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Information, analysts, and stock return co-movement*

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Abstract

Analysts disproportionately follow firms whose fundamentals correlate more with those of other firms in their industries. This supports models of profit maximizing information intermediaries preferentially producing information valuable in pricing more stocks. Designating highly followed firms whose fundamentals best predict those of other firms in the industry as bellwether firms, we observe unidirectional information spillovers from bellwether firms. Specifically, when analysts revise a bellwether firm's earnings forecast, significant changes other firms' prices change; however, revisions for less intensely followed firms do not change heavily followed firms' prices. Unidirectional information spillovers explain how more accurately priced stocks might exhibit more co-movement.

Keywords: Analysts; Return co-movement; Information spillover; earnings forecasts; bellwether firms

JEL Classification: G14

Introduction

Stocks followed by more analysts appear to be priced more accurately (Brennan et al. (1993); Walther 1997), yet their returns are also more prone to co-move (Piotroski and Roulstone 2004; Chan and Hameed 2006). This seems anomalous because a firm's stock price moves idiosyncratically as it incorporates new firm-specific information (French and Roll 1986; Roll 1988). Moreover, higher firm-specific return volatility (i.e. lower comovement) is linked to more intense information incorporation into stock prices (e.g. Morck et al. 2000, 2014; Wurgler 2000; Durnev et al. 2003ab, 2004; Jin and Myers 2006).

This paper resolves this seeming anomaly by showing that more widely followed stocks exhibit more co-movement precisely because they are priced more accurately, and are therefore used by investors as signals with which to update the prices of more opaque stocks. Thus, higher return co-movement associated with more analysts following need not imply less informative stock pricing. Rather, it reflects spillovers as granular firm-specific information changes related stocks' prices. Specifically, information about well-covered firms affects thinly covered firms prices (contemporaneously and with a lag); but no opposite effect is evident.

To examine analysts' role as information intermediaries, we derive testable propositions consistent with recent models of information intermediaries (Veldkamp 2006a). First, because information is a non-rival good, profit maximizing analysts, incurring a fixed cost of information production, produce the information that fetches the highest price from investors. All else equal, investors rationally value information useful for predicting many stocks more highly than information useful for predicting only one stock. Analysts therefore ought to disproportionately follow stocks whose fundamentals correlate more with those of other firms. Following financial practitioners, we dub these *bellwether firms*. Second, new information about a bellwether firm should commensurately change the stock prices of other firms whose fundamentals correlate highly with those of the bellwether firm because investors use it to infer changes in their fundamentals too. This spillover should be stronger to less followed stocks.

Consistent with the first proposition, we find more analysts following stocks whose fundamentals are more correlated with many other firms' fundamentals. Our findings hold after controlling for other firm characteristics found to attract more analysts following: market capitalizations, trading volumes, volatility, and institutional ownership (Bhushan 1989, Brennan and Hughes 1991; Alford and Berger 1999).

Consistent with the second proposition, we find strong evidence of information spillovers from high analyst coverage firms to other fundamentally related firms. From the highest tertile of analysts coverage in each industry each year, we select the firm whose fundamentals correlate most strongly with those of all other firms in the industry, and label these *industry bellwether firms*. When analysts revise their earnings forecasts for bellwether firms, we observe significant effects in the current and future values of other related firms. Moreover, this effect is higher for related firms with lower analyst coverage. Importantly, these information spillovers are unidirectional: earnings forecast revisions for less intensely followed firms do not predict the prices of heavily followed firms. Our estimates show an analyst's revision of a bellwether firm earnings forecast having significant cross-firm spillover for up to one month (event time).

These findings complement Kelly and Ljungqvist's (2012) finding of elevated asymmetric information following coverage terminations in the prices of other firms with correlated fundamentals, as implied by Admati (1985) and Veldkamp (2006a). Following Kelly and Ljungqvist (2012) in taking analyst coverage terminations when brokerage firms' close their research departments as exogenous, we further show that brokerage terminations causes investors to rely more heavily on the information about bellwether firms in the industry. Specifically, we again find a one-way spillover from bellwether firms to industry peers when coverage exogenously declines for the thinly covered firms.

Further tests weigh against possible alternative explanations of these findings. First, controlling for firm size, Hong, Lim and Stein (2000) confirm Hong and Stein's (1999) prediction of less covered firms exhibiting stronger price momentum – i.e. more under-reaction to information and slower information diffusion (Jegadeesh and Timan 1993). Bernard and Thomas (1989) further support general price under-reactions to earnings information. Our findings are not due to momentum effects measured using lagged returns, lagged own earnings information, or lagged earnings information about a portfolio of firms in the industry. Second, Lo and MacKinlay (1990) find small firms' stock returns lagging those of large firms, suggesting slow diffusion of information from large to small firms within an industry (Hou (2007)). Brennan, Jegadeesh, Swaminathan (1993), and Chan and Hameed (2006) find thinly followed stocks adjusting with a more significant lag to common market-wide information. Our findings are not subsumed by such effects. Rather, they contribute a new stylized fact to this literature: analysts' information about intensely covered firms is impounded immediately into their stock prices, but affects with a lag the prices of more thinly covered firms with correlated fundamentals.[1]

Our findings are highly robust. A broad range of plausible alternative econometric approaches yield results qualitatively similar to those in the tables, by which we mean comparable patterns of signs, significance, and rough point estimates. Other data also support our main findings. Thus, institutional investors buy low and zero coverage firms with correlated fundamentals upon upward revisions to a bellwether firm earnings forecast. We believe that Ockham's razor favors our conclusion that investors use information supplied by analysts about bellwether stocks to value relatively neglected stocks, inducing co-movement in their stock returns.

Our results thus validate key empirical implications of information intermediation theories (e.g. Veldkamp (2005, 2006a, 2006b)), and have other implications as well. Prior work on information generated by analysts focuses on the impact of changes in analysts' earnings forecasts for a followed firm on that firm's stock price (e.g. Stickel (1991), Park and Stice (2000), Cooper, Day and Lewis (2001), Clement and Tse (2003), and Gleason and Lee (2003)). Our findings imply

[1] Recent work posits other reasons for such lags. Menzly and Ozbas (2010) highlight lagged information transfer between firms in related product markets , and Cohen and Lou (2012) link longer delays in stock prices incorporating common industry information to greater firm diversification.

that such information affects not just that stock, but also other related stocks. Our evidence also justifies the industry practice of using "bellwether" stocks as barometers of sectoral trends – as when analysts use, for example, information about Wal-Mart to make inferences about the fundamental values of other retailers.

The next section develops our main hypotheses. Section 3 describes our data and variables, and section 4 reports our empirical findings on the bellwether effects. Section 5 considers alternative explanations and robustness checks, and we provide concluding remarks in section 6.

2. Information markets and return co-movement

Veldkamp (2006a) models profit maximizing intermediaries selling investors information produced with a fixed-cost technology. Because information is non-rival, investor demand is higher for information about firms whose fundamentals help price not just their own stocks, but also the stocks of related firms. Firm-level information intermediaries, such as financial analysts, supplying information of the highest total value, thus follow bellwether firms, whose fundamentals best predict those of many other firms. Investors, using this information to price other stocks about which information is less readily available, cause their prices to move with that of the relevant bellwether firm. Bellwether stocks thus co-move more with other stocks, but are the most accurately priced nonetheless.

Consistent with this market for information framework, analyst coverage correlates with various firm characteristics. Bhushan (1989) find analyst coverage increasing in firm size, consistent with information about larger firms being more valuable – perhaps because larger trades are possible without moving the stock greatly. Brennan and Hughes (1991) and Alford and Berger (1999) finds more analysts following more heavily traded firms – perhaps because higher turnover generates more brokerage commissions. Bhushan (1989) also finds more volatile stocks followed by more analysts – perhaps because information predicting larger price jumps yields larger arbitrage profits. Higher information production costs could explain why Bhushan (1989) finds fewer analysts following firms with more lines of business Higher information demand might explain why more analysts follow firms with higher institutional ownership (Bhushan (1989), O'Brien and Bhushan (1990)).

This motivates:

Proposition 1: Firms whose fundamentals better predict the fundamentals of other firms in their industries attract more analyst coverage, controlling for other factors affecting coverage such as firm size, trading volume, return volatility, firm diversification, and institutional ownership.

This proposition implies a *bellwether firm eff*ect. We define a bellwether firm as a firm that is intensely followed by analysts and whose fundamentals best predict the prices of other firms in its industry. Consequently, firm-specific information about bellwether firms should move the prices of other related firms, reflecting information spillovers evident as co-movement. We operationalize this prediction by examining the price impact of analysts' earnings forecast revisions about a bellwether firm on other firms in its industry, especially those followed by few or no analysts. This motivates:

Proposition 2: Analysts' earnings forecast revisions of bellwether firms influence the returns of other firms with related fundamentals, but for which information is scarcer.

3. Fundamental correlations and analyst coverage: data and analyses

3.1 Sample selection

Our sample consists of all common stocks with data available in both CRSP and COMPUSTAT during the sample period from 1984 to 2011. Each year, we start with all firms with common stocks listed on NYSE, AMEX and NASDAQ, that is, those stocks with a share code of 10 or 11 recorded in CRSP. We require the average daily stock price in December of the previous year to be above $1 to minimize market frictions associated with penny stocks, such as price discreteness and bid-ask effects. We merge the stock price and earnings information in CRSP-COMPUSTAT with analyst coverage information provided by Institutional Brokers' Estimate

System (I/B/E/S). Finally, we merge these datasets with data on quarterly institutional holdings obtained from Thomson Reuters' Institutional Holdings (13F) database. Our final sample consists of 138,633 firm-years in total and an average of 4,951 firms per year. We start with 4,283 firms in the CRSP-COMPUSTAT merged sample in 1984, which grows steadily to the peak at 6,813 firms in 1998 and then decreases gradually to 3,642 firms in 2011.

3.2 Firm specific variables

A. Analyst coverage (ANALYST)

Our analyst coverage measure, *ANALYST*, is based on the number of analysts making one-year ahead earnings (EPS) forecasts for each firm-year. Firms in our sample that are not covered by I/B/E/S are assumed to have zero analyst coverage.[2] On average, there are 1,611 firms per year (almost one-third of the firms in our CRSP-COMPUSTAT merged sample) with no analyst coverage.

B. Partial correlation in fundamentals (PCORR_ROA)

The model in Veldkamp (2006a) suggests that analyst following and information spillover are likely to be higher for stocks whose fundamentals are more correlated with many other firms. Changes in firm-specific fundamental values are typically inferred from accounting measures such as return on assets (*ROA*) or return on sales (*ROS*) (Morck et al. (2000); Piotroski and Roulstone (2004); Durnev et al. (2004); Wei and Zhang (2006); Chun et al. (2008)). Although accounting measures may be noisy proxies of firms' future performance, we expect historical correlations in *ROA* (or *ROS*) to be indicative of fundamental correlations.

Changes in the fundamental values of firms are often affected by common shocks within the same industry, arising from shifts in demand and supply for their products and services, as well

[2] The results reported in the paper are based on the number of estimates in the consensus forecasts in December of each year. Our results are unaffected if we measure a firm's analyst coverage as the number of unique analysts making one-year ahead earnings forecasts or the average monthly number of estimates used to construct the consensus earnings forecasts during the year.

as from technological, regulatory and other industry-wide shocks. Therefore, we measure a firm's the contribution to fundamental co-movement of other peer firms within the industry. We use a three step procedure to construct our measure of yearly fundamental correlations for each stock. We first run a market model of *ROA*s for each firm within the industry, using quarterly data over the previous five years,

[1] $ROA_{iq} = a_i + b_i\, ROA_{Mq} + e_{iq}$,

where ROA_{iq} is the return on assets in quarter q for firm i, measured by the ratio of earnings before extraordinary item (data item 8) to total assets (data item 44) in Compustat; and ROA_{Mq} is the asset-weighted return on assets for the market portfolio. The regression R^2 of equation [1], denoted $R^2_{i,excl.k}$, is the fraction of variation in firm i's *ROA*s explained by the market factor.

The second step is to re-run equation [1], but with firm k's return on assets, ROA_{kq}, as an additional factor,

[2] $ROA_{iq} = a_i + b_i\, ROA_{Mq} + c_i\, ROA_{kq} + e_{iq}$.

This regression generates a second R^2, which we denote $R^2_{i,incl.k}$. For a given pair of stocks k and i in the same industry, the extent to which $R^2_{i,incl.k}$ exceeds $R^2_{i,excl.k}$ gauges the partial contribution of firm k in explaining the movement in the fundamental value of firm i, controlling for market-wide common variation in fundamentals. We then calculate a partial correlation coefficient equal to the difference between the two R^2s normalized by the unexplained fraction of variation in equation [1],

[3] $PCORR\_ROA_{k,i} = (R^2_{i,incl.k} - R^2_{i,excl.k}) / (1 - R^2_{i,excl.k})$.

Defining N_I as the number of firms in industry I, the procedure above generates $(N_I - 1)$ pairwise partial correlation coefficients as specified in equation [3]. We adopt the widely used Fama and French (1997) industry classification scheme to classify firms into 48 industry groups based on four-digit SIC codes. We further require a minimum of 12 non-missing quarterly observations during the five-year window to estimate equations [1] and [2].

The third step takes us to an estimate of each firm k's overall correlation in fundamentals with other firms in its industry, each year. We average $PCORR\_ROA_{k,i}$ across all firms i ($i \neq k$) in the industry and denote this $PCORR\_ROA_k$. Since $PCORR\_ROA_k$ is bounded between zero and one, we apply a logit transformation to obtain firm k's partial correlation in fundamentals with its industry peers,

[4] $$LPCORR\_ROA_k = \log[PCORR\_ROA_k / (1 - PCORR\_ROA_k)].$$

Repeating these three steps for all firms, each year, generates a panel of $LPCORR\_ROA_{k,t}$. A higher value of $LPCORR\_ROA_{k,t}$ means that firm k's *ROA*s contribute more in explaining the variation in asset returns of all other firms in the industry, after controlling for market-wide variation.

C. Other firm-level variables

To empirically investigate the informational role of analysts, as discussed in Section 2, we incorporate various firm characteristics shown to be important in prior work on return comovement and analyst coverage (e.g. Bhushan (1989); Piotroski and Roulstone (2004); Chan and Hameed (2006); Frankel et al. (2006)). These variables, measured at yearly frequencies, include firm size (*SIZE*), daily stock turnover (*TURNOVER*), standard deviation of daily stock returns (*STDRET*), the fraction of the firm's shares held by institutional investors (*IO*) and concentration of business measured by the Herfindahl index of sales across business segments indicated by 2-digit SIC codes (*HERF_SALES*).

3.3 Summary statistics

Panel A in Table 1 reports descriptive statistics of the key variables.[3] The average number

[3] All variables are winsorized at the top and bottom 1 percentile values each year, except for *ANALYST* which is winsorized at 99 percentile value. Moreover, we obtain similar results using unwinsorized variables, suggesting that the results are robust to extreme values.

of analysts covering a firm (*ANALYST*) in a year is 4.6, and its median is 2, indicates a positive skewness in the distribution of coverage. The partial correlation in return of assets, *PCORR_ROA*, averages at 11.68 percent, and displays significant variations across firms with a standard deviation of 5.94 percent. The sales concentration variable, *HERF_SALES*, shows that more than half the firms operate in a single segment, consistent with previous findings by Piotroski and Roulstone (2004) and others.

Next, we report the characteristics of firms grouped by analyst coverage. Within each industry, stocks with coverage are sorted into three equal groups based on *ANALYST* (*High, Medium*, and *Low*), while uncovered stocks form the fourth group (*Zero*). As shown in Table 1, Panel B, the average *ANALYST* for the high group is 13.98 while the low group averages to 1.67. For each analyst group, we report the average firm characteristics obtained from the previous year. As expected, the high *ANALYST* firms are largest in market capitalization, have greatest institutional ownership, and are most heavily traded, among all *ANALYST* groups. Moreover, high *ANALYST* firms tend to have less volatile returns, compared with either zero or low *ANALYST* firms. Turning to our fundamental correlation measure, *PCORR_ROA*, high *ANALYST* firms seem to have more correlated fundamentals with other firms in the industry compared with zero *ANALYST* firms, but are not different from low *ANALYST* firms. As shown in Panel C, many of these firm characteristics, especially *ANALYST*, are also correlated with firm size, and hence, the univariate effects in Panel B are clearly not independent. We therefore turn to multivariate analyses.

3.4 Regression results

Based on our empirical proposition 1 presented in Section 2, we specify the determinants of analyst coverage for each firm *k* in year *t* as follows:

[5] $$Ln(1+ANALYST_{k,t}) = a_0 + a_1\,LPCORR\_ROA_{k,t-1} + a_2\,Ln(SIZE_{k,t-1}) + a_3\,TURNOVER_{k,t-1}$$

$$+ a_4\, HERF\_SALES_{k,t-1} + a_5\, Ln(STDRET_{k,t-1}) + a_6\, Ln(IO_{k,t-1}) + \Sigma c_I\, INDDUM_{I,k,t}$$

$$+ \Sigma dy\ YEARDUM_{y,k,t} + e_{k,t}.$$

Supplementing the firm specific variables defined in Section 3.3, we include industry and year fixed effects, *INDDUM and YEARDUM*. We estimate equation [5] as a panel regression over the full sample period of 1984 to 2011 and four seven-year sub-periods, 1984 to 1990, 1991 to 1997, 1998 to 2004 and 2005 to 2011. All t-statistics reported henceforth are therefore based on robust standard errors clustered by industry (Petersen (2009)).[4]

It is evident in Table 2 that analysts follow firms that are larger (*SIZE*), more heavily traded (*TURNOVER*), more focused on their core businesses (*HERF_SALES*), more eventful (*STDRET*) and owned more by institutional investors (*IO*). Our findings using more recent sample reinforce the results presented in Piotroski and Roulstone (2004) and Chan and Hameed (2006) on the determinants of analyst following. More importantly, consistent with our prediction in hypothesis 1, Table 2 shows that *LPCORR_ROA* attracts a positive coefficient in all sub-periods, and attains statistical significance in the full sample period and in three of the four sub-periods. This finding validates the notion that analysts follow firms whose information may be used to price many other firms.

Our findings are highly robust, in that various alternative approaches yield qualitatively similar results. The coefficient of *LPCORR_ROA* remains positive and significant in the full sample and in the last three sub-periods when the lagged value of analyst coverage ($Ln(1+ANALYST_{k,t-1})$) is added to control for persistence in analyst coverage and dependence of analyst coverage on other firm characteristics. *LPCORR_ROA* also attracts a positive coefficient in year-by-year cross-sectional regressions for every year from 1984 to 2011, except for 1987 and 1988, and the mean of these coefficients is 0.047 and highly significant (with an HAC t-statistic of 4.28). Our results are

[4] We cluster standard errors by industry because the key variable of interests, *LPCORR_ROA*, is measured within each industry. A two-way clustering of standard errors by firm and year yields larger t-statistics in most cases, especially for *LPCORR_ROA*.

qualitatively unchanged if we replace *ROA* with return on sales (*ROS*) or measure *ROA* as operating income after depreciation and amortization divided by total assets. We also account for non-linear relation between analyst following and firm size. The positive coefficient associated with LPCORR_ROA is robust to adding size-squared or size decile dummies as control variables in regression equation (5). Finally, we consider estimating *LPCORR_ROA* by classifying firms into industries using the five-digit Global Industry Classification Standard (GICS) code (available for more recent years), and obtain similar results.

Overall, our findings point to more analysts choosing to follow firms whose fundamentals are useful in predicting the value of other firms, as predicted in Veldkamp (2006a).

4 Bellwether firms

The results in Section 3 show that analysts choose to follow stocks that have high fundamental correlations with other firms. We now turn to the empirical proposition as presented in Section 2 and test the prediction that investors use information gathered about heavily covered stocks to price stocks not well followed by analysts, thereby, generating co-movement in stock returns (Veldkamp (2006a). Specifically, we use stock price reactions to revisions in analysts' earnings forecasts to infer information spillover effects. If investors use information generated by analysts about some prominent stocks to price other neglected ones, revisions in forecasted earnings of prominent stocks should affect prices of fundamentally related firms; but earnings forecast revisions for less prominent stocks should be less important in pricing other stocks.

We draw from our analyses in Section 3 to form a narrow definition of prominence: stocks that have high analyst coverage as well as high fundamental correlations with peer firms. Specifically, we define the bellwether firm for each industry as the firm that belongs to the top tercile in terms of analyst coverage in the industry and has the largest partial correlations in fundamentals with other stocks (*PCORR_ROA*), based on the premise that a bellwether firm's fundamental performance is most reflective of that of many other firms in the same industry.

The characteristics of the industry bellwether firms are presented in Table 3. By construction, the bellwether firms have high *PCORR_ROA* and analyst following. It is not surprising that the bellwether firms tend to bigger firms, with high institutional interest and are actively traded. However, the values of these firm characteristics are comparable to the average values of the firms with high coverage in Table 1. Figure 1 graphs the annual average *PCORR_ROA* across all bellwether firms, for the period 1984 to 2011. The overall average *PCORR_ROA* is 19.06 percent, with some variations over the years, ranging from 16.10 percent (in 2002) to 21.89 percent (in 2008). The average partial correlations in fundamentals with bellwether firm vary more across industries. As shown in Figure 2, the average PCORR_ROA is highest for bellwether firms in the Utilities at 35.11 percent, followed by Retail industry at 29.79 percent.[5]

In the next sub-section, we examine if the revisions of earnings forecasts of these industry bellwether firms affect stock prices of their peer firms, particularly the firms with few or zero coverage.

4.1 Spillover effects

Our first test examines the stock price reactions of peer firms to the monthly revisions in analysts' earnings forecasts of the industry bellwether firm. The earnings forecast revision for firm k in month t, $FR_{k,t}$, is measured as the change in the mean forecast of one-year ahead earnings per share from month $t\text{-}1$, scaled by firm k's stock price at the end of $t\text{-}1$. Denoting the earnings forecast revision for the industry bellwether firm as $FR_{IBW,t}$, we gauge its influence on the returns on industry peer firm k ($R_{k,t}$) via the following panel regression specification:

$$[6] \qquad R_{k,t} = a_0 + b_1 FR_{IBW,t-1} + c_1 R_{m,t} + c_2 R_{m,t-1} + d_1 R_{k,t-1} + d_2 R_{k,t-2,t-7}$$
$$+ d_3 \ln(SIZE_{k,t-1}) + d_4 \ln(BM_{k,t-1}) + d_5 TURNOVER_{k,t-1} + e_{k,t},$$

[5] The full distribution of PCORR_ROA for bellwether firms (by year and industry) is in Appendix Table A1.

where firm k excludes the bellwether firm.

We control for several variables that may influence our analysis on the effect of information about the bellwether firms ($FR_{IBW,t}$) affecting the returns of other firms in the industry. First, following Fama and French (1992), Daniel and Titman (1997) and Gervais, Kaniel and Mingelgrin (2001), we control for the several firm characteristics that have been shown to predict stock returns. These characteristics include (i) log of firm k's market capitalization at the end of month t-1 ($ln(SIZE_{k,t-1})$), (ii) log of the book-to-market equity ratio ($ln(BM_{k,t-1})$),[6] and (iii) the average daily share turnover in month t-1 ($TURNOVER_{k,t-1}$). As shown in Table 3, the bellwether firms tend to be bigger firms with high trading volume and it is important that we account for the predictive effects on returns on small firms and those with low trading volume.

There is considerable evidence that stock returns exhibit medium-term price momentum (Jegadeesh and Titman (1993)). Hong and Stein (1999), for example, develop a model where firm-specific information diffuses slowly across the investing public, generating under-reaction and momentum in stock prices. Empirical evidence supporting this hypothesis is provided in Hong, Lim and Stein (2000), who show that the momentum effect is strongest among stocks with low analyst coverage, controlling for firm size. Additionally, Bernard and Thomas (1989) show that firms also underreact to information in firm-specific earnings or information contained in the earnings forecasted by analysts (Chan, Jegadeesh and lakonishok (1996)). We account for these momentum effects by including two firm-specific variables to the regression in (6): the stock's own lagged returns in the previous six months from $t-2$ to $t-7$ ($R_{k,t-2:t-7}$) to capture price momentum and the stock's own earnings forecast revision, $FR_{k,t-1}$, to capture earnings momentum (see also Gleason and Lee (2003)).

Lo and MacKinaly (1990) show that there is a lead-lag relation between the short-term returns between large and small firms, where returns on small firms react to common information

[6] We follow Fama and French (1992) to measure book-to-market equity ratio and allow a minimum of six-month gap between the end of fiscal year and the return date.

already impounded in prices of large firms at a lag. Hou (2007) reinforces this idea by showing that the lead-lag relation is stronger within industries, suggesting a gradual diffusion of information of industry-wide information. We control for the delayed incorporation of market-wide information into stock prices in the baseline regression in (6) by adding the monthly returns on the CRSP value-weighted market portfolio in months *t* and *t*-1 ($R_{m,t}$ and $R_{m,t-1}$). Finally, we add the stock's own lagged returns in the previous month ($R_{k,t-1}$) to account for short-term reversals in Jegadeesh (1990) which is also related to stock illiquidity (Avramov, Chordia and goyal (2006)).[7]

We report the regression coefficients and robust *t-statistics* (clustered by industry) in Table 3.[8] Since $FR_{k,t-1}$ is likely to be correlated with the firm-specific control variables, especially $R_{k,t-1}$ and $R_{k,t-2,t-7,}$ we also report the estimates of equation [6] when $FR_{k,t-1}$ is omitted. For the sample of all firms, reported under the column "All Firms" in Panel A, we confirm that the control variables capture significant predictable variation in stock returns. Consistent with prior work, we find evidence of significant short-term price reversals and medium-term price momentum; high turnover and value firms earn larger returns; and firms react to market-wide returns with a lag.

Beyond these control variables, we find that when analysts revise the earnings forecasts of bellwether firms (FR_{IBW}), they have a significant positive influence on the future returns on other firms in the industry: a one percent increase in the forecasted EPS of a bellwether firm predicts an additional 0.1 percent return on peer firms. Panel A of Table 4 also presents the results when equation [6] is estimated separately for zero, low, medium and high analyst coverage groups, where firms are sorted into different groups within each industry each year based on the number of analysts following in the previous year. The predictive effect of the control variables is highest for uncovered firms and monotonically declines with increasing analyst coverage. Interestingly, we

[7] All monthly variables are measured at the middle of each month (the Thursday preceding the 3rd Friday of the month) to align with I/B/E/S consensus earnings forecast dates.

[8] A two-way clustering of standard errors by firm and month yields qualitatively similar inferences. For example, the coefficient on $FR_{IBW,t-1}$ is statistically significant at 5% level in regressions for zero and low analyst groups, but is insignificant for medium and high analyst group (t-statistics are less than 1 in magnitude).

find striking evidence on the asymmetry in price responses across firms: FR_{IBW} has the strongest impact on future returns on uncovered firms, and decreases monotonically as we move to firms with increasing coverage. For instance, a one percent increase in FR_{IBW} is associated with a significant 0.18 percent return in uncovered firms and a 0.15 percent return in low-analyst firms. This bellwether effect drops rapidly for firms with higher coverage, with a smaller 0.06 percent price reaction for firms with medium coverage and an insignificant effect among firms in the highest coverage (excluding the bellwether firm itself, of course).

Panel B of Table 4 reports the effect of adding the firm's own forecast revision in the previous month, $FR_{k,t-1}$. To conserve space and to focus on the marginal effects of forecast revisions, we suppress the coefficients associated with the control variables. While the coefficients generally do not change significantly, we note that the coefficient on $R_{k,t-2,t-7}$ becomes insignificant in the presence of earnings forecast revisions, consistent with Chordia and Shivakumar (2006) who report that price momentum is subsumed by earnings momentum. There is evidence of significant lagged adjustment to the firm's own forecast revisions, for low and medium coverage firms, but, not for the high coverage group. More importantly, accounting for FR_k does not change the coefficient on $FR_{IBW,}$ indicating that the forecast revision of the bellwether firm contains value-relevant information for other firms in the industry, beyond the information delivered by analysts covering these firms.

To provide a benchmark for the spillover effects, we investigate if similar effects exist for non-bellwether firms in the same industry. We select the firm with the lowest *LPCORR_ROA* among firms in the highest analyst tertile in each industry as our proxy for a non-bellwether firm and denote the firm's earnings forecast revision in month *t* as $FR_{INBW,t}$.[9] As shown in Panel C of Table 4, FR_{INBW} is associated with insignificant stock price response for other firms in the industry, and this applies to all analyst groups. On the contrary, the coefficient on FR_{IBW} remains almost

[9] We find qualitatively similar results if the non-bellwether firm is chosen from the middle or lowest analyst coverage tertiles.

unchanged and significant in regressions of zero and low analyst groups.

Our findings support a strong positive spillover of the information originating from information laden bellwether firms to other firms in the industry, especially those information-sparse firms. Moreover, the information spillover is unidirectional - from bellwether firms to relatively neglected firms - rather than the other way around. Our findings also complement the within industry transmission of information documented in Hou (2007), and provides a source for such a transmission process.

If information about bellwether firms moves the prices of other related firms, we also expect their earnings forecast revisions to trigger contemporaneous response in prices of other related firms, especially firms with less information. We modify the regression specification in equation [6] to examine the influence of contemporaneous earnings forecast revisions of bellwether firms:

[7] $$R_{k,t} = a_0 + b_1\, FR_{IBW,t} + b_2\, FR_{k,t} + c_1\, R_{m,t} + c_2\, R_{m,t-1} + d_1\, R_{k,t-1} + d_2\, R_{k,t-2,t-7} + d_3\, ln(SIZE_{k,t-1}) + d_4\, ln(BM_{k,t-1}) + d_5\, TURNOVER_{k,t-1} + e_{k,t},$$

where we control for stock *k*'s own contemporaneous earnings forecast revision, $FR_{k,t}$, as well as other variables defined in equation [6]. The estimate of equation [7] is reported in Panel A of Table 5. As shown in the column "All Firms" in Panel A, we find a significantly positive effect of $FR_{IBW,t}$ on contemporaneous returns on all stocks in the same industry, beyond the effect of revisions in the firm's own contemporaneous earnings forecast ($FR_{k,t}$). The effect of FR_{IBW} is largest on the contemporaneous returns of uncovered firms, and declines monotonically as analyst coverage increases. Interestingly, the information about bellwether firms has an insignificant influence on firms with highest coverage, as the prices of the information laden firms are driven primarily by their own earnings information. As shown in Panel B of Table 5, when we add the lagged forecast revisions ($FR_{IBW,t-1}$ and $FR_{k,t-1}$) to equation [7], it is not surprising that the effect of contemporaneous forecast revisions dominates. Nevertheless, $FR_{IBW,t-1}$ continues to significantly influence the next periods returns on the uncovered firms. We obtain a similar picture by looking at the cumulative effect of $FR_{IBW,t}$ and $FR_{IBW,t-1}$ on returns. Here, a one percent increase in the forecasted earnings of the bellwether firm in each month is associated with a cumulative 0.37 (0.31) percent return in uncovered (low analyst coverage) firms.

In order to understand better the uniqueness of industry bellwether firms, we consider the following experiment. Guided by our twin criteria of intense analyst coverage and high content of fundamental information to predict the information of other firms in the industry, we consider replacing the firm with highest *PCORR_ROA* with the firm the second highest *PCORR_ROA* (among stocks that belong to the highest tercile in terms of analyst following). The spillover effect of this alternate bellwether firm chosen is considerably weaker. As shown in Appendix Table A4 (Panel A), while the contemporaneous forecast revision of the alternate bellwether firm has significant influence on the returns on zero and low coverage firms, the predictive effect of lagged forecast revisions are not significant. However, the weaker predictive effect of the alternate bellwether firm is due to low *PCORR_ROA*. This observation is confirmed when the alternate bellwether firm is restricted to have *PCORR_ROA* which is close in magnitude to the bellwether firm. Specifically, we require the distance between the *PCORR_ROA* of the second and highest *PCORR_ROA* to be less than 5percent, and this applies to 28 percent of the sample-months. Here, we continue to find evidence of significant spillover effects: in the regression of stock returns on peer firms on the lagged forecast revision on the alternate bellwether firm as in equation (7), the coefficient is positive and significant for zero/low analyst coverage firms, and marginally significant for median coverage firms (the results are presented in Appendix Table A4, Panel B). The evidence suggests that while the bellwether firms in each industry is not unique, there are only very few such prominent firms in each industry and high *PCORR_ROA* serves as a strong indicator of such candidates.

Overall, the evidence in Tables 4 and 5 confirms our main hypothesis that information generated by analysts about a subset of prominent firms moves the prices of many other less information laden firms, and hence, generates co-movement in stock returns. While using contemporaneous earnings forecast revisions of bellwether firms delivers a stronger effect, it raises the concern of reverse causality that analysts revise their earnings forecasts of bellwether firms after observing price movements of all other firms in the industry. Given the strong evidence of a monotonic increase in the price responses as analyst coverage falls, such a reverse causality would imply that analysts place greater reliance on the returns of those mostly neglected firms to update their forecasts for bellwether firms' earnings. Since we cannot exclude such a remote possibility, we take the more conservative approach and make our inferences mainly based on price responses to lagged information about bellwether firms.

4.2 Evidence from an exogenous decrease in analyst coverage

Kelly and Ljungqvist (2012) examine the implications on a firm's information environment and stock price when it experiences an exogenous drop in analyst coverage due to decisions by brokerage firms to close their research departments. Since brokerage closures are driven by changes in the demand for sell-side research and tougher regulations of research operations of brokerage firms, and are unrelated to fundamental changes in the covered firms, they serve as a desirable experiment to establish the causal effect of analyst coverage on information spillovers. Moreover, Kelly and Ljungqvist (2012) show that coverage termination generates significant price effects on other firms with correlated fundamentals, consistent with Admati (1985) and Veldkam (2006a). We use the list of 43 closures of brokerage firms during the period 2000 to 2008 in Kelly and Ljungqvist (2012) as our sample events and identify firms in our dataset that had a reduction in analyst coverage as a result of these closures.[10] Our research question is whether firms affected by an exogenous decrease in coverage experience an increase in spillover of information emanating

[10] We thank Alexander Ljungqvist for sharing the data used in Kelly and Ljungqvist (2012). Please refer to their paper for details on the institutional background of these closure events. Hong and Kacperczyk (2010) use a similar identification strategy based on mergers of brokerage firms for an exogenous change in analyst coverage.

from bellwether firms, especially if the firm had scarce information. Denoting the month of coverage termination due to a brokerage closure as event month 0, we examine the change in industry bellwether effects during the three months before (the pre-event window is from month -3 to month -1) and three months after (the post-event window is from month +2 to month +4) the event, skipping month 1.[11] Specifically, we regress monthly returns on all stocks affected by the closure events on the lagged earnings forecast revisions of bellwether firms during the pre and post event periods:

$$[8]\ R_{k,t} = a_0 + b_{11}\, FR_{IBW,t-1} + b_{12}\, FR_{IBW,t-1}{*}DM\_POST_{k,t} + b_{13}\, FR_{IBW,t-1}{*}DM\_POST_{k,t}\, {*}LOWANAL_{k,t} + b_2\, FR_{k,t-1} + c_1\, R_{m,t} + c_2\, R_{m,t-1} + d_1\, R_{k,t-1} + d_2\, R_{k,t-2,t-7} + d_3\, ln(SIZE_{k,t-1}) + d_4\, ln(BM_{k,t-1}) + d_5\, TURNOVER_{k,t-1} + d_6\, DM\_POST_{k,t} + e_{k,t},$$

where $DM\_POST_{k,t}$ is a dummy variable taking the value 1 for observations in the post-event window and zero otherwise, and $LOWANAL_{k,t}$ is a dummy variable taking the value 1 if firm *k* belongs to the lowest tertile of analyst coverage during the pre-event window. All other variables are the same as those in equation [6]. The key coefficients of interest in equation [8] are the spillover effects of revisions in forecasted earnings on the bellwether firms (b_{11}), and the changes in the spillover around the exogenous reduction of coverage for all stocks (b_{12}) and, particularly, for the low coverage stocks (b_{13}). We expect the spillover effect to increase following a drop in coverage drop, especially for firms with low coverage.

As presented in Table 6, there is a significant increase in information spillover from bellwether firms to low coverage firms after an exogenous drop in analysts covering these firms, i.e. b_{13} is positive and significant. The typical firm has an average decrease of one analyst following the closure of a brokerage firms in our sample. Consequently, we do not observe increases in the spillover effects for firms with high coverage as the drop is not likely to be economically important.

[11] We skip month 1 to ensure that the forecast revision computation does not depend on information from the event month.

The coefficients for all the control variables in equation [8] are generally similar to those in Table 4, and some of the coefficients are weaker, possibly due to differences in sample size. We also observe higher stock returns during the post-event months (d_6), consistent with the decrease in liquidity due to the drop of coverage (Ljungqvist and Kelly (2012)). Table 6 also shows that the estimates are unaffected if we exclude the stock's own forecast revisions, FR_k. In unreported results, our findings are unchanged if we drop the control variables in the regression.

To summarize, the results from the experiment arising from an exogenous drop in analyst coverage are consistent with our hypothesis that investors in thinly covered firms rely on information about bellwether firms' to price the stocks, hence providing support for the information spillover explanation for the bellwether effect.

5. Alternative explanations and robustness checks

5.1 *Is the bellwether effect driven by common analyst coverage?*

Israelsen (2014) and Muslu, Rebello and Ye (2014) find that returns of firms covered by common analysts tend to co-move, which they argue is due to the common information used by the same analyst. It should be noted that their findings do not affect our interpretation of the spillover effects on firms with no analyst coverage. To examine the effect of common coverage on the information spillover in low coverage firms, we perform tests similar to those in Table 4, but restrict the sample to firms that do not share common analyst coverage with the bellwether firm. Specifically, we run a similar regression as specified in equation [6], but exclude the firm-year observations if there are analysts covering both firm k and the industry bellwether firm. We report the regression results in Table 8. As shown in Panel A of Table 8, the point estimates for the price reactions associated with $FR_{IBW,t-1}$ are similar to those in Table 4, confirming that the bellwether effect is not driven by common analyst coverage. We also consider removing bellwether firm and the peer firms that are covered by analysts from the same brokerage firms, to account for the possibility that analyst affiliated to the same institution share common information. Again, our results remain intact when we exclude these firms in the analysis (see Panel B of table 8). These results are not surprising since our primary inference relies on the finding that neglected firms with minimal (overlapping) coverage, such as those with zero or low analyst following, have the biggest spillover effects.

5.2. Is the bellwether effect driven by more precise earnings forecasts of bellwether firms?

Revisions in the consensus earnings forecast for bellwether firms contain forecasts by many analysts covering the firm, and consequently may be relatively more precise compared with forecasts of other thinly-followed firms. In other words, the spillover effects may be driven by differences in the precision in the forecasts because we are taking the average of many forecasts for the bellwether firms. To consider this possibility as the sole source of our findings, we measure the forecast revisions of a bellwether firm from earnings forecasts made by an individual analyst without aggregating across all analysts. We devise two approaches to select earnings forecast revisions of an individual analyst for bellwether firms: (a) we select the forecast revision of a single analyst and evaluate the impact on returns on other firms in the industry; and (b) we conduct an event study to gauge the stock price reactions to a revision to the forecasted earnings of the bellwether firm by each analyst.

In our first approach, we replace the bellwether firms' consensus earnings forecast revision with the revision by analyst *j*, denoted FR_{IBWj}. Specifically, among all analysts revising their earnings forecast for the bellwether firm from the previous month, the most recent revision is chosen each month. We re-estimate equation [6] using the forecast revision by an individual analyst and report the regression results in Table 9.

An important result in Table 9 is that the monthly earnings forecast revisions of the bellwether firm calculated from FR_{IBWj} significantly affect the prices of uncovered firms. This suggests that the bellwether effect is not driven purely by the precision of information produced by averaging the forecasts of many analysts. Not surprisingly, the magnitude of the bellwether effect is much lower when we go from the consensus forecasts to the forecasts by an individual analyst. For example, the spillover effect of forecast revisions by analyst j on uncovered firms is less than half of that reported in Table 4. We obtain similar results when we examine the impact of FR_{IBWj} on contemporaneous returns of other firms. In unreported results, we find that the contemporaneous forecast revisions, $FR_{IBWj,t}$, generates a return response of 0.12 (*t-statistics*=4.75) for zero-analyst firms and 0.093 (*t-statistics*=2.32) for low-analyst coverage firms.[12]

In the second approach, we conduct an event study to measure the stock price reactions of peer firms to an individual analyst's revision of the forecasted earnings of industry bellwether firms. To do this, we identify the precise date (marked as event day 0) on which an analyst announces a revision in the earnings forecasts for the bellwether firm and then look for stock price reactions in peer firms subsequent to the date. This experiment also addresses the reverse causality more unequivocally, because it begs credulity to argue that analysts time their revisions of bellwether firms' earnings forecasts to fall precisely on dates when neglected firms prices move *en masse* relative to risk benchmarks.

For each forecast revision event, we compute the cumulative abnormal return, $CAR_{k,w}$, for every firm k (excluding the industry bellwether firm) over the event window of w days. Following Gleason and Lee (2003), $CAR_{k,w}$ is stock k's cumulative w-day return is in excess of the cumulative benchmark return over the same window. While we report the results based on *CAR*s computed in excess of the market returns, our results are robust to alternative benchmarks.[13]

To mitigate any potential biases from confounding events, we apply several filters to our event study. We exclude an earnings forecast revision of an industry bellwether firm if it coincides

[12] We reach the same conclusion in our simulation exercise, where we randomly select an analyst's forecast revision each month to estimate equation [7]. In repeating the experiment 10,000 times, the average coefficient associated with $FR_{IBWj,t-1}$ for zero-analyst firms is 0.049 and is significant at 5 percent level in about 97 percent of the cases.

[13] Our results are robust to using as alternative benchmarks such as the equal-weighted return on the matched size-decile portfolio and expected returns computed from a one-factor (the return on market portfolio in excess of the risk free rate) or four-factor (Fama-French (1993) three factors plus the Carhart (1997) momentum factor) models.

with the firm's quarterly earnings announcement within a five-day window, i.e., between days -2 to +2. Similarly, we exclude the $CAR_{k,w}$ if peer firm k made an earnings announcement or had an earnings forecast revision during the same five-day window.

To analyze the price response of industry peers to each analyst's update of bellwether firm's earnings, we run the following regression,

$$[9] \qquad CAR_{k,w} = a_0 + b_1 FR\_Rank_{IBW} + d_1 R_{k,t-1} + d_2 R_{k,t-2,t-7} + d_3 \ln(SIZE_{k,t-1}) + d_4 \ln(BM_{k,t-1}) + d_5 TURNOVER_{k,t-1} + e_{k,w},$$

where FR_Rank_{IBW} is the decile rank value of each bellwether firm's earnings forecast revision and the forecast revision is the change in one-year ahead earnings forecasts scaled by the stock price one month ago. For example, FR_Rank_{IBW} takes the value of one (ten) if the forecast revision falls within the bottom (top) ten percent of all bellwether firm forecast revisions in the calendar year. All independent variables, defined earlier, for each non-bellwether firm k are the values of firm characteristics from the previous month. The regression is estimated separately for all non-bellwether firms grouped by analyst coverage: zero-analyst firms, low-analyst firms, medium-analyst firms, and high-analyst firms. We report the regression results where *CAR* is measured over a two-day [0, 1] window around the forecast revision, and a twenty-one day [2, 22] window after the revision date. We present the results in Table 10.

The main finding that emerges from Table 8 is that the stock prices of other firms in the industry, particularly, the zero and low coverage firms, react significantly when an analyst revises the prospects for the bellwether firms. In both the immediate [0, 1] and post-event [2, 22] windows, we find significant price reactions to earnings forecast revisions of the industry bellwethers. Moreover, this cross-firm effect is monotonically decreasing in the level of analyst coverage. Firms which are uncovered or thinly covered react most to the information about the bellwether firms and the reaction is muted for the firms that are well covered. A comparison of the 2-day and 21-day *CAR*s reveals a slow drift in prices, particularly for the firms followed by few or zero analysts.

Overall, the results of the event study are consistent with earnings forecast revisions of bellwether firms causing the price changes in the neglected firms, and hence, corroborate our findings based on monthly forecast revisions of the bellwether firms.

5.3 Robustness of the bellwether effects to momentum and early announcers: additional tests

There is a stream of papers that document momentum in asset prices, starting with Jegadeesh and Titman (1993). If low coverage firms exhibit greater momentum, for example, due to underreaction to information (Hong, Lim and Stein (2000)), we expect these firms to exhibit slower adjustment to earnings information. In the baseline regression model in Section 4, the momentum effect is accounted for by the lagged medium term returns and lagged own earnings forecast revision. We introduce additional robustness checks to confirm that the bellwether effects we document are not related to earnings momentum (Bernard and Thomas (1989)).

We consider the possibility that low coverage firms are merely adjusting to industry-wide earnings information at a lag, consistent with greater momentum in these firms. Piotroski and Roulstone (2003), for example, argue that analysts increase the amount of industry level information in prices through intra-industry information transfers, which in turn, increases the comovement among high coverage firms. To further investigate this issue, we aggregate (equal-weight) the earnings forecast revisions of all firms belonging to the top tercile in terms of analyst following within each industry, excluding the bellwether firm. We examine if the information contained in the revision of the earnings of the bellwether firm is different from the industry-wide earnings information. Interestingly, we find that the information contained in the industry-wide average earnings do not predict returns on stocks with low/zero coverage in the following month. Additionally, the spillover effect due to the bellwether firm is not affected by the earnings information aggregated from a wider set of firms (results are reported in Appendix Table A5). The evidence suggests that the bellwether effect cannot be explained by momentum in returns arising from a mass of revisions in earnings of several firms in an industry.

Next, we explore the possibility that bellwether firms might have had their earnings announcement earlier than peer firms and this generates the spillover effect in returns. Our findings complement the vast literature in accounting that examines how fundamental information regarding one firm could affect the returns on other firms in the same industry. For example, Thomas and Zhang (2009) show that earnings surprises of early announcers in an industry can explain both contemporaneous and future stock returns of late announcers (see also Foster (1981), Han and Wild (1990); and Ramnath (2002)). While these papers examine across-firm effect of firm-specific (earnings) announcements, we document the role of information intermediaries (analysts) on the information transfers. If earnings momentum is greater among low coverage firms, the spillover effect could also be related to early announcement of earnings of the bellwether firms. To shed light on the effect of early earnings announcements, we remove from our sample all industry-months where there is an earnings announcement by the industry bellwether firm. Consistent with spillover effects due to bellwether firms, we find that our findings are unaffected by the earnings announcements by bellwether firms. In fact, the point estimate of the coefficient associated with the spillover effect is almost identical when we exclude the earnings announcements months (see Appendix Table A6). Together, the bellwether effects causing return predictability and co-movement is different from return momentum or the effect stemming from early earning announcers.

5.4 Delayed reaction to common information, size and bellwether effects

Lo and MacKinaly (1990) show that small firms react to common information impounded in the prices of large firms with a delay, giving rise to the size-related lead-lag effects in stock returns. This lead-lag effect is reinforced in Hou (2007) who documents slow diffusion of information within industries. In our analysis so far, we control for the predictive influence of market portfolio returns, and hence, market-wide information. As a robustness check, we include $R_{IBIG,t-1}$, the lagged value-weighted return on a portfolio of large firms, defined as the firms in the top decile by market capitalization within the industry. We run the following regression,

[10] $R_{k,t} = a_0 + b_1 FR_{IBW,t-1} + b_2 FR_{k,t-1} + c_1 R_{m,t} + c_2 R_{m,t-1} + c_3 R_{IBIG,t-1} + d_1 R_{k,t-1} + d_2 R_{k,t-2,t-7}$

$+ d_3 \ln(SIZE_{k,t-1}) + d_4 \ln(BM_{k,t-1}) + d_5 TURNOVER_{k,t-1} + e_{k,t}$,

where we retain all the variables defined in equation [6]. As shown in Table 11, the coefficient c_3 in equation [10] is significant across firms with varying levels of coverage, consistent with the intra-industry diffusion of information from large firms documented in Hou (2007). More importantly, the lagged revision in forecasts of the earnings of the bellwether firms continues to significantly influence the future prices of other firms, particularly, for firms with low and zero coverage.

Another concern about the bellwether effect is that we might be simply selecting the largest firm in the industry. An examination of the distribution of the relative size of the bellwether firm shows that while they are generally large firms (as shown in Table 3), they are not typically the largest in the industry. For example, the bellwether firm is the largest firm in the industry only 7 percent of the time. Moreover, only 40 percent of the bellwether firms belong to the top size decile within the industry. To ensure that the bellwether effect is not a size effect, we consider replacing the bellwether firm with the largest firm in the industry. However, in unreported results, we do not find evidence of spillover effects coming from the biggest firm. In other words, the earnings forecast revisions of the firm with the biggest market capitalization in the industry is not associated with any predictive effect on future returns of its peer firms, after we control for the firm characteristics in equation (7). Moreover, when we include the forecast revisions of the bellwether firm and the largest firm (we delete observations where the largest firm is the bellwether firm), the spillover effect stemming from the bellwether firm continues to be significant (results are presented in Appendix Table A3). We also consider adding firm size decile dummies in the regression in (7) to account for possible non-linear size effects on stock returns. Again, our results remain unchanged. Hence, the bellwether effect we document is not subsumed by the sluggishness in the adjustment of prices of some firms to industry-wide information or simply a size-related lead-lag relation in returns.

5.5 Is the bellwether effect confined to the most illiquid stocks?

We find significant future price responses among those firms with zero or low analyst coverage to the forecast revisions in the bellwether firms. Since these neglected firms are also likely to be illiquid, it is possible that the documented return responses are solely due to illiquidity of these firms and hence reflect delayed adjustment to some common information.[14] We address this concern by discarding ten percent of firms which are most illiquid at the end of the previous year. Our liquidity measure is based on Amihud's (2002), defined as $[1/n \sum \{|R_{j,d}| / (P_{j,d} * N_{j,d})\}]$, where n is the number of trading days in each month, $|R_{j,d}|$ is the absolute return of stock j on day d, $P_{j,d}$ is the daily closing price of stock j and $N_{j,d}$ is the number of shares of stock j traded during day d. The greater the change in stock price for a given trading volume, the higher would be the value of the Amihud illiquidity measure. In un-tabulated results, we find that coefficients on FR_{IBW} in equation [6] are quantitatively similar to those reported in Table 4, and are positive and significant for the regressions of zero-analyst firms (coefficient = 0.13, t-statistics=2.75) and low-analyst firms (coefficient = 0.12, t-statistics= 2.47). Our results are also robust to excluding 30 percent of the most illiquid stocks in the industry. While we lose more firm observations with a 30 percent liquidity filter, the point estimates for zero/low coverage firms remain similar and significant (see Appendix Table A7). These findings confirm that the bellwether effect we document is not driven by the most illiquid stocks.

5.6 Evidence from institutional trading activities

In this sub-section, we investigate the trading behavior of institutional traders around the

[14] However, as reported in Section 4.1, low (and zero) coverage firms exhibit greater contemporaneous price reaction to earnings forecast revisions of bellwether firms, which indicates that thin trading is not likely to be source.

revisions in the forecasted earnings of bellwether firms. The idea is to examine if institutional traders react to information about industry bellwether firms in their trading of peer firms. To do this, we employ the data on institutional trades provided by Ancerno over the period xx to xx.

We focus on an individual analyst's revisions of the forecasted earnings of industry bellwether firms as the event, and examine institutional investors' trades around the event dates. For each bellwether forecast revision event, we construct an abnormal net volume purchased by all institutions in the Ancerno database for peer firm *k* over the window of *w*-days around the event, $ABNetBuy_{k,w}$. *ABNET* is based on few variables. First, we calculate the net buy for each firm *k* on day *d*, $NetBuy_{k,d}$, as the difference between the number of shares purchased and the number of shares sold by all institutional investors in the database, scaled by firm *k*'s number of shares outstanding.[15] Second, we compute the average the daily institutional trading imbalances in a pre-event window, $NetBuy_{k,pre}$ which is used as a benchmark to obtain the abnormal institutional net purchase in the event window. Finally, we standardize the abnormal trading imbalance by the standard deviation of daily net purchase in the pre-event window, $STD(NetBuy_{k,pre})$.[16] We consider two event windows: a two-day window from day 0 to day 1 around the forecast revision date 0, denoted [0,1]; and a twenty-one day window from day 2 to day 22 after the event date, [2,22]. The pre-event window is set as the sixty-three day period from day -73 to day -11, corresponding to a 3-month window ending ten trading days before the event date, [-73,-11]. To summarize, the abnormal institutional trading activity in industry peers around the revision in bellwether firm's earnings forecast is defined as:

$$ABNetBuy_{k,w} = (\sum_{d=1}^{w} NetBuy_{k,d} - NetBuy_{k,pre})/STD(NetBuy_{k,pre})$$

[15] A similar net buy variable is used in other studies such as Irvine et at (2007), and others. The $NetBuy_{kt}$ is set to zero if stock *k* does not have institutional trading recorded in Ancerno on day *t*. To mitigate potential biases from confounding events, we exclude an earnings forecast revision of an industry bellwether firm if it coincides with the peer firm's quarterly earnings announcement within a five-day window, i.e., between days -2 to +2.

[16] Malmendier and Shantikumar (2007) and Barber and Odean (2008) also standardized their abnormal trading volume measure by the standard deviation in daily volume in the pre-event window.

We separately analyze the response of institutional investors to upward and downward revisions in the forecasted earnings of bellwether firms. For example, if positive information about bellwether firms affects the decision to buy peer firms in the industry, we expect an increase in $ABNetBuy_k$ following a positive change in the forecasted earnings. As we also expect the bellwether effect to be strongest among the firms with the lowest coverage, we average the abnormal institutional trading of peer firms into four groups based on analyst coverage as we do in Table 4: i.e. zero, low, medium and high analyst coverage firms.

Panel A of Table 11 reports the average abnormal institutional trading in other firms in response to positive and negative forecast revisions of bellwether firms. Following positive forecast revisions of bellwether firms, there is abnormal net purchase of peer firms by institutional investors. The cross-firm trading on bellwether information is significant for zero and low coverage firms, but not for firms with better coverage. Institutional investors appear to be buying these low coverage firms in the two-day window as well as the twenty-one day window after the forecast revision date, consistent with information transmission from bellwether firms to low coverage firms.

However, the evidence of investors trading reaction to information about bellwether firms is not present for downward forecast revisions. To investigate further, we differentiate large forecast revisions of bellwether firm earnings from small ones, using forecast revisions above one percent to demarcate large revisions. As shown in Panel B of Table 11, there is some evidence of institutional net selling of peer firms following a large negative revision in expected earnings of bellwether firms, however, the evidence is statistically significant for low coverage firms in the 2-day event window only. The lack of evidence of institutions selling following negative revisions in bellwether firms is possibly related to short-sale restrictions by the majority of institutional investors reporting to Ancerno (see, for example, Arif, Ben-Repheal and Lee (2014)). On the other hand, we find evidence of significant abnormal purchases of low (or zero) coverage firms by institutional investors following small and large positive information about the earnings of the industry bellwethers. The abnormal buying of low coverage peers is significant in both the 2-day and 21-day event windows. At the same time, there is no evidence of similar buying behavior for firms which are heavily covered by analysts. Our evidence on institutional trading behavior strongly reinforces the results in Table 4 based on stock price reactions to information about bellwether firms. Overall, the evidence on institutional trading response to revisions in analysts' expectations about the earnings of bellwether firms' reinforces the information spillover effects captured in stock price reactions of industry peers.

6. Conclusions

This paper documents new evidence of information spillover from bellwether firms, which we define as firms with very heavy analyst coverage and fundamentals that are highly correlated with those of other firms in the same industry, to industry peers covered by few or no analysts. Specifically, we find that an analyst's revision of earnings forecasts for the bellwether firm significantly affects the current and future returns of firms followed by few or no analysts. The unidirectional information spillover effect survives a battery of robustness checks and is not explained by other sources identified by earlier papers. For example, the spillover effects we detect persist after controls for delays in the adjustment of prices to common information (Lo and McKinlay (1990) and Hou (2007)), common coverage (Anton and Polk (2012); Israelsen (2011); Muslu, Rebello and Ye (2012)), and forecast precision. Also, the spillovers are more pronounced in low-coverage firms after they experience exogenous drops in coverage.

These findings imply that investors use information produced by analysts following bellwether stocks to price other stocks. Indeed, the prices of more broadly followed stocks are more information laden, but nonetheless exhibit more co-movement with the market because investors use them to value numerous less heavily followed firms. This reasoning suggests that incomplete information models (e.g. Merton (1987)) might be extended to understand information spillovers.

Thus, a generally higher firm-specific variation in the returns of stocks in a sector can reflect more information entering their prices on average, while the individual stocks that exhibit the most co-movement need not be those that are priced least accurately. Moreover, if fixed information costs are reduced, analysts may extend coverage to more firms; and this should mitigate the spillover effect.

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Table 1: Summary statistics

This table presents the summary statistics of firm specific variables, computed each year. *ANALYST* is the number of analysts covering the firm; *SIZE* is the firm's market capitalization; *TURNOVER* is the average of daily share turnover; *HERF_SALES* is the Herfindahl index of sales across 2-digit business segments; *STDRET* is the standard deviation of daily returns; and *IO* is the fraction of shares outstanding held by institutional investors. *PCORR_ROA* measures the partial correlation of each firm earnings (returns on assets or *ROA*) with earnings of other firms in the same industry. In panel A, we report the mean, standard deviation and the quartile values of these variables. In Panel B, the averages are reported for stocks sorted by analyst coverage within each industry, each year, into four groups: zero, low, medium and high coverage. The last two columns report the robust t-statistics (clustered by industry) for the tests of equality of between high and low (or zero) analyst groups. Panel C reports the average correlation coefficients between the variables, where the prefix *Ln* denotes logarithmic values of the variables and *LPCORR_ROA* is the logit transformation of *PCORR_ROA*. HAC t-statistics of the average correlation coefficients are in *Italic*.

Panel A: Summary statistics

Variable	Mean	Std.	Q1	Median	Q3
ANALYST	4.603	6.354	0	2	6
PCORR_ROA(%)	11.679	5.941	7.711	10.227	13.842
SIZE ($millions)	1209.801	4414.930	31.532	119.552	557.831
TURNOVER (%)	0.517	0.610	0.144	0.307	0.648
HERF_SALES	0.857	0.235	0.715	1	1
STDRET (%)	3.571	2.038	2.089	3.077	4.526
IO (%)	33.810	28.169	9.054	27.395	54.666

Panel B: Summary statistics by analyst coverage groups

	Analyst coverage group				T-test	
Variable	Zero	Low	Medium	High	High – Zero	High – Low
ANALYST	0	1.669	4.891	13.978	*25.23*	*24.36*
PCORR_ROA(%)	10.663	12.026	12.128	11.994	*4.33*	*-0.05*
SIZE ($millions)	68.317	197.884	621.883	4502.574	*13.45*	*13.22*
TURNOVER (%)	0.296	0.453	0.625	0.777	*8.59*	*7.20*
HERF_SALES	0.899	0.873	0.846	0.792	*-7.70*	*-6.82*
STDRET (%)	4.331	3.825	3.187	2.662	*-11.57*	*-13.09*
IO (%)	12.084	29.169	44.949	58.710	*37.84*	*27.66*

Panel C: Average yearly correlation coefficients

Variable	*LPCORR_ROA*	*Ln(SIZE)*	*TURNOVER*	*HERF_SALES*	*Ln(STDRET)*	*Ln(IO)*
Ln(1+ANALYST)	0.110	0.818	0.306	-0.189	-0.362	0.655
	8.05	*140.40*	*6.12*	*-13.71*	*-7.90*	*104.81*
LPCORR_ROA		0.097	0.008	0.052	-0.124	0.049
		4.63	*0.42*	*4.27*	*-4.97*	*3.46*
Ln(SIZE)			0.213	-0.270	-0.507	0.646
			4.89	*-23.12*	*-13.18*	*55.01*
TURNOVER				0.047	0.259	0.253
				1.58	*7.19*	*6.55*
HERF_SALES					0.176	-0.212
					8.02	*-22.52*
Ln(STDRET)						-0.347
						-9.27

Table 2: Determinants of analyst coverage

This table presents the determinants of analyst coverage estimated using the following panel regression,

$$Ln(1+ANALYST_{k,t}) = a_0 + a_1 LPCORR\_ROA_{k,t-1} + a_2 Ln(SIZE_{k,t-1}) + a_3 TURNOVER_{k,t-1} + a_4 HERF\_SALES_{k,t-1} + a_5 Ln(STDRET_{k,t-1}) + a_6 Ln(IO_{k,t-1}) + \Sigma c_I INDDUM_{I,k,t} + \Sigma d_y YEARDUM_{y,k,t} + e_{k,t}$$

where, for each firm *k* and year *t*, *ANALYST* is the number of analysts covering the firm; *LPCORR_ROA* is the logit transformation of the partial correlation measure of *ROA*; *SIZE* is market capitalization; *TURNOVER* is the average of daily share turnover; *HERF_SALES* is the Herfindahl index of sales across 2-digit business segments; *STDRET* is the standard deviation of daily returns; *IO* is the fraction of shares outstanding held by institutional investors; *INDDUM*s are industry dummies; and *YEARDUM*s are year dummies. The robust *t*-statistics clustered by industry are provided in *Italic*.

	Sample Period				
Indep. Var.	1984 - 2011	1984 - 1990	1991 - 1997	1998 - 2004	2005 - 2011
$LPCORR\_ROA_{k,t-1}$	0.058	0.014	0.052	0.057	0.074
	4.35	*0.41*	*2.30*	*3.06*	*5.94*
$Ln(SIZE_{k,t-1})$	0.397	0.454	0.431	0.378	0.361
	61.55	*33.99*	*37.96*	*65.69*	*51.66*
$TURNOVER_{k,t-1}$	0.158	0.343	0.225	0.167	0.164
	12.37	*5.42*	*8.64*	*9.41*	*11.02*
$HERF\_SALES_{k,t-1}$	0.142	0.194	0.169	0.065	0.152
	6.16	*3.20*	*3.69*	*1.91*	*4.44*
$Ln(STDRET_{k,t-1})$	0.044	0.045	0.045	0.097	-0.008
	2.39	*1.81*	*1.62*	*4.54*	*-0.35*
$Ln(IO_{k,t-1})$	0.132	0.142	0.096	0.102	0.151
	11.94	*9.03*	*5.88*	*10.52*	*13.83*
Industry dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
R-squared	0.691	0.725	0.731	0.680	0.662

Table 3: Summary statistics of bellwether firms

This table presents the summary statistics of firm specific variables, computed each year, for the sample of bellwether firms. *ANALYST* is the number of analysts covering the firm; *SIZE* is the firm's market capitalization; *TURNOVER* is the average of daily share turnover; *HERF_SALES* is the Herfindahl index of sales across 2-digit business segments; *STDRET* is the standard deviation of daily returns; and *IO* is the fraction of shares outstanding held by institutional investors. *PCORR_ROA* measures the partial correlation of each firm earnings (returns on assets or *ROA*) with earnings of other firms in the same industry. We report the mean, standard deviation and the quartile values of these variables.

Variable	Mean	Std.	Q1	Median	Q3
ANALYST	13.700	6.643	9	12	18
PCORR_ROA(%)	19.077	6.248	14.897	18.048	22.022
SIZE ($millions)	4041.401	7562.544	530.872	1424.519	3705.875
TURNOVER (%)	0.720	0.716	0.254	0.473	0.891
HERF_SALES	0.760	0.277	0.501	0.958	1
STDRET (%)	2.533	1.233	1.709	2.235	2.932
IO (%)	60.279	22.486	44.801	59.953	76.807

Table 4: Impact of lagged earnings forecast revisions of bellwether firms on returns on stocks in the same industry

Panel A presents the estimates of the following panel regression,

$R_{k,t} = a_0 + b_1 FR_{IBW,t-1} + c_1 R_{m,t} + c_2 R_{m,t-1} + d_1 R_{k,t-1} + d_2 R_{k,t-2,t-7} + d_3 \ln(SIZE_{k,t-1}) + d_4 \ln(BM_{k,t-1}) + d_5 TURNOVER_{k,t-1} + d_6 Ln(IO_{k,t-1}) + e_{k,t}$

for all firms *k*, excluding the industry bellwether firms. $R_{k,t}$ is firm *k*'s stock return in month *t*. FR_{IBW} is the revision in consensus earnings forecasts for industry bellwether firms (i.e. same industry as firm *k*). R_m is the value-weighted returns of all stocks in CRSP. The firm specific independent variables include $R_{k,t-2,t-7}$, the cumulative return over the period month *t-7* to month *t-2*; $SIZE_k$, the market capitalization; BM_k, the ratio of book to market value of equity; $TURNROVER_k$, the average daily share turnover; and IO_k, the fraction of shares outstanding held by institutional investors. In Panel B, we add $FR_{k,t-1}$, the revision in earnings forecasts for firm *k*. In Panel C, we also add $FR_{INBW,t-1}$, the revisions in consensus earnings forecasts for a non-bellwether firm in the same industry as firm *k*, defined as the stock with lowest *PCORR_ROA* among stocks with high analyst coverage. The coefficients for the control variables are reported in Panel A only. The robust *t*-statistics, clustered by industry, are provided in *Italic*.

Panel A: Regression of monthly stock returns on the lagged forecast revision of the bellwether firm

	Analyst Coverage Groups				
Independent Variables	*All Firms*	*No Coverage*	*Low Coverage*	*Medium Coverage*	*High Coverage*
Intercept	-1.305	-0.972	-1.580	-2.017	-1.641
	-5.26	*-4.93*	*-4.44*	*-4.03*	*-3.91*
$FR_{IBW,t-1}$	0.094	0.182	0.147	0.063	-0.022
	3.01	*4.36*	*3.54*	*1.66*	*-0.54*
$R_{k,t-1}$	-0.017	-0.021	-0.018	-0.013	-0.002
	-5.56	*-5.84*	*-5.21*	*-2.69*	*-0.36*
$R_{k,t-2,t-7}$	0.004	0.006	0.004	0.003	0.001
	3.52	*4.48*	*2.46*	*2.49*	*0.82*
$Ln(SIZE_{k.t-1})$	0.037	0.126	0.104	0.055	0.007
	1.29	*2.89*	*1.63*	*1.27*	*0.30*
$Ln(BM_{k,t,-1})$	0.513	0.827	0.467	0.328	0.113
	11.41	*13.50*	*6.05*	*9.15*	*3.15*
$TURNOVER_{k,t-1}$	0.004	-0.017	0.004	0.006	0.005
	1.38	*-3.24*	*0.79*	*1.66*	*1.78*
$Ln(IO_{k,t-1})$	*0.319*	*0.216*	*0.288*	*0.420*	*0.369*
	4.45	*2.85*	*3.22*	*4.00*	*4.13*
$R_{m,t}$	1.087	0.876	1.090	1.206	1.207
	4.34	*5.07*	*7.85*	*9.14*	*9.52*
$R_{m,t-1}$	0.190	0.298	0.263	0.146	0.030
	2.88	*5.70*	*5.86*	*3.57*	*0.99*
Rsq	0.124	0.074	0.118	0.162	0.203

Panel B: Regression of monthly stock returns on the lagged earnings forecast revision of the bellwether firm and firm *k*.

	Analyst Coverage Groups				
Independent Variables	*All Firms*	*No Coverage*	*Low Coverage*	*Medium Coverage*	*High Coverage*
$FR_{IBW,t-1}$	0.087	0.182	0.137	0.053	-0.024
	2.69	*4.36*	*2.97*	*1.41*	*-0.59*
$FR_{k,t-1}$	0.100		0.128	0.114	0.037
	4.81		*3.84*	*4.26*	*0.82*
Other Controls	Yes	Yes	Yes	Yes	Yes
Rsq	0.124	0.074	0.118	0.162	0.203

Panel C: Regression of monthly stock returns on the lagged earnings forecast revisions of the bellwether firm, the non-bellwether firm, and firm *k*.

	Analyst Coverage Groups				
Independent Variables	*All Firms*	*No Coverage*	*Low Coverage*	*Medium Coverage*	*High Coverage*
$FR_{IBW,t-1}$	0.090	0.178	0.141	0.059	-0.026
	2.58	*4.14*	*2.77*	*1.42*	*-0.67*
$FR_{INBW,t-1}$	-0.022	0.087	-0.054	-0.088	-0.007
	-0.25	*1.09*	*-0.43*	*-0.93*	*-0.09*
$FR_{k,t-1}$	0.104		0.127	0.115	0.057
	4.79		*3.85*	*4.36*	*1.07*
Other Controls	Yes	Yes	Yes	Yes	Yes
Rsq	0.124	0.074	0.118	0.162	0.202

Table 5: Impact of contemporaneous earnings forecast revisions of bellwether firms on returns on stocks in the same industry

Panel A presents the estimates of the following panel regression,

$R_{k,t} = a_0 + b_1 FR_{IBW,t} + b_2 FR_{k,t} + c_1 R_{m,t} + c_2 R_{m,t-1} + d_1 R_{k,t-1} + d_2 R_{k,t-2,t-7} + d_3 \ln(SIZE_{k,t-1}) + d_4 \ln(BM_{k,t-1})$
$+ d_5 TURNOVER_{k,t-1} + d_6 Ln(IO_{k,t-1}) + e_{k,t}$

for all firms k, excluding the industry bellwether firms. $R_{k,t}$ is firm k's stock return in month t. FR_{IBW} is the revision in consensus earnings forecasts for industry bellwether firm (i.e. same industry as firm k). FR_k, the revision in earnings forecasts for firm k. Other control variables (not reported in the table) include R_m, the value-weighted returns of all stocks in CRSP; $R_{k,t-2,t-7}$, the cumulative return over the period month t-7 to month t-2; $SIZE_k$, the market capitalization; BM_k, the ratio of book to market value of equity; $TURNROVER_k$, the average daily share turnover; and IO_k, the fraction of shares outstanding held by institutional investors. In Panel B, we add the lagged values of FR_{IBW} and FR_k to the regression model. The robust *t*-statistics, clustered by industry, are provided in *Italic*.

Panel A: Regression of monthly stock returns on the contemporaneous earnings forecast revision of the bellwether firm

	Analyst Coverage Groups				
Independent Variables	*All Firms*	*No Coverage*	*Low Coverage*	*Medium Coverage*	*High Coverage*
$FR_{IBW,t}$	0.185	0.285	0.266	0.148	0.040
	6.31	*9.91*	*4.80*	*5.84*	*1.01*
$FR_{k,t}$	0.900		0.734	0.966	1.219
	9.04		*13.05*	*6.99*	*5.68*
Other Controls	Yes	Yes	Yes	Yes	Yes
Rsq	0.130	0.074	0.125	0.172	0.214

Panel B: Regression of monthly stock returns on the contemporaneous and lagged earnings forecast revisions of the bellwether firm

	Analyst Coverage Groups				
Independent Variables	*All Firms*	*No Coverage*	*Low Coverage*	*Medium Coverage*	*High Coverage*
$FR_{IBW,t}$	0.184	0.257	0.258	0.160	0.067
	5.89	*8.92*	*4.63*	*5.73*	*1.65*
$FR_{IBW,t-1}$	0.010	0.114	0.047	-0.032	-0.077
	0.31	*2.67*	*1.11*	*-0.81*	*-1.70*
$FR_{k,t}$	0.906		0.729	0.970	1.297
	8.91		*13.08*	*6.80*	*5.44*
$FR_{k,t-1}$	-0.037		0.092	-0.012	-0.312
	-1.54		*2.70*	*-0.32*	*-3.21*
Other Controls	Yes	Yes	Yes	Yes	Yes
Rsq	0.130	0.074	0.124	0.172	0.215
Sum of the coefficients					
$FR_{IBW,t}+FR_{IBW,t-1}$	0.194	0.371	0.305	0.129	-0.011

5.34	*7.69*	*4.40*	*3.73*	*-0.21*

Table 6: Reduction in analyst coverage and the relation between stock returns and earnings forecast revisions of industry bellwether firms

This table presents the results of the following regression over the event window of 3 months before and 3 months after the brokerage closure event,

$$R_{k,t} = a_0 + b_{11} FR_{IBW,t-1} + b_{12} FR_{IBW,t-1}{*}DM\_POST_{k,t} + b_{13} FR_{IBW,t-1}{*}DM\_POST_{k,t}{*}LOWANAL_{k,t} + b_2 FR_{k,t-1} + c_1 R_{m,t} + c_2 R_{m,t-1} + d_1 R_{k,t-1} + d_2 R_{k,t-2,t-7} + d_3 \ln(SIZE_{k,t-1}) + d_4 \ln(BM_{k,t-1}) + d_5 TURNOVER_{k,t-1} + d_6 Ln(IO_{k,t-1}) + d_7 DM\_POST_{k,t} + e_{k,t}$$

for all firms *k* that experienced coverage terminations due to brokerage closures (Kelly and Ljungqvist (2012)), excluding the industry bellwether firms. The exogenous analyst coverage termination events are for the period 2000 to 2008. The month *t* stock returns, $R_{k,t}$, during the window is regressed on FR_{IBW} (the earnings forecast revision of firm *k*'s industry bellwether firm) and its interactions with two dummy variables: DM_POST_k (equal to one in the post-event window) and $LOWANAL_k$ (equal to one if firm *k* has low analyst coverage in the pre-event window). Model 1 (2) excludes (includes) firm *k*'s revision in earnings forecasts, FR_k. Other control variables (not reported in the table) include R_m, the value-weighted returns of all stocks in CRSP; $R_{k,t-2,t-7}$, the cumulative return over the period month *t-7* to month *t-2*; $SIZE_k$, the market capitalization; BM_k, the ratio of book to market value of equity; $TURNOVER_k$, the average daily share turnover; and IO_k, the fraction of shares outstanding held by institutional investors. The robust *t*-statistics, clustered by industry, are provided in *Italic*.

Independent Variables	Model 1 (Number of events: 2462)	Model 2 (Number of events: 2446)
Intercept	-2.524	-2.972
	-1.69	*-2.05*
$FR_{IBW,t-1}$	0.023	0.016
	0.24	*0.17*
$FR_{IBW,t-1}{*}\ DM\_POST_{k,t}$	-0.033	-0.043
	-0.17	*-0.22*
$FR_{IBW,t-1}{*}DM\_POST_{k,t}{*}LOWANAL_{k,t}$	1.058	1.406
	3.05	*3.92*
$DM\_POST_{k,t}$	1.280	1.295
	2.37	*2.45*
$FR_{k,t-1}$		-0.049
		-0.18
Other Controls	Yes	Yes
Rsq	0.178	0.178

Table 7: Impact of lagged earnings forecast revisions of bellwether firms on returns on stocks in the same industry, excluding firms sharing common analyst coverage or brokerage firm with the bellwether firms

This table presents the results of the following panel regression,

$$R_{k,t} = a_0 + b_1\, FR_{IBW,t-1} + b_2\, FR_{k,t-1} + c_1\, R_{m,t} + c_2\, R_{m,t-1} + d_1\, R_{k,t-1} + d_2\, R_{k,t-2,t-7} + d_3\, ln(SIZE_{k,t-1}) + d_4\, ln(BM_{k,t-1}) + d_5\, TURNOVER_{k,t-1} + d_6\, Ln(IO_{k,t-1}) + e_{k,t}$$

for all firms *k*, excluding the industry bellwether firms. $R_{k,t}$ is firm *k*'s stock return in month *t*. FR_{IBW} is the revision in consensus earnings forecasts for the industry bellwether firm. FR_k is the revision in earnings forecasts for firm *k*. The control variables (not reported in the table) include R_m, the value-weighted returns of all stocks in CRSP; $R_{k,t-2,t-7}$, the cumulative return over the period month *t-7* to month *t-2*; $SIZE_k$, the market capitalization; BM_k, the ratio of book to market value of equity; $TURNROVER_k$, the average daily share turnover; and IO_k, the fraction of shares outstanding held by institutional investors. The robust *t*-statistics, clustered by industry, are provided in *Italic*. In Panel A, the sample excludes all firms *k* that share common analyst coverage with its industry bellwether firm, and in Panel B, the sample excludes all firms *k* that share common brokerage firm with its industry bellwether firm.

Panel A: Regression excluding firms sharing common analyst coverage

	Analyst Coverage Groups			
Independent Variables	*All Firms*	*Low Coverage*	*Medium Coverage*	*High Coverage*
$FR_{IBW,t-1}$	0.084	0.138	0.048	0.055
	2.19	*2.73*	*1.14*	*0.86*
$FR_{k,t-1}$	0.120	0.122	0.158	-0.001
	6.09	*3.30*	*6.64*	*-0.02*
Other Controls	Yes	Yes	Yes	Yes
Rsq	0.144	0.115	0.156	0.194

Panel B: Regression excluding firms sharing common brokerage firm

	Analyst Coverage Groups			
Independent Variables	*All Firms*	*Low Coverage*	*Medium Coverage*	*High Coverage*
$FR_{IBW,t-1}$	0.098	0.165	-0.025	0.079
	1.40	*2.24*	*-0.27*	*0.73*
$FR_{k,t-1}$	0.163	0.128	0.252	0.084
	5.97	*2.86*	*4.84*	*0.71*
Other Controls	Yes	Yes	Yes	Yes
Rsq	0.110	0.102	0.122	0.126

Table 8: Impact of an individual analyst's revision of earnings forecast of bellwether firms on returns on other firms in the same industry

This table presents the results of the following regression,

$$R_{k,t} = a_0 + b_1 FR_{IBW,t-1} + b_2 FR_{k,t-1} + c_1 R_{m,t} + c_2 R_{m,t-1} + d_1 R_{k,t-1} + d_2 R_{k,t-2,t-7} + d_3 ln(SIZE_{k,t-1}) + d_4 ln(BM_{k,t-1}) + d_5 TURNOVER_{k,t-1} + d_6 Ln(IO_{k,t-1}) + e_{k,t}$$

for all firms *k*, excluding the industry bellwether firms. $R_{k,t}$ is the stock return in month *t*. FR_{IBWj} is the most recent monthly revision in earnings forecasts for the industry bellwether firm made by an analyst in month *t*-1, and FR_k is the revision in earnings forecasts for firm *k*. Other control variables (not reported in the table) include R_m, the value-weighted returns of all stocks in CRSP; $R_{k,t-2,t-7}$, the cumulative return over the period month *t-7* to month *t-2*; $SIZE_k$, the market capitalization; BM_k, the ratio of book to market value of equity; $TURNROVER_k$, the average daily share turnover; and IO_k, the fraction of shares outstanding held by institutional investors. The robust *t*-statistics, clustered by industry, are provided in *Italic*.

	Analyst Coverage Groups				
Independent Variables	*All Firms*	*No Coverage*	*Low Coverage*	*Medium Coverage*	*High Coverage*
$FR_{IBWj,t-1}$	0.009	0.071	0.036	-0.014	-0.040
	0.31	*1.84*	*0.82*	*-0.54*	*-1.58*
$FR_{k,t-1}$	0.096		0.123	0.113	0.029
	4.43		*3.46*	*3.93*	*0.62*
Other Controls	Yes	Yes	Yes	Yes	Yes
Rsq	0.127	0.074	0.120	0.166	0.206

Table 9: Impact of individual analyst's revision of earnings forecast of bellwether firms on returns on other firms in the same industry: an event study analysis

This table reports the tests of the effects of the earnings forecast revision of the industry bellwether firms on the contemporaneous and post-revision returns on peer firms in the same industry. Specifically, we run the following regression:

$$CAR_{k,w} = a_0 + b_1 FR\_Rank_{I,BW} + d_1 R_{k,t-1} + d_2 R_{k,t-2,t-7} + d_3 \ln(SIZE_{k,t-1}) + d_4 \ln(BM_{k,t-1}) + d_5 TURNOVER_{k,t-1} + d_6 Ln(IO_{k,t-1}) + e_{k,w}$$

for all firms *k*, excluding the industry bellwether firms. $CAR_{k,w}$, is the cumulative return on stock *k* in excess of the market return over the *w*-day window around the industry bellwhether firm's forecast revision date. FR_Rank_{IBW} is the decile rank value of the earnings forecast revision for the industry bellwether firms (1 for the lowest decile and 10 for the highest decile). The control variables (not reported in the table) include $R_{k,t-2,t-7}$, the cumulative return over the period month *t-7* to month *t-2*; $SIZE_k$, the market capitalization; BM_k, the ratio of book to market value of equity; $TURNROVER_k$, the average daily share turnover; and IO_k, the fraction of shares outstanding held by institutional investors. The robust *t*-statistics, clustered by industry, are provided in *Italic*.

	Analyst Coverage Groups				
Independent Variables	*All Firms*	*No Coverage*	*Low Coverage*	*Medium Coverage*	*High Coverage*
CARs measured over the two-day window [0, 1]					
$FR\_Rank_{I,BW}$	1.548	2.246	1.785	0.871	0.733
	4.86	*4.48*	*3.22*	*2.40*	*1.33*
Controls	Yes	Yes	Yes	Yes	Yes
Rsq (%)	0.027	0.043	0.037	0.015	0.011
*CAR*s measured over the twenty-one-day window [2, 22]					
$FR\_Rank_{I,BW}$	6.517	6.721	9.396	5.491	3.601
	3.94	*3.72*	*4.35*	*2.52*	*1.57*
Controls	Yes	Yes	Yes	Yes	Yes
Rsq (%)	0.228	0.443	0.185	0.079	0.026

Table 10: Impact of lagged earnings forecast revisions of bellwether firms on returns on stocks in the same industry: controlling for lead-lag effects

This table presents the results of the following panel regression,

$$R_{k,t} = a_0 + b_1 FR_{IBW,t-1} + b_2 FR_{k,t-1} + c_1 R_{m,t} + c_2 R_{m,t-1} + c_3 R_{IBIG,t-1} + d_1 R_{k,t-1} + d_2 R_{k,t-2,t-7} + d_3 \ln(SIZE_{k,t-1}) + d_4 \ln(BM_{k,t-1}) + d_5 TURNOVER_{k,t-1} + d_6 Ln(IO_{k,t-1}) + e_{k,t}$$

for all firms *k*, excluding the industry bellwether firms. $R_{k,t}$ is firm *k*'s stock return in month *t*. FR_{IBW} is the revision in consensus earnings forecasts for the industry bellwether firm. FR_k is the revision in earnings forecasts for firm *k*. R_{IBIG} is the value-weighted return of stocks in the same industry that belong to the top decile in terms of market capitalization. Other control variables (not reported in the table) include R_m, the value-weighted returns of all stocks in CRSP; $R_{k,t-2,t-7}$, the cumulative return over the period month *t-7* to month *t-2*; $SIZE_k$, the market capitalization; BM_k, the ratio of book to market value of equity; $TURNROVER_k$, the average daily share turnover; and IO_k, the fraction of shares outstanding held by institutional investors. The robust *t*-statistics, clustered by industry, are provided in *Italic*.

	Analyst Coverage Groups				
Independent Variables	*All Firms*	*No Coverage*	*Low Coverage*	*Medium Coverage*	*High Coverage*
$FR_{IBW,t-1}$	0.071	0.159	0.116	0.038	-0.031
	2.11	*3.79*	*2.51*	*0.96*	*-0.74*
$FR_{k,t-1}$	0.104		0.131	0.118	0.044
	5.02		*3.98*	*4.34*	*1.00*
$R_{IBIG,t-1}$	0.114	0.117	0.128	0.119	0.075
	5.30	*4.87*	*4.54*	*5.56*	*4.38*
Other Controls	Yes	Yes	Yes	Yes	Yes
Rsq	0.126	0.075	0.120	0.164	0.204

Table 11: Earnings forecast revisions of bellwether firms and institutional trading in stocks in the same industry

This table presents the average abnormal trading imbalance by institutional investors in firms in the same industry (exclude the bellwether firm) in response to the revisions of earnings forecasts of bellwether firms by individual analysts. For each forecast revision event, the abnormal trading imbalance for an industry peer stock *k* over a specific *w*-day event window around the revision date (day 0) is calculated as the difference in the average daily trading imbalance between the event window and the sixty-three-day [-73, -11] pre-event window, where the daily trading imbalance is calculated as the difference between the number of shares purchased and the number of shares sold by all institutional investors on the date, scaled by the number of shares outstanding. The abnormal trading imbalance at the event level is then calculated at the average of firm-level abnormal trading imbalance, separately for different groups of non-bellwether firms in the industry formed on the basis of analyst coverage. Finally, event-level abnormal trading imbalances are further averaged across events in the same calendar month, based on which the mean and the associated HSC t-value are calculated. Panel A presents the average abnormal trading imbalance in non-bellwether firms in response to negative and positive forecast revision events of bellwether firms separately. Panel B presents the results of further differentiating large forecast revisions from small ones, using one percentage point as the cutoff value for earnings forecast revisions for the bellwether firms, calculated as the change in earnings forecasts scaled by the stock price at least 30 days prior to the revising date. In both panels, the abnormal trading imbalances for a two-day [0, 1] window around the forecast revision date and a twenty-one day [2, 22] window after the revision date are reported.

Panel A: Abnormal trading imbalance in peer firms in response to positive and negative forecast revisions of industry bellwether firms

	Analyst Coverage Groups				
FR Groups	*All Firms*	*No Coverage*	*Low Coverage*	*Medium Coverage*	*High Coverage*
2-day [0, 1] window					
Negative	0.005	0.052	0.009	0.000	0.002
	0.76	*1.41*	*0.56*	*0.05*	*0.22*
Positive	0.016	0.095	0.060	0.012	-0.011
	2.11	*2.47*	*2.81*	*1.29*	*-1.33*
21-day [2, 22] window					
Negative	0.005	0.023	0.009	0.004	-0.002
	0.78	*1.17*	*0.93*	*0.50*	*-0.26*
Positive	0.017	0.055	0.042	0.009	-0.014
	2.52	*2.86*	*3.57*	*1.06*	*-1.92*

Panel B: Abnormal institutional trading imbalance in peer firms in response to small/large earnings forecast revisions of industry bellwether firms

	Analyst Coverage Groups				
	All Firms	*No Coverage*	*Low Coverag e*	*Medium Coverage*	*High Coverage*
2-day [0, 1] window					
Large negative	-0.018	0.004	-0.104	-0.002	-0.003
	-1.28	*0.06*	*-2.18*	*-0.07*	*-0.13*
Small negative	0.007	0.066	0.027	-0.004	0.003
	0.91	*1.60*	*1.56*	*-0.41*	*0.34*
Small positive	0.018	0.083	0.066	0.014	-0.009
	2.07	*1.95*	*2.48*	*1.14*	*-0.93*
Large positive	0.009	0.166	0.049	0.016	-0.021
	0.51	*2.38*	*1.26*	*0.72*	*-0.83*
21-day [2, 22] window					
Large negative	-0.008	-0.026	-0.022	-0.009	0.005
	-0.75	*-0.75*	*-1.01*	*-0.53*	*0.37*
Small negative	0.006	0.035	0.015	0.003	-0.007
	0.85	*1.72*	*1.58*	*0.41*	*-0.92*
Small positive	0.017	0.050	0.042	0.010	-0.013
	2.44	*2.42*	*3.30*	*1.15*	*-1.70*
Large positive	0.020	0.080	0.055	0.003	-0.011
	1.99	*2.50*	*2.44*	*0.20*	*-0.97*