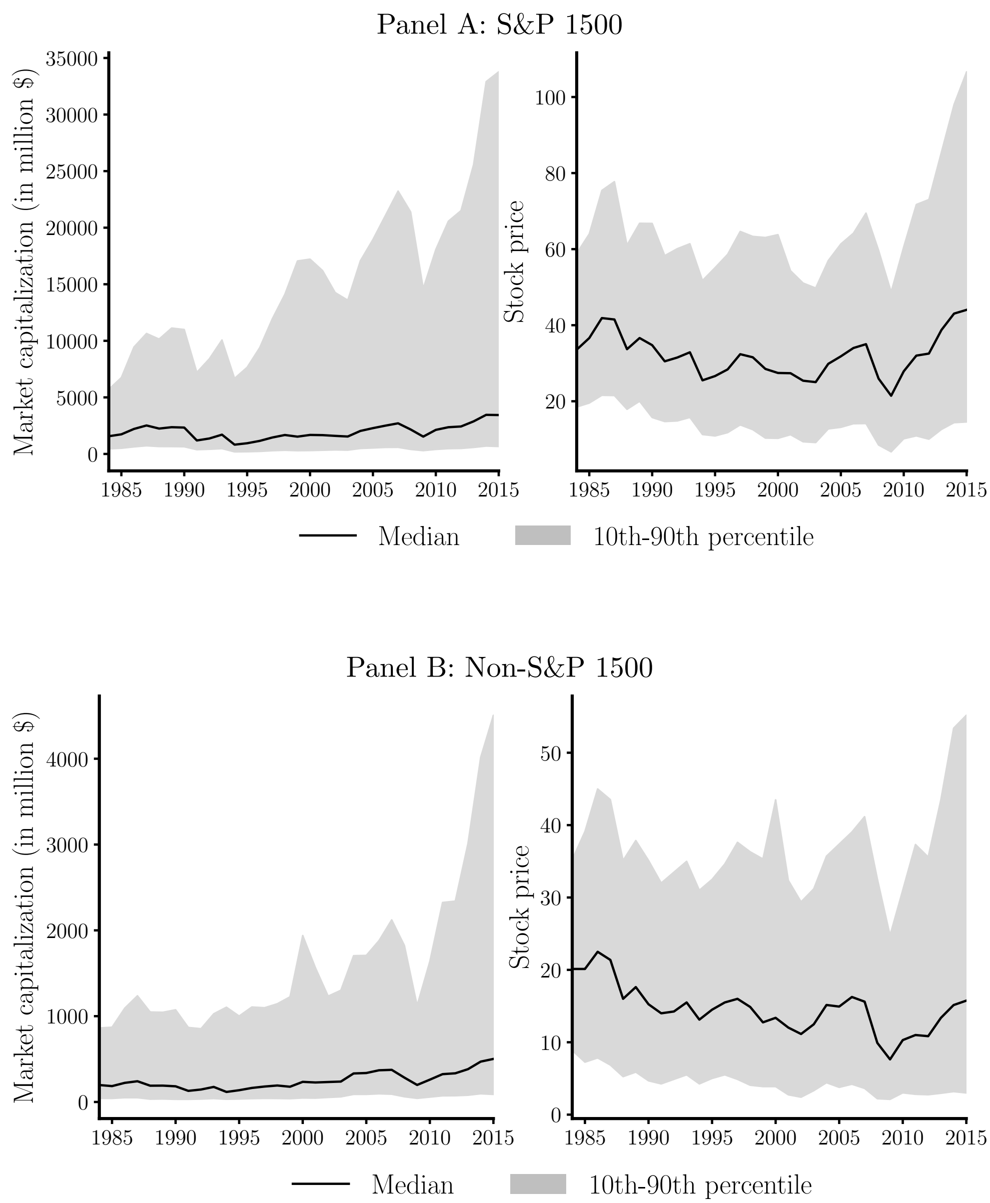


Figure 3. Summary Statistics for Earnings Surprises and Analyst Dispersions

This figure shows the median (solid black line) and the 10th-90th percentile range (shaded area) for earnings surprises in Panel A and for analyst dispersions in Panel B. The sample consists of U.S.-based firms with at least one earnings forecast in I/B/E/S with accounting data in Compustat, precisely, total assets and market capitalization, at the end of December of the previous calendar year. The analyst dispersion is calculated for earnings announcements with at least four analyst forecasts. The sample period is from January 1, 1984, to December 31, 2015.

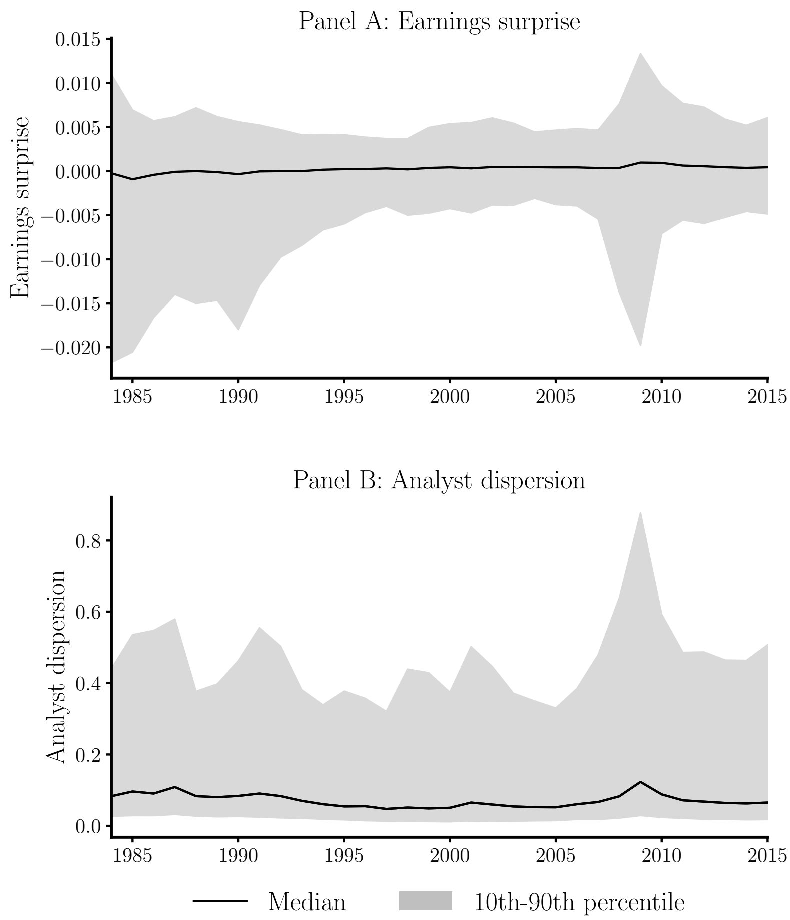


Figure 4. The Evolution of Post-Earnings Announcement Drift

This figure shows the evolution in buy-and-hold abnormal returns (BHAR) around earnings announcements for each earnings surprises quintile sort at different time periods. I define BHAR for stock-announcement i from day τ to T ($\tau < T$) as:

$$BHAR[\tau, T]_i = \prod_{k=\tau}^{T}(1 + R_{i,k}) - \prod_{k=\tau}^{T}(1 + R_{p,k}),$$

where $R_{i,k}$ is the return of the stock-announcement i and $R_{p,k}$ is the return on the size and book-to-market matching Fama-French portfolio on day k. This figure represents the BHAR[-10, T] from ten days before the announcement ($\tau = -10$) to day T where T varies from $T = -9$ to $T = 60$ trading days. Day $T = 0$ is the BHAR of the earnings announcement date reported in I/B/E/S and the following trading day. I combine both trading days because I do not have the exact earnings announcement timestamp. The shaded area is the pointwise 95% confidence bands around the average BHAR. The vertical line corresponds to the earnings announcement day. The sample period is from January 1, 1984, to December 31, 2015.

Figure 4. The Evolution of Post-Earnings Announcement Drift (Cont.)

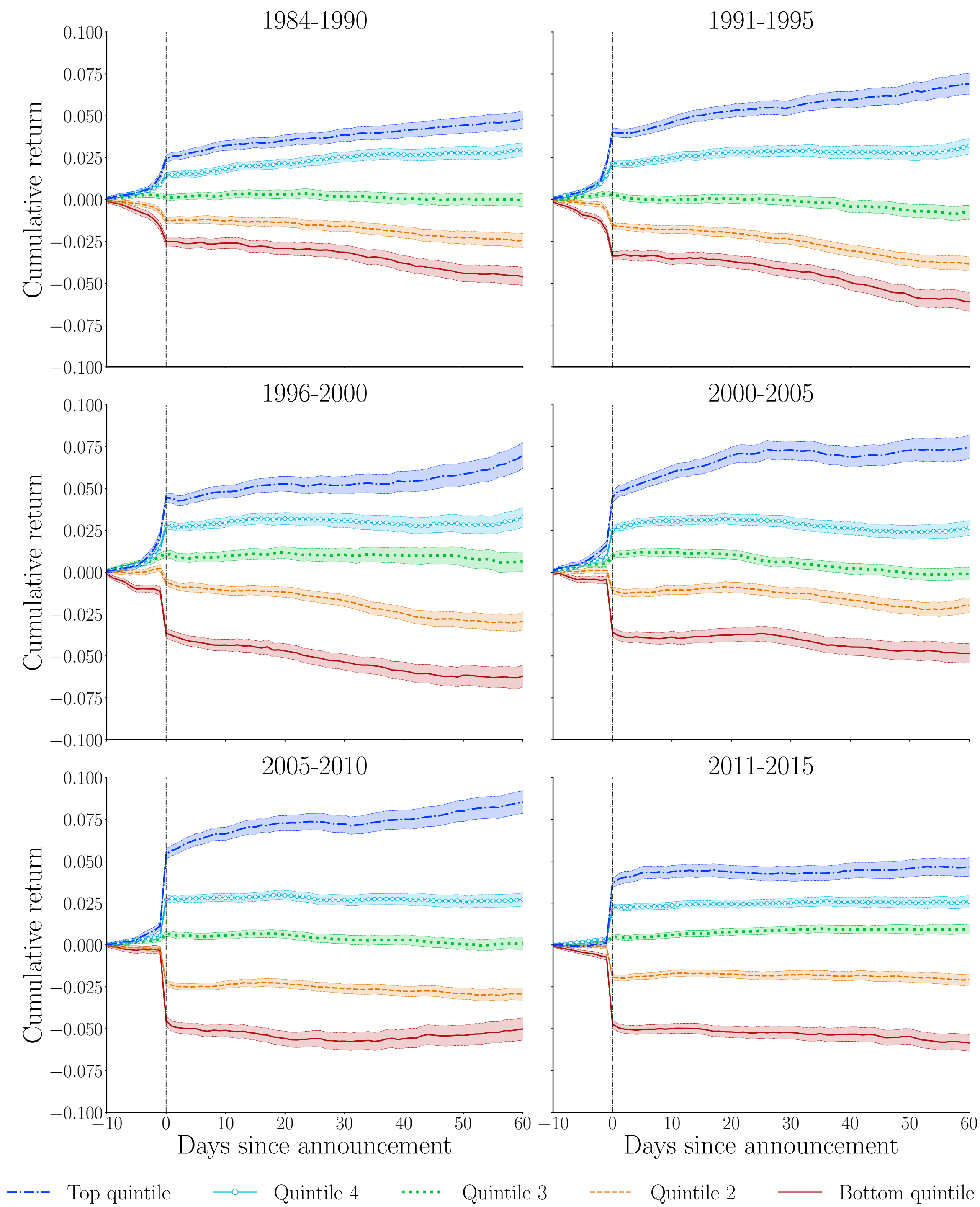


Figure 5. Post-Earnings Announcement Drift for S&P 1500 and Non-S&P 1500 Stocks from 2011 to 2015

This figure shows buy-and-hold abnormal returns (BHAR) around earnings announcements announced on day 0 for each earnings surprise quintile sort for S&P 1500 and non-S&P 1500 stocks. See caption of Figure 4 for the definition of BHAR. The shaded area is the pointwise 95% confidence bands around the average BHAR. The vertical line corresponds to the earnings announcement day. The sample period is from January 1, 2011, to December 31, 2015.

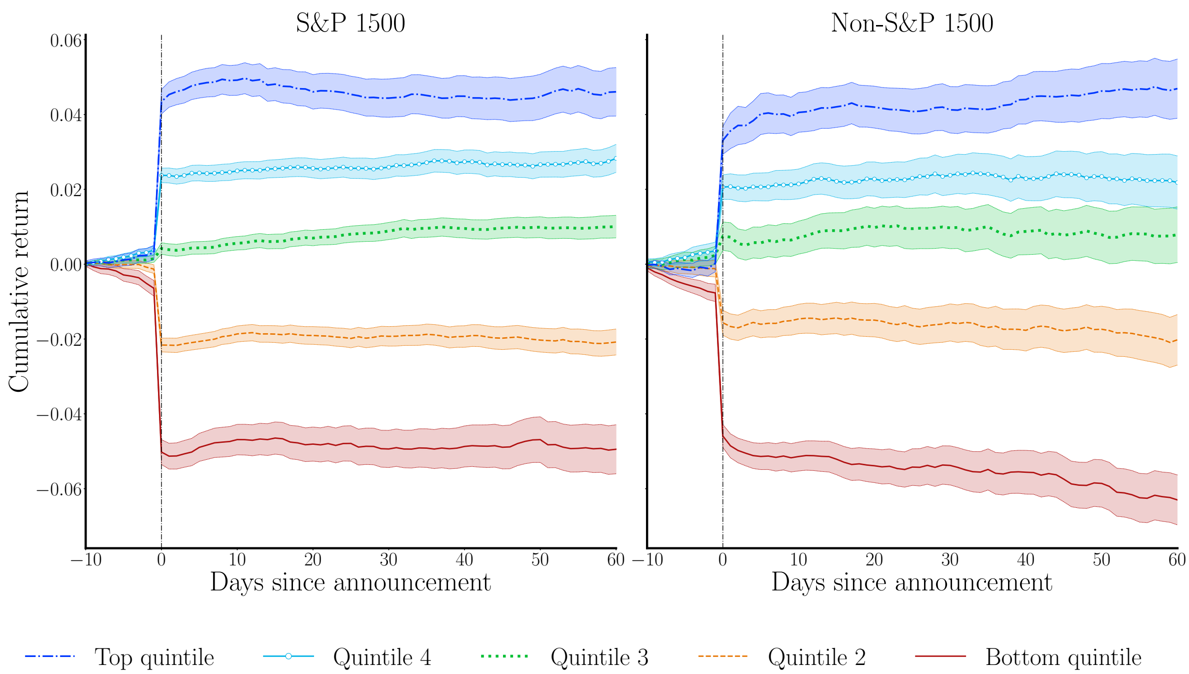


Figure 6. Post-Earnings Announcement Drift in the Top and Bottom Earnings Surprise Deciles for S&P 1500 and Non-S&P 1500 Stocks Between 2011 and 2015

This figure shows buy-and-hold abnormal returns (BHAR) around earnings announcements announced on day 0 for the top and bottom earnings surprise deciles for S&P 1500 and non-S&P 1500 stocks. See caption of Figure 4 for the definition of BHAR. The shaded area is the pointwise 95% confidence bands around the average BHAR. The vertical line corresponds to the earnings announcement day. The sample period is from January 1, 2011, to December 31, 2015.

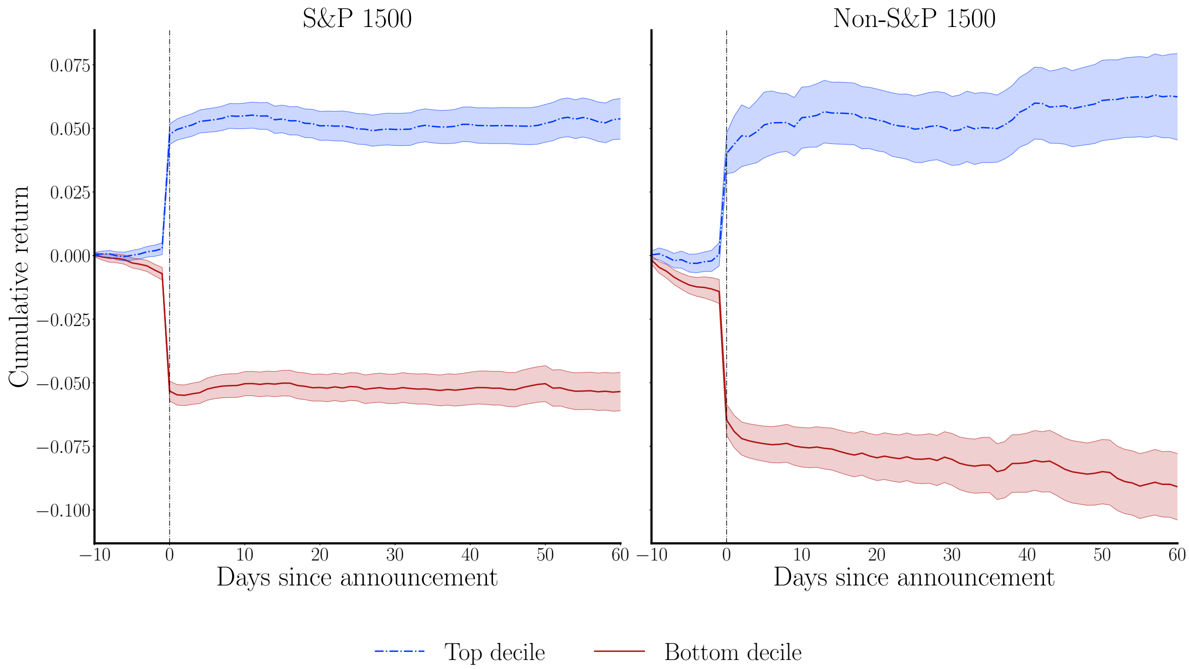


Figure 7. The Mean Difference in Long-Horizon Returns Following Big Earnings Surprises

This figure shows the yearly mean difference in BHAR[5,61] (black solide line) between earnings surprises $\geq 0.5\%$ and earnings surprises $\leq$ -0.5% and the two-year moving average (dashed red line). I define BHAR for stock-earnings announcement i from day 5 to 61 following earnings announcements as:

$$BHAR[5,61]_i = \prod_{k=5}^{61}(1 + R_{i,k}) - \prod_{k=5}^{61}(1 + R_{p,k}),$$

where $R_{i,k}$ is the return of the stock for announcement i and $R_{p,k}$ is the return on the size and book-to-market matching Fama-French portfolio on day k. The mean difference is calculated on each year. The shaded area is the pointwise 95% confidence bands around the mean difference. The sample period is from January 1, 1984, to December 31, 2015.

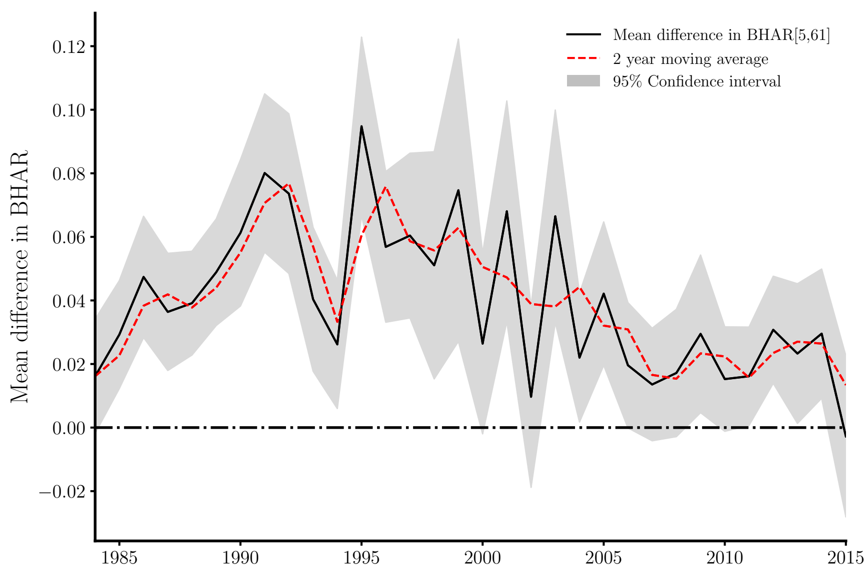


Figure 8. Trends in Stock Return Responses to Earnings Surprises

This figure shows estimated coefficients of 5-year rolling OLS regressions of BHAR[0,1] and BHAR[2,61] on earnings surprises defined in Equation (1). See caption of Figure 4 for the definition of BHAR. Panel A and B show estimated coefficients for BHAR[0,1] for S&P 1500 and non-S&P 1500 stocks, respectively. Panel C and D show the estimated coefficients for BHAR[2,61] for S&P 1500 and non-S&P 1500 stocks, respectively. The shaded area is the pointwise 95% confidence bands around the estimated coefficients. Standard errors are clustered by firm and earnings announcement date in Panel A and B and by firm and earnings announcement quarter in Panel C and D. Above each plot is a linear time trend τ (plotted in red dots) with p-value based on Newey-West standard errors with five lags. The sample period is from January 1, 1984, to December 31, 2015.

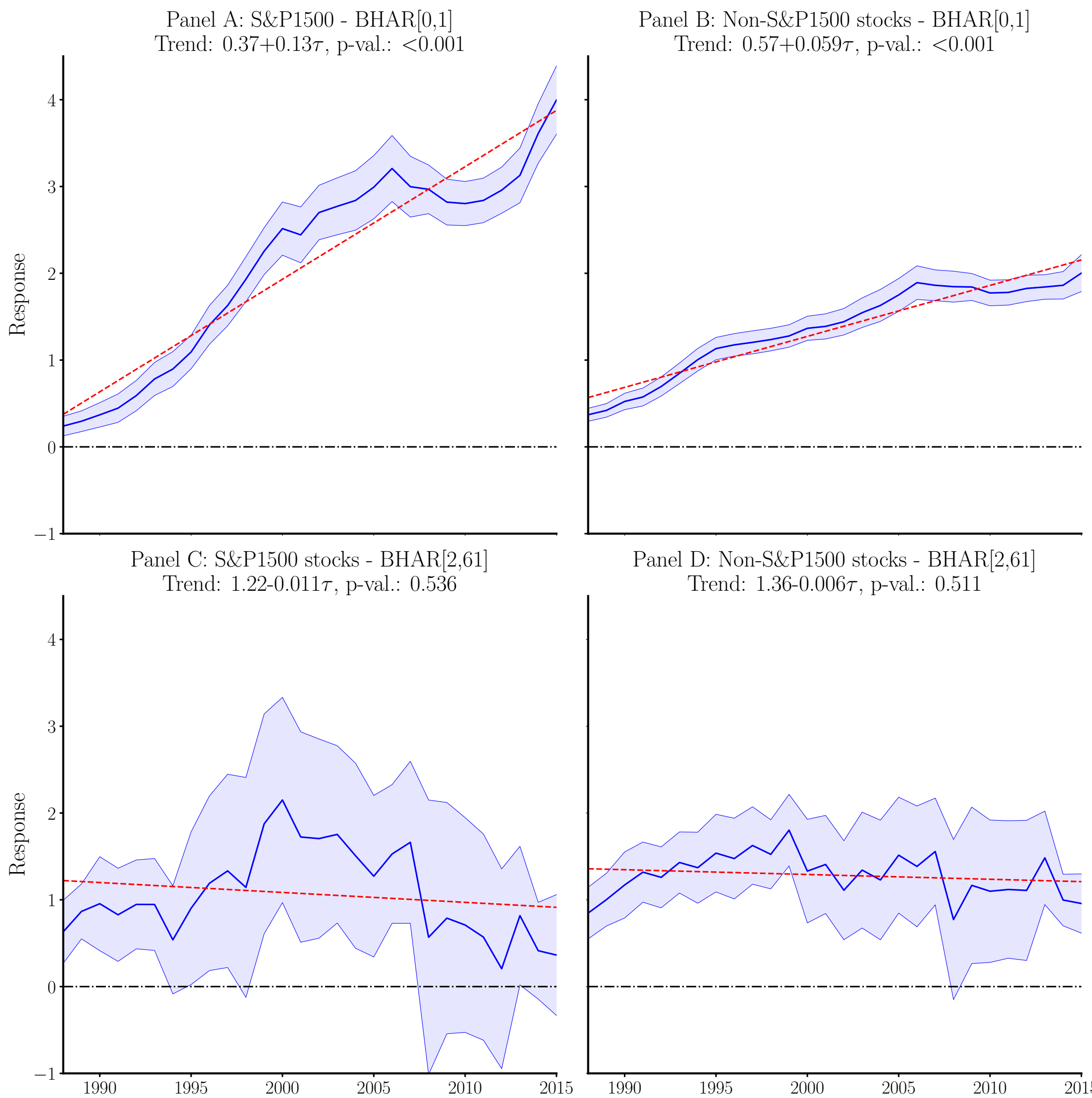


Figure 9. Abnormal Idiosyncratic Volatility Around Earnings Announcement Days

This figure shows the two-day average abnormal idiosyncratic volatility (AIVOL), for days [-2,-1], [0,1], and [2,3] around earnings announcements. The date of the earnings announcement is day 0. The definition of AIVOL is defined in Equation (8). The sample period is from January 1, 1973, to December 31, 2015.

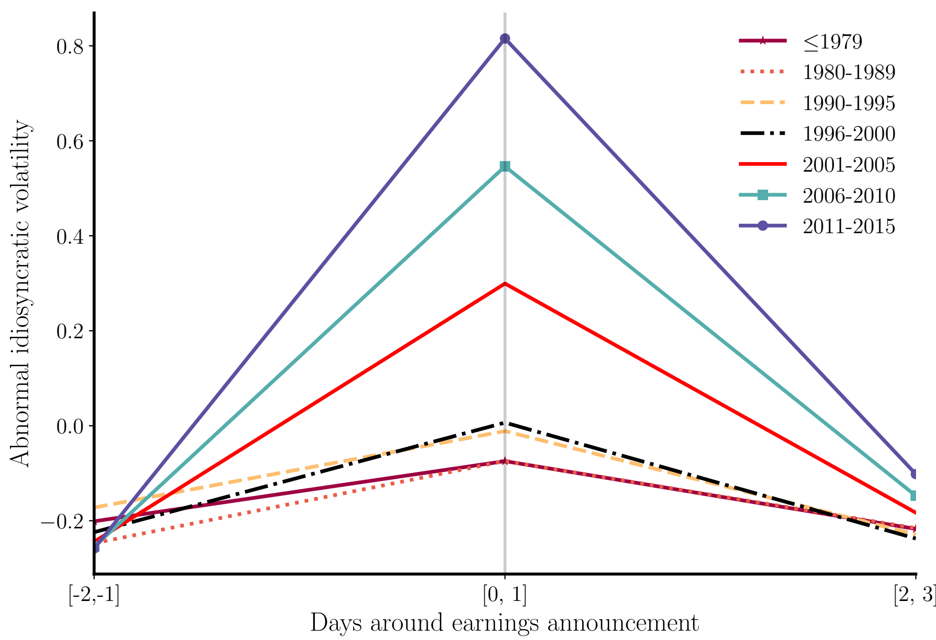
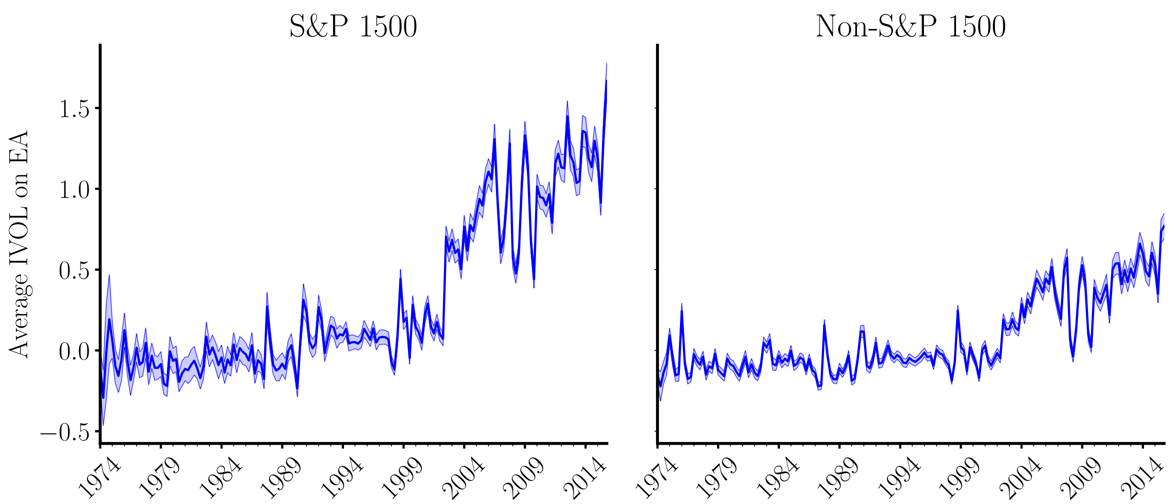


Figure 10. Abnormal Idiosyncratic Volatility on Earnings Announcement Days

This figure shows the cross-sectional average of the two-day average abnormal idiosyncratic volatility (AIVOL) on days[0,1] where day 0 is the earnings announcement day. Panel A shows the average at the quarterly frequency and Panel B at the yearly frequency. The results are shown separately for S&P 1500 and non-S&P 1500 stocks. The definition of AIVOL is defined in Equation (8). The shaded area is the pointwise 95% confidence bands around the average AIVOL. Standard errors are clustered by firm and earnings announcement date. The sample period is from January 1, 1974, to December 31, 2015.

Panel A: Quarterly frequency



Panel B: Yearly frequency

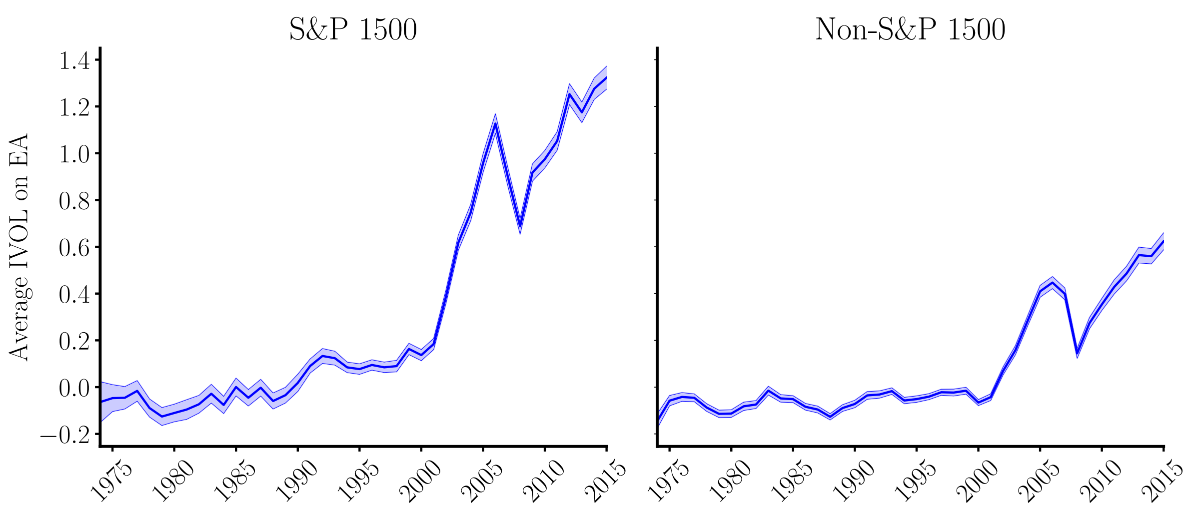
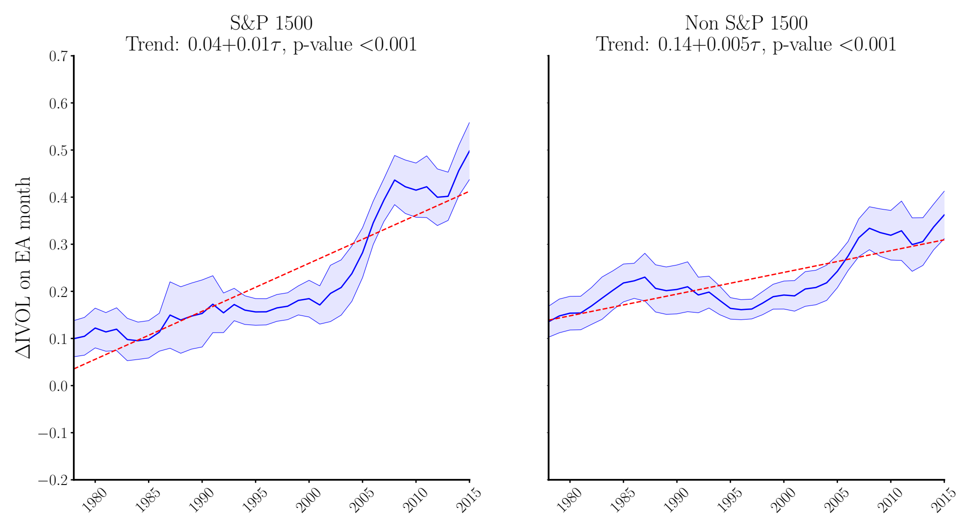


Figure 11. Changes in Monthly Idiosyncratic Volatility Around Earnings Announcement Months

Panel A shows the cross-sectional average change in monthly idiosyncratic volatility (IVOL) from $m-1$ to m where m is the earnings announcement month on each year, and Panel B shows the cross-sectional average change in IVOL from m to $m+1$ where $m+1$ is the month following the earnings announcement month. I show the results separately for S&P 1500 and non-S&P 1500 stocks. The definition of IVOL is defined in Equation (9). The shaded area is the pointwise 95% confidence bands around the average change in IVOL. Standard errors are clustered by firm and earnings announcement calendar month. Above each plot is a linear time trend τ (plotted in red dots) with p-value based on Newey-West standard errors with five lags. The sample period is from January 1, 1974, to December 31, 2015.

Panel A: Changes in ΔIVOL on Earnings Month



Panel B: Changes in ΔIVOL following Earnings Month

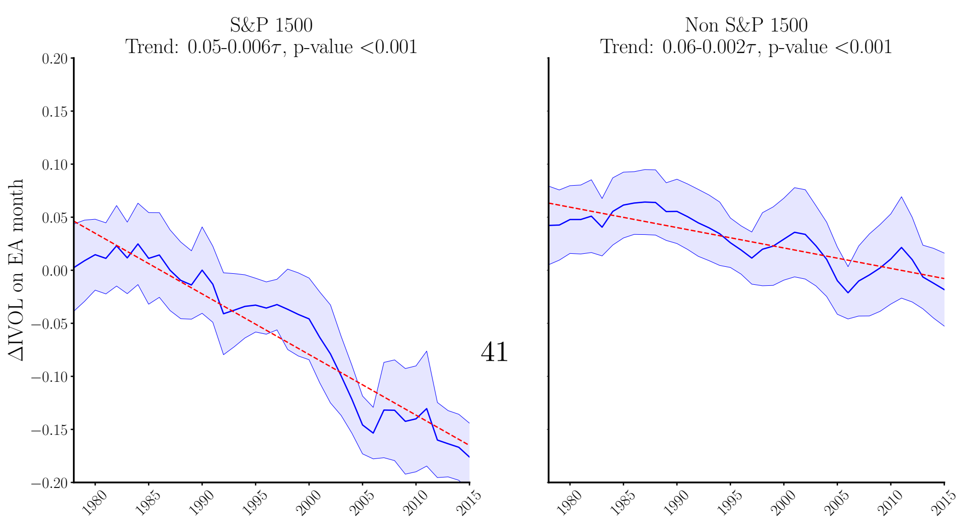


Figure 12. Idiosyncratic Volatility on Earnings Announcement Months Relative to Non-Earnings Announcement Months

This figure shows the cross-sectional average of the ratio in the average monthly idiosyncratic volatility on earnings announcement month divided by the average idiosyncratic volatility on non-earnings announcement month. The sample period is from January 1, 1974, to December 31, 2015.

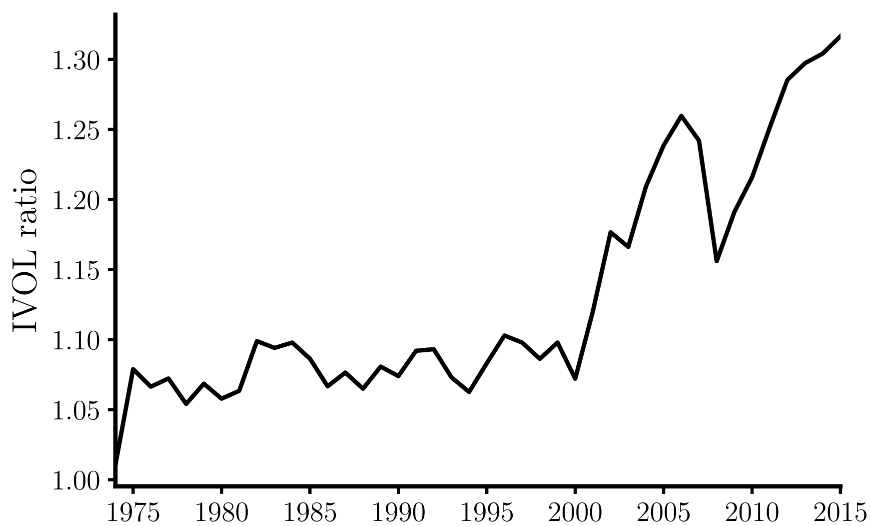


Figure 13. The Number of Analysts Forecasts per Earnings Announcement

This figure shows the median number of analysts forecasts from I/B/E/S per earnings announcement for S&P 500 (solid black line) and non-S&P 500 stocks (dotted blue line). The sample period is from January 1, 1984, to December 31, 2015.

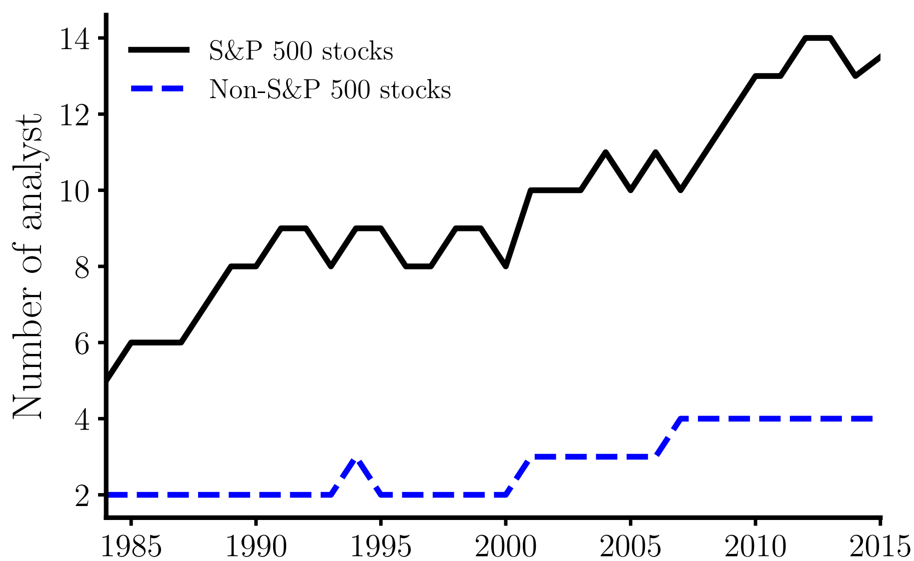


Figure 14. Dow Jones Newswire Coverage

This figure shows the evolution of media coverage in Dow Jones Newswires from 1980 to 2015. Panel A shows the total number of newswires, the fraction of total newswires, and the average number of newswires per stock for S&P 500 (in red) and non-S&P 500 stocks (dashed blue line), respectively. Panel B shows the average number of newswires for S&P 500 and non-S&P 500 stocks around earnings announcements at different time periods where days[0,1] corresponds to the earnings announcement day and the following trading day. Panel C shows the fraction of earnings announcements in I/B/E/S with at least one newswire article in Dow Jones on earnings announcement days[0,1].

Panel A: Newswires Coverage

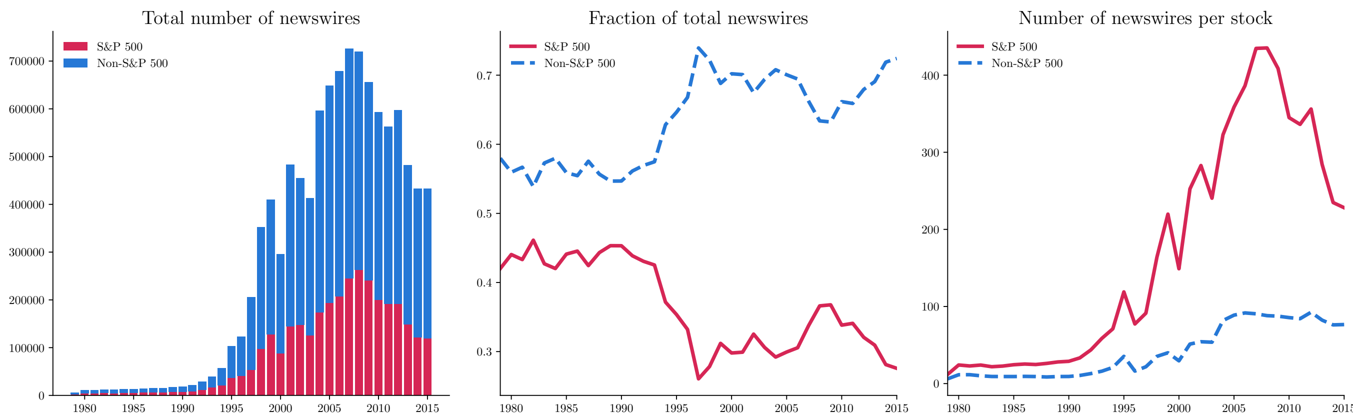
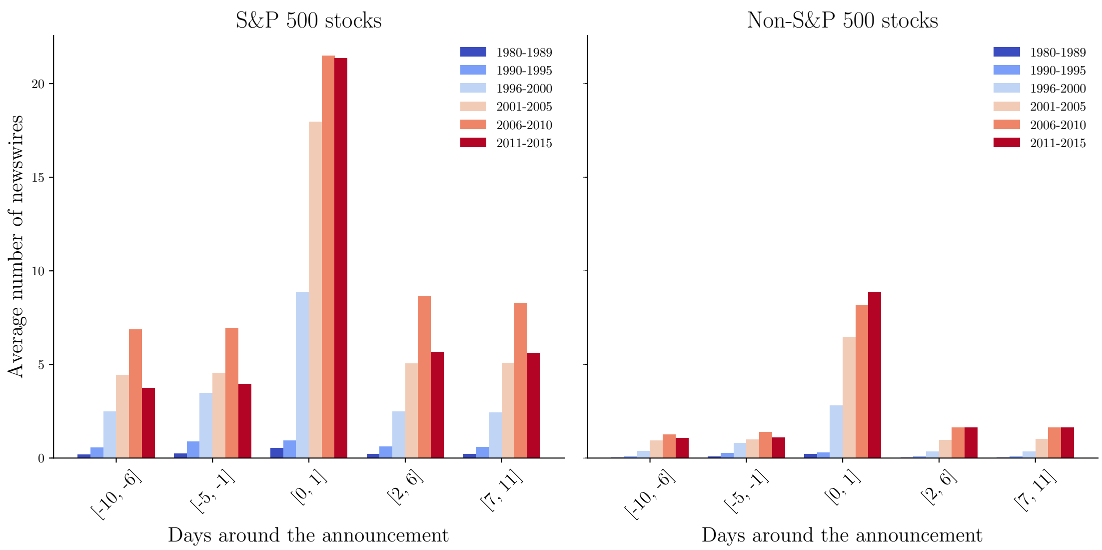


Figure 14. Dow Jones Newswires (Cont.)

Panel B: The average number of newswires around earnings announcements



Panel C: The fraction of earnings announcements with newswires coverage

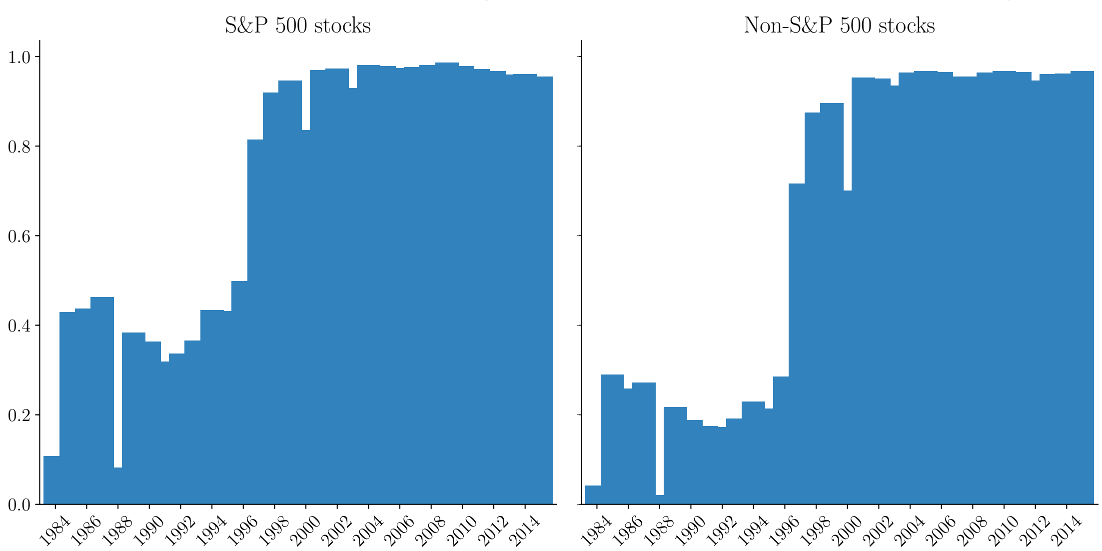


Table I
Descriptive Statistics

This table reports summary statistics of earnings surprises defined in Equation (1) for the I/B/E/S sample. The table shows the total number of earnings announcements (EA), the mean, the 25th (P25), 50th (P50), and 75th (P75) percentiles, and the standard deviation (St. dev.) for earnings surprises in percent at different periods for S&P 1500 and non-S&P 1500 stocks. The sample period is from January 1, 1984, to December 31, 2015.

	1984-1990		1991-1995		1996-2000	
	S&P	Non-S&P	S&P	Non-S&P	S&P	Non-S&P
Number of EA	8041	20483	16417	20388	24301	31199
Mean	-0.222	-0.654	-0.056	-0.295	0.001	-0.132
P25	-0.213	-0.538	-0.098	-0.296	0.000	-0.084
P50	0.000	-0.049	0.009	0.000	0.026	0.036
P75	0.153	0.187	0.119	0.174	0.107	0.195
St. dev.	1.749	3.014	0.719	1.428	0.578	1.193

	2001-2005		2006-2010		2011-2015	
	S&P	Non-S&P	S&P	Non-S&P	S&P	Non-S&P
Number of EA	25658	26191	26218	27193	25671	22347
Mean	0.041	-0.015	-0.068	-0.351	0.065	-0.016
P25	0.000	-0.083	-0.025	-0.300	-0.024	-0.238
P50	0.037	0.051	0.061	0.038	0.047	0.045
P75	0.133	0.254	0.215	0.344	0.168	0.345
St. dev.	0.554	1.145	1.673	2.808	0.532	1.313

Table II
Buy-and-Hold Abnormal Returns for the Top and Bottom Deciles

This table reports mean buy-and-hold abnormal returns (BHAR) at different periods following earnings announcements for earnings surprises in the top and the bottom deciles for S&P 1500 and non-S&P 1500 stocks. See caption of Figure 4 for the definition of BHAR. Numbers in bold represents mean BHAR that are statistically different from zero at the 5% statistical significance. Standard errors are clustered by firm and earnings announcement date for BHAR [0,1] and by firm and calendar quarter for the remaining BHAR. The sample period is from January 1, 1984, to December 31, 2015.

Panel A: 1984 to 1995

	1984-1990				1991-1995			
	S&P1500		Non-S&P1500		S&P1500		Non-S&P1500	
BHAR	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom
$[0,1]$	**0.55**	**-0.58**	**1.16**	**-1.07**	**1.9**	**-1.31**	**2.69**	**-2.11**
$[2,5]$	0.07	-0.02	0.22	0.01	0.09	0.15	0.07	0.15
$[5,10]$	**0.36**	0.05	**0.3**	-0.14	**0.63**	-0.2	**0.57**	-0.14
$[11,20]$	0.23	0.15	0.36	**-0.6**	**0.64**	-0.04	**0.66**	-0.39
$[21,30]$	**0.55**	-0.17	0.4	-0.12	0.31	-0.23	0.13	**-0.76**
$[31,40]$	-0.14	-0.39	0.42	**-0.8**	0.0	**-0.49**	**0.86**	-0.57
$[41,50]$	-0.02	-0.32	**0.53**	**-0.64**	-0.1	**-0.64**	**0.96**	**-1.03**
$[51,61]$	-0.07	0.07	**0.53**	-0.28	0.3	-0.14	**1.0**	-0.49
$[2,61]$	1.01	-0.63	**2.76**	**-2.61**	**1.84**	-1.61	**4.22**	**-3.43**

Panel B: 1996 to 2005

	1996-2000				2001-2005			
	S&P1500		Non-S&P1500		S&P1500		Non-S&P1500	
BHAR	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom
$[0,1]$	**2.74**	**-2.42**	**2.87**	**-3.21**	**3.67**	**-3.17**	**3.24**	**-4.06**
$[2,5]$	**1.02**	**-0.44**	**-0.6**	**-0.8**	**1.72**	-0.13	0.46	-0.38
$[5,10]$	**0.57**	-0.02	0.17	-0.42	**0.74**	0.08	**1.02**	-0.01
$[11,20]$	**0.58**	-0.31	0.35	-0.64	**1.28**	**0.48**	1.28	-0.13
$[21,30]$	-0.17	-0.17	-0.22	**-1.28**	0.19	0.35	1.06	-0.42
$[31,40]$	0.09	-0.47	0.37	-0.38	-0.71	-0.67	-0.57	**-0.84**
$[41,50]$	**0.8**	0.15	0.51	-0.17	0.5	-0.04	0.77	-0.17
$[51,61]$	**0.85**	0.15	**2.02**	-0.35	-0.06	0.03	0.54	-0.1
$[2,61]$	**3.7**	-1.17	2.65	-3.71	**3.63**	0.12	4.81	-1.9

Table II
Buy-and-Hold Abnormal Returns for the Top and Bottom Deciles (Cont.)

Panel C: 2006 to 2015

	2006-2010				2011-2015			
	S&P1500		Non-S&P1500		S&P1500		Non-S&P1500	
BHAR	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom
$[0, 1]$	**5.37**	**-4.92**	**5.04**	**-4.59**	**4.5**	**-4.62**	**3.96**	**-5.05**
$[2, 5]$	**0.99**	0.0	**1.28**	**-0.99**	**0.54**	0.08	**1.12**	**-0.93**
$[5, 10]$	**0.56**	-0.03	0.48	-0.23	0.18	**0.22**	0.28	-0.16
$[11, 20]$	0.4	-0.1	**1.16**	**-1.23**	**-0.4**	-0.17	-0.1	-0.41
$[21, 30]$	-0.01	0.1	-0.07	-0.21	-0.14	-0.05	-0.45	-0.08
$[31, 40]$	0.1	0.07	0.62	0.32	0.08	-0.04	0.41	-0.39
$[41, 50]$	**0.72**	0.06	0.75	1.05	0.12	0.2	0.45	-0.34
$[51, 61]$	0.64	**0.99**	0.82	0.67	0.2	-0.27	0.08	**-0.67**
$[2, 61]$	3.36	1.25	**5.06**	-0.64	0.65	-0.17	1.93	**-2.69**

Table III
Regression of Buy-and-Hold Abnormal Returns on Earnings Surprises

This table reports coefficients of OLS regressions of abnormal buy-and-hold returns (BHAR) for BHAR[0,1] and BHAR[2,61] on earnings surprises for the full sample of stocks (Panel A and D), for S&P 1500 stocks (Panel B and E) and for non-S&P 1500 stocks (Panel C and F). See caption of Figure 4 for the definition of BHAR. Standard errors are clustered by firm and earnings announcement date in Panel A to C and by firm and calendar quarter in Panel D to E. * denotes statistical significance at the 5% level. The sample period is from January 1, 1984, to December 31, 2015.

Panel A: BHAR[0,1] for the full sample of stocks

	Full sample	84-90	91-95	96-00	01-05	06-10	11-15
Intercept	0.001*	0.001*	0.002*	0.001*	0.000	0.001*	-0.001*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Surprise	1.571*	0.422*	1.031*	1.503*	1.907*	2.059*	2.283*
	(0.03)	(0.03)	(0.05)	(0.05)	(0.08)	(0.06)	(0.09)
Adj-R2	0.04	0.02	0.03	0.02	0.04	0.07	0.06
N	274,107	28,525	36,805	55,499	51,849	53,411	48,018

Panel B: BHAR[0,1] for S&P 1500 stocks

	Full sample	84-90	91-95	96-00	01-05	06-10	11-15
Intercept	0.002*	0.000	0.001*	0.003*	0.003*	0.002*	-0.002*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Surprise	2.305*	0.304*	1.000*	2.328*	2.914*	2.802*	3.899*
	(0.07)	(0.05)	(0.10)	(0.15)	(0.17)	(0.13)	(0.18)
Adj-R2	0.05	0.01	0.02	0.03	0.04	0.08	0.08
N	126,307	8,042	16,417	24,301	25,658	26,218	25,671

Panel C: BHAR[0,1] for non-S&P 1500 stocks

	Full sample	84-90	91-95	96-00	01-05	06-10	11-15
Intercept	0.000	0.002*	0.002*	-0.001	-0.002*	0.000	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Surprise	1.390*	0.448*	1.041*	1.334*	1.667*	1.819*	1.958*
	(0.03)	(0.03)	(0.06)	(0.06)	(0.09)	(0.07)	(0.10)
Adj-R2	0.04	0.02	0.03	0.02	0.03	0.07	0.06
N	147,800	20,483	20,388	31,198	26,191	27,193	22,347

Table III
Regression of Buy-and-Hold Abnormal Returns on Earnings Surprises (cont.)

Panel D: BHAR[2,61] for the full sample of stocks

	Full sample	84-90	91-95	96-00	01-05	06-10	11-15
Intercept	-0.000	0.003	-0.003	-0.005	-0.001	0.003	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Surprise	1.156*	1.009*	1.350*	1.505*	1.453*	1.006*	0.847*
	(0.14)	(0.13)	(0.21)	(0.24)	(0.26)	(0.46)	(0.16)
Adj-R2	0.00	0.01	0.00	0.00	0.00	0.00	0.00
N	268,149	28,477	36,491	54,395	51,190	52,631	44,965

Panel E: BHAR[2,61] for S&P 1500 stocks

	Full sample	84-90	91-95	96-00	01-05	06-10	11-15
Intercept	0.000	0.002	-0.005	-0.002	-0.000	0.003	0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Surprise	0.940*	0.593*	1.157*	1.552*	1.508*	0.742	0.335
	(0.25)	(0.21)	(0.36)	(0.62)	(0.53)	(0.64)	(0.33)
Adj-R2	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N	124,021	8,041	16,368	23,977	25,464	25,961	24,210

Panel F: BHAR[2,61] for non-S&P 1500 stocks

	Full sample	84-90	91-95	96-00	01-05	06-10	11-15
Intercept	-0.001	0.004	-0.001	-0.006	-0.001	0.003	-0.002
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Surprise	1.204*	1.093*	1.425*	1.484*	1.440*	1.090*	0.942*
	(0.13)	(0.15)	(0.23)	(0.27)	(0.35)	(0.42)	(0.16)
Adj-R2	0.00	0.01	0.00	0.00	0.00	0.00	0.00
N	144,128	20,436	20,123	30,418	25,726	26,670	20,755

Table IV
The Role of Analysts and Newswire Coverage to News Dissemination

This table reports coefficients from OLS regressions of BHAR[0,1] on earnings surprises, earnings surprises interacted with a dummy Analyst equal to one if the abnormal number of analyst coverage is greater than the median, earnings surprise interacted with a dummy News^{EA} equal to one if the abnormal number of newswire coverage on the earnings announcement day is greater than the median and following trading day, earnings surprise interacted with a dummy News^{Before} equal to one if the abnormal number of newswire coverage preceding an earnings announcement in the 60 trading day window is greater than the median, and the Analyst and News dummies. See the main text for the definition of abnormal analyst and newswire coverage. Regressions are estimated separately for S&P 500 and non-S&P 500 stocks for different time periods starting from January, 1, 1996 to December 31, 2015. The median is calculated within the respective sample of S&P 500 or non-S&P 500 stocks and within the chosen time period. The table omits the estimated coefficients for the three dummy variables and the intercept. Standard errors are clustered by firm and by earnings announcement date. * denotes statistical significance at the 5% level.

	1996-2000		2001-2005		2006-2010		2011-2015	
	S&P	Non-S&P	S&P	Non-S&P	S&P	Non-S&P	S&P	Non-S&P
Surprise	3.785*	1.892*	4.253*	2.134*	3.552*	2.165*	4.699*	2.468*
	(0.76)	(0.14)	(0.75)	(0.15)	(0.45)	(0.12)	(0.73)	(0.15)
Surprise×Analyst	-1.068	-0.152	-0.638	-0.362*	-0.954*	0.061	0.319	-0.206
	(0.57)	(0.12)	(0.66)	(0.15)	(0.40)	(0.10)	(0.57)	(0.16)
Surprise×News^{EA}	1.915*	0.552*	1.344*	1.081*	1.818*	0.571*	1.406*	0.527*
	(0.46)	(0.13)	(0.54)	(0.16)	(0.34)	(0.11)	(0.63)	(0.17)
Surprise×News^{Before}	-1.118	-0.886*	-2.006*	-0.863*	-2.423*	-0.611*	-2.537*	-0.553*
	(0.72)	(0.13)	(0.69)	(0.16)	(0.43)	(0.11)	(0.74)	(0.15)
Adj-R^2	0.03	0.03	0.05	0.04	0.06	0.08	0.07	0.07
N	8,825	46,674	9,222	42,627	9,213	44,198	9,072	38,946

Table V
Abnormal Idiosyncratic Volatility Before and After Regulatory and Market Structure Events

This table reports coefficients from OLS regressions of abnormal idiosyncratic volatility (AIVOL) on earnings announcement days[0,1] on a dummy Post-Event equal to one if the earnings announcement occurs in the +1 to +90 days following the event and zero otherwise. For each regressions, I use all earnings announcement observations that occurs in the -90 to +90 day window around the event. Panel A and B show the results around regulatory events and market structure events, respectively. Standard errors are clustered by firm and by earnings announcement date. * denotes statistical significance at the 5% level. Market structure events with a "+" refer to a purchase of one venue by another.

Panel A: Regulatory events

	Reg FD	Decimalization	SOX	Autoquote	Reg NMS
Intercept	-0.116*	0.106*	0.095	0.308*	0.567*
	(0.02)	(0.04)	(0.08)	(0.05)	(0.05)
Post-Event	0.228*	-0.134*	0.210*	-0.005	0.328*
	(0.05)	(0.04)	(0.08)	(0.08)	(0.08)
R^2	0.01	0.00	0.01	0.00	0.01
N	9,611	9,506	8,693	7,754	8,466

Panel B: Market structure events

	Instinet+ Island	Nasdaq+ Instinet	NYSE+ Arca	NYSE+ Euronext	BATS+ Direct
Intercept	0.292*	0.739*	0.739*	0.411*	0.958*
	(0.06)	(0.04)	(0.04)	(0.03)	(0.08)
Post-Event	-0.032	-0.097	-0.097	0.005	-0.105
	(0.07)	(0.07)	(0.07)	(0.05)	(0.09)
R^2	0.00	0.00	0.00	0.00	0.00
N	8,949	8,396	8,401	8,290	6,599

Appendix

A. Event Dates

Below are the dates used in the analysis as "event dates" in the analysis of Section IV.B.

Regulations

Regulation Fair Disclosure: 2000-10-23 (Effective date)
Sarbanes-Oxley Act: 2002-07-30 (Implementation date)
Decimalization: 2001-01-19 to 2001-04-09 (NYSE and AMEX were fully decimalized on January 19, 2001 and the NASDAQ on April 9, 2001.)
Autoquote: 2003-01-29 to 2003-05-27 (Beginning to complete implementation date)
Regulation National Market Systems: 2005-06-29 to 2007-10-01 (Beginning to complete implementation date)

Changes in the financial market landscape

Instinet acquires Island: 2002-09-20 (Acquisition completion date)
Nasdaq acquires Instinet: 2006-02-24 (This is the date when the technology of Instinet was implemented in Nasdaq, commonly known as Nasdaq-ITCH.)
NYSE acquires Arca: 2006-02-26 (Acquisition completion date)
NYSE acquires Euronext: 2007-04-04 (Acquisition completion date)
BATS acquires Direct Edge: 2014-01-3 (Acquisition completion date)

B. Figures

Figure B1. Abnormal Idiosyncratic Volatility on Earnings Announcement Days Around the Passage of the Sarbanes-Oxley Act

This figure shows the cross-sectional average of the two-day average abnormal idiosyncratic volatility (AIVOL) on earnings announcement days[0,1] on each month between January 1, 2001, to December 31, 2004. See Equation (8) in the main text for the definition of AIVOL. The vertical dashed line shows the month with the passage of the Sarbanes-Oxley Act (SOX).