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INFORMATION, ANALYSTS, AND STOCK RETURN COMOVEMENT

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ABSTRACT

We examine information spillover as a source of stock return synchronicity, where information about highly-followed "prominent" stocks is used to price other "neglected" stocks sharing a common fundamental component. We find that stocks followed by few analysts co-move significantly with firm-specific fluctuations in the prices of highly followed stocks in the same industry, but do not observe the converse. This effect is more prominent in industries where analysts follow fewer stocks. Earnings forecast revisions for highly followed stocks cause price changes in little followed stocks, but the converse is again not observed. This is consistent with information spillover being primarily unidirectional – flowing from prominent to neglect stocks, but not vice versa. These findings also validate models of specialized information intermediaries in stock markets assisting the information capitalization process.

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1. Introduction

In his American Finance Association presidential address, Merton (1987, p. 486) points out that "recognition of the different speeds of information diffusion is particularly important in empirical research, where the growth in sophisticated and sensitive techniques to test ever more refined financial behavior patterns severely strains the simple information structure of our asset pricing models." Merton goes on to develop a model of investors confining their attention, and money, to a subset of "high profile" stocks about which they have readily accessible information, potentially leaving other "neglected" stocks mispriced. Using analyst following to identify high profile firms, we show that investors use the information about these firms to help value related "neglected" stocks.

It is well established that informed risk arbitrage generates stock price movements and profit-maximizing arbitrageurs presumably pay for additional information until their expected revenue from a marginal bit no longer covers its costs (Diamond and Verrecchia (1981); Grossman and Stiglitz (1980); Shleifer and Vishny (1997)). Different kinds of information have different costs, yield different likely arbitrage revenues, and therefore provide different opportunities for private sector information intermediaries. Governments provide much macroeconomic information, though financial analysts provide economy-level forecasts for fees. Governments also provide some industry information, but leave analysts more substantial roles here. Securities regulations make firms disclose standardized firm-specific information, but distilling this into fundamental valuation estimates requires resources and expertise. Thus, financial analysts' firm-specific forecasts are their most important contribution to asset pricing (Brown et. al

(1987); Bhushan (1989)) by privately informed arbitrageurs (Roll (1988)).

Veldkamp (2006a) insightfully models intermediaries specializing in the provision of information to arbitrageurs in the context of a market for information. All else equal, arbitrageurs pay more for information about a mispriced stock with a larger market capitalization or higher turnover, which allows the accumulation of a larger position without attracting notice and moving the price. Consistent with this, we find more analysts following stocks that have larger market cap and are more heavily traded (Bhushan (1989); Alford and Berger (1999)).

Stocks that intermediaries find cost-ineffective to analyze have prices nonetheless. Such a neglected stock must be priced using such information as is available: market and industry trends plus information about prominent firms with correlated fundamentals. For instance, Foster (1981), Han and Wild (1990), and Ramnath (2002) show that announcements of earnings information about some firms move the prices of other firms in the same industry. All else equal, information useful for valuing more stocks should fetch a higher price and attract greater analysts coverage (Veldkamp (2006a)). We find more analysts following firms whose fundamentals correlate more with those of other firms. We also find high profile stocks, identified by large analyst followings, commove more extensively with other stocks in the same industry. This information spillover effect is greater in industries where analysts focus on fewer stocks, and where their forecasts for heavily followed stocks are more convergent.

Additionally, we show that revisions in analysts' earnings forecasts for heavily followed firms cause changes in the prices of less followed firms' shares; but revisions in sparsely followed firms' earnings forecasts do not affect the prices of heavily followed stocks. This is consistent with investors using information about prominent stocks to value neglected stocks, but not vice versa. That is, information spillover appears to be unidirectional – from heavily followed to sparsely follows stocks.

Our results validate modeling information intermediaries as important players in information generation and capitalization, as in Veldkamp (2005, 2006a, 2006b). In addition, our findings justify the industry practice of using "bellwether" stocks as barometers of sector trends – as when analysts use, for example, Wal-Mart's latest quarterly results to infer the fate of retailing in general.

Finally, our findings reconcile a seeming discord between recent work linking elevated firm-specific returns variation to more accurate pricing (Morck et al. (2000); Campbell et al. (2001); Durnev et al. (2004); Jin and Myers (2006); and others), showing stocks followed by many analysts to be priced more accurately (Brennan et al. (1993); Walther (1997)) and to commove more with the market (Piotroski and Roulstone (2004); Chan and Hameed (2006)). These findings are reconciled in that more widely followed stocks exhibit more comovement because they are priced more accurately, and are therefore used to infer values for more opaque stocks. Thus, a generally higher firm-specific variation across all or most stocks in a market or sector can signify more accurate pricing, but the individual stocks that exhibit the most comovement need not be those that are priced least accurately. This reasoning suggests that Merton's (1987) model might be usefully supplemented by considering information spillovers, where investors use information about one stock to price another that is likely affected by similar fundamentals.

The next section describes our data and variables, and section 3 reports our main empirical results on the relation between analysts following and return comovement, while section 4 provides specific tests on the causal relation between the two. Finally, section 5 concludes.

2. Data, construction of variables, and sample

Examination of the empirical propositions in our paper involves explaining a firm's analyst following and also its contribution to stock return comovement using firm characteristics. In this section, we describe our data sources, variables, and sample.

2.1 Data sources

Daily stock price and return data for all common stocks listed on NYSE, AMEX and NASDAQ are obtained from the Center for Research in Security Prices (CRSP). The sample stocks are restricted to ordinary common stocks with share code 10 and 11 for the period January 1984 to December 2007. ADRs, shares of beneficial interest, companies incorporated outside U.S., Americus Trust components, close-ended funds, preferred stocks, and REITs are excluded.

The stock return data from CRSP is merged with data from two additional sources. The first data source is COMPUSTAT, which is used to collect quarterly earnings data. For each firm in our sample, we compute the return on asset (ROA) for each quarter as the ratio of earnings before extraordinary item (data item 8) to total assets (data item 44). The second database is I/B/E/S which provides information on analyst coverage for each firm and the analysts' earnings forecasts and revisions in forecasts. The number of analysts making one-year ahead earnings forecasts for each firm *k* during the year t is used to measure analyst coverage ($ANALYST_{k,t}$).

2.2 Variables

Marginal contribution to returns comovement (LPCORR)

The central variable in our empirical investigation measures the contribution of an individual firm's return to stock return comovement. We do this by estimating partial correlations for every stock with every other stock in its industry, and then averaging these to gauge each stock's contribution to the overall comovement of stocks in its industry. The construction of this variable has three steps:

The first step in assessing firm k's contribution to comovement in its industry I is to run two-factor OLS market model regressions for all other stocks in the industry pretending firm k did not exist. That is, we run

$$[1] \qquad r_{iw} = a_i + b_i r_{Mw}^k + c_i r_{Iw}^k + e_{iw},$$

each year for every other firm i in industry I, with r_{iw} firm i's total stock return in week w and with r_{Mw}^k and r_{Iw}^k contemporaneous weekly value-weighted total market and industry returns, respectively, both recalculated to exclude both i and k. Our market return is a modified value-weighted CRSP market index, and our industry return is a value-weighted index of all industry I stocks, save i and k. We assign each firm to its primary five-digit Global Industry Classification Standard (GICS) code. Our sample spans 69 such industries.

The R^2 of [1], denoted $R_{i,excl.k}^2$, is the fraction of variation in firm i's returns explained by market and industry factors, excluding firm k. Defining N_I as the number of firms in industry I in the year in question, this first step thus generates an $R^2_{i,excl.k}$, from each of $N_I - 1$ regressions of the form [1], one for every other firm $i \neq k$ in industry I.

Our second step is to rerun [1], but with the previously excluded firm k's total return, r_{kw}, as a third factor. That is, for every firm $i \neq k$ in industry I, we run

$$[2] \qquad r_{iw} = a_i + b_i r^k_{Mw} + c_i r^k_{Iw} + d_i r_{kw} + e_{iw}.$$

This procedure generates a second set of $N_I - 1$ regression R^2s, which we denote $R^2_{i,incl.k}$. The extent to which the R^2 of [2] exceeds the R^2 of [1] for a given pair of stocks (k, i) gauges the extent to which firm k makes a marginal contribution to firm i's returns variation.

For each pair of firms (k, i) in the same industry I, we thus calculate a partial correlation coefficient equal to the difference between the two R^2s normalized by the unexplained fraction of variation in [1]:

$$[3] \qquad PCORR_{k,i} = \left(\frac{R^2_{i,incl.k} - R^2_{i,excl.k}}{1 - R^2_{i,excl.k}}\right).$$

For each firm k in industry I, the regressions in equation [1] and [2] produce N_I minus one partial correlation coefficients, defined in [3]. Intuitively, a larger $PCORR_{k,i}$ means firm k's returns have larger correlation with firm i's returns, after purging market and industry-related comovement.

Our third step takes us to an estimate of each firm *k*'s overall contribution to the comovement of other stocks in its industry each year. We average $PCORR_{k,i}$ across all other firms $i \neq k$ in industry I and denote this $PCORR_k = \frac{1}{N_I - 1}\sum_{i=1, i\neq k}^{N_I} PCORR_{k,i}$. Since $PCORR_k$ is bounded between zero and one, we apply a logistic transformation to obtain our operational measure of each firm *k*'s marginal contribution to comovement in its industry,

[4] $$LPCORR_k = \log\left(\frac{PCORR_k}{1 - PCORR_k}\right).$$

Repeating these three steps for every stock *k* every year generates a panel of $LPCORR_k$ based on weekly returns that year. Intuitively, a higher value of $LPCORR_k$ means that firm *k's* returns add more to the common variation in returns across firms in its industry.

In addition to explaining the role of financial analysts on return comovement, we are also interested in the factors that may influence a firm's attractiveness to analysts, such as the degree of fundamental correlations in asset returns, firm size, the amount of trading activity and the level of concentration of the firm's business within the industry. These variables are described next.

Contribution to fundamental comovement (LPCORR_ROA)

Stock returns intrinsically co-move because of commonalities in the variation of fundamentals. At the same time, more analysts are expected to follow firms whose fundamentals are more correlated with other firms' fundamentals (Veldkamp (2006a)). Hence, in tracking the impact of analyst following on stock return comovement, we need to control for the correlations in fundamentals returns. 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)). While *ROA* is based on historical data, stock returns also incorporate changes in expected future cash flows and shifts in investors' risk preferences. Nevertheless, we expect a firm's level of analyst coverage and its contribution to return comovement to be related to the correlation in its *ROA* to that of other firms.

As with our construction of *PCORR* based on stock returns, we construct the partial correlation of the return on assets (*ROA*) of firm *k* with the *ROA* of other firms in the industry for each year. We begin by estimating the linear regression equations similar to equations [1] and [2] based on a five year moving window of quarterly data:

[5] $$ROA_{iq} = a_i + b_i ROA^k_{Mq} + c_i ROA^k_{Iq} + e_{iq},$$

[6] $$ROA_{iq} = a_i + b_i ROA^k_{Mq} + c_i ROA^k_{Iq} + d_i ROA_{kq} + e_{iq},$$

where ROA_{iq} and ROA_{kq} are the return on assets in quarter *q* for firms *i* and *k*, and both firms *i* and *k* belong to the same industry. ROA^k_{Mq} and ROA^k_{Iq} are the value-weighted return on assets in quarter *q* for the market and industry portfolios respectively, where both firms *k* and *i* are excluded from these portfolios. Denoting the R-square from equations [5] and [6] as $R^2_{ROA,i,excl.k}$ and $R^2_{ROA,,i,incl.k}$ respectively, the partial correlation coefficient between ROA_{kt} and ROA_{it} is computed as follow

$$[7] \qquad PCORR\_ROA_{k,i} = \left(\frac{R^2_{ROA,i,incl.k} - R^2_{ROA,i,excl.k}}{1 - R^2_{ROA,i,excl.k}}\right).$$

Averaging the partial correlation estimates for firm k with all other firms in the same industry and taking a logistic transformation gives us $LPCORR\_ROA_k$. A high value of $LPCORR\_ROA_k$ suggests that firm *k*'s *ROA* contributes much in explaining the fundamental variation in asset returns of all other firms in the industry, after controlling for market and industry effects.

Other firm-level variables

In empirically investigating the informational role of analysts, we must incorporate various firm characteristics shown to be important in prior work on information markets (e.g. Veldkamp (2006a)) and analyst followings (e.g. Bhushan 1989; Piotroski and Roulstone (2004); Chan and Hameed (2006); Frankel et al. (2006)).

All else equal, more analysts should follow larger firms. This might be because larger feasible arbitrage plays on such firms make information about their mispricing more valuable (Veldkamp (2006a)), or because more media coverage stimulates demand for analyst services (Lang and Lundholm (1996); Frankel et al. (2006)). We use the beginning of year *t* market value of each firm *k* to measure the size of firm k, denoted $SIZE_{k,t}$. We expect the variable to explain both a firm's analyst following and its impact on return comovement.

More analysts should follow more heavily traded stocks, all else equal. This could be because higher turnover permits less conspicuous, and therefore more profitable arbitrage plays; or because higher turnover generates more commissions for brokerage firms, and thus more demand for forecasts (Brennan and Hughes (1991); Alford and Berger (1999)). We define $TURNOVER_{k,t}$ as the average daily share turnover of stock *k* in the previous year *t-1*.

More analysts might also follow less diversified firms, all else equal. This might be because a more focused firm has a higher partial correlation in fundamentals with other firms in its primary industry, and is thus a better potential bellwether stock; or because a more focused firm is simpler to value (Bhushan (1989)). For each firm *k*, we use the *Herfindahl* index of sales for the fiscal year ending in year *t* across business segments indicated by 2-digit SIC code to measure the level of concentration of its business and denote this as $HERF\_SALES_{k,t}$.

Finally, information about more volatile stocks might fetch higher prices (Bhushan (1989)), perhaps because more volatility corresponds to more "eventful" stocks whose fundamentals are changing faster (Morck et al. (2000)). Hence, demand for analyst services might be higher for stocks whose returns have higher standard deviations. We measure $STDRET_{k,t}$ as the standard deviation of stock *k*'s weekly returns over the prior year *t-1*.

2.3 Final sample

We combine the securities from CRSP and COMPUSTAT that meet the following selection criteria. For CRSP NYSE/AMEX and NASDAQ securities, we apply two filters: (a) there are at least 40 weekly non-missing observations, the minimum number of observations to estimate the market model regressions in equations [1] and [2]; and (b) the average daily stock price in the December of previous year is above $5 to minimize market frictions associated with low price stocks, such as price discreteness and bid-ask effects. Since we perform yearly analysis of data, we require that each firm has valid market capitalization value at the beginning of each year. Common stocks from COMPUSTAT are required to have at least 12 valid quarterly data during the past five-year moving window to estimate $LPCORR\_ROA_k$ each year. We merge the stock information in CRSP-COMPUSTAT with analyst coverage information in I/B/E/S.

The number of securities in each database and the merged sample is reported in Table 1. There is an increasing trend in the number of firms each year. We start with 2220 firms in the CRSP, COMPUSTAT and I/B/E/S merged sample in 1984, which grows steadily to the peak at 3998 firms in 1997. The difference between number of firms in our final merged sample and the CRSP and COMPUSTAT combined sample reflects the number of firms without corresponding analyst coverage information in I/B/E/S. We perform our tests on both samples, treating firms that appear in CRSP-COMPUSTAT but not in I/B/E/S as firms with zero analyst coverage during the year. On average, there are 725 firms per year (or about 20 percent of the firms in our CRSP-COMPUSTAT merged sample) with zero analyst following during the sample period.

3. Empirical results

3.1 Summary statistics and preliminary results

Panel A in Table 2 reports simple descriptive statistics of key variables. The pooled average value of the marginal contribution of a single stock to comovement in returns, $PCORR_k$, is 2.6 percent, and its median is 2.4 percent.[1] The partial correlation measure for fundamental returns, $PCORR\_ROA_k$, shows larger cross-sectional variation and a higher mean value of 10.9 percent, indicating a higher marginal value of *ROA* of a given firm in explaining the comovement in *ROA* among firms in the industry. Substantial variation in firm size and turnover variables is also evident. The sales concentration variable shows at least half of all firms operating in a single segment, consistent with previous findings by Piotroski and Roulstone (2004) and others.

Next, we sort stocks with analyst coverage into three groups based on the number of analysts covering the stock each year. Firms with no analyst coverage form a separate group. The averages of the variables in each sub-group are presented in Panel B. The lowest coverage tertile has an average of 2.6 analysts following each firm, and the coverage increases to 18.5 analysts for the highest coverage tertile. Most interestingly, the partial correlations of stock returns, *PCORR*, are monotonically increasing in analyst coverage. The *PCORR* of 2.7 percent for firms with high analyst coverage is significantly higher than the 2.5 (2.4) percent for firms with low (zero) coverage.

Panels B of Table 2 show more analysts following larger cap and more heavily traded stocks, and the stocks of less focused firms. Panel C shows that larger firms are

[1] Roll (1988), Morck et al. (2000) and others use [1] to estimate mean R^2s for groups of firms. Consistent with these earlier results, our firm-level regressions of weekly returns on market and industry indexes excluding the firm itself yield a mean R^2 of 20 percent. Adding the excluded firm as in [2] raises the R-square to 22 percent. Since the current exercise does not use these variables, they are not in the tables.

more diversified, so the effects in Panel B are clearly not independent.

Finally, Table 2 presents rather mixed evidence linking analyst coverage with the partial correlations in fundamentals, *PCORR_ROA*. Firms with low or medium analyst coverage have *ROA*s with higher partial correlations to other firms' *ROA*s than do firms with zero coverage. However, this is not true of firms with high analyst coverage. However, Panel C again shows significant correlations of *PCORR_ROA* with other firm characteristics. We therefore turn to multivariate analyses.

3.2 Multivariate regressions of analyst coverage

Given the work cited above, we specify the determinants of analyst following for each firm k in year t as follows:

[8]
$$\begin{aligned}&\ln(1+ANALYST_{k,t}) = a_0 + a_1 LPCORR\_ROA_{k,t} + a_2 \ln(SIZE_{k,t}) + a_3 TURNOVER_{k,t}\\&+a_4 HERF\_SALE_{k,t} + a_5 \ln(STDRET_{k,t}) + \sum_{I=1}^{68} d_I INDDUM_{I,t} + \sum_{y=1984}^{2006} c_y YEARDUM_y + e_{k,t}\end{aligned}.$$

Supplementing the firm specific variables, we include industry and year fixed effects, *INDDUM and YEARDUM*. We estimate equation [8] as a pooled regression over the full sample period of 1984 to 2007 and four six-year sub-periods, 1984 to 1989, 1990 to1995, 1996 to 2001 and 2002 to 2007. All t-statistics reported henceforth are therefore based on heteroskedasticity consistent standard errors with clustering by industry (Petersen (2007)).

Table 3 shows significantly more analysts following firms that are larger (*SIZE*), more heavily traded (*TURNOVER*), more eventful (*STDRET*) and more focused on their core businesses (*HERF_SALES*). But $LPCORR\_ROA_{k,t}$ also attracts a positive coefficient in all sub-periods, and attains statistical significance in three of the four sub-periods.

These findings are highly robust, in that various alternative approaches yield qualitatively similar results. By this we mean identical patterns of signs and significance, as well as roughly concordant point estimate magnitudes. Winsorizing the key variables (*LPCORR_ROA*, *TURNOVER*, and *STDRET*) at the 1 and 99 percentile within each year generates similar results, suggesting that our results are not due to extreme observations. The results also hold if we control for other firm-specific variables that may be correlated with the analyst coverage, such as the fraction of institutional ownership (Bhushan (1989); Rock et al. (2000)), or book-to-market ratio and the past one-year stock return which may proxy for glamour stocks (Jegadeesh et al. (2004)). Using Tobit regression model to deal with truncation of the dependent variable (*ANALYST*) at zero does not change the results qualitatively.

Using alternative measures of fundamental correlations yields qualitatively similar results. Measuring the partial correlation in *ROA* as the R^2 of [2] minus that of [1] without normalizing as in [3] yields qualitatively similar results. Qualitatively similar results are obtained if we use quarterly returns on sales to construct $LPCORR\_ROS_{k,t}$ to replace $LPCORR\_ROA_{k,t}$ as an alternative gauge of each firm's contribution to other firms' fundamentals. Including both $LPCORR\_ROS_{k,t}$ and $LPCORR\_ROA_{k,t}$ throughout also yields qualitatively similar results. We estimate $LPCORR\_ROA_{k,t}$ by defining industries differently throughout according to the 17-industry classification in Fama and French (1997), and obtain similar results except that the coefficient on $LPCORR\_ROA_{k,t}$ is insignificant in the first two sub-periods, 1984 to 1989, and 1990 to 1995. Finally, the number of analysts also attracts a positive coefficient in year-by-year cross-sectional regressions for every year from 1984 to 2007 except 1991 and 1993, and attains significance in 12 out of the 24 years with standard errors clustered by industry. The mean of these coefficients is also significant using the Newy-West HAC standard error to account for the autocorrelation in estimated yearly coefficients.

These findings are consistent with significantly more analysts following firms whose fundamentals are more useful in predicting the fundamentals of other firms in their industries.

3.3 Stock return comovement and analyst following

If information about more prominent stocks is used to price less prominent stocks, stock price fluctuations in the former should correlate more strongly with other stocks' price fluctuations, all else equal. To explore this, we run panel regressions of the form:

$$\begin{aligned} [9] \quad & LPCORR_{k,t} = a_0 + a_1 \ln(1 + ANALYST_{k,t}) + a_2\, LPCORR\_ROA_{k,t} + a_3 \ln(SIZE_{k,t}) \\ & + a_4\, TURNOVER_{k,t} + a_5 HERF\_SALES_{k,t} + a_6 \ln(STDRET_{k,t}) \\ & + \sum_{I=1}^{68} d_I\, INDDUM_{I,t} + \sum_{y=1984}^{2006} c_y YEARDUM_y + e_{k,t} \end{aligned} .$$

As explained above, the dependent variable $LPCORR_{k,t}$ is the marginal contribution of stock *k*'s return to the returns of other stocks in its industry. Table 4 reveals a significantly larger such contribution by stocks whose fundamentals contribute more to those of other stocks (*LPCORR_ROA*); as well as for stocks that are larger (*SIZE*), more eventful (*STDRET*), more heavily-traded (*TURNOVER*), and more focused

(*HERF_SALES*). These variables attract statistically significant coefficients over the full sample period and all sub-periods except the late 1980s and early 2000s, when eventfulness is insignificant, and the early 1990s, when the fundamentals correlation and trading activity variables are insignificant.

Of primary interest to the issue at hand, a stock whose returns have larger marginal contributions to the returns of other stocks in its industry attracts a significantly larger following of analysts, all else equal. This holds across the whole sample period and all sub-periods, after multiple controls are included.

These findings are highly robust, and survive the same battery of robustness checks as above. The sole exception is when we define industries using the 17 industry classification of Fama and French (1997), and estimate $LPCORR_{k,t}$ and $LPCORR\_ROA_{k,t}$ accordingly. The coefficient on $Ln(1+ANALYST_{k,t})$ is marginally significant (at 10% level) for the whole sample period, and is significant in all sub-periods except 1984 to 1989. Finally, year-by-year cross-sectional regressions yield positive coefficients on the number of analysts every year except 1988, and these coefficients are significant in 17 of the 24 years (using tests for significance which are clustered by industry). The mean of these coefficients is also significant using the Newey-West HAC standard error to account for the autocorrelation in estimated yearly coefficients.

These results are consistent with price fluctuations in more prominent stocks, identified as those followed by more analysts, having disproportionate echoes in the price fluctuations of other stocks.

3.4. Return comovement and analyst concentration

More analysts cover more firms in some industries than others. An industry where analysts follow a larger set of prominent stocks is more likely to generate mixed messages to investors trying to price neglected stocks, and thus should exhibit less information spillover from prominent to neglected stocks (Veldkamp (2006a)). To explore this, we turn to our measure of the concentration of analyst coverage within an industry: a Herfindhal index constructed each year t for each industry I:

[10] $$HERF\_ANALYST_{I,t} = \sum_{k=1}^{N_I} \left(\frac{ANALYST_{k,t}}{\sum_{k=1}^{N_I} ANALYST_{k,t}} \right)^2,$$

where $ANALYST_{k,t}$ is the number of analysts following firm k in year t and N_I is the number of firms in industry I.

In one extreme industry, where all analysts follow one and the same firm, $HERF\_ANALYST_I$ equals one. At the other extreme, where an equal number of analysts follow every firm in the industry, $HERF\_ANALYST_I$ equals $1/N_I$. The variable thus falls within the semi-open interval (0, 1], with higher values indicating analysts focusing more intensely on fewer stocks.

To explore this, we include an interaction of $HERF\_ANALYST_{I,t}$ with the number of analysts as an additional variable, and rerun the regressions [9]. These now have the form:

$$
\begin{aligned}
[11]\quad & LPCORR_{k,t} = a_0 + a_1 \ln(1+ANALYST_{k,t}) \\
& + b_1 \ln(1+ANALYST_{k,t}) * HERF\_ANALYST_{I,t} + a_2\, LPCORR\_ROA_{k,t} \\
& + a_3 SIZE_{k,t} + a_4\, TURNOVER_{k,t} + a_5 HERF\_SALE_{k,t} + a_5 \ln(STDRET_{k,t}) \\
& + \sum_{I=1}^{68} d_I\, INDDUM_{I,t} + \sum_{y=1984}^{2006} c_y YEARDUM_y + e_{k,t}
\end{aligned}
$$

Table 5 shows that analysts concentrating on fewer stocks significantly magnifies the importance of more prominent stocks in the pricing of other stocks. The coefficient on the interaction of *ANALYST* and *HERF_ANALYST* is highly significant across the full sample period and all the sub-sample periods except 2002-2007.

These findings also pass the battery of robustness checks used above. The sole exception is when we define industries differently using the 17 industry classification of Fama and French (1997), and estimate $LPCORR_{k,t}$ and $LPCORR\_ROA_{k,t}$ accordingly. Though the coefficient on *ANALYST* remains strongly significant in the full sample and all sub-periods, the coefficient on the interaction of *ANALYST* and *HERF_ANALYST* becomes insignificant in the 1990 to 1995 and 2002 to 2007 sub-periods. Finally, estimating [11] with year-by-year cross-sectional regressions yields positive coefficient for interaction each year, except for 2003 and 2007, and these coefficients are significant in 11 out of 24 years. Their average is also significant using the Newy-West HAC standard error to account for the autocorrelation in estimated yearly coefficients.

These results are consistent with analysts spreading their attention across more stocks in an industry damping information spillover to neglected stocks, validating information spillover models of the sort developed by Veldkamp (2006a).

4 Causality

Tables 3 through 5 demonstrate correlations, but are silent as to what causes what. An absence of defensible instruments precludes instrumental variables regressions. However, we can use stock price reactions to revisions in analysts' earnings forecasts (Griffin (1976); Givoly and Lakonishok (1979)) to test causality directly. If investors use information about prominent stocks to price neglected ones, earnings forecast revisions for highly-followed stocks should affect neglected stocks' prices; but earnings forecast revisions for less followed stocks should be less important in pricing highly-followed stocks.

4.1 Event studies using portfolio-mean forecast revisions

Our first test of this hypothesis uses aggregate forecast revisions at the portfolio level. We construct a firm-month panel of analysts' earnings forecast revisions by calculating changes in mean one-year forward annual EPS forecasts in I/B/E/S for each firm each month, normalizing each observation by the previous month's closing stock price and winsorizing the resulting data at 1% to limit outlier influence. Each year we sort the firms in each of our 69 industries by analyst coverage. Firms whose earnings are forecast by no analysts we call *no coverage* stocks. All others are then sorted into tertiles of *high*, *medium*, and *low coverage* stocks. Each month t, the revisions in earnings forecasts are aggregated across each tertile within each industry to obtain $FR_{J,t}$, the value-weighted mean revisions in consensus earnings forecasts across all firms in tertile J, with J = 1 (*low*), 2(*medium*), or 3(*high*). FR_J thus measures information produced by analysts at a portfolio level.

Our tests regress, $r_{k,t}$, the return in month t for firm k, on contemporaneous mean earnings forecast revisions for the low, medium and high coverage tertile portfolios[2]:

$$[12] \quad \begin{aligned} r_{k,t} &= a + b\, r_{m,t} + \sum_{j=1}^{3} c_j\, FR_{j,t} + d_1\, FR_{k,t} + d_2 r_{k,t-1} + d_3 r_{k,t-2,t-7} + d_4 \ln(SIZE_{k,t}) \\ &+ d_5 \ln(BM_{k,t}) + d_6\, TURNOVER_{k,t} + e_{k,t} \end{aligned}$$

Regression [12] controls for market-wide fluctuations with $r_{m,t}$, the return on CRSP value-weighted market portfolio; and for various firm-specific characteristics. These include the stock's own return the previous month ($r_{k,t-1}$) and over the six months prior to that (t-2 to t-7) to remove time series predictability (Jegadeesh (1990); Jegadeesh and Titman (1993)). We also control for firm size, *ln(SIZE)*; book-to-market ratios, *ln(BM)*; and monthly trading volume over shares outstanding, *TURNOVER*. Changes in analysts' forecast of firm *k*'s earnings obviously can affect firm k's returns, and so we also include $FR_{k,t}$ in [12]. The coefficients c_1, c_2 and c_3 thus measure abnormal returns in stock *k* associated with mean earnings forecast revisions for portfolios of *low*, *medium*, and *high* coverage stocks in the same industry after removing market-related fluctuations, price changes due to revisions in stock k's own earnings forecasts in that month, and effects associated with the other control variables.

Table 6 displays the results. First, the table replicates the standard finding in the literature: revisions to a firm's own earnings forecast have a strong contemporaneous price effect. But to the issue at hand, revisions in the mean forecast earnings of the

[2] Since I/B/E/S reports the consensus earnings forecasts in the middle of each month, we measure the monthly stock return from mid-month to correspond with the period of change in earnings forecast. Measuring monthly returns and other monthly variables from the beginning to the end of the month gives similar results.

portfolios of other firms in their industries also affect firms' stock prices.

This effect is strikingly asymmetric. The first column, using all firms, shows that mean forecast revisions for high coverage firms most strongly affect other stocks in their industries; revisions for medium coverage firms exert a lesser, but still significant effect on other stocks; and revisions for low coverage stocks have even smaller effect on their industry peers' stock prices. However, high coverage firms' contribution to industry comovement is not significantly greater than that of medium coverage firms ($t = 1.47$), and the latter's contribution is insignificantly different from that of low coverage firms ($t = 1.47$). High coverage firms revisions do, however, have a significantly greater contribution to comovement than low coverage firms revisions ($t = 4.05$).

The middle three columns rerun the regression on the tertiles of covered firms with high, medium, and low analyst followings; and the final column uses only firms followed by no analysts. This sample partition reveals the same asymmetry: Earnings forecast revisions for high coverage firms significantly affect the stocks of all four subsamples. Revisions for medium coverage firms affect the stock prices of only low-coverage and no coverage firms, with a larger effect on the latter's prices.

Moreover, the high followings tertile revisions' effect is significantly larger than that of medium coverage firms in the high ($t = 2.01$) and medium ($t = 3.21$) coverage subsample regressions; but the two are insignificantly ($t = 1.46$) different in the low coverage subsample regression. The revisions of medium and low coverage tertiles have insignificantly different effects in all three subsamples. However, revisions of high coverage firms have significantly larger effects than those of the low coverage firms across the board (t = 3.02, 4.09, and 3.91) for the high, medium and low coverage subsamples, respectively.

The major discrepancy in this asymmetric pattern is in the final column, which runs the regression on the subsample of firms followed by no analysts at all. While forecast revisions for all three tertiles of followed firms affect unfollowed firms' prices, the asymmetry in the other four regressions is not preserved. Medium coverage tertile revisions affect unfollowed stock prices significantly more than either low-coverage (t = 4.41) or high-coverage tertile revisions (t = 2.38).

This last finding raises the possibility that information spillover to very neglected firms might come primarily from somewhat prominent firms, rather than from an industry's most intensely followed firms.

The pattern in Table 6 is economically significant. When analysts raise their EPS forecasts for the most highly followed tertile by one percent of their stock prices, on average, stocks with low, medium, and high analyst followings post monthly abnormal returns of 1.5%, 1.3% and 0.8% percent, respectively. These price changes are economically significant, in that they are comparable in magnitude to price effects of own firm forecast revisions (see Stickle (1991) and Gleason and Lee (2003)).

The results in Table 6 are also quite robust. The findings hold in all six-year subperiods except 1990 to 1995, in which there is only a marginally significant (at 10 percent level) effect of the revisions in the earnings forecasts for high coverage firms on the returns of less prominent firms. Our results are also qualitatively unchanged if we drop all the control variables or add additional control variables such as the fraction of shares outstanding held by institutional investors, and the size, book-to-market and momentum factors . Also, including forecast revisions for the previous and next months yields similarly strong price effect of earnings forecast revisions of high coverage firms. Our results are qualitatively unchanged if we replace individual firms' returns with the returns on tertile portfolios, sorted on analyst coverage, as the dependent variable. Qualitatively similar results likewise ensue if we sort firms into quintiles based on analyst followings. The earnings forecast revisions in highest coverage firms have the strongest effect on the stock returns across the board except in the regression of zero coverage firms.

However, the asymmetry in the price effects of earnings forecast revisions changes when we define industries differently throughout, using the 17 industries classification of Fama and French (1997) and classify firms based on analyst coverage accordingly. The price effect of earnings forecast revisions in highest coverage firms is still significant and stronger than that of earnings forecast revisions in lowest coverage firms across the board except in the regression of zero coverage firms. But the earnings forecast revisions of medium coverage firms turn out to have the strongest price effect. By defining industries more broadly from 69 industries to 17 industries, those prominent firms in the original 69 industries are likely to be classified as medium analyst firms in the broader 17 industries, which should explain the swing in the asymmetry between price effects of earnings forecast revisions in high versus medium analyst firms.

Overall, these findings are consistent with revisions in prominent firms' earnings forecasts spilling over to affect neglected stocks' prices.

The converse – that changes in neglected firms' prices affect analysts earnings forecasts for prominent firms, even after controlling for the latter' own price changes, seems to us decidedly implausible. Reverse causality, though unlikely, is not inconceivable: perhaps highly focused analysts are caught off guard by events that primarily affect neglected firms, and then revise their forecasts for prominent firms' earnings. To preclude this, we modify our event study in various ways.

4.2 Fuzzy signals

If information about prominent stocks sets neglected stocks' prices, more ambiguous signals about the former ought to have weaker effects on the latter, all else equal. This suggests a more nuanced way of testing for information spillover if we can measure information *ambiguity*. We therefore gauge the ambiguity of the information about high coverage firms' fundamentals by the standard deviation of the mean of analysts' forecast revisions for high coverage firms in each industry each month, and denote this $DISP_{3,t}$.

Table 7 thus reruns the regressions in Table 6, but including as an additional explanatory variable the interaction of $FR_{3,t}$ with $DISP_{3,t}$; that is

$$\text{[13]} \quad \begin{aligned} r_{k,t} = a + b\, r_{m,t} + \sum_{j=1}^{3} c_j\, FR_{j,t} + \hat{c}_3\, FR_{3,t} * DISP_{3,t} + d_1\, FR_{k,t} \\ + d_2 r_{k,t-1} + d_3\, r_{k,t-2,t-7} + d_4 \ln(SIZE_{k,t}) + d_5 \ln(BM_{k,t}) + d_6\, TURNOVER_{k,t} + e_{k,t} \end{aligned}$$

The main result from Table 6 is preserved: revisions of high coverage firms' forecast earnings again have more impact than revisions of less followed firms' forecast earnings on other stocks in their industry.

The significant negative coefficient on our signal fuzziness measure indicates that more conflicting information about the fundamentals of different prominent firms in an industry lessens the information spillover from prominent to neglected firms. Moreover, signal fuzziness curtails information spillover more strongly for low coverage than high coverage firms.

These results also survive the battery of robustness checks applied to Table 6. The only exceptions are that our signal fuzziness measure becomes insignificant in the regressions of low and zero coverage firms when we use the returns on analyst tertile portfolios as the dependent variable, and in the regressions of low and medium coverage firms when we define industries using the 17 industries classification of Fama and French (1997). In yet another robustness check, we also include interaction terms of forecast revisions with dispersion for low and medium analyst firms. Qualitatively similar results ensue.

Overall, these findings are consistent with less ambiguous revisions in prominent firms' earnings forecasts affecting neglected stocks' prices more strongly. Reverse causality here would require analysts to revise prominent firm's earning forecasts more homogeneously when caught off guard by more important events that primarily affect neglected stocks. While this is not impossible, we know of no theoretical or empirical work giving credence to such a scenario.

4.3 Event studies using bellwether stocks

So far, we define prominent firms as those in the highest tertile, ranked by the number of analysts following them. This portfolio approach to distinguishing prominent from neglected stocks means we have no precise event dates, and cannot perform precisely timed daily frequency event studies, which can more reliably preclude reverse causality.

We therefore turn to an alternative, deliberately narrow, definition of prominence.

We define each industry's *bellwether firm* as that followed by the most analysts, within each industry. In a similar vein, the non-bellwether firm refers to the firm with highest coverage among the firms in the lowest analyst coverage tertile.[3] In case of a tie, we choose the largest firm by market capitalization. To be sure this alternative definition yields similar results to those shown above, we replace portfolio level mean forecast revisions in [12] with monthly revisions in earnings forecast of the bellwether firm, $FR_{BW,t}$, and the non-bellwether firm, $FR_{NBW,t}$:

$$\begin{aligned}[14] \quad r_{k,t} &= a + b\, r_{m,t} + c_1\, FR_{BW,t} + c_2\, FR_{NBW,t} + d_1\, FR_{k,t} + d_2 r_{k,t-1} + d_3\, r_{k,t-2,t-7} \\ &\quad + d_4\, \ln(SIZE_{k,t}) + d_5 \ln(BM_{k,t}) + d_6\, TURNOVER_{k,t} + e_{k,t}\end{aligned}$$

Panel A of Table 8 shows revisions to bellwether firms earnings forecasts affecting the returns on all other firms in the industry. The effect illustrates the same asymmetry evident above: it is largest for low coverage firms, and smaller, but significant, for medium coverage firms, and insignificant for high coverage firms (excluding the bellwether firm, of course). Firms not covered by any analyst exhibit a significant price effect in reaction to the forecast revision of the bellwether firm but to a lesser extent than the low coverage firms. The revisions in earnings forecasts of the non-bellwether firms, on the other hand, do not have a similar price effect on other firms. The revisions in earnings forecasts of the non-bellwether firms have a significantly smaller price impact on other peer firms with low and medium coverage. The returns on uncovered firms appear to react to revisions in earnings forecasts of both the bellwether

[3] An alternative definition of the non-bellwether firm as the firm with the lowest analyst coverage yields very few forecast revisions each year, although the results are qualitatively similar.

and non-bellwether firms, suggesting a more general spillover of information to these firms. These results confirm the asymmetry in price effects associated with the revisions in earnings forecasts of prominent firms versus relatively neglected firms.

Panel B reruns [14] but also includes an interaction of the revision in consensus earnings forecast of the bellwether firm in month *t*, $FR_{BW,t}$, with its dispersion in earnings forecasts, $DISP_{BW,t}$, as in [13]. The panel shows lower dispersion across bellwether firm's forecast revisions significantly magnifying information spillover into the abnormal returns on less prominent stocks in the same industries.

This effect is economically significant: if forecast dispersion is near zero, indicating near uniformity across analysts' forecast revisions, a one percent increase in forecast earnings for the bellwether firm corresponds to a 0.80 percent rise in low coverage firms' prices, versus an unconditional effect of 0.57 percent in Panel A. A one standard deviation increase in the dispersion of analysts forecast for the bellwether firm damps the same mean revision's impact on low coverage firm's prices by about 0.05 percent. Using firms followed by no analysts yields a significant damping effect due to dispersion in revisions of the bellwether firm's earnings forecasts that is statistically identical in magnitude to that for low coverage firms.

These results also survive the battery of robustness checks applied to Table 6 with a few exceptions. The price impact of $FR_{BW,t}$ on other peer firms reported in Panel A is significant in all sub-periods except for 1990-1995. When we interact the forecast revision with the dispersion measure, $DISP_{BW,t}$, the interaction coefficients are generally significant, except for a couple of analyst tertiles in the sub-period 1996-2001 and when we reclassify the industries according to the 17-industry classification as in Fama and

French (1997). Finally, defining an industry's bellwether firms as the portfolio of largest three firms by analyst coverage yields qualitatively similar results.

We interpret these findings as consistent with information spillover from bellwether firms to other firms, but not in the reverse direction. This spillover is larger when revisions to analysts forecasts of bellwether firms' earnings are more similar.

4.4 Event studies of bellwether stocks using daily data

Isolating bellwether firms lets us address causality more unequivocally, since we can now identify precise dates upon which the bellwether firm's forecast earnings are revised and then look for stock price changes in other firms on those dates. That analysts time their revisions of bellwether firms' forecast earnings to fall precisely on dates when neglected firms prices move *en masse* relative to industry and market benchmarks begs credulity.

We designate day zero as the event day on which one or more analysts announce revised earnings forecasts for the bellwether firm. We then compute a three-day cumulative abnormal return, CAR_j, for every firm j (excluding the bellwether firm) in that industry from the prior to the subsequent day. Following Gleason and Lee (2003), we measure CAR_j as the excess return over a contemporaneous value-weighted return of all other stocks in j's size decile. An alternative measure of CAR_j is the excess return over the expected return from a four-factor model comprising the Fama-French three factors (i.e. excess return on the value-weighted CRSP market index over the one-month T-bill return; small minus big return premium (SMB) and the high book-to-market minus low book-to-market return premium (HML)) and the momentum factor in Carhart (1997). Again following previous studies, we treat CAR_j associated with upward and downward revisions to the bellwether firm's forecast earnings separately.

To mitigate bias from confounding events, we apply several filters to our event study. We exclude the event days when the bellwether firm earnings forecast revisions coincide with the same firm's quarterly earnings announcement within a five-day window, i.e. days -2 to +2 around the event day. When we compute CAR_j for each event day, we drop the CAR_j of other firms in the industry if firm j made an earnings announcement or had earnings forecast revision during the five-day window around the event day. This leaves a set of events on which the only relevant news is most likely to be the bellwether firm's earnings forecast revision announcement. To facilitate comparison with previous work using such data, we split these events into upward and downward earnings forecast revisions.

Table 9 reports our results. First, we reproduce the standard finding of previous studies: a firm's earnings forecast revisions cause its stock price to move in the same direction. The coefficients on CAR_{BW}, the three-day cumulative abnormal returns for the bellwether stock whose earnings are revised, are similar in magnitude to the numbers reported in Stickel (1991) and Gleason and Lee (2003). For example, we find an average 3-day *CAR* for the bellwether firm of 0.31 (-0.35) percent following an upward (downward) revision in its own forecasted earnings. This compares with the corresponding average *CAR* of 0.7 (-1.3) percent for all firms in the sample reported in Gleason and Lee (2003).

The main result in Table 9 is that the stock prices of other firms in the same industry also change significantly when bellwether firms' forecast earnings are revised, and in the same direction as those revisions. This effect is larger for low coverage firms than for firms in the medium coverage tertile. Firms followed by no analysts post even more negative significant *CAR*s than low coverage firms upon downward revisions to bellwether firms' forecast earnings. Upon upward revisions to bellwether firms' forecast earnings, stocks followed by no analysts appear to rise less than those in the low coverage tertile, but the two *CAR* estimates are statistically indistinguishable.

These results also survive a battery of robustness checks. Specifically, the results remain unchanged if we winsorize the extreme 1% of CARs across all earnings forecast revision events, or expand the event window from three to five days. When we sort the firms into quintiles (instead of tertiles) of analyst coverage within each industry, we also obtain comparable results. We interpret these results as consistent with earnings revisions for bellwether firms *causing* neglected firms' prices to change.

5. Conclusions

Firm-specific information flows more directly into the prices of some stocks than others. Informed investors collectively generate greater trading revenues with private information about larger stocks, since larger informed trades are required to move prices. Since investors and arbitrageurs are willing to pay more for such information, specialized information intermediaries, like financial analysts, focus their efforts on such stocks (Bhushan (1989) and Veldkamp (2006a)). We find that indeed more analysts follow firms which are larger, more actively traded, and whose fundamentals correlate strongly with those of other firms.

We document that the stock returns of firms followed by many analysts contribute to the synchronicity of stock returns, even after controlling for fundamental correlations (see also Piotroski and Roulstone (2004) and Chan and Hameed (2006)), and this effect attenuates where more firms are directly followed by analysts. This is consistent with investors using information about a firm not just to trade that firm's stock, but also to value and trade other firms as well. Hence, higher comovement associated with the number of analysts following a stock thus reflects rational information intermediation.

We also find that information contained in the forecasted earnings of firms with intense coverage (or bellwether firms) diffuses to the prices of other firms with low or zero coverage, especially when there is greater certainty (lower dispersion) in the earnings forecasts. The converse is not true: revisions in the earnings forecasts of low coverage firms do not affect the prices of bellwether firms.

Our findings validate models casting information intermediaries in general, and financial analysts in particular, in key roles in financial markets. Our results also suggest that a degree of stock price comovement may well be consistent with rationality given costly information as in Veldkamp (2006a). Yet, our results also suggest that large scale stock price comovement indicates that many stock returns are driven not by direct firm specific information but by inferred industry wide information. More importantly, this paper provides an empirical understanding of the transmission of information via analysts and trading in equity markets.

While a behavioral basis for comovement (Barberis et al. (2005)) or correlated demand shocks in Greenwood (2008) are not precluded, our findings better accord with a basis in costly information. However, our results are obtained in a highly developed capital market with strong institutions. In less developed financial markets, behavioral considerations might loom more important.

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Table 1: Number of firms in the sample

The sample consists of common stocks listed on NYSE, AMEX and NASDAQ (CRSP dataset) over the period 1984 to 2007. These firms in the CRSP database are merged with those in COMPUSTAT and I/B/E/S. The final sample consists of firms in CRSP-COMPUSTAT merged sample in which firms not covered by I/B/E/S are treated as firms with zero analyst coverage.

Year	CRSP sample	CRSP, COMPUSTAT merged Sample	CRSP, COMPUSTAT and I/B/E/S merged sample
1984	6,968	3,207	2,220
1985	7,099	3,058	2,292
1986	7,544	3,110	2,366
1987	7,896	3,251	2,508
1988	7,865	2,963	2,309
1989	7,613	3,085	2,444
1990	7,411	3,108	2,477
1991	7,430	2,730	2,183
1992	7,760	3,161	2,488
1993	8,262	3,692	2,931
1994	8,837	4,185	3,267
1995	9,243	4,150	3,301
1996	9,821	4,536	3,678
1997	10,080	4,760	3,998
1998	9,984	4,655	3,887
1999	9,690	4,068	3,390
2000	9,362	4,180	3,314
2001	8,678	3,541	2,821
2002	7,945	3,450	2,750
2003	7,507	3,062	2,443
2004	7,347	3,434	2,762
2005	7,365	3,452	2,808
2006	7,431	3,377	2,763
2007	7,677	3,319	2,728
Total number of firm-years	196,815	85,534	68,128
Average number of firms per year	8,201	3,564	2,839

Table 2: Summary Statistics

In this table, $PCORR_k$ measures the partial correlation of firm k's returns with returns of other firms in the industry. Each year, for a given pair of firm k and firm i in industry I, we estimate a two-factor market model regression:

$$r_{iw} = a_i + b_i r_{Mw}^k + c_i r_{Iw}^k + e_{iw}, \qquad [1]$$

where r_{iw} is the return on firm i in week w, and r_{Mw}^k and r_{Iw}^k are the value-weighted return on the market and industry portfolios excluding firms i and k. We estimate a second regression model which adds r_{kw}, return of firm k in week w, as an additional explanatory variable:

$$r_{iw} = a_i + b_i r_{Mw}^k + c_i r_{Iw}^k + d_i r_{kw} + e_{iw}. \qquad [2]$$

The r-squares from equations [1] and [2] are denoted as $R_{i,excl.k}^2$ and $R_{i,incl.k}^2$ respectively. The partial correlation of firm k with each other firm i [$PCORR_{k,i} = (\frac{R_{i,incl.k}^2 - R_{i,excl.k}^2}{1 - R_{i,excl.k}^2})$] is averaged across all firms in the industry to produce $PCORR_k$. A similar measure is constructed using quarterly return on assets (ROA) and denoted as $PCORR\_ROA_k$. $ANALYST_k$ is the number of analysts making one-year forward earnings forecast for firm k each year. $SIZE_k$ is the beginning-of-year market capitalization of firm k. $TURNOVER_k$ is the average of daily share turnover in the previous year. $HERF\_SALES_k$ is the Herfindahl index of sales across 2-digit business segments for the fiscal year ending in the year. $STDRET_k$ is the standard deviation of weekly returns in the previous year. In Panel B, we group stocks into tertiles based on the number of analysts following each year within each industry. Group zero refers to stocks with zero coverage while groups 1 to 3 have increasing coverage. The last two columns report the robust T-statistics cluster by industry of the tests for the null hypothesis of equality for high and low (or zero) analyst coverage groups. Panel C presents the average of correlation coefficients calculated every year.

Panel A: Summary statistics for the pool sample

Variable	Mean	Std.	Q1	Median	Q3
$PCORR_k$ (%)	2.558	0.934	2.041	2.359	2.824
$ANALYST_k$	7.462	8.814	1	4	11
$PCORR\_ROA_k$(%)	10.884	5.873	7.289	9.581	12.858
$SIZE_k$ ($billion)	1.981	11.074	0.063	0.209	0.829
$TURNOVER_k$ (%)	0.528	0.829	0.147	0.304	0.624
$HERF\_SALES_k$	0.818	0.255	0.587	1	1
$STDRET_k$ (%)	5.652	2.806	3.642	5.086	7.046

Panel B: Summary statistics across analyst coverage groups

	Analyst coverage group				T-test	
Variable	0 (Zero)	1 (Low)	2	3 (High)	High – Zero	High – Low
$ANALYST_k$	0	2.641	7.373	18.480	NA	NA
$PCORR_k$ (%)	2.359	2.476	2.636	2.722	8.040	6.171
$PCORR\_ROA_k$ (%)	10.720	11.013	11.119	10.669	-0.124	-1.547
$SIZE_k$ ($billion)	0.316	0.265	0.738	6.357	7.342	7.360
$TURNOVER_k$ (%)	0.313	0.474	0.606	0.676	7.378	5.089
$HERF\_SALES_k$	0.827	0.848	0.829	0.768	-4.232	-5.833
$STDRET_k$ (%)	5.306	6.077	5.890	5.240	-0.296	-7.286

Panel C: Correlation coefficients

Variable	$PCORR_k$	$ANALYST_k$	$PCORR\_ROA_k$	$SIZE_k$	$TURNOVER_k$	$HERF\_SALES_k$	$STDRET_k$
$PCORR_k$(%)	1	0.175***	0.052***	0.075***	0.079***	0.012*	0.016***
$ANALYST_k$		1	0.002	0.484***	0.177***	-0.123***	-0.093***
$PCORR\_ROA_k$(%)			1	-0.023***	-0.007	0.109***	-0.053***
$SIZE_k$($billion)				1	-0.026***	-0.150***	-0.148***
$TURNOVER_k$ (%)					1	0.149***	0.443***
$HERF\_SALES_k$						1	0.256***
$STDRET_k$(%)							1

*, **, and *** indicate that the average correlation coefficient is statistically significant at 10%, 5% and 1% level respectively based on time series standard deviations of the average correlation coefficients.

Table 3: Determinants of analyst coverage

$$\ln(1+ANALYST_{k,t}) = a_0 + a_1 LPCORR\_ROA_{k,t} + a_2 \ln(SIZE_{k,t}) + a_3 TURNOVER_{k,t}$$

$$+a_4 HERF\_SALE_{k,t} + a_5 \ln(STDRET_{k,t}) + \sum_{I=1}^{68} d_I INDDUM_{I,t} + \sum_{y=1984}^{2006} c_y YEARDUM_y + e_{k,t}$$

where, for each firm *k* and year *t*, $ANALYST_{k,t}$ is the number of analysts making one-year ahead earnings forecast; $LPCORR\_ROA_{k,t}$ is the logit transformation of the partial correlation measure based on *ROA*; $SIZE_{k,t}$ is the beginning-of-year market value; $TURNOVER_{k,t}$ is the average of daily share turnover; $HERF\_SALES_{k,t}$ is the Herfindahl index of sales across 2-digit business segments; $STDRET_{k,t}$ is the standard deviation of weekly returns; *INDDUM*s are industry dummies; and *YEARDUM*s are year dummies. The robust *t*-statistics cluster by industry are provided in *Italic*.

	Sample Period				
Indep. Var.	1984 - 2007	1984 - 1989	1990 - 1995	1996 - 2001	2002 - 2007
$LPCORR\_ROA_{k,t}$	0.048	0.025	0.027	0.054	0.055
	3.847	*1.680*	*1.641*	*2.994*	*2.763*
$ln(SIZE_{k,t})$	0.494	0.575	0.491	0.450	0.459
	72.632	*68.377*	*60.411*	*61.610*	*48.417*
$TURNOVER_{k,t}$	0.114	0.620	0.356	0.134	0.070
	5.129	*9.825*	*11.374*	*6.632*	*3.325*
$HERF\_SALES_{k,t}$	0.264	0.271	0.328	0.233	0.214
	9.300	*5.714*	*7.811*	*7.257*	*4.011*
$ln(STDRET_{k,t})$	0.231	0.075	0.094	0.205	0.337
	10.856	*2.112*	*3.499*	*6.898*	*8.052*
Industry Dummies	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes
Adj. Rsq	0.631	0.700	0.674	0.624	0.600

Table 4: Return comovement and analyst coverage

$$LPCORR_{k,t} = a_0 + a_1 \ln(1 + ANALYST_{k,t}) + a_2 LPCORR\_ROA_{k,t} + a_3 \ln(SIZE_{k,t}) + a_4 TURNOVER_{k,t}$$
$$+ a_5 HERF\_SALES_{k,t} + a_6 \ln(STDRET_{k,t}) + \sum_{I=1}^{68} d_I INDDUM_{I,t} + \sum_{y=1984}^{2006} c_y YEARDUM_y + e_{k,t}$$

where, for each firm k and year t, $LPCORR_{k,t}$ and $LPCORR\_ROA_{k,t}$ are the logit transformation of the partial correlation measures based on stock returns and *ROA*; $ANALYST_{k,t}$ is the number of analysts making one-year ahead earnings forecast; $SIZE_{k,t}$ is the beginning-of-year market value; $TURNOVER_{k,t}$ is the average of daily share turnover; $HERF\_SALES_{k,t}$ is the Herfindahl index of sales across 2-digit business segments; $STDRET_{k,t}$ is the standard deviation of weekly returns; *INDDUM*s are industry dummies; and *YEARDUM*s are year dummies. The robust *t*-statistics cluster by industry are provided in *Italic*.

	Sample Period				
Indep. Var.	1984 - 2007	1984 - 1989	1990 - 1995	1996 - 2001	2002 - 2007
$ln(1+ANALYST_{k,t})$	0.020	0.012	0.021	0.029	0.037
	3.064	*2.129*	*2.787*	*2.896*	*4.372*
$LPCORR\_ROA_{k,t}$	0.023	0.008	0.007	0.029	0.049
	4.105	*1.852*	*0.699*	*2.911*	*2.865*
$ln(SIZE_{k,t})$	0.021	0.008	0.019	0.015	0.030
	6.799	*1.898*	*3.850*	*4.469*	*6.556*
$TURNOVER_{k,t}$	0.023	0.034	0.012	0.029	0.011
	5.274	*1.799*	*0.928*	*5.749*	*2.353*
$HERF\_SALES_{k,t}$	0.043	0.042	0.044	0.033	0.038
	3.319	*2.993*	*2.450*	*1.912*	*2.053*
$ln(STDRET_{k,t})$	0.025	-0.012	0.029	0.026	0.027
	2.591	*-0.848*	*1.954*	*1.953*	*1.614*
Industry Dummies	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes
Adj. Rsq	0.169	0.170	0.128	0.204	0.193

Table 5: Return comovement, analyst coverage and concentration

$$LPCORR_{k,t} = a_0 + a_1 \ln(1 + ANALYST_{k,t}) + b_1 \ln(1 + ANALYST_{k,t}) * HERF\_ANALYST_{I,t}$$
$$+ a_2 LPCORR\_ROA_{k,t} + a_3 \ln(SIZE_{k,t}) + a_4 TURNOVER_{k,t} + a_5 HERF\_SALE_{k,t} + a_6 \ln(STDRET_{k,t})$$
$$+ \sum_{I=1}^{68} d_I INDDUM_{I,t} + \sum_{y=1984}^{2006} c_y YEARDUM_y + e_{k,t}$$

where, for each firm *k* and year *t*, $LPCORR_{k,t}$ and $LPCORR\_ROA_{k,t}$ are the logit transformation of the partial correlation measures based on stock returns and *ROA*; $ANALYST_{k,t}$ is the number of analysts making one-year ahead earnings forecast; $HERF\_ANALYST_{I,t}$ is the Herfindhal index of analyst coverage in the industry; $SIZE_{k,t}$ is the beginning-of-year market value; $TURNOVER_{k,t}$ is the average of daily share turnover; $HERF\_SALES_{k,t}$ is the Herfindahl index of sales across 2-digit business segments; $STDRET_{k,t}$ is the standard deviation of weekly returns; *INDDUM*s are industry dummies; and *YEARDUM*s are year dummies. The robust *t*-statistics cluster by industry are provided in *Italic*.

	Sample Period				
Indep. Var.	1984 - 2007	1984 - 1989	1990 - 1995	1996 - 2001	2002 - 2007
$ln(1+ANALYST_{k,t})$	0.029	0.021	0.033	0.039	0.045
	4.798	*3.043*	*3.827*	*4.361*	*5.065*
$ln(1+ANALYST_{k,t})*$ $HERF\_ANALYST_{I,t}$	0.403	0.296	0.449	0.565	0.312
	3.524	*1.955*	*2.534*	*2.624*	*1.616*
$LPCORR\_ROA_{k,t}$	0.023	0.007	0.018	0.033	0.036
	4.702	*2.414*	*2.488*	*3.448*	*3.387*
$ln(SIZE_{k,t})$	0.019	0.006	0.017	0.016	0.028
	6.420	*1.486*	*3.561*	*4.803*	*6.326*
$TURNOVER_{k,t}$	0.023	0.028	0.013	0.029	0.012
	5.368	*1.459*	*1.098*	*5.657*	*2.669*
$HERF\_SALES_{k,t}$	0.043	0.037	0.046	0.031	0.044
	3.427	*2.876*	*2.666*	*1.903*	*2.472*
$ln(STDRET_{k,t})$	0.026	-0.007	0.029	0.032	0.024
	2.713	*-0.540*	*2.183*	*2.545*	*1.448*
Industry Dummies	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes
Adj. Rsq	0.180	0.186	0.120	0.212	0.206

Table 6: Impact of earnings forecast revisions on stock returns

$$r_{k,t} = a + b\, r_{m,t} + \sum_{j=1}^{3} c_j\, FR_{j,t} + d_1\, FR_{k,t} + d_2 r_{k,t-1} + d_3 r_{k,t-2,t-7} + d_4 \ln(SIZE_{k,t}) + d_5 \ln(BM_{k,t}) + d_6\, TURNOVER_{k,t} + e_{k,t}$$

where, for each firm k in month t, $R_{k,t}$ is the monthly stock return; $FR_{k,t}$ is the monthly revision in earnings forecasts for firm *k*; $FR_{j,t}$ is the value-weighted average of revisions in earnings forecasts for firms in analyst coverage tertile *j* (within the same industry); $r_{m,t}$ is the monthly value-weighted return of all stocks in CRSP; $r_{k,t-2,t-7}$ is firm k's cumulative return over month *t-7* to month *t-2*; $SIZE_{k,t}$ is beginning-of-month market value; $BM_{k,t}$ is book-to-market ratio; $TURNROVER_{k,t}$ is the average daily share turnover in the previous month. The equation is estimated for all firms and separately for each group of firms sorted on analyst coverage. The robust *t*-statistics cluster by industry are provided in *Italic*.

	Analyst Coverage Groups				
Independent Variables	*All firms*	*High Coverage*	*Medium Coverage*	*Low Coverage*	*No Coverage*
Intercept	0.673	3.451	4.157	1.659	0.465
	1.754	*7.625*	*7.231*	*3.618*	*0.676*
$FR_{1(low)}$	0.185	-0.034	0.057	0.378	0.458
	1.817	*-0.276*	*0.363*	*3.187*	*3.149*
$FR_{2(medium)}$	0.635	0.148	0.307	0.911	1.571
	2.269	*0.517*	*1.075*	*2.377*	*6.129*
$FR_{3(high)}$	1.100	0.838	1.349	1.518	0.826
	5.759	*3.422*	*5.072*	*5.855*	*4.481*
FR_k	1.637	2.091	2.042	1.244	
	13.983	*5.251*	*13.026*	*17.307*	
$r_{m,t}$	1.024	1.135	1.122	1.011	0.749
	14.686	*17.537*	*14.884*	*15.421*	*9.600*
$r_{k,t-1}$	-0.011	-0.022	-0.014	-0.007	0.002
	-3.790	*-5.849*	*-2.580*	*-1.757*	*0.351*
$r_{k,t-2,t-7}$	0.000	-0.002	-0.001	0.000	0.005
	0.035	*-0.921*	*-0.587*	*0.182*	*3.450*
$ln(SIZE_k)$	0.021	-0.170	-0.268	-0.081	0.062
	1.208	*-5.367*	*-5.905*	*-2.015*	*1.400*
$ln(BM_{k,})$	0.248	0.214	0.136	0.239	0.447
	5.694	*3.117*	*2.350*	*4.186*	*12.355*
$TURNOVER_k$	0.044	0.086	0.068	-0.114	-0.141
	0.924	*1.392*	*0.864*	*-1.217*	*-1.635*
Adj. Rsq (%)	12.530	18.420	15.040	10.840	6.289

Table 7: Impact of earnings forecast revisions and dispersion in revisions on stock returns

$$r_{k,t} = a + b\ r_{m,t} + \sum_{j=1}^{3} c_j\ FR_{j,t} + \hat{c}_3\ FR_{3,t} * DISP_{3,t} + d_1\ FR_{k,t}$$
$$+ d_2 r_{k,t-1} + d_3 r_{k,t-2,t-7} + d_4 \ln(SIZE_{k,t}) + d_5 \ln(BM_{k,t}) + d_6\ TURNOVER_{k,t} + e_{k,t}$$

where, for each firm k in month t, $R_{k,t}$ is the monthly stock return; $FR_{k,t}$ is the monthly revision in earnings forecasts for firm *k*; $FR_{j,t}$ is the value-weighted average of revisions in earnings forecasts for firms in analyst coverage tertile j (within the same industry); $DISP_3$ is the standard deviation of revision in earnings forecast for the highest analysts coverage tertile; $r_{m,t}$ is the monthly value-weighted return of all stocks in CRSP; $r_{k,t-2,t-7}$ is firm k's cumulative return over month *t-7* to month *t-2*; $SIZE_{k,t}$ is beginning-of-month market value; $BM_{k,t}$ is book-to-market ratio; $TURNROVER_{k,t}$ is the average daily share turnover in the previous month. The equation is estimated for all firms and separately for each group of firms based on analyst coverage. The robust *t*-statistics cluster by industry are provided in *Italic*.

		Analyst Coverage Groups			
Independent Variables	*All firms*	*High Coverage*	*Medium Coverage*	*Low Coverage*	*No Coverage*
Intercept	0.375	1.800	2.187	0.927	0.243
	2.031	*8.108*	*8.007*	*4.259*	*0.707*
$FR_{1(low)}$	0.164	-0.051	0.040	0.353	0.435
	1.613	*-0.415*	*0.247*	*3.010*	*3.001*
$FR_{2(medium)}$	0.638	0.138	0.342	0.958	1.548
	2.673	*0.530*	*1.417*	*3.136*	*6.343*
$FR_{3(high)}$	1.893	1.507	2.290	2.606	1.533
	6.118	*4.350*	*5.938*	*6.682*	*7.014*
FR_3*DISP_3	-0.879	-0.684	-1.156	-1.245	-0.760
	-4.108	*-3.124*	*-3.881*	*-5.443*	*-4.399*
FR_k	1.638	2.086	2.043	1.249	
	13.928	*5.235*	*13.100*	*17.351*	
$r_{m,t}$	1.025	1.135	1.122	1.011	0.750
	14.670	*17.570*	*14.864*	*15.403*	*9.537*
$r_{k,t-1}$	-0.011	-0.023	-0.014	-0.007	0.002
	-3.835	*-5.940*	*-2.552*	*-1.768*	*0.339*
$r_{k,t-2,t-7}$	0.000	-0.002	-0.001	0.000	0.005
	-0.067	*-0.978*	*-0.691*	*0.135*	*3.401*
$ln(SIZE_k)$	0.019	-0.175	-0.279	-0.093	0.062
	1.144	*-5.566*	*-6.308*	*-2.351*	*1.424*
$ln(BM_{k,})$	0.249	0.219	0.140	0.238	0.443
	5.620	*3.180*	*2.410*	*4.155*	*12.174*
$TURNOVER_k$	0.039	0.082	0.060	-0.126	-0.147
	0.807	*1.329*	*0.764*	*-1.331*	*-1.660*
Adj. Rsq (%)	12.550	18.440	15.060	10.850	6.300

Table 8: Impact of earnings forecast revisions of bellwether firms on stock returns

$$r_{k,t} = a + b\, r_{m,t} + c_1\, FR_{BW,t} + c_2\, FR_{NBW,t} + d_1\, FR_{k,t}$$
$$+ d_2 r_{k,t-1} + d_3\, r_{k,t-2,t-7} + d_4 \ln(SIZE_{k,t}) + d_5 \ln(BM_{k,t}) + d_6\, TURNOVER_{k,t} + e_{k,t}$$

where, for each firm k in month t, $R_{k,t}$ is the monthly stock return; $FR_{k,t}$ is the monthly revision in earnings forecasts for firm *k*; $FR_{BW,t}$ and $FR_{NBW,t}$ are the revisions in earnings forecasts for the bellwether firm and the comparing non-bellwether firm within the same industry; $r_{m,t}$ is the monthly value-weighted return of all stocks in CRSP; $r_{k,t-2,t-7}$ is firm k's cumulative return over month *t-7* to month *t-2*; $BM_{k,t}$ is book-to-market ratio; $TURNROVER_{k,t}$ is the average daily share turnover in the previous month. In Panel B, we interact FR_{BW} with $DISP_{BW}$, the standard deviation of revision in earnings forecast for the bellwether firms:

$$r_{k,t} = a + b\, r_{m,t} + c_1\, FR_{BW,t} + \hat{c}_1\, FR_{BW,t} * DISP_{BW,t} + c_2\, FR_{NBW,t} + d_1\, FR_{k,t}$$
$$+ d_2 r_{k,t-1} + d_3\, r_{k,t-2,t-7} + d_4 \ln(SIZE_{k,t}) + d_5 \ln(BM_{k,t}) + d_6\, TURNOVER_{k,t} + e_{k,t}$$

These equations are estimated for all firms and separately for each group of firms based on analyst coverage (the coefficients associated with the control variables are suppressed). The robust *t*-statistics cluster by industry are provided in *Italic*.

Panel A

	Analyst Coverage Groups				
Independent Variables	*All Firms*	*High Coverage*	*Medium Coverage*	*Low Coverage*	*Zero Coverage*
FR_{BW}	0.318	0.098	0.403	0.569	0.283
	2.215	*0.852*	*2.170*	*4.368*	*2.196*
FR_{NBW}	-0.006	-0.088	-0.017	0.057	0.093
	-0.181	*-2.198*	*-0.412*	*0.985*	*2.270*
FR_{BW} - FR_{NBW}	0.325	0.186	0.419	0.512	0.190
	2.260	*1.545*	*2.179*	*3.606*	*1.398*
Adj. Rsq (%)	12.450	18.120	15.040	10.720	6.164

Panel B

	Analyst Coverage Groups				
Independent Variables	*All Firms*	*High Coverage*	*Medium Coverage*	*Low Coverage*	*Zero Coverage*
FR_{BW}	0.574	0.327	0.680	0.799	0.567
	3.555	*1.973*	*3.218*	*5.105*	*3.371*
FR_{BW}*$DISP_{BW}$	-0.889	-0.785	-0.960	-0.823	-0.985
	-2.456	*-2.726*	*-2.249*	*-2.270*	*-1.999*
FR_{NBW}	-0.010	-0.092	-0.020	0.056	0.090
	-0.267	*-2.204*	*-0.487*	*0.958*	*2.169*
Adj. Rsq (%)	12.470	18.130	15.050	10.730	6.182

Table 9: Stocks returns and earnings forecast revisions of bellwether firms: event study

This table presents the average cumulative abnormal return (*CAR*) of firms in the same industry in response to the analyst forecast revisions of bellwether firms. *CAR* is defined as either cumulative excess return over the average return corresponding to the firm's size deciles (Size-adjusted CAR) or cumulative abnormal return adjusted for Fama-French 3-factor plus momentum factor (Four-factor CAR) over the 3 day window [-1, +1] surrounding the forecast revision. FR_{BW} is the magnitude of revisions in earnings forecasts for the bellwether firm (for each industry); CAR_{BW}, CAR_{ZERO}, CAR_{LOW}, CAR_{MED} are the 3-day cumulative abnormal returns corresponding to the bellwether, zero coverage, low-coverage and medium-coverage firms within each industry respectively. $CAR_{MED\text{-}ZERO}$ ($CAR_{MED\text{-}LOW}$) is the difference between CAR for medium analyst firms and that for zero (low) analyst firms. All variables are expressed in basis points. The average value across forecast revision events and the robust *t*-statistics (in *Italic*) cluster by industry are reported.

	Upward Forecast Revisions (Number of observations = 20751)		Downward Forecast Revisions (Number of observations = 28817)	
	Size-adjusted CAR	*Four-factor CAR*	*Size-adjusted CAR*	*Four-factor CAR*
FR_{BW}	38.397		-63.167	
CAR_{BW}	31.450	28.359	-34.958	-29.952
	7.639	*6.663*	*-10.435*	*-9.837*
CAR_{ZERO}	6.785	5.928	-7.518	-6.637
	2.529	*2.456*	*-2.485*	*-2.227*
CAR_{LOW}	10.731	7.407	-6.252	-4.550
	4.344	*3.276*	*-3.230*	*-2.910*
CAR_{MED}	8.048	4.038	-2.284	-0.509
	3.912	*2.244*	*-1.258*	*-0.310*
$CAR_{MED - ZERO}$	1.263	-1.890	5.234	6.128
	0.485	*-0.717*	*1.763*	*1.980*
$CAR_{MED - LOW}$	-2.684	-3.370	3.967	4.041
	-1.348	*-1.589*	*1.866*	*2.028*