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JEL Classification: G12; G14

Keywords: Predictability of Stock Returns; Information; Analyst Reports; Momentum; Reversals

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1. Introduction

A large body of evidence suggests that at certain times investors underreact to information contained in stock returns and at other times overreact. At the very shortest horizons of up to a month, stock returns exhibit reversals (Lo and MacKinlay, 1990; Lehmann, 1990; Jegadeesh, 1990). For 3- to 12-month horizons, there is strong evidence for positive autocorrelation in returns (Jegadeesh and Titman, 1993). Finally, over long horizons of between three and five years, we again find reversals (DeBondt and Thaler, 1985). The question of which circumstances lead to underreaction and which ones to overreaction has been the focus of much recent work, both on the theory and empirical fronts. This paper explores the behavior of returns after significant stock price movements. Major price changes can be driven by a number of factors, including new information about a firm's prospects, liquidity shocks affecting current shareholders, and shifts in demand by uninformed investors. My focus is on publicly available information. I compare how stock prices evolve subsequent to large moves based on whether these moves are associated with new information that is available to investors.

As a proxy for the presence of public information, I use recommendation-issuing analyst reports.[1] My basic logic is very simple: price events associated with new information are more likely to be accompanied by analyst reports. I am not specifically interested in whether reports cause prices to move or whether they are released in reaction to moves. The former cases obviously should be classified as information-based price movements. The latter are a bit more complicated, as they require analysts to be more prone to issue reports (either changing or maintaining their recommendations) when price changes are a result of new information. This seems like a reasonable assumption, and to the extent that it does not hold, it would bias against me finding any difference in the post-event returns of the two groups of stocks.

I restrict my sample to stocks that are actively covered by sell-side analysts and experience

[1] These reports are immediately available to a large group of investors, and their content quickly leaks to non-subcribers as well.

major price changes. A price event is classified as information-based if at least one analyst report is published around it. In a regression framework, I find that no-information price events experience strong reversals, while information-based ones exhibit momentum. This result is robust to inclusion of various controls (including volume and momentum), different post-event horizons (ranging from five to 40 trading days), various methods of measuring abnormal returns, and exclusion of stocks most affected by possible bid-ask bounce problems. It holds for both large and small cap stocks, and is not driven by post-earnings announcement drift well-established in the literature (Bernard and Thomas, 1989, 1990).[2] When I include only earnings announcements in my analysis, price events are followed by drift regardless of their information status.[3]

Next I test whether investors can profit from the differential market response to information revealed by analysts relative to other catalysts for price changes. I form four calendar-time portfolios based on the direction of the price movement and on whether it was information-based or not. Consistent with the regression findings, stocks that move based on analyst information exhibit strong momentum, while no-information stocks experience reversals. Both phenomena are not only statistically significant but also economically very meaningful. An equally weighted portfolio that is long no-information losers and short no-information winners (no-information portfolio) earns annualized abnormal returns of 20% over a 20-trading day horizon (with an extraordinary Sharpe ratio of 1.66), and these returns are substantially higher at short holding periods. A portfolio that is long information winners and short information losers (information portfolio) earns annualized abnormal returns of 16% (with a Sharpe ratio of 1.21), with the returns again higher for shorter horizons. Combining the phenomena yields annual returns of close to 37%, indicating a potentially extremely profitable trading strategy.

[2] Vega (2006) finds that stocks associated with high probability of private information-based trading, uniformly accepted public news surprises, and low media coverage experience low post-earnings announcement drift, providing an example of how the presence of information (public or private) can affect post-event returns.

[3] This should not be surprising given previous work. Moreover, it is quite probable that these price movements reflect new information about the firm, even if no analyst reports came out.

The numbers are similar for value-weighted portfolios. They are weaker for the no-information portfolio and substantially stronger for the information portfolio, resulting in combined abnormal returns of 30% per year. As before, the results hold when I exclude stocks most subject to the bid-ask bounce effect. They also do not change if I place more weight on periods when the portfolios contain more stocks (by running weighted least squares regressions).

One interpretation of my findings is that investors underreact to relevant new information about a firm and overreact to price movements caused by other factors (such as shifts in investor sentiment or liquidity shocks). Analysts can distinguish between these two potential drivers of stock returns, but the market does not fully take into account the information (or lack thereof) analysts provide. In support of this hypothesis, I find that price events accompanied by analyst reports are more positively correlated with future earnings than no-information price events. When earnings surprises are measured by abnormal returns, this positive correlation holds only for information-based price shocks. When earnings surprises are measured using analyst forecasts or the seasonal random walk model, the relation holds for both types of price movements, but is significantly stronger for information-based ones. These results suggest analysts can determine whether a price shock was caused by fundamental news about the firm, and are consistent with the view that post-event momentum is based on gradual incorporation of such news into prices.

To test this hypothesis further, I explore how the content of analyst reports influences their impact on post-event returns. I find that momentum exists only when analysts agree with the direction of the price change (i.e., when analyst recommendations are positive for a price increase or negative for a price decrease). If analysts disagree with it, the price change is actually followed by a reversal. This result suggests that the content of analyst reports matters, and it is not the case that reports only represent a sun-spot coordination device for investors.[4] This test illustrates an important advantage that my approach has over other

[4] I thank the referee for pointing out this potential alternative explanation.

studies (discussed below) utilizing media-based measures of information: it is much easier to determine whether the information was positive or negative with analyst reports.

A number of behavioral models try to explain momentum and reversals, either by grouping investors into those acting on private information and those trading on momentum (Hong and Stein, 1999) or by assuming investor behavior is driven by behavioral biases (Daniel, Hirshleifer, and Subrahmanyam, 1998; Barberis, Shleifer, and Vishny, 1998). Brav and Heaton (2002) show that (the appearance of) overreaction and underreaction can arise even with fully rational investors if they only possess incomplete information about the structure of the economy. Broadly speaking, these models all predict that investors underreact to relevant new information about a firm, which is consistent with my results. While my findings do not distinguish between theories based on investor irrationality or on rational structural uncertainty, they are less supportive of models relying on asymmetric information (Tetlock, 2010) combined with persistent liquidity shocks (though in this case, there are no reversals, just more or less momentum). Since asymmetric information is presumably always reduced when news is released, these theories, at least in their simplest form, do not predict differential outcomes based on whether analysts agree or disagree with the direction of the price change.

Interestingly, positive price shocks outnumber negative ones by close to 40%, and this difference is fully driven by no-information price events. This is a somewhat surprising result, given the conventional view that analysts prefer issuing positive news, in which case they should be more likely to comment on positive price changes. One possible explanation is short sales constraints, which could make it harder for arbitrageurs to counteract positive no-information price shocks than negative ones. In support of this view, I find that for no-information price shocks the magnitude of the average increase exceeds that of the average decline, whereas for information-based price shocks the opposite is true.

The ratio of no-information to information-based price events is strongly correlated with average aggregate implied volatility, with an intriguing potential implication that during periods of high uncertainty, the relative importance of news about firm-specific fundamentals falls relative to other shocks to stock prices. Furthermore, I find that this ratio predicts future momentum profits in an economically very meaningful way. The relation is especially strong in the second half of my sample, where a one standard deviation increase in the (quarterly) ratio forecasts a 5.9% decline in quarterly momentum returns, with an R^2 of 32.3%. This result suggests that the phenomena documented in this paper play a significant role in the profitability of price momentum, and are consistent with theories that attribute momentum to investor underreaction to new information.

The research approach in this paper is most similar to that of Pritamani and Singal (2001), Chan (2003), and Tetlock (2010). Pritamani and Singal (2001) study a subset of New York Stock Exchange (NYSE) and American Stock Exchange (Amex) stocks that experienced large price changes between 1990 and 1992. Conditional on a public announcement or volume increase associated with the event, these stocks exhibit momentum.[5] Chan (2003) constructs an index of news headlines for a random subset of Center for Research in Security Prices (CRSP) stocks, and finds momentum after news and reversal after no news, with the effect mostly driven by loser stocks. Tetlock (2010) uses the entire daily Dow Jones news archive from 1979 to 2007 to study how presence of public news affects subsequent returns. He finds that reversals are significantly lower after news days and that for many stocks, volume-induced momentum exists only on these days. Generally, these results are consistent with my own. However, this paper is the only one that documents both momentum after news and reversals after no-news, with the findings holding equally for winners and losers and not restricted to small stocks. Moreover, the magnitudes are significantly greater than those in previous work, confirming this is an important economic phenomenon, perhaps unlikely to be explained purely by asymmetric information (Kim and Verrecchia, 1991; Tetlock, 2010).

To compare my results directly to those in Chan (2003), I merge my data set with the headline news data set from that paper.[6] Using headlines as a proxy for information, I find

[5]Other papers analyzing stock returns after big price shocks include Brown, Harlow, and Tinic (1988), Atkins and Dyl (1990), Bremer and Sweeney (1991), Cox and Peterson (1994), and Park (1995).

[6]I am extremely thankful to the editor, William Schwert, the referee, and Wesley Chan for sharing this data.

strong reversals after no-information price events, but no momentum after information-based ones.[7] The latter are actually also followed by reversals, though the effect is substantially weaker than after no-information price moves. When I include both information proxies, the reversal effect disappears for information-based events. Thus, while both headlines and analyst reports seem to capture the same general phenomenon, the latter represent a more powerful measure of whether a price change is accompanied by new significant information, which is perhaps not surprising given the different roles played by general media and stock analysts. To the extent that analyst reports focus more on news about fundamentals than newspapers, it seems that investors underreact most to this type of news.

The second contribution of this paper is to examine whether analyst recommendations convey useful information to investors. A large literature shows that recommendations result in significant contemporaneous stock price reactions,[8] and that investors can profit by trading on recommendations even after they are released.[9] More recently, Altinkilic and Hansen (2009) dispute both sets of results, arguing that they stem from analysts' tendency to piggyback on corporate news.[10] Chen, Francis, and Schipper (2005) find that a typical analyst report does not produce a price reaction that is higher than the average on days without reports. Loh and Stulz (2011) report that the majority of analyst recommendations are not informative, but they also show that recommendations of a subset of analysts persistently impact stock prices.

My findings provide new evidence that analysts produce relevant information. Even if their recommendations do not directly influence prices, analysts seem to be able to distinguish between different large price movements, identifying those that signal future drift. One

[7] This is not inconsistent with the results in Chan (2003), which also does not document news-based momentum over the horizons studied in my paper.

[8] See Davies and Canes (1978), Elton, Gruber, and Grossman (1986), Beneish (1991), Stickel (1995), Womack (1996), Francis and Soffer (1997), Mikhail, Walther, and Willis (2004), Ivkovic and Jegadeesh (2004), and Asquith, Mikhail, and Au (2005).

[9] See Stickel (1995), Womack (1996), Michaely and Womack (1999), Barber, Lehavy, McNichols, and Trueman (2001), Jegadeesh, Kim, Krische, and Lee (2004), and Mikhail, Walther, and Willis (2004).

[10] Womack (1996) and Asquith, Mikhail, and Au (2005) also find that most reports do not offer new information or occur simultaneously with other important news.

interpretation of this evidence is that analysts recognize which price events are caused by news about firm fundamentals and which ones stem from other factors (such as shifts in investor sentiment or liquidity shocks). Consistent with this hypothesis, I show that price events accompanied by analyst reports predict future earnings better than no-information price events, while Hong, Lim, and Stein (2000) find that momentum in stock returns is stronger for stocks with low analyst coverage.[11] I also find that the relation between analyst recommendations and post-event returns does not change after the enactment of Regulation Fair Disclosure, suggesting that at least some analyst skills are not dependent on access to privileged information sources.

Finally, this paper could add to the literature on investor attention. Most of this work argues that limited investor attention causes underreaction (Hirshleifer and Teoh, 2003; DellaVigna and Pollet, 2007, 2009), which leads to drift in stock prices.[12] My findings suggest that limited attention may not always lead to underreaction. Insofar as the presence of analyst reports represents a proxy for whether investors take note of a large price move, I show that stock prices can actually overreact when investors are paying less attention.

The remainder of the paper is organized as follows. Section 2 describes my methodology, outlines how I construct my sample, and defines all the variables. Section 3 presents my findings, and Section 4 concludes.

2. Data and methodology

2.1. Methodology

My basic approach is straightforward. I classify stocks that experience major price shocks into two groups: those where the price change is accompanied by new information and those

[11] Analysts also sometimes respond slowly to past news, especially for poorly performing stocks (Chan, Jegadeesh, and Lakonishok, 1996).

[12] Some examples of this effect include earnings announcements occurring outside of trading hours (Francis, Pagach, and Stephan, 1992), on Fridays (DellaVigna and Pollet, 2009), or at the same times as announcements of other firms (Hirshleifer, Lim, and Teoh, 2009). Post-announcement drift is also stronger when the announcement is not covered in the *Wall Street Journal* (Peress, 2008) and for low-volume stocks (Hou, Peng, and Xiong, 2009).

where it is not. As my proxy for information, I use recommendation-issuing analyst reports. These reports could indicate that analysts believe an event occurred that is significant enough to warrant a comment. Alternatively, analyst activity itself could be the cause of the market's reaction. Current evidence shows that both of these are possible scenarios, as analysts are both sources of new information and interpreters of already released information (Asquith, Mikhail, and Au, 2005; Altinkilic and Hansen, 2009). For the purposes of my analysis, either of the cases qualifies as an information-based event, since I am interested in any relevant publicly available information about the firm, regardless of its source. While any proxy for information is imperfect, analyst recommendations satisfy two important criteria for such a proxy. First, they are very frequently newsworthy, at least in the eyes of investors.[13] Second, for actively covered stocks, analysts are likely to comment on most events that significantly affects investors' view of a firm's prospects.

2.2. Sample construction

The sample studied in this paper consists of stocks that are actively covered by sell-side analysts and experience large price changes. I get information on analyst coverage from the Institutional Brokers' Estimate System (IBES) Recommendations database, which documents analyst recommendations issued by brokerage or research houses. Each observation in the database corresponds to a recommendation by a specific house for a particular firm. These recommendations can take the form of upgrades, downgrades, reiterations, or initializations of coverage. The period covered by the database begins in November 1993 and ends in December 2009.

The first step in constructing my sample narrows the universe of all stocks in IBES to only those that had at least five recommendation-issuing analyst reports published over the previous 12 months. The goal behind imposing this screen is to ensure that all the firms in the sample are adequately followed by analysts. My methodology relies on the presence of analyst

[13] See Davies and Canes (1978), Elton, Gruber, and Grossman (1986), Beneish (1991), Stickel (1995), Womack (1996), Francis and Soffer (1997), Mikhail, Walther, and Willis (2004), Ivkovic and Jegadeesh (2004), and Asquith, Mikhail, and Au (2005).

reports as an indicator of whether a significant price movement is based on information. This approach is obviously not valid for stocks with no or very sparse coverage, as in those cases there are simply no analysts to write a report, even if the event causing the market reaction is a new development crucial to the firm's prospects. The threshold I employ is admittedly arbitrary, but my results are robust to various different treatments.[14] To allow for enough time for a history of published reports to build up, my sample starts in 1995 and ends in 2009.[15]

The next step is to identify major price movements. I calculate a firm's abnormal return, defined as its daily return ($R_{i,t}$) in excess of its return predicted by the Fama-French three-factor plus momentum model ($\overline{R}_{i,t}$), and define as a significant price movement any firm-date observation where the absolute value of this number, $\left|R_{i,t} - \overline{R}_{i,t}\right|$, exceeds 10%. This threshold should be high enough to screen out most price movements that do not reflect either substantial changes in fundamentals (or market perception thereof) or in investor sentiment, defined by Shleifer (2000, pp. 11-12) as "beliefs based on heuristics rather than Bayesian rationality." Atkins and Dyl (1990) and Bremer and Sweeney (1991) both use the 10% number in their studies of stock performance following large price declines. My results are robust to different thresholds, both higher and lower, and to different methods of adjusting returns, such as raw returns, market-adjusted returns, market-model excess returns, or Fama-French three-factor model excess returns.[16]

Some more recent literature studying significant price events (e.g., Pritamani and Singal, 2001) uses returns scaled by volatilities instead of absolute thresholds. The logic behind this approach is that what constitutes a significant price change is different for high-volatility stocks than for low-volatility stocks. However, return volatility is not exogenous. It reflects the industry a firm operates in and the degree to which investor sentiment or liquidity shocks

[14] The paper's findings do not change regardless of whether I use a higher or lower threshold. They also remain the same if I replace the number of reports issued with the number of analysts covering the stock.

[15] The analyst coverage screen could make it harder to detect momentum, given the result in Hong, Lim, and Stein (2000) that momentum is stronger for stocks with low analyst coverage.

[16] These findings, and all subsequent untabulated ones, are available upon request.

affect trading activity in the stock. For example, Internet stocks in the late 1990s were extremely volatile, at least partly due to the influence of shifting investor sentiment, which makes those stocks of particular interest for my analysis. If I adjusted their returns to take into account their high volatility, I would lose many observations where significant changes in fundamentals or investor sentiment occurred. Absolute thresholds do mean that my sample is biased towards highly volatile stocks, but again, those stocks might be the ones I am more interested in in the first place. In any case, this assumption is not crucial for my findings, all of which continue to hold if I scale returns by their lagged volatility.

I obtain data on daily stock returns, firm size, and trading volume from the Center for Research in Security Prices (CRSP) and annual accounting data from the CRSP/Compustat merged database. Earnings announcement dates are collected from Compustat. NYSE size breakpoints come from Kenneth French's Web site.

The final sample ("Full sample") is made up of all firm-trading day observations that satisfy both the analyst coverage and the major price movement criteria, which amounts to 166,470 data points. My sample size greatly exceeds that of samples used in other studies of large price movements. For example, the sample in Pritamani and Singal (2001) contains 4,873 observations. I further divide the Full sample into four subsamples, based on the direction of the price change and on whether an analyst report was released around the price event. I classify a price movement as accompanied by an analyst report if at least one is published on the day the movement occurred, a trading day before, or a trading day after. I broaden the window beyond the price event day itself because the timing of reports does not always correspond to the market reaction. For instance, if a company reports earnings after the market closes, analysts might react that day, while investors will only be able to do so the next trading day. Sometimes analysts actually precipitate a price movement by issuing a report, and this again might take place when the market already closed for the day. I allow analysts to issue a report after the price event to give them more time to react. The resulting four subsamples are:

i. "Reported negative sample" which consists of all negative price events accompanied by one or more analyst reports (17,566 observations).

ii. "Unreported negative sample" which consists of all negative price events unaccompanied by analyst reports (52,666 observations).

iii. "Reported positive sample" which consists of all positive price events accompanied by one or more analyst reports (17,056 observations).

iv. "Unreported positive sample" which consists of all positive price events unaccompanied by analyst reports (79,182 observations).

Table 1 shows the time-series distribution of these observations. One fact that immediately jumps out is the clustering of observations in the middle part and in the last two years of my sample. The 1998–2002 period makes up only 33% of the Full sample when measured in years, but represents 58% of its observations. The last two years, when the financial crisis was raging, account for 20% of observations and only 13% of years. This clustering is driven mostly by increases in the volatility of stock returns. One can observe this in Table 2, which presents the total number of CRSP stocks, significant price movements (using the 10% criterion), and recommendation-issuing analyst reports by year. While the total number of stocks changes over time (first increasing and then decreasing), these changes are much less pronounced than the changes in the number of large price events. The clustering could potentially complicate my analysis, but my research methodology takes the problem into account (both in the regression framework and in portfolio construction).

[Tables 1 and 2 about here.]

2.3. Variable definitions

Book equity is computed as in Cohen, Polk, and Vuolteenaho (2003). I assume markets get access to financial statement information four months after the fiscal year ends.[17] I use

[17] The Securities and Exchange Commission used to require that firms under its jurisdiction file their 10-K reports within 90 days of fiscal year-end. This rule changed recently (the deadline was shortened to 75 days

the financial statement data that reflect the latest information available to the public. Book-to-market ratio is computed using the previous month's closing market price. Firm size is calculated using the closing market price one trading day before the event day. Trading volume is computed as the percentage of shares outstanding that is traded. All returns are cumulative, but my results do not change if I use buy-and-hold returns instead. Momentum is calculated as the return over the previous 12 months. If there are less than six valid monthly returns over that period, the momentum variable is set to missing.

I estimate abnormal returns using a four-factor model, consisting of three Fama-French factors (Fama and French, 1993) plus a momentum factor (Carhart, 1997). More specifically, for each firm-trading day observation, I use pre-event returns to estimate the following regression model:

$$R_{i,t} - R_{f,t} = \alpha + \beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,smb}SMB_t + \beta_{i,hml}HML_t + \beta_{i,umd}UMD_t + u_{i,t}, \quad (1)$$

where R_i is the firm's daily return, R_m is the market return (CRSP value-weighted), R_f is the risk-free rate, SMB is the return of a portfolio of small stocks minus the return of a portfolio of big stocks (size factor), HML is the return of a portfolio of high book-to-market stocks minus the return of a portfolio of low book-to-market stocks (value factor), and UMD is the return of a portfolio of winner stocks minus the return of a portfolio of loser stocks (momentum factor). The factor returns are obtained from Kenneth French's Web site, which also provides more details on their construction. I estimate the model by ordinary least squares (OLS) regressions for a 255 trading day-period starting 31 trading days before the event day. I require at least 30 data points before I use the resulting coefficients. Otherwise, I delete the observation from my sample. With the coefficients obtained from Eq. (1), I then compute post-event abnormal returns (AR) as:

in 2004 for most firms and then to 60 days in 2006 for large firms), but was in effect during most of my sample period. I add an extra month to account for late filers.

$$AR_{i,t} = (R_{i,t} - R_{f,t}) - \left[\beta_{i,m}(R_{m,t} - R_{f,t}) + \beta_{i,smb}SMB_t + \beta_{i,hml}HML_t + \beta_{i,umd}UMD_t\right]. \tag{2}$$

3. Results

3.1. Summary statistics

Table 3 presents summary statistics for the Full sample and the various subsamples. There are substantially more no-information price events than information-based ones, with the ratio of the former to the latter being close to 4:1. Even for actively covered stocks, the majority of major price movements are not associated with a recommendation-issuing report. Presuming analyst reports are a valid proxy for new information released to investors, this shows that there are other important drivers of stock returns. I do not attempt to directly identify these drivers, but possible candidates include private information, shifts in investor sentiment, and liquidity shocks. This finding confirms previous work showing that publicly available information cannot fully explain stock market gyrations.[18]

[Table 3 about here.]

Interestingly, positive price shocks outnumber negative ones by 37%, with all of the difference stemming from no-information price events. Consequently, the ratio of no-information to information-based price shocks is much higher for positive price jumps (4.6 for positive changes versus 3.0 for negative ones). This result is especially surprising given the arguments that analysts, for a variety of reasons (including preserving access to management and winning investment banking business for their employers), prefer discussing or issuing

[18] There is little or no relation between news and aggregate market returns (Schwert, 1981; Mitchell and Mulherin, 1994). Macroeconomic variables explain less than half of the variance in aggregate stock prices, and large market movements often do not coincide with new information of corresponding importance (Cutler, Poterba, and Summers, 1989). For individual firms, a model that includes aggregate economic developments, industry effects, and firm-specific news explains only a fraction of daily and monthly return variance (Roll, 1988). Volatility of stock returns is much too high to be explained just by changes in dividends (Shiller, 1981), and even after controlling for information release, returns are more volatile during market hours (French and Roll, 1986).

positive news. A combination of liquidity shocks or shifting investor sentiment and short sales constraints provides one possible explanation. When a stock suddenly drops with no new information coming out, arbitrageurs may start buying it and so ameliorate the ultimate decrease. Faced with a price increase, arbitrageurs may find it harder to react in a similar fashion because of short sales constraints, resulting in a bigger price jump.[19] Providing further support for this hypothesis, I find that for no-information price shocks, the magnitude of the average increase exceeds that of the average decrease, while the opposite is true for information-based price shocks.

Measured by market equity, firms with information-based price moves are significantly larger. One interpretation is that private signals or shifts in investor sentiment are more important determinants of stock returns for smaller firms. Alternatively, analyst reports might represent a better public information proxy for larger firms. Analyst coverage is positively correlated with size, and analysts might also be more likely to react to developments affecting a larger firm. As support for this hypothesis, firms that experience no-information price shocks have less analyst coverage, with an average of 10.4 reports published over the previous year versus 14.3 for firms that experience information-based price shocks. The latter type of price moves is also accompanied by higher trading volume, perhaps because more investors trade when new public information about a firm comes out. This result is consistent with theoretical models of asymmetric information in trading, such as Kim and Verrecchia (1991) and Tetlock (2010).

For the purposes of this paper, the most relevant observation here concerns post-event returns. These depend both on the direction of the price shock and on its information status. After a price decline, the average cumulative abnormal return over a 20-trading day horizon is 0.7% if it was information-based and 7.2% if it was not. At first glance, it appears that stocks experiencing negative price shocks accompanied by information severely underperform those where no information is released. This pattern is reversed for price increases. Over

[19] Arbitrageurs would not try to trade in the opposite direction of information-based price moves, as those are followed by drift.

a 20-trading day horizon, the average abnormal return after a positive price shock is -0.1% if it is information-based and -0.4% if it is not. The evidence here is consistent with the hypothesis that post-event returns depend on whether the price shock is accompanied by information. The next step is to test more rigorously whether information presence really affects post-event returns.

3.2. Regression analysis of post-event returns

I start by examining what factors determine post-event returns. My dependent variable is the cumulative abnormal return over holding periods ranging between five and 40 trading days ($AR_{m,n}$). The main focus of my analysis is the impact of event day abnormal return (AR_0), but I also include various control variables, resulting in the following specification:

$$AR_{m,n} = \alpha + \beta AR_0 + \gamma' X + u. \tag{3}$$

X is a set of explanatory variables other than the event day return, which includes log size ($\log(ME)$), log book-to-market ratio ($\log(BE/ME)$), return over the previous 12 months (mom), and trading volume (vol). Size, book-to-market, and momentum are well-known predictors of the cross-section of stock returns (Fama and French, 1992, 1993; Jegadeesh and Titman, 1993). Lee and Swaminathan (2000) find that trading volume can help reconcile shorter-term underreaction to longer-term overreaction in stock returns, while Conrad, Hameed, and Niden (1994) show that stocks with low trading volume actually experience drift over weekly horizons.

To estimate Eq. (3), I employ the weighted least squares (WLS) approach. Each cross-section is weighted equally, in a similar manner to the eponymous method proposed by Fama and MacBeth (1973), which means I assign each firm-trading day observation a weight equal to the inverse of the number of firms in the corresponding cross-section. This approach is the same as the one applied by Vuolteenaho (2002). I opt for WLS because my panel is unbalanced, but my results remain unaltered if I instead use OLS. t-Statistics are calculated using clustered (Rogers) standard errors (Rogers, 1983, 1993), where each trading day represents one cluster.[20] Alternative methods for addressing cross-sectional correlation, such as the Fama-MacBeth procedure, do not change any of the paper's findings. The same is the case if my clustered standard errors reflect both potential cross-sectional and time-series correlation.

Panel A in Table 4 presents coefficient estimates for the Full sample. My discussion will focus on the case in which the dependent variable is the abnormal return over a 20-trading day holding period, but the results are substantially the same for all other horizons. The coefficient of most interest is the one on the event day return, which is negative and statistically very significant (t-stat=-7.1). This indicates that stocks with major price shocks unconditionally experience reversals. The coefficient magnitude of -0.081 implies that about 8% of the event day move is reversed over a 20-trading day holding period. The size coefficient is negative (t-stat=-18.7), the book-to-market one is positive (t-stat=8.1), and the momentum one is negative (t-stat=-20.3). The coefficient on volume is negative, but its economic significance is not very high and it is barely statistically significant (t-stat=-2.1).

[Table 4 about here.]

The previous results pool together stocks with large information-based price movements and stocks with no-information price movements. Now I test whether post-event returns differ across the two groups. Panel B in Table 4 shows coefficient estimates when only price events unaccompanied by analyst reports are considered. The event day return coefficient is more negative than before, equaling -0.108 (t-stat=-6.8). The coefficients on size, book-to-market, momentum, and volume are about the same as before. Panel C reports coefficient estimates when only price events accompanied by at least one analyst report are included. The major differences are that the event day return coefficient is no longer significant (t-stat=-1.2) and is

[20] I choose clustered standard errors because, unlike regular standard errors, they reflect any cross-sectional correlation of the residuals across stocks, which can make the former significantly biased downwards. Clustered standard errors will be unbiased as long as the number of clusters is sufficiently large. With its 3,040 clusters, my sample easily satisfies this criterion. Using a simulation, Petersen (2009) finds that 500 clusters is enough to make clustered standard errors correct.

about ten times smaller in magnitude than the point estimate for no-information price events. Unlike stocks experiencing no-information price shocks, stocks with information-based ones do not exhibit reversals.

An alternative specification for testing the impact of information includes a dummy variable indicating whether information accompanies a price shock. I use the following regression:

$$AR_{m,n} = \alpha + \beta AR_0 + \gamma(AR_0 * un) + \delta' X + \varepsilon(AR_0 * vol) + u. \tag{4}$$

un is a dummy variable set to one if no analyst reports were published around the event day and to zero otherwise. I add an interaction term between volume and event day return because previous research shows price momentum or shocks predict returns differently conditional on volume (Lee and Swaminathan, 2000; Pritamani and Singal, 2001; Llorente, Michaely, Saar, and Wang, 2002; Tetlock, 2010).

Coefficient estimates for Eq. (4) are presented in Table 5. Panel A gives results for the Full sample. The coefficient of most interest is the one on the interaction term $AR_0 * un$, which is negative and both economically and statistically significant (t-stat=-7.0). With the interaction term included, the event day return coefficient actually becomes positive and statistically significant (t-stat=2.7). Information presence appears to be a key determinant of post-event performance. While no-information stocks experience large reversals (amounting to 9.6% of the initial price shock), information ones do not and even exhibit drift. Another interesting finding is that the interaction term $AR_0 * vol$ is not significant (t-stat=-1.4). One possible reconciliation of this finding with previous results is that volume reflects new information, and once this aspect is controlled for, volume ceases to be important.

[Table 5 about here.]

Interestingly, the strength of the signal provided (or proxied for) by analyst reports does not seem to depend on their number. In unreported tests, I show that the number of analyst reports that come out around a price shock has no impact on subsequent returns (controlling for whether any reports were issued at all).

The rest of Table 5 provides various robustness checks. One potential complication regarding my general approach is the bid-ask bounce effect. Some prior studies claim that reversals stem, at least in part, from this very microstructure issue (Atkins and Dyl, 1990; Cox and Peterson, 1994; Park, 1995). More broadly, as a result of transactions costs such as spreads, any trading strategy trying to take advantage of (and so arbitrage away) differential post-event performance of information and no-information stocks could be unprofitable. Both the bid-ask bounce and transactions costs should most affect small, illiquid stocks. Consequently, I attempt to lessen the influence of microstructure effects by excluding such stocks from my sample.

In Panel B, I re-run regression (4) for firms whose closing stock price one day before the event day is higher than \$5. With this restriction, the number of observations drops by 40%, indicating that (potentially) illiquid stocks make up a nontrivial but not dominant portion of my sample. Firms that experience no-information price shocks still experience reversals, as the coefficient on the interaction term remains negative (t-stat=-5.9), and the ones with information-based price changes exhibit drift (t-stat=3.2). The importance of the size coefficient is somewhat diminished, but it continues to be significant (t-stat=-2.5). These findings continue to hold when I replace a price screen with a size screen in Panel C, which is limited to stocks with market capitalization above the NYSE bottom decile breakpoint.

Regardless of the exact method used, once I eliminate stocks most subject to microstructure effects, information-based price shocks are followed by drift and no-information ones by reversals. The fact that the AR_0 coefficient becomes more positive (indicating stronger momentum after information-based price shocks) also supports the hypothesis that some of the post-event reversal after large price movements can be attributed to the bid-ask bounce effect.

Another way to reduce the impact of the bid-ask bounce effect is to introduce a lag between the event day and the first day of the holding period. Panel D presents coefficient estimates when post-event returns are computed with a one trading day lag. The interaction term coefficient is again negative (t-stat=-3.7), although its magnitude decreases somewhat relative to the no-lag case. This again suggests that the bid-ask bounce might play a role in the observed reversals after no-information price shocks, but, even if that were the case, it explains a relatively small part.

In Panel E, I restrict the sample to price events that do not occur around earnings announcements. Prior work (Bernard and Thomas, 1989, 1990) shows strong short-term drift associated with these announcements, where positive (negative) earnings surprises lead to positive (negative) returns. Analyst reports are more likely to be released at times when firms are issuing earnings reports, so the post-earnings announcement drift phenomenon could explain my result that news-based price events are followed by drift. However, the event day return coefficient is still positive (t-stat=2.4) even when I exclude earnings announcements, while the $AR_0 * un$ coefficient is negative (t-stat=-6.9).

Panel F provides coefficient estimates for price shocks associated with earnings announcements. Only about 5% of observations fall into this category, showing that earnings announcements are not the dominant driver behind my findings. A large majority of earnings announcements coinciding with major price movements probably involve new information released to the market, even if no analyst reports are published. Analyst reports are an imperfect proxy for information release, and this subsample very likely includes many information-based price events where, for whatever reason, no reports come out. This conjecture is confirmed in the data. The coefficient on the event day return is positive (t-stat=1.3) and more than twice as large as the coefficient in the no-earnings-announcement sample. The interaction term is, on the other hand, no longer significant (t-stat=-1.8). The coefficient magnitudes imply a 20-trading day horizon drift of about 6% of the event day return. The finding should not be surprising, given that the post-earnings announcement drift is a very well-documented phenomenon, but it also offers additional support for the hypothesis that post-event performance depends on whether a price shock is accompanied by information.

3.3. Portfolio analysis

The regression analysis presented above suggests that the presence of information (or lack thereof) affects post-event returns. Price shocks unaccompanied by information (as proxied by analyst reports) are followed by significant reversals, while information-based ones are not. Next I test whether this potential anomaly leads to a profitable trading strategy.

Each of the stocks in the Full sample is assigned to one of four portfolios depending on the direction of the price move and its information status. The resulting portfolios are: Negative no-information portfolio, which consists of stocks that suffer a no-information price decline; Negative information portfolio, which consists of stocks that suffer an information-based price decline; Positive no-information portfolio, which consists of stocks that enjoy a no-information price increase; and Positive information portfolio, which consists of stocks that enjoy an information-based price increase. At any point in time, these portfolios are made up of all stocks that experienced the required price event over the previous N trading days, where N depends on the specified holding period. A portfolio's return is computed as an equal-weighted average of the constituent stocks' returns. For example, with a 20-trading day horizon, Positive information portfolio's return on a given day is the equal-weighted average return of all stocks that had a positive information-based price shock over the previous 20 trading days.

Using these portfolios, I then create two zero-investment portfolios, one each for no-information and information-based price shocks, which go long losers and short winners. If no-information price events are indeed followed by reversals, we would expect the former portfolio to enjoy a positive abnormal return. If information-based price events are followed by drift, we would expect the latter portfolio to suffer a negative abnormal return. To test these hypotheses, I use the time-series of returns for each long-short portfolio to estimate the following regression:

$$R_{port,t} = \alpha_{port} + \beta'_{port} X_t + u_{port,t}, \tag{5}$$

where R_{port} is a portfolio's daily return and X is a set of factor portfolio returns, which includes the market excess return ($R_m - R_f$), the size factor (SMB), the value factor (HML), and the momentum factor (UMD). If the intercept term (alpha) is significantly different from zero, we can reject the null hypothesis of no abnormal return.[21]

Panel A in Table 6 reports coefficient estimates for the no-information long-short portfolio. I present results for the market model, the Fama-French three-factor model, and the Fama-French three-factor plus momentum model. Neither the alpha's magnitude nor significance level changes with the specification, showing that my findings do not depend on the choice of a particular asset pricing model.[22] For a 20-trading day horizon, the no-information long-short portfolio enjoys a positive abnormal return, which on an annualized basis equals 20.2% (t-stat=7.3).[23] The positive intercept supports the hypothesis that price shocks not based on information result in post-event reversals, and the strategy exploiting this phenomenon delivers extraordinary returns per unit of risk. Assuming independent and identically distributed (i.i.d.) returns, the annualized Sharpe ratio is 1.66, which is much higher than the market's (0.32), the value factor's (0.39), or the momentum factor's (0.40) over the same period. The alpha remains positive and significant over all other horizons. However, its magnitude declines with the holding period, indicating that the degree of reversal following no-information price shocks is more pronounced early after the event. The only consistently significant factor loading is the momentum one, which is negative but not economically important (always less than 0.1).

[Table 6 about here.]

Panel B then shows coefficient estimates for the information-based long-short portfolio. The alpha is now significantly negative over all holding periods. For a 20-trading day horizon, its magnitude implies an annualized abnormal return of -15.1% (t-stat=-4.1) and a Sharpe

[21] Given that the number of stocks constituting a portfolio varies over time, the error term in the regression could be heteroskedastic. Lyon, Barber, and Tsai (1999) apply simulation methods and find that the resulting heteroskedasticity does not impact significance tests on the intercept term; consequently, I do not try to correct for this.

[22] When I discuss statistical significance, I always refer to t-statistics obtained from the Fama-French three-factor plus momentum model.

[23] Assuming there are 252 trading days in a year and given the daily alpha in Table 6 of 0.0008, this translates to: 252 * 0.0008 = 0.2016.

ratio of -1.21. The negative intercept is consistent with the hypothesis that information-based price shocks are followed by drift. As in Panel A, the alpha's magnitude decreases with the holding period, but this decline is much less severe than in that case. The momentum loading is again the only significant one, with a negative sign.

Finally, in Panel C I present abnormal returns for a trading strategy that exploits both reversals after no-information price events and drift after information-based price events. Over a 20-trading day horizon, the strategy yields an annualized abnormal return of 35.3% (t-stat=8.2). This is obviously a very meaningful number economically, but the strategy also requires frequent trading activity, which might limit its attractiveness or restrict its application to those investors who can trade most cheaply. However, given the potential profits, it is at least reasonable to conclude that substantial implementation costs would be required to completely eliminate this opportunity.

The fact that in Panel A the magnitude of alpha decreases with the horizon suggests that the bid-ask bounce might partly explain reversal after no-information price shocks. To explore how important this effect might be, in Tables 7 and 8 I repeat my analysis after excluding firms with a stock price below $5 or with market capitalization below the NYSE bottom decile breakpoint. My findings remain unaltered in both cases. For the no-information long-short portfolio, the intercept is significantly positive over all but the longest holding period. Even when stocks most subject to the bid-ask bounce are eliminated, major price moves unaccompanied by information are still followed by reversals. The magnitude of the intercept term is lower than previously, possibly revealing that this effect does play a role in my results. While the reversal phenomenon is weaker when price or size restrictions are imposed, drift after information-based price shocks is actually stronger. The information-based long-short portfolio suffers a negative abnormal return over all horizons, with an alpha that is more negative than in Table 6.

[Tables 7 and 8 about here.]

In Table 9, I use value-weighted portfolios instead of equal-weighted ones. The only major change is that the no-information portfolio no longer has a positive alpha at the longest horizons. The results for the information portfolio are actually stronger than in the equal-weighted case. Combined with evidence in Tables 7 and 8, this shows that neither reversals after no-news nor momentum after news are restricted to small stocks.

[Table 9 about here.]

In an unreported robustness test, I estimate Eq. (5) using WLS, where the weights are given by the number of stocks in a portfolio at a given time. This method gives more weight to those periods when the portfolios contain more stocks, which could be important given that my price events are not distributed uniformly across time. This alternative approach does not affect any of my results.

3.4. Headline news

My findings of momentum after information-based price moves and reversal after no-information price moves are similar to those in Chan (2003), who relies on headline news as a proxy for presence of information. More specifically, he uses the Dow Jones Interactive Publications Library to obtain all the dates when a stock is mentioned in a major daily publication. Importantly, he does not include analyst reports in his study, ensuring there is no direct overlap between our respective measures of information.[24] The approach in Chan (2003) is also quite different from mine, focusing on monthly returns and longer horizons. At horizons that are comparable to those in this paper, he finds only weak evidence of drift following news.

Given these differences, it is not immediately possible to determine whether this paper and Chan (2003) are capturing the same phenomena. To address these issues directly, I combine the headline-news data set from Chan (2003) with my own. His sample covers approximately one-quarter (randomly chosen) of all CRSP stocks over the 1980–2000 period, so I lose a large number of observations in the merge process. The resulting subsample contains 11,877 price events between 1995 and 2000.

[24] Of course, it is possible that newspapers sometimes carry stories about just-published analyst reports.

I now create an additional measure of information: a dummy variable un^{head} that equals one if no headline news came out around a price event and zero otherwise. Unsurprisingly, the two measures of information (analyst reports and headline news) are highly correlated. The unconditional probability of headline news occurring around a major price move is 56%. If a price event is accompanied by analyst reports, the probability increases to 81%. Similarly, the unconditional probability of an analyst report being issued around a price shock is 19%, which rises to 28% in the presence of headline news. These numbers also show that headline news is much more common than analyst reports, at least on the days when significant price moves occur.[25]

[Table 10 about here.]

In Panel A of Table 10, I present coefficient estimates for Eq. (4) with the headline news variable replacing the one based on analyst reports (un^{an}). The interaction term coefficient $AR_0 * un^{head}$ is strongly negative and significant over all horizons, mirroring the results obtained using my analyst-based measure. With either measure, no-news price events are followed by reversals. However, for headline news, in contrast to analyst reports, reversals also happen after news-based price moves, with the event day coefficient always being negative and significant. With headline news as a proxy, reversals are observed for both types of price events, though they are significantly stronger after no-news moves. Table 11 confirms this result in calendar time. Both the no-information and the information-based portfolios experience reversals, and the effect is much stronger for the former.

[Table 11 about here.]

In Panel B of Table 10, I add my un^{an} dummy variable to the regression specification, interacting it as before with the event day return. The event day coefficient is now no longer significant, showing that, unlike price moves accompanied by headline news, price moves based on new analyst-originated information do not experience reversals. As in my previous tests, the coefficient on the interaction term $AR_0 * un^{an}$ is negative. Interestingly, the

[25] As with the analyst report-based measure, the ratio of no-information to information-based price shocks is higher for positive price jumps (0.83 for positive changes versus 0.70 for negative ones).

$AR_0 * un^{head}$ coefficient does not change much. Its magnitude drops somewhat, but it remains strongly negative. It seems that both analyst reports and headline news independently reflect new information, and that the absence of such information results in bigger reversals of significant price moves.

Earnings announcements represent another potential information source for investors. In Panel C, I introduce a dummy variable ($noann$) that equals one if the price event did not coincide with an earnings announcement and zero otherwise. This addition does not change any of my results. The coefficients on both $AR_0 * un^{head}$ and $AR_0 * un^{an}$ remain negative and significant. Interestingly, the $AR_0 * noann$ interaction coefficient is not significant, which suggests that earnings announcements do not impact post-event returns once one controls for analyst reports and headline news. However, an important caveat here is that my sample is restricted to stocks actively covered by analysts, which makes it unlikely that an earnings announcement associated with a large price move would pass without comment by either analysts or news media (there are only 157 such earnings announcements in the 1995–2000 period).

Analyst reports typically focus on various fundamental performance metrics, such as earnings per share and revenues. Newspaper articles, on the other hand, frequently discuss other topics that are perhaps less germane to a firm's future prospects, but may still attract the attention of investors. My findings here suggest that investors underreact more to new information about fundamentals, despite such information perhaps being more relevant for future firm performance (which I show below).

3.5. Analyst report content

In addition to being focused on fundamentals, another advantage of analyst reports is that it is relatively easy to determine whether they contain good or bad news about a firm. This information can be helpful in distinguishing between various theories of momentum and reversals. One interpretation of my results so far is that investors underreact to new firm-specific fundamental information and overreact to other shocks to stock prices (such as liquidity shocks or changes in investor sentiment). Analysts can differentiate between these various drivers of stock returns, which is why they sometimes issue reports around significant stock price changes and sometimes do not.

If this explanation is correct, the content of analyst reports should matter. Or, more specifically, what should matter is whether analysts "agree" with the direction of the price move. If a firm's stock price rises (drops), but the new information is actually negative (positive), we would not expect to observe subsequent momentum. Instead, we should see reversals.

A straightforward measure of an analyst report's informational content is simply its recommendation. If an analyst upgrades (downgrades) his recommendations, I classify the resulting report as positive (negative) news. If there is no change or coverage is just initiated, the news is neutral. For each price event, I sum up recommendation changes across all reports issued around it, and use this aggregate recommendation change as my measure. I rely on the standardized Strong buy/Buy/Hold/Sell/Strong sell classification scheme used by IBES, and take into account not only the direction of recommendation changes but also their magnitude (e.g., an upgrade from Hold to Strong buy counts for more than an upgrade from Buy to Strong buy).[26]

I restrict my analysis to only information-based price events, and define two dummy variables that reflect whether a price move is accompanied by supporting or conflicting analyst recommendations. *Agree* equals one if the aggregate change in analyst recommendations is of the same sign as the event day price move and zero otherwise. *Disagree* equals one if the aggregate change in analyst recommendations is of the opposite sign as the event day price move and zero otherwise. Importantly, analysts do reasonably frequently disagree with the direction of the price shock: 18% of their recommendations have the opposite sign (and 55% have the same sign).

[26] Strong buy/Buy/Hold/Sell/Strong sell scheme translates into numerical rankings of 2/1/0/-1/-2.

To examine the impact of analyst report content, I estimate the following regression:

$$AR_{m,n} = \alpha + \beta AR_0 + \gamma^{agree}(AR_0 * agree) + \gamma^{dis}(AR_0 * disagree) + \delta' X + \varepsilon(AR_0 * vol) + u. \quad (6)$$

Table 12 presents the results. The key terms of interest are $AR_0 * agree$ and $AR_0 * disagree$. The first one is positive (t-stat=2.6 for a 10-day horizon), showing that momentum is stronger if analyst recommendations agree with the direction of the event day price change. In contrast, the second term is negative (t-stat=-3.6 for a 10-day horizon). When analyst reports contradict a price change, it is followed by reversal. Finally, when analyst reports convey neutral news (i.e., when there is no net change in analyst recommendations), I find neither drift nor reversals after a price event. These findings are broadly consistent with behavioral theories of momentum and reversals, which rely on investors underreacting to certain new information (in this case, the content of analyst reports).

[Table 12 about here.]

They are less consistent with theories based on asymmetric information (combined with persistent liquidity shocks for informed investors), where momentum ensues after the degree of informational asymmetry is reduced (Tetlock, 2010). Since analyst reports presumably help disseminate new information regardless of whether they agree or disagree with the direction of a price move, the asymmetric information theories do not predict a differential response depending on analyst report content, contrary to what I find in the data. My results also do not support the theory that analyst reports represent a sun-spot coordination mechanism for investors, who ignore their content and simply trade in the direction of the price change.

3.6. Price shocks and future earnings

What kind of information do analyst reports issued around large-move days provide? If analysts can distinguish between major price changes that are caused by news about fundamentals and those related to other shocks, one would expect information-based price events to be stronger predictors of future firm performance than no-information ones. Moreover, such price moves should be positively correlated with future performance.

As my measure of firm performance, I use earnings announcements for the subsequent two quarters. To ensure the price shock itself is not directly caused by an earnings announcement, I limit my analysis to earnings announcements occurring at least one week after the price event. I compute earnings surprises ($EarnSur$) employing three different approaches. First, I calculate abnormal announcement returns using the Fama-French plus momentum model over a three-day window starting one day before the announcement and ending one day after. The announcement dates come from Compustat. Second, I calculate standardized unexpected earnings (SUEs) using analyst forecasts, which are defined as the actual earnings per share (EPS) minus the median analyst EPS forecast, scaled by the standard deviation of analyst forecasts. Analyst forecasts come from IBES. Finally, I calculate SUEs using a seasonal random model, where an SUE equals actual EPS minus EPS in the same quarter of the previous year, scaled by the standard deviation of earnings surprises.

In Table 13, I estimate the following regression, which is similar to the specification in Tetlock, Saar-Tsechansky, and Macskassy (2008):

$$EarnSur = \alpha + \beta AR_0 + \gamma(AR_0 * un) + \delta' X + \varepsilon(AR_0 * vol) + u. \tag{7}$$

If information-based price events are positively correlated with future earnings, the event day return coefficient should be positive. If such price events are better predictors of earnings than no-information ones, the interaction term $AR_0 * un$ should be negative. Both of these hypotheses are confirmed by the data. The AR_0 coefficient is positive and significant for all three surprise measures in the first quarter following the price event and also for both SUE measures in the second quarter. The interaction term is always negative and also significant in all but two cases. The magnitudes show that only information-based price changes are positively correlated with future announcement returns. For SUEs, the positive correlation holds for both types of price shocks, but is significantly stronger for the ones accompanied by analyst reports.

[Table 13 about here.]

My results here show that price shocks predict future earnings (with a positive sign), and that the relation is always stronger for information-based price shocks than for no-information price shocks. In other words, a given positive (negative) price move predicts a higher (lower) earnings surprise if it is accompanied by analyst reports. These findings are consistent with the hypothesis that analysts are able to identify price shocks caused by news about changes in fundamentals (or that their reports reveal the changes), and that post-event momentum is based on gradual incorporation of such news into prices. To the extent that investors follow analyst recommendations (and in the process move stock prices), they do so at least in part because analysts provide useful information about firms' future performance.[27] However, investors seem to underreact to this information, resulting in post-event drift. Interestingly, given that one measure of earnings surprises is computed using analyst forecasts, even analysts themselves do not fully incorporate the information contained in the recommendations of (presumably) other analysts (otherwise, there would be no predictability).

3.7. Aggregate volatility, price shocks, and momentum profits

Table 3 shows that the number of price shocks varies greatly over time. Significant price moves are much more common during volatile periods, such as the bursting of the Internet bubble (2000–2001) and the financial crisis (2008–2009). This finding is probably not overly surprising (even taking into account that I measure price changes using idiosyncratic returns). Instead of just focusing on their total number, it is perhaps more interesting to study the relative proportion of information-based (reported) and no-information (unreported) price changes.

Fig. 1 plots the evolution over time of average implied volatility, which I define as the quarterly average of the constant-maturity 30-day implied volatility from the Chicago Board Options Exchange (CBOE) Standard & Poor's (S&P) 500 Volatility Index (VIX), and of the

[27] In other words, it is not the case that analyst recommendations by themselves attract the attention of investors and so induce buying or selling. Instead, it is the information provided by analyst reports that causes investors to trade in a certain way.

quarterly ratio of no-information price changes to information-based price changes. The two series track each other very closely, with their correlation being 0.50.

[Fig. 1 about here.]

However, this graph still likely underestimates the effect, as analyst coverage for a typical stock increased during my sample period, making it less likely that a price event will be unaccompanied by an analyst report in the later years. Therefore, I adjust the ratio for growth in analyst coverage. More specifically, I use the ratio of the number of analysts to the total number of CRSP stocks in a given year (calculated using figures from Table 2) to adjust the probability of a price event being unreported. For example, the ratio is 0.76 in 1995 and 0.87 in 1996, making the probability of an analyst report being released, holding everything else constant (including, crucially, the propensity of analysts to issue new recommendations), 14% higher in 1996. Since one should thus expect there to be 14% more analyst reports in 1996 relative to 1995, I adjust the number of information-based price events in 1996 down by 14%, and use that number to calculate the no-information/information-based ratio.

Fig. 2 shows how this adjusted ratio and implied volatility vary over time. The two are extremely highly correlated (0.80), tracking each other almost perfectly.[28] When the VIX index is high, both information-based and no-information price shocks occur more frequently, but the increase is much greater for the latter. One intriguing interpretation here is that during periods of heightened uncertainty, the relative importance of news about firm-specific fundamentals falls compared to other shocks to individual stock prices. In other words, increases in aggregate volatility are not driven primarily by new information about firm fundamentals. This, however, is pure speculation at this stage and requires future research.[29]

[Fig. 2 about here.]

The ratio of no-information to information-based price changes could be related to future performance of momentum trading strategies. In their simplest form, such strategies buy

[28] When I use the headline news measure to calculate the no-information to information-based price change ratio, I find that the ratio and average implied volatility are only weakly correlated (0.2).

[29] An alternative possibility is that during such periods, analysts simply get overwhelmed by the quantity of news, making their reports a less useful proxy for new information.

stocks with high past returns (winners) and short sell stocks with low past returns (losers). My results show that stocks that experience major price moves, which are quite likely to find themselves in winner or loser portfolios, have very different subsequent performance, depending on whether these moves were accompanied by information. Since drift follows only information-based price shocks, one would expect that a lower fraction of such shocks leads to lower momentum returns. I test this hypothesis by running the following simple OLS regression:

$$MOM_t = \alpha + \beta Ratio_{t-1} + u_t, \tag{8}$$

where MOM is the quarterly return of the momentum factor UMD, and $Ratio$ is the ratio of no-information to information-based price shocks in a given quarter.

Over the entire sample period, β is negative (-0.01) and somewhat statistically significant (t-stat=-1.68), with an R^2 of 4.7%. The coefficient magnitude implies that a one standard deviation increase in the $Ratio$ variable predicts a 2.2% decrease in momentum strategy profits next quarter (relative to the sample average of 1.8%), which is a major effect. This relation is much stronger in the second half of my sample period (2003–2009): β is again negative (-0.02) and now strongly significant (t-stat=-3.45). A one standard deviation increase in the $Ratio$ variable forecasts a 5.9% decrease in momentum profits. Furthermore, the R^2 jumps to 32.3%, indicating that the $Ratio$ variable is a very strong predictor of momentum profits in the 2003–2009 period.

These results suggest that the phenomena documented in this paper, reversals after no-information price shocks and drift after information-based shocks, play a significant role in explaining the profitability of price momentum. They are consistent with theories that argue momentum arises because investors underreact to new information, and also provide new insights about the exact channel. Specifically, major price movements seem to represent an important factor in driving future momentum in stock prices (and especially so in the 2003–2009 period).

3.8. Post-Regulation FD results

Substantial regulatory changes affecting security analysts occurred during the period covered in my sample. Regulation Fair Disclosure (Reg FD), which mandates that all public companies must disclose material information to all investors at the same time, was adopted by the Securities and Exchange Commission in August 2000. Global Analyst Settlement, which addresses potential conflicts of interest for analysts, was concluded in April 2003. As Loh and Stulz (2011) point out, it is not immediately clear how increased regulation will affect the quality of analyst reports (measured in terms of how much they help investors make good decisions). On the one hand, reduced analyst access to sources of useful information, such as firm executives or analysts' colleagues working in other divisions, could hurt their ability to produce informative research. On the other hand, regulations could eliminate (or at least mitigate) conflicts of interest that adversely impact analyst report quality.[30]

The shift to more restrictive regulations provides an opportunity to explore the source of analyst ability to distinguish between price movements that are followed by reversals and those that are followed by drift. If it stems from information provided by firm insiders or investment banking colleagues, then one would expect my results to be much weaker after the regulations went into effect. Table 14 explores this hypothesis. It presents Eq. (4) results for the period starting in 2003. As before, there is drift after price events accompanied by analyst recommendations, whereas after those without, there are reversals. The magnitudes for all the relevant coefficients are almost the same as for the entire 1995–2009 period, showing that new regulations did not affect the relation between analyst recommendations and post-large price movement returns. This evidence suggests that analysts possess at least some skills that are not dependent on access to privileged information sources.

[Table 14 about here.]

[30] The evidence so far is mixed. Gintschel and Markov (2004) find that Reg FD was successful in decreasing selective disclosure of information to analysts, thereby reducing the price impact of their reports. Kadan, Madureira, Wang, and Zach (2009) show that recommendations overall became less informative after the Global Analyst Settlement, though the impact is different for buys and sells. In a longer sample, however, Loh and Stulz (2011) obtain opposite results. They find that analyst recommendations are more likely to be influential in the post-Reg FD and the post-Settlement periods.

4. Conclusion

This paper studies how information presence affects post-event performance of stocks experiencing large price changes. I use recommendation-issuing analyst reports as a proxy for whether new publicly available information about a firm is released. After first restricting the sample to stocks that are actively covered by analysts, I classify those price shocks accompanied by newly released analyst reports as information-based and the remaining ones as not. Both regression analysis and calendar-time portfolios show that no-information price events experience reversals, while information-based ones exhibit momentum.

These two phenomena are economically very meaningful and statistically significant. A portfolio that is long no-information losers and short no-information winners earns annualized abnormal returns of 20% over a 20-trading day horizon (with a Sharpe ratio of 1.66). A portfolio that is long information winners and short information losers earns abnormal returns of 16% per year (with a Sharpe ratio of 1.21). My findings are robust to various controls, different horizons, and exclusion of small and illiquid stocks. They are also not driven by post-earnings announcement drift. If only earnings announcements are included in the sample, price shocks are followed by drift regardless of their information status.

I show that my measure of information is complementary to the headline news-based one used in Chan (2003). Under both measures, the absence of information predicts reversals after price shocks. However, only the presence of analyst reports results in drift, suggesting their content is perhaps more relevant to investors than that of newspapers.

My results are consistent with the hypothesis that investors underreact to new information about a firm and overreact to price movements caused by other factors (such as shifts in investor sentiment or liquidity shocks). In support of this explanation, I find that post-event momentum exists only in those instances when the direction of the price move coincides with the "direction" of news (as proxied by changes in analyst recommendations). When analyst reports contradict the price move, I actually document reversals. Furthermore, I show that information-based price moves are more strongly correlated with future earnings shocks than no-information ones.

One question not addressed here is what are the other drivers of large price moves apart from new public information. Private information is one candidate, but it is not immediately clear why one would then observe post-event reversals. To the extent it takes a longer period of time for private information to be reflected in stock prices, one would expect stronger drift in those situations rather than reversals. Investor sentiment is another possibility, in which case the question becomes what causes sentiment shifts. A related explanation are liquidity shocks, where the issue is why they result in such significant price changes and take such a long time to dissipate. A potential clue comes from my finding that no-information price changes are relatively more common during periods of heightened uncertainty. One could plausibly argue in favor of any of these three factors (private information, changing investor sentiment, and liquidity shocks) becoming more important during such periods. This is a topic for future research.

References

Altinkilic, O., Hansen, R. S. , 2009. On the information role of stock recommendation revisions. Journal of Accounting and Economics 48, 17–36.

Asquith, P., Mikhail, M. B., Au, A. S., 2005. Information content of equity analyst reports. Journal of Financial Economics 75, 245–282.

Atkins, A. B., Dyl, E. A., 1990. Price reversals, bid-ask spreads, and market efficiency. Journal of Financial and Quantitative Analysis 25, 535–547.

Barber, B., Lehavy, R., McNichols, M., Trueman, B., 2001. Can investors profit from the prophets? Security analyst recommendations and stock returns. Journal of Finance 56, 531–563.

Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. Journal of Financial Economics 49, 307–343.

Beneish, M. D., 1991. Stock prices and the dissemination of analysts' recommendations. Journal of Business 64, 393–416.

Bernard, V. L., Thomas, J. K., 1989. Post-earnings-announcement drift: Delayed price response or risk premium? Journal of Accounting Research 27, 1–36.

Bernard, V. L., Thomas, J. K., 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. Journal of Accounting and Economics 13, 305–340.

Brav, A., Heaton, J. B., 2002. Competing theories of financial anomalies. Review of Financial Studies 15, 575–606.

Bremer, M., Sweeney, R. J., 1991. The reversal of large stock-price decreases. Journal of Finance 46, 747–754.

Brown, K. C., Harlow, W. V., Tinic, S. M., 1988. Risk aversion, uncertain information, and market efficiency. Journal of Financial Economics 22, 355–385.

Carhart, M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57–82.

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

Chan, W. S., 2003. Stock price reaction to news and no-news: Drift and reversal after headlines. Journal of Financial Economics 70, 223–260.

Chen, Q., Francis, J., Schipper, K., 2005. The applicability of the fraud on the market presumption to analysts' Forecasts. Unpublished working paper. Duke University.

Cohen, R. B., Polk, C., Vuolteenaho, T., 2003. The value spread. Journal of Finance 58, 609–641.

Conrad, J. S., Hameed, A., Niden, C., 1994. Volume and autocovariances in short-horizon individual security returns. Journal of Finance 49, 1305–1329.

Cox, D. R., Peterson, D. R., 1994. Stock returns following large one-day declines: Evidence on short-term reversals and longer-term performance. Journal of Finance 49, 255–267.

Cutler, D. M., Poterba, J. M., Summers, L. H., 1989. What moves stock prices? Journal of Portfolio Management 15, 4–12.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and overreactions. Journal of Finance 53, 1839–1885.

Davies, P., Canes, J., 1978. Stock prices and the publication of second-hand information. Journal of Business 51, 43–56.

DeBondt, W. F. M., Thaler, R., 1985. Does the stock market overreact? Journal of Finance 40, 793–805.

DellaVigna, S., Pollet, J. M., 2007. Demographics and industry returns. American Economic Review 97, 1667–1702.

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

Elton, E. J., Gruber, M. J., Grossman, S., 1986. Discrete expectational data and portfolio performance. Journal of Finance 41, 699–713.

Fama, E. F., French, K. R., 1992. The cross-section of expected stock returns. Journal of

Finance 47, 427–465.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E. F., MacBeth, J. D., 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81, 607–636.

Francis, J., Pagach, D., Stephan, J., 1992. The stock market response to earnings announcements released during trading versus nontrading periods. Journal of Accounting Research 30, 165–184.

Francis, J., Soffer, L., 1997. The relative informativeness of analysts' stock recommendations and earnings forecast revisions. Journal of Accounting Research 35, 193–211.

French, K. R., Roll, R., 1986. Stock return variances: The arrival of information and the reaction of traders. Journal of Financial Economics 17, 5–26.

Gintschel, A., Markov, S., 2004. The effectiveness of Regulation FD. Journal of Accounting and Economics 37, 293–314.

Hirshleifer, D., Lim, S. S., Teoh, S. H., 2009. Driven to distraction: extraneous events and underreaction to earnings news. Journal of Finance 64, 2289–2325.

Hirshleifer, D., Teoh, S. H., 2003. Limited attention, information disclosure, and financial reporting. Journal of Accounting and Economics 36, 337–386.

Hong, H., Lim, T., Stein, J. C., 2000. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. Journal of Finance 55, 265–295.

Hong, H., Stein, J. C., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. Journal of Finance 54, 2143–2184.

Hou, K., Peng, L., Xiong, W., 2009. A tale of two anomalies: The Implications of investor attention for price and earnings momentum. Unpublished working paper. Ohio State University, Baruch College, and Princeton University.

Ivkovic, Z., Jegadeesh, N., 2004. The timing and value of forecast and recommendation revisions. Journal of Financial Economics 73, 433–463.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. Journal of Finance 45, 881–898.

Jegadeesh, N., Kim, J., Krische, S. D., Lee, C. M. C., 2004. Analyzing the analysts: When do recommendations add value? Journal of Finance 59, 1083–1124.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48, 65–91.

Kadan, O., Madureira, L., Wang, R., Zach, T., 2009. Conflicts of interest and stock recommendations: The effects of the global settlement and related regulations. Review of Financial Studies 22, 4189–4217.

Kim, O., Verrecchia, R. E., 1991. Trading volume and price reactions to public announcements. Journal of Accounting Research 29, 302–321.

Lee, C. M. C., Swaminathan, B., 2000. Price momentum and trading volume. Journal of Finance 55, 2017–2069.

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

Llorente, G., Michaely, R., Saar, G., Wang, J., 2002. Dynamic volume-return relation of individual stocks. Review of Financial Studies 15, 1005–1047.

Lo, A. W., MacKinlay, C. A., 1990. When are contrarian profits due to stock market overreaction? Review of Financial Studies 3, 175–205.

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

Lyon, J. D., Barber, B. M., Tsai, C. L., 1999. Improved methods for tests of long-run abnormal stock returns. Journal of Finance 54, 165–201.

Michaely, R., Womack, K. L., 1999. Conflict of interest and the credibility of underwriter analyst recommendations. Review of Financial Studies 12, 653–686.

Mikhail, M. B., Walther, B. R., Willis, R., 2004. Do security analysts exhibit persistent differences in stock picking ability? Journal of Financial Economics 74, 67–91.

Mitchell, M. L., Mulherin, J. H., 1994. The impact of public information on the stock market. Journal of Finance 49, 923–950.

Park, J., 1995. A market microstructure explanation for predictable variations in stock returns following large price changes. Journal of Financial and Quantitative Analysis 30, 241–256.

Peress, J., 2008. Media coverage and investors attention to earnings announcements. Unpublished working paper. INSEAD.

Petersen, M. A., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. Review of Financial Studies 22, 435–480.

Pritamani, M., Singal, V., 2001. Return predictability following large price changes and information releases. Journal of Banking and Finance 25, 631–656.

Rogers, W. H., 1983. Analyzing complex survey data. Unpublished working paper. Rand Corporation, Santa Monica, CA.

Rogers, W. H., 1993. Regression standard errors in clustered samples. Stata Technical Bulletin 13, 19–23, reprinted in Stata Technical Bulletin Reprints, vol. 3, 88–94.

Roll, R., 1988. R2. Journal of Finance 43, 541–566.

Schwert, G. W., 1981. The adjustment of stock prices to information about inflation. Journal of Finance 36, 15–29.

Shiller, R. J., 1981. Do stock prices move too much to be justified by subsequent changes in dividends? American Economic Review 71, 421–436.

Shleifer, A., 2000. Inefficient Markets: An Introduction to Behavioral Finance. Oxford University Press, New York.

Stickel, S., 1995. The anatomy of the performance of buy and sell recommendations. Financial Analysts Journal 51, 25–39.

Tetlock, P. C., 2010. Does public financial news resolve asymmetric information? Review of Financial Studies 23, 3520–3557.

Tetlock, P. C., Saar-Tsechansky, M., Macskassy, S., 2008. More than words: Quantifying language to measure firms' fundamentals. Journal of Finance 63, 1437–1467.

Vega, C., 2006. Stock price reaction to public and private information. Journal of Financial Economics 82, 103–133.

Vuolteenaho, T., 2002. What drives firm-level stock returns? Journal of Finance 57, 233–264.

Womack, K. L., 1996. Do brokerage analysts' recommendations have investment value? Journal of Finance 51, 137–167.

Table 1
Time-series distribution of major price events

Full sample consists of all firm-trading day observations where i) at least five recommendation-issuing analyst reports on the firm were published over the previous 12 months (measured using the IBES Recommendations database) and ii) the firm's abnormal return is either greater than 10% or lower than -10%. Reported negative sample is a subsample of Full sample that includes all negative price events accompanied by one or more analyst reports. Unreported negative sample is a subsample of Full sample that includes all negative price events unaccompanied by analyst reports. Reported positive sample is a subsample of Full sample that includes all positive price events accompanied by one or more analyst reports. Unreported positive sample is a subsample of Full sample that includes all positive price events unaccompanied by analyst reports. Firm size is computed using the closing market price one trading day before the event day.

	Full sample		Reported negative sample		Unreported negative sample		Reported positive sample		Unreported positive sample	
Year	N	Mean firm size (MM)	N	Mean firm size (MM)	N	Mean firm size (MM)	N	Mean firm size (MM)	N	Mean firm size (MM)
1995	4,020	448.4	389	900.9	1,230	309.6	345	1,269.5	2,056	308.1
1996	6,215	538.1	612	1,452.6	1,760	374.1	568	1,034.8	3,275	369.3
1997	6,850	626.0	655	1,531.2	2,057	460.9	589	1,135.9	3,549	469.9
1998	14,087	705.9	1,265	1,785.5	4,450	435.0	1,185	1,443.1	7,187	562.1
1999	15,453	1,302.1	1,418	2,767.7	3,965	777.1	1,865	2,402.6	8,205	1,052.4
2000	28,844	2,537.5	2,227	6,223.4	10,326	1,843.8	2,332	4,888.8	13,959	2,069.9
2001	23,070	1,290.4	2,048	3,607.3	8,233	888.0	1,782	3,003.4	11,007	882.9
2002	14,943	986.8	2,002	2,769.4	5,064	640.9	1,489	1,718.9	6,388	531.8
2003	6,316	777.1	890	1,902.2	1,452	494.7	961	1,266.1	3,013	424.8
2004	3,453	1,455.9	768	2,682.5	682	892.2	632	2,108.3	1,371	748.4
2005	3,000	1,452.1	646	2,216.2	640	832.9	631	2,418.5	1,083	799.3
2006	2,993	1,792.6	646	3,596.4	652	951.1	609	2,345.2	1,086	914.9
2007	4,038	1,413.9	732	2,315.4	1,027	1,026.6	661	2,278.2	1,618	898.7
2008	20,201	1,608.5	2,148	3,302.1	7,373	1,221.0	1,899	3,159.6	8,781	1,184.1
2009	12,987	1,073.6	1,120	1,805.5	3,755	979.8	1,508	1,916.7	6,604	810.3
Total	166,470	1,375.7	17,566	3,047.7	52,666	1,002.8	17,056	2,526.8	79,182	1,004.8

Table 2
Time-series distribution of CRSP stocks, price events, and analyst reports

CRSP stocks column represents all CRSP stocks that were traded at least once during the calendar year. Price events column gives all stock-trading day observations where the firm's abnormal return either is greater than 10% or lower than -10%. Analysts column represents all analysts covered by the IBES Recommendations database who published at least one recommendation-issuing report during the calendar year. Analyst reports column gives the total number of recommendation-issuing reports published during the calendar year.

Year	CRSP stocks	Price events	Analysts	Analyst reports
1995	8,191	90,085	6,207	53,130
1996	8,462	90,777	7,337	60,854
1997	9,038	90,919	8,435	65,921
1998	9,100	113,637	9,104	68,322
1999	8,690	104,170	9,366	68,185
2000	8,359	144,662	9,677	63,916
2001	8,117	112,812	9,926	64,001
2002	7,428	82,005	9,953	72,973
2003	7,013	41,207	9,640	69,996
2004	6,680	22,240	9,412	68,363
2005	6,721	18,168	9,704	67,766
2006	6,739	15,522	10,495	73,367
2007	6,843	18,821	11,239	79,623
2008	6,994	82,718	11,336	80,307
2009	6,779	67,321	11,273	84,278

Table 3
Summary statistics

Abnormal returns over a (m, n) window centered on the event day ($AR_{m,n}$) are estimated by a four-factor model, consisting of three Fama-French factors (Fama and French, 1993) plus a momentum factor (Carhart, 1997). All returns are expressed as percentages. Firm size (ME) is calculated using the closing market price one trading day before the event day. The total number of analyst reports published over the previous 12 months (*analysts*) and the number of analyst reports issued around the event day (*report*) are obtained from the IBES Recommendations database. Trading volume (*vol*) is computed as the percentage of shares outstanding that is traded on event day.

Panel A: Full sample (N = 166,470)

	AR_0	ME	*analysts*	*report*	*vol* (%)	$AR_{1,5}$	$AR_{1,10}$	$AR_{1,20}$
Mean	2.6	1,375.7	11.1	0.3	4.2	0.9	1.5	2.7
Median	9.3	261.1	8.0	0.0	2.0	-0.2	0.1	0.7

Panel B: Reported negative sample (N = 17,566)

	AR_0	ME	*analysts*	*report*	*vol* (%)	$AR_{1,5}$	$AR_{1,10}$	$AR_{1,20}$
Mean	-17.0	3,047.7	14.1	1.7	8.7	0.1	0.4	0.7
Median	-13.9	616.1	11.0	1.0	4.9	-0.2	-0.1	0.2

Panel C: Unreported negative sample (N = 52,666)

	AR_0	ME	*analysts*	*report*	*vol* (%)	$AR_{1,5}$	$AR_{1,10}$	$AR_{1,20}$
Mean	-13.3	1,002.8	10.2	0.0	3.2	3.3	4.8	7.2
Median	-11.9	189.0	8.0	0.0	1.5	2.1	2.9	4.4

Panel D: Reported positive sample (N = 17,056)

	AR_0	ME	*analysts*	*report*	*vol* (%)	$AR_{1,5}$	$AR_{1,10}$	$AR_{1,20}$
Mean	15.7	2,526.8	14.5	1.4	6.3	-0.3	-0.2	-0.1
Median	12.9	590.0	11.0	1.0	3.6	-0.6	-0.5	-0.2

Panel E: Unreported positive sample (N = 79,182)

	R_0^{mar}	ME	*analysts*	*report*	*vol* (%)	$AR_{1,5}$	$AR_{1,10}$	$AR_{1,20}$
Mean	16.0	1,064.0	10.5	0.0	3.4	-0.2	0.0	-0.4
Median	13.2	219.9	8.0	0.0	1.8	-1.4	-1.3	-0.9

Table 4
Determinants of post-event returns: Reported vs. unreported

The table reports coefficient estimates of the following regression:

$$AR_{m,n} = \alpha + \beta AR_0 + \gamma' X + u.$$

$AR_{m,n}$ is the cumulative abnormal return over a period starting m and ending n trading days after the event day, and AR_0 is the event day abnormal return. X includes log size ($\log(ME)$), log book-to-market ratio ($\log(BM)$), return over the previous 12 months (mom), and trading volume (vol). Parameter estimates are computed using the WLS approach, where weights are set so that each cross-section has an equal weight. t-Statistics (in brackets) are calculated using clustered standard errors.

Panel A: Full sample (N = 120,221)

	Intercept	AR_0	$\log(ME)$	$\log(BM)$	*mom*	*vol*	R^2 (%)
$AR_{1,5}$	0.047	-0.062	-0.007	0.002	-0.006	-0.014	1.3
	[14.4]	[-13.2]	[-12.5]	[3.2]	[-11.0]	[-1.2]	
$AR_{1,10}$	0.082	-0.065	-0.012	0.005	-0.012	-0.019	1.9
	[17.1]	[-6.0]	[-15.3]	[5.3]	[-15.2]	[-1.7]	
$AR_{1,20}$	0.140	-0.081	-0.020	0.010	-0.026	-0.028	3.3
	[21.4]	[-7.1]	[-18.7]	[8.1]	[-20.3]	[-2.1]	
$AR_{1,40}$	0.245	-0.115	-0.033	0.022	-0.055	-0.065	6.2
	[29.6]	[-12.2]	[-25.3]	[12.7]	[-24.2]	[-3.4]	

Panel B: Unreported samples (N = 93,041)

	Intercept	AR_0	$\log(ME)$	$\log(BM)$	*mom*	*vol*	R^2 (%)
$AR_{1,5}$	0.052	-0.095	-0.008	0.002	-0.006	-0.005	1.7
	[12.6]	[-15.2]	[-10.5]	[1.9]	[-9.7]	[-0.3]	
$AR_{1,10}$	0.095	-0.090	-0.014	0.005	-0.011	-0.035	2.1
	[14.9]	[-5.9]	[-12.8]	[4.0]	[-12.2]	[-2.1]	
$AR_{1,20}$	0.164	-0.108	-0.025	0.009	-0.024	-0.044	3.5
	[19.0]	[-6.8]	[-16.4]	[5.4]	[-16.7]	[-2.4]	
$AR_{1,40}$	0.289	-0.157	-0.042	0.020	-0.053	-0.062	6.5
	[27.8]	[-12.3]	[-23.9]	[9.1]	[-20.9]	[-1.9]	

Panel C: Reported samples (N = 27,180)

	Intercept	AR_0	$\log(ME)$	$\log(BM)$	*mom*	*vol*	R^2 (%)
$AR_{1,5}$	0.025	-0.003	-0.004	0.004	-0.006	-0.001	0.6
	[4.0]	[-0.4]	[-4.2]	[2.7]	[-7.0]	[-0.1]	
$AR_{1,10}$	0.037	-0.012	-0.005	0.005	-0.015	0.009	1.7
	[5.3]	[-1.6]	[-5.2]	[3.1]	[-11.8]	[0.6]	
$AR_{1,20}$	0.059	-0.012	-0.007	0.011	-0.028	-0.004	3.2
	[6.4]	[-1.2]	[-5.4]	[4.7]	[-12.4]	[-0.2]	
$AR_{1,40}$	0.139	-0.025	-0.015	0.025	-0.057	-0.053	5.8
	[9.6]	[-1.9]	[-7.5]	[8.2]	[-13.5]	[-1.9]	

Table 5
Determinants of post-event returns: Information dummy

The table reports coefficient estimates of the following regression:

$$AR_{m,n} = \alpha + \beta AR_0 + \gamma(AR_0 * un) + \delta' X + \varepsilon(AR_0 * vol) + u.$$

$AR_{m,n}$ is the cumulative abnormal return over a period starting m and ending n trading days after the event day, and AR_0 is the event day abnormal return. X includes log size ($\log(ME)$), log book-to-market ratio ($\log(BM)$), return over the previous 12 months (mom), and trading volume (vol). un is a dummy variable set to one if no analyst reports were published around the event day. Parameter estimates are computed using the WLS approach, where weights are set so that each cross-section has an equal weight. t-Statistics (in brackets) are calculated using clustered standard errors.

Panel A: Full sample (N = 120,221)

	$Int.$	AR_0	$AR_0 * un$	$\log(ME)$	$\log(BM)$	mom	vol	$AR_0 * vol$	R^2 (%)
$AR_{1,5}$	0.041	0.013	-0.106	-0.007	0.002	-0.006	-0.006	0.007	1.5
	[11.5]	[1.7]	[-11.6]	[-13.0]	[2.8]	[-11.2]	[-0.5]	[0.2]	
$AR_{1,10}$	0.066	0.024	-0.105	-0.012	0.005	-0.012	-0.007	-0.045	2.0
	[12.6]	[2.5]	[-6.3]	[-15.5]	[5.0]	[-15.4]	[-0.7]	[-1.4]	
$AR_{1,20}$	0.110	0.031	-0.127	-0.020	0.010	-0.026	-0.015	-0.050	3.4
	[14.9]	[2.7]	[-7.0]	[-19.0]	[7.9]	[-20.4]	[-1.1]	[-1.4]	
$AR_{1,40}$	0.190	0.025	-0.185	-0.034	0.022	-0.055	-0.048	-0.028	6.3
	[20.6]	[1.5]	[-10.1]	[-25.6]	[12.5]	[-24.2]	[-2.5]	[-0.6]	

Panel B: Full sample + price>=$5 ($N$ = 72,898)

	$Int.$	AR_0	$AR_0 * un$	$\log(ME)$	$\log(BM)$	mom	vol	$AR_0 * vol$	R^2 (%)
$AR_{1,5}$	0.014	0.024	-0.076	-0.002	0.002	-0.005	-0.003	0.005	0.8
	[4.7]	[2.5]	[-8.9]	[-4.8]	[2.5]	[-9.2]	[-0.2]	[0.1]	
$AR_{1,10}$	0.015	0.030	-0.078	-0.002	0.005	-0.010	-0.004	-0.040	1.3
	[3.9]	[3.1]	[-7.8]	[-3.0]	[5.1]	[-13.7]	[-0.4]	[-1.0]	
$AR_{1,20}$	0.026	0.038	-0.080	-0.002	0.011	-0.022	-0.005	-0.052	2.6
	[5.0]	[3.2]	[-5.9]	[-2.5]	[8.0]	[-19.4]	[-0.4]	[-1.2]	
$AR_{1,40}$	0.048	0.041	-0.087	-0.002	0.025	-0.046	-0.017	-0.071	5.6
	[6.4]	[2.3]	[-4.6]	[-1.6]	[13.3]	[-23.8]	[-0.8]	[-1.0]	

Panel C: Full sample + ME>bottom NYSE decile (N = 78,791)

	$Int.$	AR_0	$AR_0 * un$	$\log(ME)$	$\log(BM)$	mom	vol	$AR_0 * vol$	R^2 (%)
$AR_{1,5}$	0.026	0.017	-0.066	-0.003	0.002	-0.005	-0.006	-0.010	0.8
	[7.0]	[2.0]	[-6.7]	[-5.9]	[2.8]	[-10.3]	[-0.5]	[-0.3]	
$AR_{1,10}$	0.040	0.022	-0.077	-0.003	0.005	-0.011	-0.012	-0.049	1.4
	[7.8]	[2.3]	[-6.8]	[-5.1]	[4.5]	[-14.4]	[-1.2]	[-1.7]	
$AR_{1,20}$	0.068	0.029	-0.074	-0.004	0.011	-0.024	-0.024	-0.045	2.6
	[9.5]	[2.3]	[-4.7]	[-4.3]	[7.6]	[-19.4]	[-1.7]	[-1.1]	
$AR_{1,40}$	0.121	0.037	-0.098	-0.004	0.024	-0.050	-0.063	-0.050	5.7
	[11.6]	[2.0]	[-4.3]	[-3.1]	[12.9]	[-24.1]	[-3.1]	[-0.8]	

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Panel D: Full sample with one day lag (N = 120,234)

	$Int.$	AR_0	$AR_0 * un$	$\log(ME)$	$\log(BM)$	mom	vol	$AR_0 * vol$	R^2 (%)
$AR_{2,6}$	0.021	-0.005	-0.042	-0.004	0.002	-0.005	-0.010	0.021	0.7
	[6.5]	[-0.8]	[-5.8]	[-7.9]	[3.1]	[-11.1]	[-1.2]	[0.9]	
$AR_{2,11}$	0.046	0.006	-0.042	-0.009	0.004	-0.011	-0.013	-0.032	1.4
	[9.0]	[0.7]	[-2.7]	[-11.7]	[5.1]	[-15.4]	[-1.5]	[-1.2]	
$AR_{2,21}$	0.090	0.014	-0.064	-0.017	0.010	-0.025	-0.020	-0.042	2.8
	[12.4]	[1.3]	[-3.7]	[-16.2]	[7.9]	[-20.6]	[-1.7]	[-1.3]	
$AR_{2,41}$	0.171	0.010	-0.121	-0.031	0.022	-0.054	-0.054	-0.028	5.8
	[18.6]	[0.7]	[-7.0]	[-23.5]	[12.6]	[-24.4]	[-3.1]	[-0.7]	

Panel E: Full sample + non-earnings announcements (N = 113,631)

	$Int.$	AR_0	$AR_0 * un$	$\log(ME)$	$\log(BM)$	mom	vol	$AR_0 * vol$	R^2 (%)
$AR_{1,5}$	0.042	0.008	-0.103	-0.007	0.002	-0.006	-0.008	0.022	1.6
	[11.4]	[0.9]	[-10.5]	[-12.6]	[2.5]	[-10.8]	[-0.6]	[0.7]	
$AR_{1,10}$	0.068	0.019	-0.104	-0.013	0.005	-0.012	-0.007	-0.037	2.1
	[12.5]	[1.9]	[-6.1]	[-15.1]	[4.7]	[-14.9]	[-0.6]	[-1.1]	
$AR_{1,20}$	0.115	0.029	-0.131	-0.021	0.010	-0.026	-0.011	-0.050	3.4
	[15.0]	[2.4]	[-6.9]	[-18.7]	[7.6]	[-20.1]	[-0.8]	[-1.3]	
$AR_{1,40}$	0.198	0.025	-0.194	-0.035	0.022	-0.055	-0.042	-0.040	6.3
	[20.9]	[1.5]	[-10.1]	[-25.3]	[12.2]	[-23.8]	[-2.1]	[-0.8]	

Panel F: Full sample + earnings announcements (N = 6,590)

	$Int.$	AR_0	$AR_0 * un$	$\log(ME)$	$\log(BM)$	mom	vol	$AR_0 * vol$	R^2 (%)
$AR_{1,5}$	0.010	0.068	-0.095	-0.002	0.003	-0.006	0.018	-0.112	0.9
	[0.6]	[2.6]	[-3.0]	[-1.2]	[0.7]	[-2.5]	[0.7]	[-2.1]	
$AR_{1,10}$	0.044	0.063	-0.089	-0.007	0.004	-0.014	-0.007	-0.134	1.7
	[2.1]	[1.8]	[-2.0]	[-2.6]	[0.7]	[-5.1]	[-0.2]	[-1.8]	
$AR_{1,20}$	0.087	0.059	-0.110	-0.012	0.010	-0.029	-0.056	-0.023	3.5
	[3.0]	[1.3]	[-1.8]	[-3.1]	[1.4]	[-6.1]	[-1.1]	[-0.2]	
$AR_{1,40}$	0.138	0.039	-0.077	-0.019	0.019	-0.069	-0.121	0.161	6.6
	[3.7]	[0.7]	[-1.0]	[-3.9]	[2.3]	[-8.2]	[-1.9]	[1.3]	

Table 6
Intercept tests for calendar-time portfolios

The table reports coefficient estimates of the following OLS regression:

$$R_{port,t} = \alpha_{port} + \beta^{'}_{port} X_t + u_{port,t},$$

where R_{port} is a portfolio's daily return, and X is a set of factor returns, which includes the market excess return, size factor, value factor, and momentum factor. t-Statistics are given in brackets.
In Panel A, the dependent variable is the return of a zero-investment portfolio that is long stocks that suffered no-information price declines and short stocks that enjoyed no-information price increases (No-information portfolio). In Panel B, the dependent variable is the return of a zero-investment portfolio that is long stocks that suffered information-based price declines and short stocks that enjoyed information-based price increases (Information-based portfolio). In Panel C, the dependent variable is the return of a zero-investment portfolio that is long the No-Information portfolio and short the Information-based portfolio.

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	Panel A: No-information portfolio					Panel B: Information-based portfolio				
	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}
5-days	0.0044	0.0390				-0.0011	0.0323			
	[15.5]	[1.8]				[-2.9]	[1.1]			
5-days	0.0044	0.0452	-0.0392	0.0737		-0.0011	0.0374	0.0350	0.0383	
	[15.5]	[2.0]	[-0.9]	[1.7]		[-3.0]	[1.2]	[0.6]	[0.7]	
5-days	0.0044	0.0188	-0.0389	0.0274	-0.0845	-0.0010	-0.0226	0.0354	-0.0672	-0.1924
	[15.6]	[0.8]	[-0.8]	[0.6]	[-2.7]	[-2.7]	[-0.7]	[0.6]	[-1.1]	[-4.6]
10-days	0.0019	0.0205				-0.0008	0.0095			
	[11.2]	[1.5]				[-3.3]	[0.5]			
10-days	0.0019	0.0233	-0.0069	0.0302		-0.0008	0.0185	0.0581	0.0680	
	[11.1]	[1.7]	[-0.2]	[1.2]		[-3.3]	[1.0]	[1.5]	[1.9]	
10-days	0.0019	-0.0038	-0.0066	-0.0174	-0.0870	-0.0007	-0.0331	0.0587	-0.0226	-0.1654
	[11.4]	[-0.3]	[-0.2]	[-0.6]	[-4.7]	[-3.0]	[-1.6]	[1.6]	[-0.6]	[-6.5]
20-days	0.0008	0.0259				-0.0007	-0.0019			
	[7.1]	[2.9]				[-4.3]	[-0.2]			
20-days	0.0008	0.0317	0.0091	0.0532		-0.0007	0.0087	0.0366	0.0911	
	[7.0]	[3.4]	[0.5]	[3.1]		[-4.4]	[0.7]	[1.5]	[3.9]	
20-days	0.0008	0.0077	0.0094	0.0111	-0.0769	-0.0006	-0.0309	0.0370	0.0217	-0.1267
	[7.3]	[0.8]	[0.5]	[0.6]	[-6.2]	[-4.1]	[-2.3]	[1.5]	[0.9]	[-7.6]
40-days	0.0003	0.0273				-0.0005	-0.0080			
	[3.7]	[5.1]				[-4.7]	[-0.9]			
40-days	0.0002	0.0331	0.0333	0.0454		-0.0005	0.0039	0.0164	0.1099	
	[3.5]	[6.0]	[3.0]	[4.4]		[-4.9]	[0.4]	[0.9]	[6.7]	
40-days	0.0003	0.0090	0.0335	0.0031	-0.0772	-0.0005	-0.0377	0.0169	0.0369	-0.1331
	[4.1]	[1.5]	[3.1]	[0.3]	[-10.4]	[-4.4]	[-4.1]	[1.0]	[2.1]	[-11.5]

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Panel C: Combined portfolio

	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}
5-days	0.0055	0.0056			
	[12.3]	[0.2]			
5-days	0.0055	0.0069	-0.0709	0.0363	
	[12.3]	[0.2]	[-1.0]	[0.5]	
5-days	0.0054	0.0409	-0.0711	0.0961	0.1089
	[12.2]	[1.0]	[-1.0]	[1.3]	[2.2]
10-days	0.0026	0.0109			
	[10.0]	[0.5]			
10-days	0.0027	0.0048	-0.0650	-0.0378	
	[10.1]	[0.2]	[-1.5]	[-0.9]	
10-days	0.0026	0.0293	-0.0653	0.0051	0.0784
	[9.9]	[1.3]	[-1.5]	[0.1]	[2.7]
20-days	0.0015	0.0278			
	[8.3]	[2.0]			
20-days	0.0015	0.0230	-0.0275	-0.0379	
	[8.4]	[1.6]	[-1.0]	[-1.4]	
20-days	0.0014	0.0385	-0.0277	-0.0106	0.0498
	[8.2]	[2.5]	[-1.0]	[-0.4]	[2.6]
40-days	0.0008	0.0353			
	[6.6]	[3.9]			
40-days	0.0008	0.0292	0.0168	-0.0645	
	[6.7]	[3.2]	[0.9]	[-3.7]	
40-days	0.0007	0.0467	0.0166	-0.0339	0.0559
	[6.5]	[4.7]	[0.9]	[-1.8]	[4.5]

Table 7
Intercept tests for calendar-time portfolios: Price>$5

The table reports coefficient estimates of the following OLS regression:

$$R_{port,t} = \alpha_{port} + \beta_{port}^{'} X_t + u_{port,t},$$

where R_{port} is a portfolio's daily return and X is a set of factor returns, which includes the market excess return, size factor, value factor, and momentum factor. t-Statistics are given in brackets.
The analysis is limited to Full sample firms with a stock price above $5. In Panel A, the dependent variable is the return of a zero-investment portfolio that is long stocks that suffered no-information price declines and short stocks that enjoyed no-information price increases (No-information portfolio). In Panel B, the dependent variable is the return of a zero-investment portfolio that is long stocks that suffered information-based price declines and short stocks that enjoyed information-based price increases (Information-based portfolio).

Panel A: No-information portfolio						Panel B: Information-based portfolio				
	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}
5-days	0.0028	0.0751				-0.0015	0.0356			
	[9.6]	[3.3]				[-4.2]	[1.2]			
5-days	0.0027	0.0777	-0.0309	0.0361		-0.0015	0.0401	-0.0028	0.0449	
	[9.6]	[3.4]	[-0.7]	[0.8]		[-4.2]	[1.3]	[-0.0]	[0.8]	
5-days	0.0028	0.0406	-0.0305	-0.0290	-0.1187	-0.0015	-0.0273	-0.0025	-0.0736	-0.2160
	[9.8]	[1.6]	[-0.7]	[-0.6]	[-3.8]	[-3.9]	[-0.8]	[-0.0]	[-1.2]	[-5.3]
10-days	0.0012	0.0508				-0.0010	0.0249			
	[6.5]	[3.5]				[-4.3]	[1.4]			
10-days	0.0012	0.0531	-0.0065	0.0248		-0.0010	0.0381	0.0599	0.1091	
	[6.5]	[3.6]	[-0.2]	[0.9]		[-4.4]	[2.0]	[1.6]	[3.1]	
10-days	0.0012	0.0192	-0.0061	-0.0349	-0.1089	-0.0009	-0.0183	0.0605	0.0101	-0.1808
	[6.7]	[1.2]	[-0.2]	[-1.2]	[-5.4]	[-4.0]	[-0.9]	[1.6]	[0.3]	[-7.1]
20-days	0.0004	0.0487				-0.0007	0.0041			
	[3.6]	[5.1]				[-4.8]	[0.3]			
20-days	0.0004	0.0556	0.0211	0.0605		-0.0008	0.0175	0.0429	0.1159	
	[3.5]	[5.7]	[1.1]	[3.3]		[-5.0]	[1.4]	[1.7]	[4.9]	
20-days	0.0005	0.0277	0.0214	0.0114	-0.0896	-0.0007	-0.0311	0.0434	0.0306	-0.1556
	[3.8]	[2.6]	[1.1]	[0.6]	[-6.8]	[-4.6]	[-2.3]	[1.7]	[1.2]	[-9.2]
40-days	0.0001	0.0443				-0.0005	0.0058			
	[1.4]	[7.1]				[-5.0]	[0.7]			
40-days	0.0001	0.0516	0.0512	0.0544		-0.0006	0.0218	0.0347	0.1438	
	[1.2]	[8.1]	[4.0]	[4.5]		[-5.3]	[2.5]	[2.0]	[8.8]	
40-days	0.0001	0.0227	0.0516	0.0036	-0.0927	-0.0005	-0.0286	0.0353	0.0555	-0.1613
	[1.7]	[3.3]	[4.0]	[0.3]	[-10.8]	[-4.8]	[-3.1]	[2.1]	[3.2]	[-14.0]

Table 8
Intercept tests for calendar-time portfolios: ME>bottom decile

The table reports coefficient estimates of the following OLS regression:

$$R_{port,t} = \alpha_{port} + \beta'_{port} X_t + u_{port,t},$$

where R_{port} is a portfolio's daily return and X is a set of factor returns, which includes the market excess return, size factor, value factor, and momentum factor. t-Statistics are given in brackets.
The analysis is limited to Full sample firms with market capitalization above that of firms in the bottom NYSE decile. In Panel A, the dependent variable is the return of a zero-investment portfolio that is long stocks that suffered no-information price declines and short stocks that enjoyed no-information price increases (No-information portfolio). In Panel B, the dependent variable is the return of a zero-investment portfolio that is long stocks that suffered information-based price declines and short stocks that enjoyed information-based price increases (Information-based portfolio).

	Panel A: No-information portfolio					Panel B: Information-based portfolio				
	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}
5-days	0.0024	0.0760				-0.0014	0.0218			
	[7.5]	[3.0]				[-3.7]	[0.7]			
5-days	0.0024	0.0786	-0.0619	0.0469		-0.0014	0.0210	-0.0231	-0.0004	
	[7.5]	[3.0]	[-1.2]	[1.0]		[-3.7]	[0.7]	[-0.4]	[-0.0]	
5-days	0.0024	0.0485	-0.0618	-0.0059	-0.0960	-0.0013	-0.0385	-0.0226	-0.1048	-0.1903
	[7.6]	[1.7]	[-1.2]	[-0.1]	[-2.7]	[-3.5]	[-1.2]	[-0.4]	[-1.7]	[-4.5]
10-days	0.0009	0.0481				-0.0009	-0.0005			
	[4.6]	[3.0]				[-3.6]	[-0.0]			
10-days	0.0009	0.0482	-0.0204	0.0083		-0.0009	0.0079	0.0426	0.0676	
	[4.6]	[2.9]	[-0.6]	[0.3]		[-3.7]	[0.4]	[1.1]	[1.9]	
10-days	0.0010	0.0154	-0.0200	-0.0494	-0.1051	-0.0008	-0.0396	0.0431	-0.0157	-0.1522
	[4.8]	[0.9]	[-0.6]	[-1.5]	[-4.7]	[-3.4]	[-1.9]	[1.1]	[-0.4]	[-5.8]
20-days	0.0002	0.0462				-0.0008	-0.0158			
	[1.7]	[4.6]				[-4.8]	[-1.3]			
20-days	0.0002	0.0536	0.0311	0.0614		-0.0008	-0.0056	0.0271	0.0904	
	[1.6]	[5.2]	[1.5]	[3.1]		[-5.0]	[-0.4]	[1.1]	[3.8]	
20-days	0.0002	0.0253	0.0315	0.0117	-0.0907	-0.0007	-0.0445	0.0275	0.0220	-0.1247
	[1.9]	[2.3]	[1.5]	[0.6]	[-6.4]	[-4.7]	[-3.2]	[1.1]	[0.9]	[-7.2]
40-days	0.0000	0.0438				-0.0005	-0.0096			
	[0.0]	[6.6]				[-4.9]	[-1.1]			
40-days	0.0000	0.0527	0.0553	0.0678		-0.0006	0.0038	0.0162	0.1248	
	[-0.2]	[7.8]	[4.0]	[5.3]		[-5.1]	[0.4]	[0.9]	[7.4]	
40-days	0.0000	0.0235	0.0556	0.0166	-0.0934	-0.0005	-0.0372	0.0166	0.0528	-0.1315
	[0.3]	[3.3]	[4.1]	[1.2]	[-10.3]	[-4.7]	[-3.9]	[0.9]	[2.9]	[-10.9]

Table 9
Intercept tests for calendar-time portfolios: Value-weighted portfolios

The table reports coefficient estimates of the following OLS regression:

$$R_{port,t} = \alpha_{port} + \beta'_{port} X_t + u_{port,t},$$

where R_{port} is a portfolio's daily return and X is a set of factor returns, which includes the market excess return, size factor, value factor, and momentum factor. t-Statistics are given in brackets.
In Panel A, the dependent variable is the value-weighted return of a zero-investment portfolio that is long stocks that suffered no-information price declines and short stocks that enjoyed no-information price increases (No-information portfolio). In Panel B, the dependent variable is the value-weighted return of a zero-investment portfolio that is long stocks that suffered information-based price declines and short stocks that enjoyed information-based price increases (Information-based portfolio).

	Panel A: No-information portfolio					Panel B: Information-based portfolio				
	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}
5-days	0.0018	0.1449				-0.0021	0.0778			
	[4.6]	[4.6]				[-4.4]	[2.1]			
5-days	0.0018	0.1617	-0.0978	0.1959		-0.0021	0.1020	-0.0443	0.2506	
	[4.5]	[5.0]	[-1.5]	[3.2]		[-4.5]	[2.7]	[-0.6]	[3.5]	
5-days	0.0019	0.1179	-0.0973	0.1189	-0.1405	-0.0021	0.0408	-0.0439	0.1430	-0.1961
	[4.6]	[3.4]	[-1.5]	[1.8]	[-3.2]	[-4.3]	[1.0]	[-0.6]	[1.8]	[-3.7]
10-days	0.0008	0.0688				-0.0014	-0.0176			
	[2.9]	[3.3]				[-4.3]	[-0.7]			
10-days	0.0008	0.0781	-0.0476	0.1055		-0.0014	0.0090	-0.0424	0.2718	
	[2.9]	[3.6]	[-1.1]	[2.6]		[-4.5]	[0.4]	[-0.8]	[5.6]	
10-days	0.0008	0.0462	-0.0472	0.0495	-0.1022	-0.0013	-0.0384	-0.0418	0.1886	-0.1518
	[3.0]	[2.0]	[-1.1]	[1.1]	[-3.5]	[-4.3]	[-1.4]	[-0.8]	[3.6]	[-4.4]
20-days	0.0001	0.0669				-0.0011	-0.0228			
	[0.6]	[4.4]				[-4.6]	[-1.2]			
20-days	0.0001	0.0834	0.0171	0.1548		-0.0011	-0.0019	-0.0541	0.2212	
	[0.4]	[5.4]	[0.5]	[5.3]		[-4.8]	[-0.1]	[-1.4]	[6.2]	
20-days	0.0001	0.0608	0.0174	0.1151	-0.0724	-0.0011	-0.0387	-0.0537	0.1566	-0.1178
	[0.6]	[3.6]	[0.6]	[3.7]	[-3.4]	[-4.6]	[-1.9]	[-1.4]	[4.1]	[-4.6]
40-days	-0.0001	0.0625				-0.0009	-0.0454			
	[-0.4]	[5.6]				[-5.1]	[-3.4]			
40-days	-0.0001	0.0778	0.0649	0.1274		-0.0009	-0.0246	-0.0462	0.2175	
	[-0.6]	[6.9]	[2.8]	[5.9]		[-5.4]	[-1.8]	[-1.7]	[8.5]	
40-days	-0.0001	0.0561	0.0652	0.0892	-0.0696	-0.0009	-0.0597	-0.0458	0.1558	-0.1127
	[-0.4]	[4.6]	[2.8]	[3.9]	[-4.5]	[-5.1]	[-4.1]	[-1.7]	[5.7]	[-6.1]

Table 10
Determinants of post-event returns: Analyst reports and headline news

The table reports coefficient estimates of the following regression:

$$AR_{m,n} = \alpha + \beta AR_0 + \gamma^{head}(AR_0 * un^{head}) + \gamma^{an}(AR_0 * un^{an}) + \gamma^{ann}(AR_0 * ann) + \delta' X + \varepsilon(AR_0 * vol) + u.$$

$AR_{m,n}$ is the cumulative abnormal return over a period starting m and ending n trading days after the event day, and AR_0 is the event day abnormal return. X includes log size ($\log(ME)$), log book-to-market ratio ($\log(BM)$), return over the previous 12 months (mom), and trading volume (vol). un^{head} is a dummy variable set to one if no news articles were published around the event day using the data set from Chan (2003), un^{an} is a dummy variable set to one if no analyst reports were published, and $noann$ is a dummy variable set to one if no earnings announcements occurred. $Int.$ is the intercept term. The analysis is restricted to stocks covered in Chan (2003) and to the period intersecting his and my data (1995–2000). Parameter estimates are computed using the WLS approach, where weights are set so that each cross-section has an equal weight. t-Statistics (in brackets) are calculated using clustered standard errors.

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	$Int.$	AR_0	$AR_0 * un^{head}$	$AR_0 * un^{an}$	$AR_0 * noann$	$\log(ME)$	$\log(BM)$	mom	vol	$AR_0 * vol$	R^2 (%)
Panel A: Headline news (N = 11,877)											
$AR_{1,5}$	0.049	-0.082	-0.086			-0.007	0.000	-0.002	-0.079	0.104	3.0
	[7.3]	[-6.6]	[-4.1]			[-6.3]	[0.1]	[-1.7]	[-4.2]	[3.4]	
$AR_{1,10}$	0.077	-0.063	-0.126			-0.011	0.003	-0.004	-0.100	0.033	3.2
	[9.0]	[-3.8]	[-4.8]			[-7.7]	[1.5]	[-2.7]	[-3.6]	[0.7]	
$AR_{1,20}$	0.127	-0.094	-0.149			-0.019	0.003	-0.011	-0.112	0.114	4.3
	[10.9]	[-4.3]	[-4.0]			[-9.4]	[1.0]	[-5.0]	[-3.3]	[2.0]	
$AR_{1,40}$	0.213	-0.123	-0.106			-0.032	0.009	-0.028	-0.186	0.181	7.2
	[13.5]	[-4.0]	[-2.1]			[-10.9]	[2.0]	[-6.7]	[-4.1]	[2.3]	
Panel B: Headline news + analyst reports (N = 11,877)											
	$Int.$	AR_0	$AR_0 * un^{head}$	$AR_0 * un^{an}$	$AR_0 * noann$	$\log(ME)$	$\log(BM)$	mom	vol	$AR_0 * vol$	R^2 (%)
$AR_{1,5}$	0.049	-0.022	-0.068	-0.084		-0.007	0.000	-0.002	-0.060	0.083	3.1
	[7.3]	[-1.5]	[-3.1]	[-4.2]		[-6.3]	[0.0]	[-1.8]	[-3.1]	[2.5]	
$AR_{1,10}$	0.077	-0.012	-0.111	-0.073		-0.011	0.003	-0.004	-0.083	0.015	3.2
	[9.0]	[-0.6]	[-4.0]	[-2.7]		[-7.8]	[1.5]	[-2.8]	[-3.0]	[0.4]	
$AR_{1,20}$	0.127	-0.040	-0.133	-0.077		-0.019	0.003	-0.011	-0.094	0.095	4.3
	[10.9]	[-1.4]	[-3.5]	[-2.2]		[-9.4]	[0.9]	[-5.1]	[-2.7]	[1.8]	
$AR_{1,40}$	0.213	-0.067	-0.088	-0.080		-0.032	0.009	-0.029	-0.167	0.161	7.2
	[13.5]	[-1.6]	[-1.7]	[-1.6]		[-10.9]	[2.0]	[-6.7]	[-3.7]	[2.2]	
Panel C: Headline news + analyst reports + earnings announcements (N = 11,877)											
	$Int.$	AR_0	$AR_0 * un^{head}$	$AR_0 * un^{an}$	$AR_0 * noann$	$\log(ME)$	$\log(BM)$	mom	vol	$AR_0 * vol$	R^2 (%)
$AR_{1,5}$	0.049	-0.034	-0.068	-0.085	0.013	-0.007	0.000	-0.002	-0.060	0.083	3.1
	[7.3]	[-0.9]	[-3.1]	[-4.2]	[0.4]	[-6.3]	[0.0]	[-1.8]	[-3.1]	[2.5]	
$AR_{1,10}$	0.077	-0.029	-0.112	-0.074	0.019	-0.011	0.003	-0.004	-0.083	0.014	3.2
	[9.0]	[-0.7]	[-4.1]	[-2.8]	[0.4]	[-7.8]	[1.5]	[-2.8]	[-3.0]	[0.4]	
$AR_{1,20}$	0.127	-0.086	-0.135	-0.079	0.051	-0.019	0.003	-0.011	-0.095	0.094	4.3
	[10.9]	[-1.1]	[-3.5]	[-2.3]	[0.7]	[-9.4]	[0.9]	[-5.1]	[-2.7]	[1.8]	
$AR_{1,40}$	0.213	-0.005	-0.085	-0.078	-0.068	-0.032	0.009	-0.029	-0.166	0.162	7.2
	[13.5]	[-0.0]	[-1.6]	[-1.6]	[-0.6]	[-10.9]	[2.0]	[-6.7]	[-3.6]	[2.2]	

Table 11
Intercept tests for calendar-time portfolios: Headline news-based portfolios

The table reports coefficient estimates of the following OLS regression:

$$R_{port,t} = \alpha_{port} + \beta'_{port} X_t + u_{port,t},$$

where R_{port} is a portfolio's daily return and X is a set of factor returns, which includes the market excess return, size factor, value factor, and momentum factor. t-Statistics are given in brackets. The sample covers all stocks in the headline news data set used in Chan (2003). In Panel A, the dependent variable is the return of a zero-investment portfolio that is long stocks that suffered no-information price declines and short stocks that enjoyed no-information price increases (No-information portfolio). In Panel B, the dependent variable is the return of a zero-investment portfolio that is long stocks that suffered information-based price declines and short stocks that enjoyed information-based price increases (Information-based portfolio).

Panel A: No-information portfolio						Panel B: Information-based portfolio				
	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}
5-	0.0077	-0.0414				0.0017	-0.0779			
days	[7.6]	[-0.4]				[2.1]	[-1.0]			
5-	0.0078	-0.0990	0.0663	-0.1273		0.0018	-0.2236	-0.2387	-0.2394	
days	[7.6]	[-0.6]	[0.3]	[-0.5]		[2.1]	[-1.5]	[-1.5]	[-1.1]	
5-	0.0078	-0.0980	0.0677	-0.1327	-0.0119	0.0019	-0.2148	-0.2273	-0.2842	-0.0996
days	[7.6]	[-0.6]	[0.4]	[-0.5]	[-0.1]	[2.2]	[-1.5]	[-1.4]	[-1.2]	[-0.7]
10-	0.0037	-0.0591				0.0007	-0.0687			
days	[5.3]	[-0.9]				[1.5]	[-1.5]			
10-	0.0037	-0.0086	0.0557	0.0887		0.0007	-0.0473	-0.0797	0.0591	
days	[5.3]	[-0.1]	[0.4]	[0.5]		[1.4]	[-0.6]	[-0.9]	[0.5]	
10-	0.0038	-0.0002	0.0667	0.0454	-0.0959	0.0007	-0.0403	-0.0706	0.0234	-0.0794
days	[5.3]	[-0.0]	[0.5]	[0.2]	[-0.8]	[1.5]	[-0.5]	[-0.8]	[0.2]	[-1.0]
20-	0.0022	-0.0158				0.0003	-0.0231			
days	[4.9]	[-0.4]				[0.9]	[-0.8]			
20-	0.0022	0.0423	0.0786	0.0988		0.0003	-0.0229	-0.0377	0.0082	
days	[4.9]	[0.5]	[0.9]	[0.8]		[0.8]	[-0.4]	[-0.7]	[0.1]	
20-	0.0023	0.0515	0.0906	0.0517	-0.1047	0.0003	-0.0189	-0.0325	-0.0121	-0.0451
days	[5.0]	[0.7]	[1.1]	[0.4]	[-1.4]	[0.9]	[-0.4]	[-0.6]	[-0.1]	[-0.9]
40-	0.0011	-0.0085				-0.0002	-0.0537			
days	[3.6]	[-0.3]				[-0.9]	[-3.0]			
40-	0.0011	0.0264	0.0694	0.0549		-0.0002	0.0029	0.0454	0.1029	
days	[3.6]	[0.5]	[1.2]	[0.7]		[-1.1]	[0.1]	[1.2]	[2.0]	
40-	0.0011	0.0316	0.0762	0.0283	-0.0591	-0.0002	0.0049	0.0480	0.0929	-0.0221
days	[3.7]	[0.6]	[1.4]	[0.3]	[-1.2]	[-1.0]	[0.1]	[1.3]	[1.7]	[-0.7]

Table 12
Determinants of post-event returns: Analyst report content

The table reports coefficient estimates of the following regression:

$$AR_{m,n} = \alpha + \beta AR_0 + \gamma^{agree}(AR_0 * agree) + \gamma^{dis}(AR_0 * disagree) + \delta' X + \varepsilon(AR_0 * vol) + u.$$

$AR_{m,n}$ is the cumulative abnormal return over a period starting m and ending n trading days after the event day, and AR_0 is the event day abnormal return. X includes log size ($\log(ME)$), log book-to-market ratio ($\log(BM)$), return over the previous 12 months (mom), and trading volume (vol). $agree$ is a dummy variable set to one if the net change in analyst recommendations around the event day is of the same sign as the event day return, and $disagree$ is a dummy variable set to one if the net change in analyst recommendations around the event day is of a different sign than the event day return. The analysis is restricted to the Reported samples, which include all price events accompanied by analyst reports. Parameter estimates are computed using the WLS approach, where weights are set so that each cross-section has an equal weight. t-Statistics (in brackets) are calculated using clustered standard errors.

	$Int.$	AR_0	$AR_0 * agree$	$AR_0 * disagree$	$\log(ME)$	$\log(BM)$	mom	vol	$AR_0 * vol$	R^2 (%)
$AR_{1,5}$	0.027	-0.017	0.064	-0.076	-0.004	0.004	-0.007	0.020	-0.035	5.2
	[4.3]	[-1.3]	[4.3]	[-4.3]	[-4.4]	[2.9]	[-7.9]	[1.2]	[-0.9]	
$AR_{1,10}$	0.038	-0.011	0.053	-0.083	-0.005	0.006	-0.016	0.028	-0.063	6.1
	[5.5]	[-0.6]	[2.6]	[-3.6]	[-5.4]	[3.3]	[-12.4]	[1.7]	[-1.7]	
$AR_{1,20}$	0.060	-0.022	0.066	-0.059	-0.007	0.011	-0.029	0.014	-0.075	8.0
	[6.5]	[-0.9]	[2.4]	[-1.8]	[-5.6]	[4.8]	[-12.6]	[0.7]	[-1.6]	
$AR_{1,40}$	0.139	-0.006	0.027	-0.071	-0.015	0.026	-0.058	-0.043	-0.100	12.3
	[9.7]	[-0.2]	[0.8]	[-1.7]	[-7.5]	[8.3]	[-13.5]	[-1.5]	[-1.7]	

Table 13
Presence of information and future earnings

The table reports coefficient estimates of the following regression:

$$EarnSur_i = \alpha + \beta AR_0 + \gamma(AR_0 * un) + \delta' X + \varepsilon(AR_0 * vol) + u.$$

$EarnSur_i$ is the earnings surprise in quarter i (relative to the event day), computed as the abnormal announcement return (Panel A), standardized unexpected earnings measured using analyst forecasts (Panel B), and standardized unexpected earnings calculated using a seasonal random walk model (Panel C). AR_0 is the event day abnormal return. X includes log size ($\log(ME)$), log book-to-market ratio ($\log(BM)$), return over the previous 12 months (mom), and trading volume (vol). un is a dummy variable set to one if no analyst reports were published around the event day. t-Statistics (in brackets) are calculated using clustered standard errors.

Panel A: Abnormal announcement return (N = 110,010)

	$Int.$	R_0	$R_0 * un$	$\log(ME)$	$\log(BM)$	mom	vol	$R_0 * vol$	R^2 (%)
$EarnSur_1$	0.015	0.014	-0.022	-0.002	0.002	-0.002	-0.045	-0.074	0.3
	[2.3]	[2.4]	[-3.2]	[-2.2]	[1.3]	[-2.5]	[-4.0]	[-4.1]	
$EarnSur_2$	0.027	-0.003	-0.017	-0.004	0.000	-0.003	-0.041	-0.010	0.4
	[4.2]	[-0.5]	[-2.4]	[-4.0]	[-0.3]	[-3.5]	[-3.7]	[-0.6]	

Panel B: SUE - analyst forecasts (N = 83,744)

	$Int.$	R_0	$R_0 * un$	$\log(ME)$	$\log(BM)$	mom	vol	$R_0 * vol$	R^2 (%)
$EarnSur_1$	-6.563	3.900	-0.837	0.737	-0.660	0.481	-2.074	-2.811	1.2
	[-7.3]	[9.5]	[-1.4]	[6.4]	[-3.4]	[5.5]	[-2.5]	[-2.4]	
$EarnSur_2$	-2.496	1.948	-0.787	0.252	-0.329	0.211	-1.451	-0.557	0.5
	[-6.0]	[4.1]	[-1.5]	[3.9]	[-4.1]	[4.1]	[-1.4]	[-0.4]	

Panel C: SUE - seasonal random walk (N = 82,064)

	$Int.$	R_0	$R_0 * un$	$\log(ME)$	$\log(BM)$	mom	vol	$R_0 * vol$	R^2 (%)
$EarnSur_1$	-3.188	11.541	-3.606	-0.263	-0.651	2.773	-8.874	-7.088	0.4
	[-1.6]	[5.0]	[-1.7]	[-0.8]	[-0.9]	[5.1]	[-0.9]	[-0.8]	
$EarnSur_2$	3.943	10.866	-7.354	-0.884	0.918	1.095	-0.429	1.348	0.2
	[2.0]	[7.2]	[-3.3]	[-3.1]	[1.7]	[4.1]	[-0.1]	[0.3]	

Table 14
Determinants of post-event returns: 2003–2009

The table reports coefficient estimates of the following regression:

$$AR_{m,n} = \alpha + \beta AR_0 + \gamma(AR_0 * un) + \delta' X + \varepsilon(AR_0 * vol) + u.$$

$AR_{m,n}$ is the cumulative abnormal return over a period starting m and ending n trading days after the event day, and AR_0 is the event day abnormal return. X includes log size ($\log(ME)$), log book-to-market ratio ($\log(BM)$), return over the previous 12 months (mom), and trading volume (vol). un is a dummy variable set to one if no analyst reports were published around the event day. Parameter estimates are computed using the WLS approach, where weights are set so that each cross-section has an equal weight. t-Statistics (in brackets) are calculated using clustered standard errors.

Panel A: Full sample (N = 39,259)

	$Int.$	AR_0	$AR_0 * un$	$\log(ME)$	$\log(BM)$	mom	vol	$AR_0 * vol$	R^2 (%)
$AR_{1,5}$	0.031	0.031	-0.077	-0.004	0.002	-0.010	-0.001	-0.032	0.8
	[4.8]	[2.8]	[-5.8]	[-4.3]	[1.7]	[-10.5]	[-0.1]	[-0.9]	
$AR_{1,10}$	0.062	0.041	-0.063	-0.009	0.004	-0.021	-0.002	-0.110	1.5
	[7.2]	[3.1]	[-2.3]	[-6.6]	[2.5]	[-14.6]	[-0.1]	[-2.8]	
$AR_{1,20}$	0.110	0.037	-0.084	-0.015	0.009	-0.041	-0.001	-0.133	2.6
	[8.8]	[2.5]	[-2.9]	[-7.6]	[4.6]	[-16.4]	[-0.1]	[-3.0]	
$AR_{1,40}$	0.216	0.017	-0.158	-0.027	0.024	-0.087	-0.023	-0.104	5.5
	[12.8]	[0.8]	[-5.9]	[-10.6]	[8.2]	[-20.7]	[-1.0]	[-1.8]	

Panel B: Full sample + price>=$5 ($N$ = 21,564)

	$Int.$	AR_0	$AR_0 * un$	$\log(ME)$	$\log(BM)$	mom	vol	$AR_0 * vol$	R^2 (%)
$AR_{1,5}$	-0.006	0.019	-0.044	0.000	0.000	-0.008	0.008	-0.009	0.8
	[-1.2]	[1.4]	[-3.5]	[0.5]	[0.2]	[-8.2]	[0.5]	[-0.1]	
$AR_{1,10}$	-0.015	0.016	-0.034	0.002	0.002	-0.016	0.012	-0.073	1.8
	[-2.5]	[1.2]	[-2.3]	[2.0]	[1.1]	[-11.6]	[0.8]	[-1.5]	
$AR_{1,20}$	-0.018	0.013	-0.028	0.002	0.005	-0.033	0.018	-0.094	3.9
	[-2.0]	[0.8]	[-1.4]	[1.9]	[2.4]	[-13.9]	[0.9]	[-1.7]	
$AR_{1,40}$	-0.029	0.009	-0.045	0.006	0.021	-0.070	0.016	-0.113	8.4
	[-2.3]	[0.4]	[-1.6]	[3.4]	[6.4]	[-17.8]	[0.6]	[-1.3]	

Panel C: Full sample + ME>bottom NYSE decile (N = 23,712)

	$Int.$	AR_0	$AR_0 * un$	$\log(ME)$	$\log(BM)$	mom	vol	$AR_0 * vol$	R^2 (%)
$AR_{1,5}$	0.008	0.018	-0.037	-0.001	0.000	-0.010	0.000	-0.027	0.9
	[1.4]	[1.5]	[-2.3]	[-1.5]	[-0.1]	[-9.0]	[0.0]	[-0.7]	
$AR_{1,10}$	0.016	0.012	-0.051	-0.002	0.000	-0.019	-0.002	-0.078	1.8
	[2.1]	[0.9]	[-2.8]	[-2.0]	[0.3]	[-12.0]	[-0.2]	[-2.2]	
$AR_{1,20}$	0.026	0.004	-0.036	-0.002	0.006	-0.037	-0.011	-0.094	3.5
	[2.4]	[0.2]	[-1.6]	[-1.6]	[2.5]	[-13.4]	[-0.6]	[-1.9]	
$AR_{1,40}$	0.029	0.001	-0.062	0.001	0.023	-0.076	-0.046	-0.097	8.4
	[1.9]	[0.0]	[-2.0]	[0.3]	[7.4]	[-17.3]	[-1.8]	[-1.3]	

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Panel D: Full sample with one day lag (N = 39,262)

	$Int.$	AR_0	$AR_0 * un$	$\log(ME)$	$\log(BM)$	mom	vol	$AR_0 * vol$	R^2 (%)
$AR_{2,6}$	0.018	-0.003	-0.025	-0.002	0.001	-0.009	-0.009	0.014	0.5
	[3.2]	[-0.4]	[-2.4]	[-2.7]	[0.5]	[-10.5]	[-0.8]	[0.5]	
$AR_{2,11}$	0.047	0.008	-0.010	-0.007	0.002	-0.019	-0.012	-0.066	1.2
	[5.8]	[0.7]	[-0.4]	[-5.3]	[1.5]	[-14.7]	[-1.0]	[-2.1]	
$AR_{2,21}$	0.096	0.006	-0.028	-0.013	0.008	-0.040	-0.010	-0.096	2.3
	[7.8]	[0.4]	[-1.0]	[-6.7]	[3.9]	[-16.5]	[-0.7]	[-2.5]	
$AR_{2,41}$	0.203	-0.013	-0.098	-0.025	0.023	-0.085	-0.033	-0.075	5.2
	[12.0]	[-0.7]	[-3.8]	[-9.9]	[7.8]	[-21.0]	[-1.5]	[-1.5]	

Panel E: Full sample + non-earnings announcements (N = 36,004)

	$Int.$	AR_0	$AR_0 * un$	$\log(ME)$	$\log(BM)$	mom	vol	$AR_0 * vol$	R^2 (%)
$AR_{1,5}$	0.030	0.025	-0.075	-0.004	0.001	-0.010	-0.004	-0.014	0.7
	[4.6]	[2.0]	[-5.1]	[-4.0]	[1.3]	[-9.9]	[-0.3]	[-0.4]	
$AR_{1,10}$	0.062	0.035	-0.064	-0.009	0.004	-0.021	-0.001	-0.099	1.5
	[6.9]	[2.5]	[-2.3]	[-6.3]	[2.4]	[-14.0]	[-0.1]	[-2.5]	
$AR_{1,20}$	0.113	0.032	-0.089	-0.015	0.009	-0.042	0.003	-0.127	2.5
	[8.5]	[2.0]	[-2.9]	[-7.4]	[4.5]	[-16.2]	[0.1]	[-2.8]	
$AR_{1,40}$	0.225	0.013	-0.171	-0.028	0.025	-0.087	-0.017	-0.105	5.5
	[12.6]	[0.6]	[-6.1]	[-10.5]	[8.1]	[-19.8]	[-0.7]	[-1.8]	

Panel F: Full sample + earnings announcements (N = 3,255)

	$Int.$	AR_0	$AR_0 * un$	$\log(ME)$	$\log(BM)$	mom	vol	$AR_0 * vol$	R^2 (%)
$AR_{1,5}$	0.032	0.118	-0.075	-0.004	0.011	-0.010	0.040	-0.207	2.6
	[0.9]	[3.9]	[-2.0]	[-1.1]	[1.2]	[-2.7]	[1.4]	[-4.3]	
$AR_{1,10}$	0.058	0.115	-0.030	-0.008	0.009	-0.019	0.015	-0.239	3.1
	[1.6]	[2.9]	[-0.5]	[-1.7]	[1.0]	[-4.6]	[0.4]	[-3.8]	
$AR_{1,20}$	0.117	0.083	-0.025	-0.014	0.020	-0.037	-0.002	-0.190	5.4
	[2.5]	[1.6]	[-0.4]	[-2.4]	[1.7]	[-4.5]	[-0.0]	[-2.8]	
$AR_{1,40}$	0.242	0.010	-0.027	-0.029	0.027	-0.088	-0.077	-0.014	7.6
	[3.3]	[0.1]	[-0.3]	[-2.9]	[1.9]	[-6.8]	[-1.0]	[-0.2]	

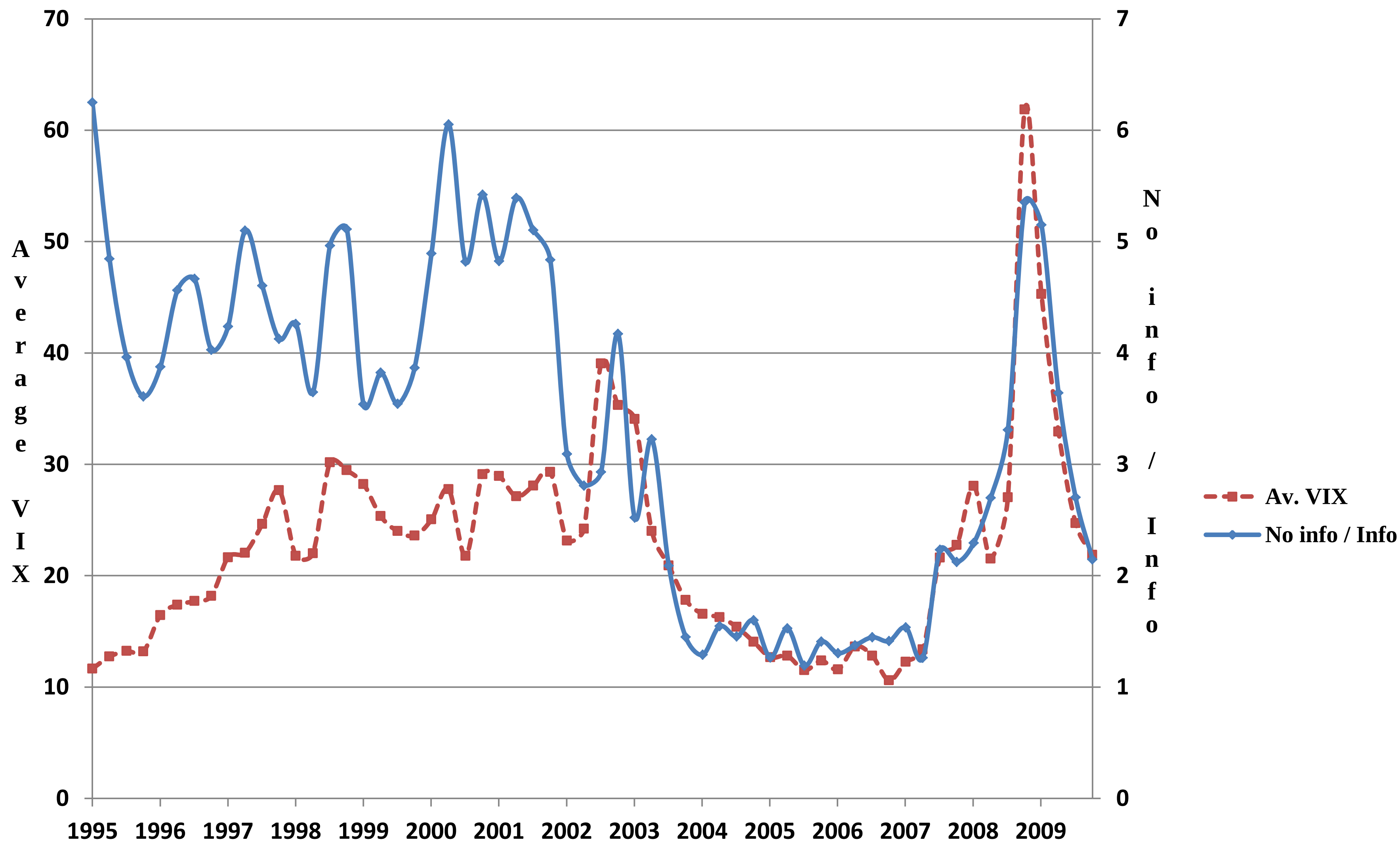

Fig. 1. Implied volatility and the price event ratio. This graph plots the time-series distribution of the average implied volatility (VIX) and the ratio of no-information to information-based price events. The left axis presents the average quarterly VIX, computed as the average of daily implied volatilities obtained from the CBOE S&P 500 VIX. The right axis presents the ratio of the no-information and information-based price events, computed quarterly. No-information price events are those unaccompanied by analyst reports, and information-based price events are those accompanied by analyst reports.

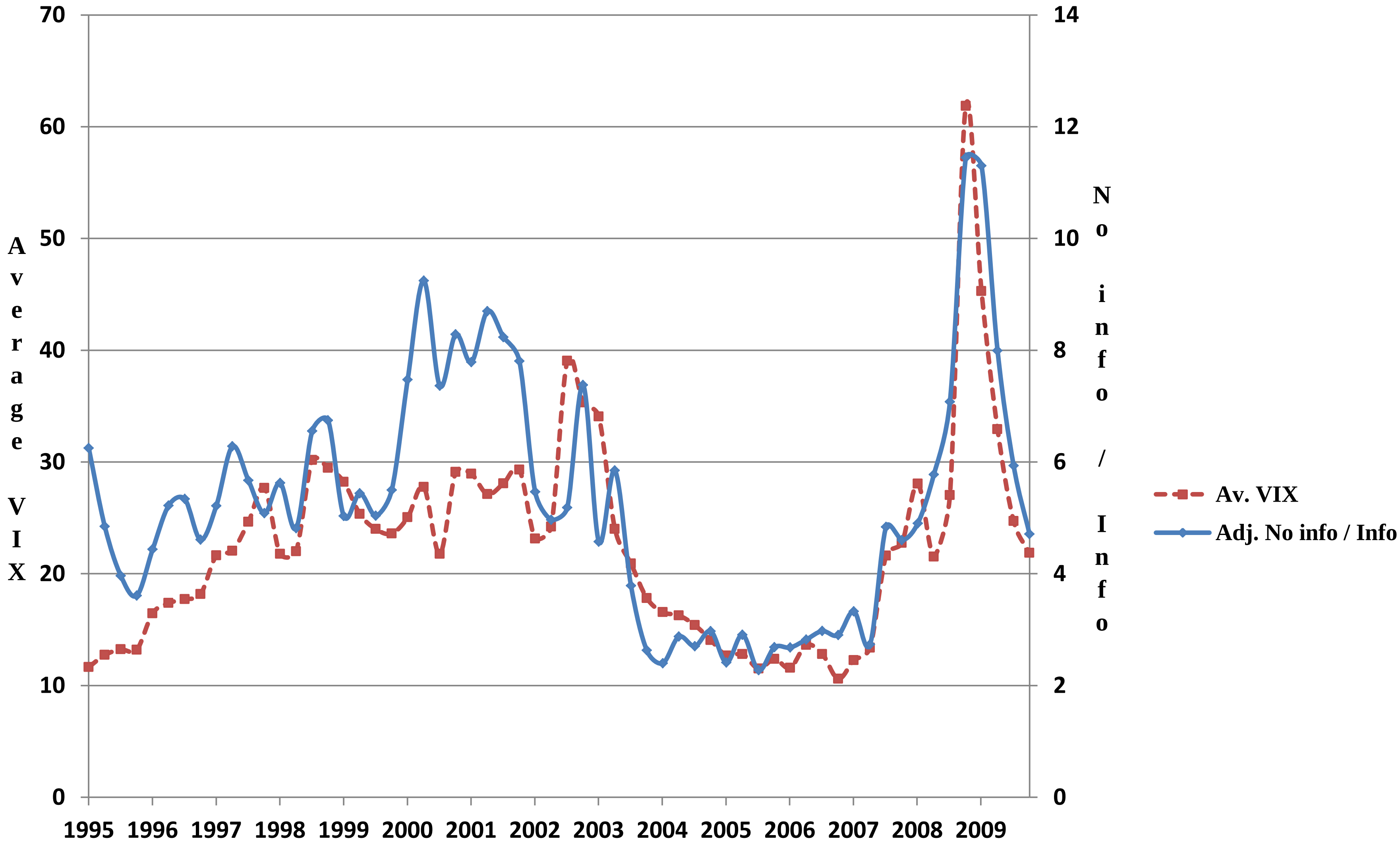

Fig. 2. Implied volatility and the adjusted price event ratio. This graph plots the time-series distribution of the average implied volatility (VIX) and the adjusted ratio of no-information to information-based price events. The left axis presents the average quarterly VIX, computed as the average of daily implied volatilities obtained from the CBOE S&P 500 VIX. The right axis presents the adjusted ratio of the no-information and information-based price events, computed quarterly and taking into account changes in analyst coverage. No-information price events are those unaccompanied by analyst reports, and information-based price events are those accompanied by analyst reports.