Information markets, analysts, and comovement in stock returns

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Abstract

We examine the idea of information spillover as the source of stock return comovement, where one (neglected) stock is priced using readily available information about other stocks that share similar fundamentals. We use the number of analysts following a stock to distinguish “high profile” stocks from neglected stocks and find that the prices of neglected stocks tend to comove with those of intensively covered stocks in the same industry. Consistent with recent theories about the information markets, we also find that the return comovement is more prominent in industries where analysts concentrate their coverage intensely on very few stocks. Finally, using earnings forecast data, we show that information spillover from high-coverage firms to low-coverage ones is larger when the information is more certain (there is less dispersion in earnings forecast).

In his presidential address to the American Finance Association, 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 then goes on to develop a model in which investors confine their attention, and money, to a subset of stocks about which they have readily accessible information, and in which other "neglected" stocks can be mispriced. This paper is about how prices nonetheless emerge for relatively obscure stocks. We use the number of analysts following a stock to distinguish "high profile" stocks from neglected ones, and find that the prices of neglected stocks tend to comove with those of "similar" high profile stocks. This suggests that Merton's (1987) model might be usefully supplemented by considering information spillovers – using readily available information about one stock to price another that is likely affected by similar fundamentals.

Information is a costly input to a profit maximizing arbitrage business that buys additional information until its marginal revenue from trading on an additional bit of information no longer covers its marginal cost (Diamond and Verrecchia (1981), Grossman and Stiglitz (1981) and Shleifer and Vishny (1997)) and more expensive information is not capitalized into asset prices. In many cases, arbitrageurs do not mine and process their own information, but buy it from information intermediaries, such as financial analysts, who reduce their information gathering and processing costs through specialization (see e.g. Brown et al. (1987), Bhushan (1989) and Veldkamp (2006a)). In other cases, the two activities may be vertically integrated.

Different sorts of information have different costs, and therefore provide different opportunities for information intermediaries to make money by providing "asset-payoff-relevant" information. For example, information pertaining to the whole economy is usually provided by the government as a public service, though financial analysts also provide economy-level forecasts for fees. Some industry specific information is also provided by government agencies, but industry analysts have a more substantial role at this level. Some firm-specific information must be provided for free to satisfy securities and corporate disclosure requirements, but most firm-level information appears to enter stock prices through the trading of private information (Roll (1988)).

Specialized information intermediaries, like financial analysts, are thus likely to play their most economically important role in assisting in the capitalization of firm-specific information into stock prices (Bhushan (1989) and Veldkamp (2006a)). The above considerations motivate us to examine why analysts specialize in a few firms and the implications for information diffusion and equity return co-movement.

First, more analysts should follow companies with larger market capitalizations and trading volumes. This is because informed investors can take larger arbitrage positions in such stocks without attracting notice and moving prices. This results in greater trading profits per unit of private information than would ensue in an otherwise similar smaller or less traded stock. Consequently, at the margin, more analysts should follow larger cap stocks that are more heavily traded (Bhushan (1989) and Alford and Berger (1999)).

Second, more analysts should follow a stock whose fundamentals correlate strongly with other stocks. Again, this is because investors pay for information up to the point where their marginal revenue from informed trading equals the marginal cost of additional information. All else equal, information that can be used to value more stocks generates more trading revenue and is therefore more valuable. We identify such stocks and observe more analysts following them.

It follows that returns on firms that are intensely followed by analysts contain fundamental information about the firm as well as common information about the trends in the industry. Veldkamp (2006a) shows that in a competitive information market with fixed production costs, analysts choose to supply low-cost, high-value information that is used to price many assets. This is consistent with the observation that analysts choose to concentrate their coverage on a few firms in the industry. Changes in the value of widely followed stocks induces like changes in other neglected stocks as investors use common signals to price these assets. Consequently, widely followed stocks should co-move with many other stocks (and the market index), while neglected stocks should co-move with few other stocks. In addition, the higher co-movement should be more prominent in industries where analysts focus intensely on very few stocks, but less evident when analyst following is dispersed across a wide range of stocks. We find empirical support for these propositions.

Finally, we examine the impact of information contained in the earnings forecasts of firms heavily or thinly covered by analysts on the prices of other firms in the same industry. Our evidence supports the notion that the forecast of earnings of widely followed firms contains value relevant information for firms that are less followed, but the reverse is not true. We also find that the information spillover is larger when the information is more certain (there is less dispersion in earnings forecast).

These findings validate the importance of information flowing into financial markets through specialized information intermediaries as in Veldkamp (2005) and Veldkamp (2006a, b). They also suggest that investors use information about relatively transparent companies to value less transparent ones, suggesting a less abrupt demarcation of “high profile” versus “neglected stocks” than in Merton (1987), but nonetheless validating the general intuition dividing the market into such categories. Our findings also illuminate recent work on the synchronicity of stock returns (Morck et al. (2000), Campbell et al. (2001)). While much evidence links elevated firm-specific price movements to more accurate pricing (Morck et al. (2000), Durnev et al. (2004), Jin and Myers (2006), and others), other studies find that stocks followed by many analysts tend to co-move more with the market (Piotroski and Roulstone(2004), and Chan and Hameed (2006)). Our findings reconcile these seemingly discordant studies by showing that widely followed stocks exhibit more co-movement precisely because they are priced more accurately and are therefore useful benchmarks for valuing more opaque stocks. Yet, large scale comovement itself suggests that many firms’ returns are not driven by firm specific information but by inferred general information.

The next section motivates our empirical hypotheses. The third section describes our data and variables, and Section IV reports our empirical results. Finally, section V concludes.

II. The information market theory and analysts

Informed risky arbitrage creates demand and supply curves for information (Diamond and Verrecchia (1981), Grossman and Stiglitz (1980)). Information has many of the qualities of a public good, and this motivates theoretical arguments with direct implications about the behavior of asset prices. Veldkamp (2006a), for example, shows that competitive forces in an information market generates two equilibrium outcomes: (a) many buyers are willing to pay for the same, low cost signal; and (b) suppliers sell information that has the highest value, i.e. signals that can be used to predict the value of many assets. To motivate our analysis, we summarize the intuition underlying Veldkamp (2005, 2006b) and Bhushan (1989). For simplicity, we designate *analysts* as firm level information intermediaries who analyze a firm and produce firm-specific information, which investors can then use to make further inferences about share values.

In order to focus on the main strands of intuition underlying these models, we adopt a few simplifying assumptions. First, we assume that the information cost in getting to know a company is a fixed amount, *C*. Second, we assume that all analysts have the same capability and generate information of the same quality.[1] Analysts sell their information to generate revenue and/or internalize the market for information by integrating the information production and application activities (see Admati and Pfeleiderer (1990) for the contrast between indirect and direct sale of information). We assume that re-selling of the information produced by analysts is prohibited. Finally, the supplier's revenue is assumed to be monotonically increasing in the buyers' aggregate willingness to pay.[2]

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[1] Allowing for information costs to vary, (e.g., according to company size or quality of information) or differential ability/ risk aversion of analysts would generate interesting insights on the labor market for analysts but not the overall understanding of the main issues examined in this paper.

[2] Each buyer's willingness to pay is, of course, inevitably diluted by her expectations on the supplier's multiple sales of the same information. At the same time, the multiple sales are expected to be at the point where the aggregated willingness to pay is maximized.

Let the maximized total revenue be $R^M_{k,j}$ where *k*, *j*, denotes analyst *j* following company *k*. Analyst *j*'s expected reward for generating information for company *k* is $R^M_{k,j}$ - *C*.[3] It should be noted that a low $R^M_{k,j}$ could lead to zero analyst following for some companies, particularly companies of marginal importance. Competition among analysts would reduce $R^M_{k,j}$ and in a competitive market, $R^M_{k,j}$ is equal to *C* for all analysts. A key concern at this juncture is the number of analysts covering firm *k* (J_k) for which $R^M_{k,j}$ = *C*. While $R^M_{k,j}$ declines in the number of analyst following, J_k depends on users' aggregate valuation of the information about firm *k*, i.e. (J_k x $R^M_{k,j}$), similar to the idea in Bhushan (1989).[4]

Investors use firm specific information for several purposes. First, they naturally use the information to make their own projection about firm *k*. This implies that as more investors trade firm *k*'s stocks, the greater the analyst following. Second, investors may also use the information to infer general information useful in making projections about other firms. The criterion is that information about firm *k* includes information related to other firms' business.

To illustrate, consider that the information about firm *k* contains two pieces of uncorrelated information, s_k and $p_k g$, bundled together as (s_k+$p_k g$) where s_k is a stochastic variable revealing specific information about firm *k* uncorrelated with general trends, *g* is

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[3] We should note that $R^M_{k,j}$ is higher with better property rights protection laws. Thus, the property rights regime is likely to affect analyst following and possibly the implied stock return characteristics. For example Bushman, Piotroski and Smith (2005) report that analyst coverage increases significantly upon the initial enforcement of insider trading laws, particularly in emerging markets.

[4] There could be users who free-ride – investors who do not pay for the information but instead infer the information from traders who have paid to acquire the information. That is explicitly modeled in Grossman and Stiglitz (1980) and Veldkamp (2005). Free-riding does not affect the argument here – analyst following depends on the aggregate valuation of the information.

a stochastic variable revealing the general trends in firm k's industry and the economy, and p_k is the "impact" of g on firm k that manifests itself in firm k's economic data. Signal extraction based on (s_k+p_kg) implies that investors can infer "g" to be $\beta_k(s_k+p_kg)$ where β_k is $\frac{p_k\sigma_g^2}{(\sigma_{s_k}^2 + p_k^2\sigma_g^2)}$. Thus, firm k has high information revelation value if its fortune is more affected by the general trends (high p_k and lower $\sigma_{\varepsilon_k}^2$); such firms attract greater analyst following, beyond the influence of firm size on analyst coverage.

The overall implication is that analysts would follow firms whose information is most valued by investors in the aggregate:

Empirical proposition 1: Firms that attract more analyst following are (i) larger, (ii) more actively traded, and (iii) more strongly correlated with other firms in fundamentals.[5]

The characterization also leads to empirical propositions on how analyst following is related to stock return correlations. As described above, the informed investors would use specific information about firm k to make projections on the economic value of firm k itself, the underlying economic trends, and thus projections on the economic value of other firms too. Trading by the informed should lead to co-movement between firm k's stock return and returns on the stock of companies whose

[5] This is the empirical version of the proposition in Veldkamp (2006a) which suggests that there should be more analyst following stocks whose payoffs explain/forecast contemporaneously the payoffs of many other assets. Of course, when we empirical examine the hypothesis, we need to incorporate other established determinants of analyst following, e.g., Bhushan (1989) and Frankel, Kothari, and Weber (2006).

fundamentals are correlated with the underlying general trends inferable from information about firm *k*.[6]

One implication of the analyses is that the correlation between firm *k* and other firms would be greater the higher the concentration of analysts following firm *k* relative to other firms in the industry. However, return co-movement goes down as all firms are equally covered by analysts. The above characterization of how investors use firm specific information leads to the following empirical propositions:

> ***Empirical proposition 2: The returns on stocks of firms with greater analyst following contribute more in explaining other firms' stock returns (that is, generate more comovement with returns on other firms' stock), even after controlling for the contemporaneous correlation of the fundamentals between the followed firms and other firms.***[7]

> ***Empirical proposition 3: The impact of "analyst following" on comovement is reduced when analyst coverage is more widely spread among the firms in a given industry.***

It is indeed common market practice to use bellwether stocks to gauge the industry's trends in demand, factor costs, innovations, and other material changes. For example, one would expect that information about GM contains information about the auto industry, or information about Wal-Mart contains information about retailing

[6] To the extent that the uninformed infer information from the trading of the informed, their trading will reinforce the process.

[7] Note that a positive and significant influence of "analyst following" *per se*, after we control for "fundamental correlation," supports the "excessive" comovement idea in Proposition I of Veldkamp (2006a). Yet, the comovement is excessive only in the sense that it would be less if investors are fully informed instead of relying on information extracted from analysts reports and trading accordingly.

industry, etc. Foster (1981), Han and Wild (1990) and Ramnath (2002) provide evidence of intra-industry information transfers from firms announcing their earnings to other competing firms. Specifically, they find that the announcement of earnings information about some firms affect the prices of other firms in the industry.

Our algebraic illustration above suggests that when analysts forecast earnings of some firm *k*, the forecasts contain information about both the firm as well as the industry trends. This implies that revisions in earnings forecast of firms with intense analyst coverage should affect the valuation of other firms in the same industry. Our analyses further imply that the impact of the revisions in earnings forecast on other firms would be negatively related to the uncertainty in the forecast revisions, measured by the dispersion in analyst forecasts revisions.

> ***Empirical proposition 4: Revision in the earnings forecast of firms with large (few) analyst following will have bigger (smaller) impact on the prices of other firms in the same industry. This relation due to signal extraction is expected to be stronger when there is lesser uncertainty (dispersion) about the forecasted earnings.***

III. Data, Construction of Variables, and Sample

Examination of the empirical propositions 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.

III. A. 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 stock 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).[8] The second database is I/B/E/S which provides information on analyst coverage for each firm and the analysts' earnings forecasts and revision in forecasts. The number of analyst making one-year ahead earnings forecast for each firm *k* during the year *t* is used to measure analyst coverage ($ANALYST_{k,t}$).

III.B. Variables

Measuring contribution to stock return comovement (LPCORR)

One important variable in our empirical investigation is the contribution of an individual firm's return to stock return comovement. We capture the contribution of a target firm *k* in industry *I* to return co-movement in the following way. We first estimate

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[8] We also consider using quarterly returns on sales (ROS) as an alternative measure and find similar results.

a two-factor market model for the return on each firm using OLS regression, where the two factors are the market and industry returns:

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

where r_{iw} is the return on firm *i* in week *w*, r_{Mw}^k and r_{Iw}^k are the value-weighted return on the market and industry portfolios excluding firms *i* and *k*. Each year, Equation (1) is estimated for all firms *i*, where $i = 1, \ldots, N_I - 1$, N_I is the number of firms in industry *I*, and $i \neq k$. The value-weighted CRSP index is used to measure the return on the market portfolio. To classify firms by industries, we adopt the five-digit Global Industry Classification Standard (GICS) codes to assign each stock to one of 69 industries.[9] The r-square from the regression in equation (1), $R_{i,excl.k}^2$, represents the proportion of variation in returns for firm *i* explained by the market and industry portfolios, excluding firm *k*.

We estimate a second regression model with return of firm *k* in week *w* (r_{kw}) as an explanatory variable, in addition to the market and industry factors:

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

The regression in equation (2) produces a second r-square value, $R_{i,incl.k}^2$. The marginal contribution of firm *k* to return comovement is measured by the partial correlation of its return with returns on other firms in the industry. Given a pair of firms *k* and *i* (in the same industry *I*), the contribution of returns on firm *k* in explaining the returns on firm *i*,

[9] We also employ the 17 industry classification in Fama and French (1996) as an alternative classification scheme and obtain similar results.

over and above the explanatory power of market and industry factors, is captured by the partial correlation coefficient, $PCORR_{k,i}$, defined as:[10]

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

Essentially, $PCORR_{k,i}$ measures the correlation between r_{kw} and r_{iw}, controlling for the effect of market and industry returns on r_{iw}. The higher the value of $PCORR_{k,i}$, the higher the effect of firm *k*'s returns on the returns on firm *i*. For each firm *k* in industry *I*, the regressions in equation (1) and (2) produce N_I-*1* estimates of partial correlation coefficients. To gauge the overall contribution of firm *k*'s return to the level of comovement in returns among all firms in the industry, we compute the average $PCORR_k$:

$$PCORR_k = \left(\frac{\sum_{i=1, i \neq k}^{N_I} PCORR_{k,i}}{N_I - 1}\right).$$

Since PCORR values are bounded between zero and one, we use its logit transformation $LPCORR_k$:

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

By construction, $LPCORR_k$ is a year by year observation based on weekly returns that measures the marginal contribution of firm *k* to comovement in stock returns of other firms in the same industry. A high value indicates that firm *k's* stock returns add much to the common variation of returns among firms in the industry.

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[10] In unreported results, we consider an alternative measure of partial correlations, a simple difference in the r-square from equations (2) and (1): $R^2_{i,excl.k}$ - $R^2_{i,excl.k}$. We obtain qualitatively identical results using this alternate measure.

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 firm's business within the industry. These variables are described next.

Partial correlation in fundamental asset returns (LPCORR_ROA)

Stock returns intrinsically co-move because of commonalities in the variation of fundamentals. As depicted in our first empirical hypothesis, analyst following is greater for firms whose fundamentals are more correlated with other firms' fundamentals. 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*). For example, Morck, Yeung and Yu (2000), Piotroski and Roulston (2003), and Durnev, Morck and Yeung (2004) all use co-movement in *ROA* to capture common variation in fundamental values and find that return synchronicity and fundamental asset return synchronicity are positively related. 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.

Similar to 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:

$$ROA_{iq} = a_i + b_i ROA^k_{Mq} + c_i ROA^k_{Iq} + e_{iq}, \quad (5)$$

and,

$$ROA_{iq} = a_i + b_i ROA^k_{Mq} + c_i ROA^k_{Iq} + d_i ROA_{kq} + e_{iq}, \quad (6)$$

where ROA_{iq} and ROA_{kq} are the return on asset 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 asset in quarter *q* for the market and industry portfolios respectively, where both firm *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[11]:

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

Averaging the partial correlation estimates for firm k with all other firms in the same industry and taking a logit 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-Specific Variables

In empirically investigating the hypotheses in Section 2, we need to incorporate various important firm characteristics as indicated in the information market literature

[11] Our results are unaffected if we define the incremental comovement in fundamental returns as the simple difference between $R^2_{ROA,,i,incl.k}$ and $R^2_{ROA,i,excl.k}$.

(e.g., Veldkemp 2006a) and in the literature on analyst following (e.g., Bhushan (1989), Patrioski and Roulstone (2004), Chan and Hameed (2006), and Frenkel, Kothari, and Weber (2006)).

Following Veldkemp (2006a), our empirical hypothesis suggests that investors are willing to pay more for information about larger firms because more investors invest in larger firms and because larger firms may contain more valuable market and industry wide information that is useful in inferring other firms' future value. Although greater availability of public information about these firms arising from better media coverage and firm level disclosure may reduce the demand for analyst services, several papers find informativeness of analyst research and quality of other information are complements (see, for example, Lang and Lundholm (1996), and Frankel, Kothari and Weber (2006)). We use the beginning of year *t* market value of each firm *k* to measure the size of firm k, denoted as $SIZE_{k,t}$. We expect the variable to explain both a firm's analyst following and its impact on stock comovement.

The incentive for analysts to collect and supply information is higher for stocks that are heavily traded. This is because higher turnover is associated with a greater shareholder base and, hence, demand for analyst services. Also, Brennan and Hughes (1991) and Alford and Berger (1999) suggest that high *TURNOVER* generates more commissions for their brokerage firms and thus attracts greater analyst coverage. In addition, to gauge a firm's impact on return comovement, we need to incorporate *TURNOVER* because the level of trading activity in a firm affects the speed at which information is incorporated into its price. Infrequently traded stocks are slow in incorporating information, resulting in delays in information transmission, while the opposite is true for heavily traded firms. We define $TURNOVER_{k,t}$ as the average daily share turnover of stock *k* in the previous year *t-1*.

The information contained in a firm's stock returns is more valuable for pricing other firms in the industry if the firm's business is concentrated within the same industry. Also, as suggested in Bhushan (1989), it is more costly for analysts to acquire and supply information about firms in multiple business segments as compared to firms in a single segment due to higher information set-up costs and effort required in following many lines of business. We therefore expect a firm's analyst following to be positively related to level of concentration of the firm's business. As well, we expect more focused firms to have higher partial correlation of returns with other firms in the industry. 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 $HERF\_SALES_{k,t}$.

Bhushan (1989) shows that information produced by analysts is more valuable when stock returns are more volatile. Hence, demand for analyst services is higher when the stock returns have higher standard deviation ($STDRET_{k,t}$). We measure $STDRET_{k,t}$ as the standard deviation of weekly returns on stock *k* in the previous year *t-1*.

III.C 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 IBES merged sample in 1984, which grows steadily to 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.

IV Empirical Results

IV. A Summary statistics and preliminary results

Simple descriptive statistics of our key variables are reported in Table 2 Panel A. The pooled average value of the marginal contribution of a single stock to correlations in returns, $PCORR_k$, is 2.6 percent (median PCORR is 2.4 percent).[12] The partial correlation measure for fundamental returns, $PCORR\_ROA_k$, shows larger cross-sectional variation and 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. We note a large variation in firm size and turnover variables in our sample, as expected. Our sales concentration variable shows that at least one half of the firms concentrate their business in a single segment, consistent with those previously reported in Patroiski and Roulstone (2003) and others.

Next, we sort the stocks with analyst coverage into three groups based on the number of analysts covering the stock each year and the firms with zero analyst coverage are reported as a separate group. The averages of the variables in each sub-group are presented in Panel B. The lowest coverage thirtile has an average of 2.6 analysts following each firm and the coverage increases to 18.5 analysts for the highest coverage thirtile. 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. The finding that a firm's stock return's marginal contribution in explaining other stocks' return increases with analyst following is consistent with the information market theory in Veldkemp (2006a) – information from high analyst following stocks are used to price other stocks which in turn increases the correlation of

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[12] For clarity we do not report the average r-square estimate across all firms as defined in equations (1) and (2) and denoted as $R^2_{I,excl.k}$ and $R^2_{I,incl.k}$, respectively. Consistent with previous results in Roll (1988), Morck, Yeung and Yu (2000) and others, the average r-square of the 2-factor market model of weekly returns is 20 percent for U.S. firms. Adding firm *k* to the 2-factor market model increases the r-square by about 2 percent to 22 percent.

the returns of high analyst following stocks with those of other stocks in the same industry.

Panels B and C of Table 2 also reveal that analyst following is related to the set of firm-specific variables that we introduced earlier. First, firms with low (high) analyst following are dominated by small (large) firms, and are thinly (heavily) traded. Second, while firms with higher analyst following have a lower Herfindhal concentration index value, it should be noted that more diversified firms are also likely to be bigger in market capitalization. Finally, the evidence is somewhat mixed for the correlation between analyst coverage and the partial correlation in the fundamental asset values, *PCORR_ROA*. *ROA* of firms with low or medium analyst coverage contribute more in explaining other firms' *ROA*, i.e., they exhibit higher *PCORR_ROA*, compared to firms with zero coverage, but it is not the case for firms with high analyst coverage. However, these findings are confined to univariate analysis, and we also find in Panel C of Table 2 that firm-specific variables are significantly correlated with each other. In the following sub-section, we perform multivariate analyses, taking into account the effects of these other variables.

IV.B Determinants of Analyst Coverage

Building on the literature (e.g., Bhushan (1989), Patrioski and Roulstone (2004), Chan and Hameed (2006), and Frenkel, Kothari, and Weber (2006)), the empirical hypotheses in Veldkemp (2006a), and the discussion in Section III.B, we specify the determinants of analyst following for each firm *k* in year *t* as follows:

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

In addition to the firm specific variables, we add industry dummies, *INDDUM*, and year dummies, *YEARDUM*, to control for industry level and yearly fixed effects. We estimate equation (8) as a pooled regression over the full sample period of 1984 to 2007 and four five-year sub-periods, 1984 to 1989, 1990 to1995, 1996 to 2001 and 2002 to 2007. For the rest of the paper, the t-statistics reported in the tables are based on heteroskedasticity consistent standard errors clustered at the firm and year level (Petersen (2007)).

Table 3 indicates that analyst following is significantly and positively related to firm size (*SIZE*), trading volume (*TURNOVER*), volatility (*STDRET*) and concentration of business activity (*HERF_SALES*). More interestingly, there is strong evidence that analysts choose to follow firms whose changes in fundamentals are more useful in predicting the changes in fundamentals of other firms in the industry (the coefficient on $LPCORR\_ROA_{k,t}$ is positive in all sub-periods and statistically significant in three out of the four sub-periods). These results are consistent with the predictions in our hypothesis 1: analysts follow those firms which are larger, more actively traded, and more strongly correlated with other firms in fundamentals.

IV. C. Return Comovement and Analyst Following

To test our empirical hypothesis 2, which relates analyst coverage to a firm's contribution to stock return comovement, we run the following pooled regression:

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

Table 4 presents the estimated regression equation to explain *LPCORR*$_{k,t}$, the marginal contribution of firm *k's* stock returns to comovement with other firms' stock returns. As expected, the contribution of a firm to return comovement is positively affected by its contribution to fundamental comovement (*LPCORR_ROA*), trading activity (*TURNOVER*), industry concentration (*HERF_SALES*) and firm size (*SIZE*). These variables' regression coefficients are statistically significant in the whole sample period and are mostly significantly in the sub-sample periods. The exceptions are as follows: *LPCORR_ROA* is insignificant in the 1990-1995 sub-sample period, and firm size (*SIZE*) and volatility (*STDRET*) are insignificant in the 1984-1989 sub-sample period.

Most critical in Table 4 is the strong evidence of a positive effect of analyst following (*ANALYST*) on return comovement, in the overall sample period and in all the sub-sample periods, after multiple controls are included. As a check on the robustness of our results in Table 4, we estimate equation (9) using yearly regressions. In unreported results, we found *LPCORR* to be positively related to *ANALYST* in each year from 1984 to 2007 except for 1988, and the relation is significant in 17 years out of 24 years based on the standard error clustered by industry.

On the whole, the results in Table 4 support empirical proposition 2, which is derived from the implication of information market theory for return comovement – investors use the information generated by analysts to value other firms in the industry and, hence, returns on firms with more analysts following contribute more to return comovement.

IV. D. Return Comovement and Analyst Concentration

The information market theory in Veldkemp (2006a), as stated in our hypothesis 3, also predicts a stronger effect of analyst coverage on return comovement when analyst coverage is more concentrated. When analyst coverage clusters in fewer firms in the industry, investors have a smaller set of firms with information. However, they use this set of information to infer about the fundamentals of other firms. The result is that information of each followed firm carries more weight in affecting returns on other stocks, which exacerbates return comovement.

To measure the concentration of analyst coverage within an industry, we construct the Herfindhal index of analyst coverage in a given year t for industry I as:

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

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 the one extreme, if all analysts in the industry concentrate their coverage in a single firm, then $HERF\_ANALYST_I$ takes a maximum value of 1.0. On the other hand, if analyst following is equally distributed across all firms, then, $HERF\_ANALYST_I$ reduces to the reciprocal of N_I. A concern about $HERF\_ANALYST_I$ is that this metric does not account for firms that are not covered by analysts, where $ANALYST_{k,t}$ takes a value of zero. To minimize this shortcoming, we consider a modified measure of analyst concentration, where we multiply the Herfindhal index of analyst coverage, $HERF\_ANALYST_{I,t}$, by the proportion of firm that have zero coverage. Our main results are unaffected by this modification.

Since we expect the effect of analyst coverage on return comovement to be higher when there is a greater concentration of analyst coverage in the industry, we add $HERF\_ANALYST_{I,t}$ as an interacting variable into equation (9) as follows:

$$\begin{aligned}
& LPCORR_{k,t} = a_0 + a_1 \ln(1 + ANALYST_{k,t}) \\
& + b_1 \ln(1 + ANALYST_{k,t}) * HERF_ANALYST_{I,t} + a_2\, LPCORR_ROA_{k,t} \\
& + a_3 SIZE_{k,t} + a_4\, TURNOVER_{k,t} + a_5 \ln(HERF_SALE_{k,t}) + a_5 \ln(STDRET_{k,t}) \\
& + \sum_{I=1}^{68} d_I\, INDDUM_{I,t} + \sum_{y=1984}^{2006} c_y\, YEARDUM_y + e_{k,t}
\end{aligned} \tag{11}$$

Table 5 reports the estimate of equation (11) and shows that the effect of analyst coverage on return comovement gets a significant positive boost when analysts concentrate their coverage. The coefficient associated with the interaction term of *ANALYST* and *HERF_ANALYST* is highly significant in the overall sample period and in the sub-sample periods (except for 2002-2007). Hence, we find support for the hypothesis that information spillover generates “excess” comovement, especially when less firms are covered by analysts.[13]

Since analyst may prefer to follow firms that have stronger correlation with other firms in stock returns, analyst coverage and the contribution to return comovement are possibly endogenous. To address this issue, we turn to more direct tests of information produced by analysts. Specifically, the next sub-sections will examine the effect of information contained in the forecasted earnings of firms that are intensely followed by analysts on the prices of other firms in the same industry.[14]

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[13] When we estimate equation (11) for each year, the interaction term capturing the effect of analyst concentration is positive in all years except for 1990 and 2007, and the cross-year average coefficient is significant while the significance in individual years is slightly weaker.

[14] In unreported results, we use the simultaneous estimation approach to estimate the parameters in equations (8) and (9) using two-stage least squares (2SLS), where we explicitly allow $LPCORR_{k,t}$ to be a determinant of analyst coverage and vice versa. We obtain results similar to Table 4, indicating that our results are robust.

IV.F Analysts' Earnings Forecasts Revisions and Stock Returns

So far we have shown that stocks followed by many analysts contribute to movement in returns of other stocks in the same industry. Our interpretation is that analysts' activities facilitate the discovery and diffusion of industry-wide information. In this section, we strengthen the investigation by focusing on an important set of information produced by analysts, firm-specific earnings forecasts as indicated in empirical proposition 4. Specifically, we investigate whether analysts' revision of their forecasted earnings affects the returns of other firms in the industry, particularly when the forecasts come from firms that are intensely covered by analysts.

We start by calculating the monthly revision of analysts' earnings forecast for each firm-month as the change in the mean 1-year forward forecast of annual EPS reported in I/B/E/S divided by the closing stock price in the previous month.[15] As we are interested in the relevance of the earnings forecast information for valuation of other firms in the industry, it becomes necessary to control for similar information produced on these other firms. Moreover, our conjecture is that the relevance of the information depends on the intensity of analyst coverage.

To accommodate these issues, we adopt two levels of analyses. In the first set of analyses, we aggregate the forecast revisions at the portfolio level. Each year we sort firms followed by analysts into thirtiles based on the analyst coverage within each of the sixty-nine industries. Firms in our sample without any analyst earnings forecasts are classified into a fourth group, labeled as thirtile zero. Each month t, the revisions in earnings forecasts are aggregated for each thirtile within each industry to obtain $FR_{J,t}$, the

[15] We winsorize the individual firm's monthly revisions of earnings forecasts at 1% and 99% level.

value-weighted average of the revisions in consensus earnings forecasts across all firms in thirtile *j*. *FR* provides a measure of information produced by analysts at a portfolio level, within each of our 69 industries.[16] We also conduct our analysis of information transmission from firms most intensively covered by analysts. In this alternative set of analyses, the results of which will be reported in the next sub-section, we define the bellwether stocks as the top three firms with most analyst coverage, belonging to the largest market capitalization thirtile within the industry.

Next, we regress, $r_{k,t}$, the return in month *t* for firm *k*, on the revision in earnings forecasts for firms in analyst thirtiles j ($FR_{j,t}$), where j=1(low coverage) , 2 (medium coverage) and 3 (high coverage):[17]

$$r_{k,t} = a_0 + \sum_{j=1}^{3} a_j\, FR_{j,t} + b_1\, FR_{k,t} + c_1\, r_{m,t} + c_2\, r_{k,t-1} + c_3\, r_{k,t-2,t-7} + c_4 \ln(SIZE_{k,t}) + c_5 \ln(BM_{k,t}) + c_6\, TURNOVER_{k,t} + e_{k,t} \quad (12)$$

As shown in (12), we add several firm specific characteristics at monthly frequency as control variables.[18] They include return on stock over the previous month ($r_{k,t-1}$) and the past six months from t-2 to t-7 to account for time series predictability in returns documented in Jegadeesh (1990) and Jegadeesh and Titman (1993). We also include firm size (ln(SIZE)), the ratio of book value of equity to market value of equity (ln(BM)) and the ratio of monthly trading volume to total shares outstanding as additional control variables. The systematic relation between stock returns and returns of market portfolio is captured by $r_{m,t}$, the return on CRSP value-weighted market portfolio. Finally, inclusion of $FR_{k,t}$, the revision in forecasted earnings on firm *k*, in equation (12) ensures that the

[16] Our results are qualitatively unchanged if we sort firms into quintiles based on analyst following.
[17] The results are similar if we replace the individual firms' returns with the returns on portfolios sorted on analyst coverage as the dependent variable.
[18] The results are quantitatively unchanged if we don't include any control variable.

documented impact of revisions in high-analyst firms on firm *k* is beyond that due to the revision in its own forecasted earnings. The multivariate regression model is estimated for the pool sample and also separately for each analyst group. The results are reported in Table 6.

As can be seen from Table 6, individual firm stock returns are significantly related to some, but not all of the control variables. For example, it is not surprising to see the revision in a firm's own forecasted earnings has a strong contemporaneous price effect, indicating that changes in forecasted earnings explain changes in stock prices. The more interesting result in Table 6 is that stock returns are affected by the revisions in the forecasted earnings of other firms in the industry (beyond the information contained in own forecast revisions). Here, we document a striking asymmetric effect: changes in forecasted earnings in the high (low) analyst group have a stronger (weaker) effect on prices of industry peers. For example, if the mean estimate of annual EPS in high-analyst firms increases by the amount of one percentage of stock price, the stock price of low-analyst firms will increase by 1.5 percents, which is even higher than the magnitude of price change in other high analyst coverage peers. On the other hand, the earnings forecast revisions of low-analyst firms only affect stock prices of zero and low analyst firms. In general, the impact of revisions in earnings forecasts on stock prices declines monotonically as we move from high to low coverage firms. In a similar vein, prices of uncovered firms react more to revisions in high than low coverage firms. These findings are consistent with our hypothesis that information contained in earnings forecast revisions of some firms are used to value other firms. Hence, earnings information produced about high-coverage firms diffuses to other, lower and zero coverage firms in the same industry.[19]

Given that forecasted earnings for high-analyst firms contain important signal for industry wide trends in earnings, and hence, affects the returns of firms in the industry, the quality of the signal should depend on the degree of (un)certainty in the forecasts. We explore whether the relation between stock returns and revision in forecasted earnings is stronger (weaker) when the dispersion in the forecast revisions are smaller (larger). Since we are especially interested in the uncertainty in the signal extracted from the forecasts for firms with high analyst following, we compute the standard deviation of mean forecast revisions for high-analyst firms, for each industry and each month t, denoted as $DISP_{3,t}$. We expect a stronger relation between the earnings forecast revisions of the high-analyst firms and firm level stock returns when the dispersion in forecast revisions is low. This expectation of a negative effect of the dispersion measure is estimated by interacting $FR_{3,t}$ in equation (12) with $DISP_{3,t}$.[20]

Table 7 presents the results. The qualitative results in Table 6 remain when we add the interaction terms: FR_3 has a higher impact on the returns of other firms in the industry than FR_1. More importantly, Table 7 shows that a decrease in the dispersion of forecasted revisions for high-analyst firms significantly increases its impact on stock returns. Further, the point estimates of the relation between individual stock returns and earnings forecast revisions (and the corresponding dispersion) are higher for the low coverage firms. Overall, our evidence is consistent with the notion that the revisions in

[19] We also consider adding forecast revisions in the month before and after (ie months t-1 and t+1) and find similarly stronger effect of earnings forecast revisions of high following firms on stock returns.

[20] In the un-reported results, we also add the interaction terms of forecast revisions and the dispersion measures for low and medium analyst firms and firm k itself. The results are qualitatively identical.

earnings forecasts of high-analyst firms contain more information for industry peers than those of low-analyst firms, and the information content decreases with the uncertainty in the forecast revisions.

IV.G Stock Returns and Revisions in Earnings Forecasts of Bellwether Stocks

In the previous sub-section, we found that the average revision in forecasted earnings of a portfolio of firms in the highest analyst coverage thirtile affects the returns on other less-followed firms in the same industry, controlling for the revision in the firm's own earnings forecast. An alternative approach is to see whether earnings forecast of individual firms with intense coverage affect the returns of peer firms. To do this, we choose the top three firms within each industry with the highest analyst following and are biggest in terms of market capitalization, which represents our bellwether firms. If information produced on these bellwether firms causes an increase in comovement in returns with other firms, we should observe revision in their forecasted earnings to affect other firms as well. Empirically, we replace the portfolio level forecast revision in equation (12) with the monthly revision in forecasted earnings of the bellwether firms ($FR_{BW,t}$):

$$r_{k,t} = a_0 + a_1 FR_{BW,t} + b_1\, FR_{k,t} + c_1 r_{m,t} + c_2\, r_{k,t-1} + c_3\, r_{k,t-2,t-7} + c_4 \ln(SIZE_{k,t}) + c_5 \ln(BM_{k,t}) + c_6\, TURNOVER_{k,t} + e_{k,t} \quad . \tag{13}$$

The estimated equation (13) presented in Table 8, shows that FR_{BW} affects the returns on all other firms in the industry. The effect of FR_{BW} on returns on other stocks is significant even for the firms that belong to the high coverage thirtile. Similar to our findings in the previous section, monthly returns on firms in the low coverage group demonstrate the biggest reaction to FR_{BW}, even comparable with the firm's own forecast revisions.

Similarly, we compute the standard deviation of forecast revisions for firms in the bellwether group, for each industry and each month t, denoted as $DISP_{BW,t}$, and add the interaction term of $FR_{BW,t}$ and $DISP_{BW,t}$ in equation (13). The results are presented in Table 9, which shows that a decrease in the dispersion of forecasted revisions among these intensely followed firms significantly increases its impact on stock returns. For example, when the forecast dispersion reaches close to zero (almost certainty in the aggregate earnings information for bellwether firms), the impact of a one percent increase in forecasted earnings of the bellwether firms drives prices of firms with low coverage firms higher by about 1.5 percents (compared to the unconditional effect of 1.2 percents in Table 8). Again, the point estimate of the relation between individual stock returns and earnings forecast revisions is higher for the low coverage firms. Overall, our evidence is consistent with the notion that analysts concentrate their coverage to a small subset of firms, and investors use the information generated to price other securities in the industry, and hence, causing greater return comovement.

IV.H An Event Study of Revisions in Earnings Forecasts of Bellwether Stocks

In the previous sub-section, we found that the revisions in earnings forecasts of individual firms with highest analyst coverage are associated with the returns of peer firms in the industry. We measured the revision in earnings forecasts as the monthly change in consensus earnings forecasts and related it to the monthly stock return. The monthly change in consensus earnings forecasts is due to the revisions in earnings forecasts by individual analysts throughout the whole month. Thus a more direct inference could be made from an event study about the information content of forecast revisions by individual analysts. The event study also helps to address the potential concern about the direction of causality between revisions of earnings forecasts and stock price changes which is difficult to infer from the findings in the previous sub-section. Specifically, we examine the returns of industry peers within a short window around the individual analysts' revisions of earnings forecasts in bellwether firms. Similarly as in the previous sub-section, we define the bellwether firms as the top one firm with the highest analyst following and among the top thirtile in terms of market capitalization in each industry.[21]

Table 10 presents the average cumulative abnormal return (CAR) of zero or low analyst firms in response to the analyst forecast revisions of bellwether firms in the same industry.[22] Following Gleason and Lee (2003), we measure CAR as either ret in excess of value-weighted market return or ret in excess of value-weighted return of corresponding

[21] We focus on the revisions of earnings forecast for the top one firm in the industry with the highest analyst coverage to increase the testing power. However, the results are similar, albeit a bit weaker than those reported, if we choose top three firms with highest analyst coverage as the bellwether firms.

[22] In order to mitigate the potential bias induced by contaminating events, we apply the following filters: 1) forecast revisions within the (-1, +1) window around the quarterly earnings announcements of bellwether firms are excluded; and 2) stock returns of other firms in the industry within the (-1, +1) window of the firms' own quarterly earnings announcement and revisions of analyst earnings forecasts are also excluded. We focus only on the response of zero or low analyst firms to the earnings forecast revisions of bellwether firms based on two considerations. First, the potential effect of contaminating events should be relatively small for zero or low analyst firms. And second, the spillover of information contained in bellwether firms' forecast revisions should be especially relevant for zero or low analyst firms due to the lack of analyst coverage. However, we also find significant CARs of medium or high analyst firms around the forecast revisions of bellwether firms in the same industry.

size deciles over the (-1, +1) window surrounding the forecast revision.[23] It is interesting to notice that analysts tend to revise the earnings forecasts downward more frequently and more significantly, as is reflected in bigger number of observations and magnitude of revisions, FR_{BW}. Further, these revisions actually carry value-relevant information for the underlying firms. Average CAR is highly significant for both positive and negative forecast revisions, whether it is measured as market-adjusted or size-adjusted return. Most importantly, revisions of earnings forecasts in bellwether firms are also value-relevant for zero or low analyst firms in the same industry. For zero (low) analyst firms, the average 3-day size-adjusted CAR is 4.2 (4.6) basis points for positive revisions and -9.9 (-8.1) basis points for negative revisions. Overall, the results suggest that analysts' revisions of earnings forecasts in bellwether firms are value-relevant for not only the bellwether firms themselves but other firms in the same industry also.

A potential criticism about the inference made above is that the revisions of earnings forecasts in the so-called bellwether firms may not carry more value-relevant information for other firms in the industry than revisions in non-bellwether firms. Adding to that, even if revisions in bellwether firms do affect other firms in the industry more significantly compared with non-bellwether firms, it may be due to the superior forecasting ability of analysts following bellwether firms rather than the fundamentals of bellwether firms. To address these two concerns, we compare the information contents of revisions of earnings forecasts in bellwether firms versus the revisions in non-bellwether firms, controlling the difference in analysts' forecasting ability. Specifically, we compare the CARs of other firms in the industry in response to the forecast revisions in bellwether

[23] Alternative definitions of CAR, such as measuring expected return from market model and lengthening the event window to (-2, +2), give similar results.

firms versus low or medium analyst firms by those analysts covering both sets of firms.[24] We get rid of the concern of different forecasting capabilities by studying only forecast revisions of analysts covering both bellwether firms and low or medium analyst firms in an industry. First, we calculate the average CARs of zero analyst firms and low analyst firms respectively associated with each revision events, where CAR is defined as 3-day cumulative size-adjusted return or market-adjusted return as above. Second, we average the CARs associated with an analyst's positive (or negative) revisions of earnings forecasts in bellwether firms and non-bellwether firms respectively for each analyst. Finally, we obtained the average CARs associated with positive (or negative) revisions of earnings forecasts in bellwether firms and non-bellwether firms respectively across analysts.

The comparison results reported in Table 11 indicate that revisions of earnings forecasts in bellwether firms have more significant value implication for other firms in the industry relative to the revisions in low or medium analyst firms. For both positive and negative revisions in earnings forecasts, though the revisions are on average of smaller magnitude in bellwether firms, they are associated with more economically and statistically significant CARs of zero or low analyst firms in the same industry. Taking the negative forecast revisions for example, the size-adjusted CAR of zero (low) analyst firms is 7.6 (14.1) basis points lower in response to the revisions in bellwether firms compared with CARs associated with the revisions in non-bellwether firms. The differences in CARs in response to revisions in bellwether firms versus non-bellwether

[24] We drop high-analyst, non-bellwether firms in the comparison due to their similarity to bellwether firms. The choice of bellwether firms in our empirical tests is only for practical consideration and follows the general principle that investors may use their information to price other less-followed firms.

firms are all statistically significant except for CAR of low analyst firms associated with positive revisions. To conclude, the event study results indicate that analysts' revisions of earnings forecasts in bellwether firms carry much more value-relevant information for other firms in the industry compared with the revisions in non-bellwether firms, which is not caused by the superior forecasting capability of analysts following bellwether firms.

V. CONCLUSION

This paper explores how stock markets process information, and shows that information flows more directly into the prices of some stocks than others. Informed investors can 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. Consistent with this and the evidence Bhushan (1989) and others, we find that indeed more analysts following larger and more actively traded firms.

But we also observe more analysts following firms whose fundamentals correlate more strongly with those of other firms. This is consistent with information about a firm being more valuable if it can be used to value other firms as well, and suggests that investors use information about some firms not just to trade that firm's stock, but also to value and trade other firms as well. Consistent with this, the stock returns of firms followed by many analysts contribute to the synchronicity of stock returns, even after controlling for fundamentals correlations (see also Piotroski and Roulstone (2004) and Chan and Hameed (2006)). This higher comovement associated with the number of analyst following a stock thus reflects rational information intermediation. Expectedly, this effect attenuates where more firms are directly followed by information intermediaries. We also find that information contained in the forecasted earnings of firms with intense coverage diffuses to the prices of other firms with lower or zero coverage, especially when there is greater certainty (lower dispersion) in the earnings forecasts. We report robust empirical evidence consistent with these propositions using US data from 1984 to 2007.

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 co-movement 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.

While a behavioral basis for co-movement (Barberis, Shleifer and Wurgler, 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.

References:

Admati, Anat R., and Paul Pfleiderer, 1990, "Direct and indirect sale of information," *Econometrica*, Vol. 58, 910-928.

Alford, Andrew W., and Philip G. Berger, 1999, "A simultaneous equations analysis of forecast accuracy, analyst following and trading volume," *Journal of Accounting, Auditing and Finance*, Vol. 14, 219-240.

Barberis, Nicholas, Andrei Shleifer, Jeffery Wurgler, 2005, "Comovement," *Journal of Financial Economics*, Vol. 75, 283-317.

Brennan, Michael J., and Patricia J. Hughes, 1991, "Stock prices and the supply of information," *Journal of Finance*, Vol. 46, 1665-1691.

Bhushan, Ravi, 1989, "Firm characteristics and analyst following," *Journal of Accounting and Economics*, Vol. 11, 255 - 274.

Bushman, Robert M., Joseph D. Piotroski, and Abbie J. Smith, 2005, "Insider trading restrictions and analysts' incentives to follow firms," *Journal of Finance*, Vol. 60, 35-66.

Brown, Lawrence D., Robert L. Hagerman, Paul A. Griffin, and Mark E. Zmijewski, 1987, "Security analyst superiority relative to univariate time series models in forecasting quarterly earnings," *Journal of Accounting and Economics*, Vol. 9, 61–87.

Campbell, John Y., Martin Lettau, Burton G. Malkiel, and Yexiao Xu, "Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk," *Journal of Finance*, Vol. 56, 1-43.

Chan, Kalok and Allaudeen Hameed, 2006, "Stock price synchronicity and analyst coverage in emerging markets," *Journal of Financial Economics*, Vol. 80, 115-147.

Diamond, Douglas W. and Robert E. Verrecchia, 1981, "Information aggregation in a noisy rational expectations economy," *Journal of Financial Economics*, Vol. 9, 221–235.

Durnev, Artyom, Randall Morck, and Bernard Yeung, 2004, "Value enhancing capital budgeting and firm-specific stock returns variation," *Journal of Finance*, Vol. 59, 65 – 105.

Foster, George, 1981, "Intra-industry information transfers associated with earnings releases," *Journal of Accounting and Economics*, Vol. 3, 201-232.

Frankel, Richard, S. P. Kothari, and Joseph Weber, 2006, "Determinants of the informativeness of analyst research," *Journal of Accounting and Economics*, Vol. 41, 29-54.

Greenwood, Robin, 2008, "Excess comovement of stock returns: evidence from cross-sectional variation in Nikkei 225 weights," *Review of Financial Studies,* forthcoming.

Grossman, Sanford and Joseph Stiglitz, 1980, "On the impossibility of informationally efficient markets," *American Economic Review*, Vol. 70, 393-408.

Han, Jerry C. Y., and John J. Wild, 1990, "Unexpected earnings and intra-industry information transfers: further evidence," *Journal of Accounting Research*, Vol. 28, 211–219.

Jin, Li and Stewart Myers, 2006, "R-squared around the world: new theory and new tests," *Journal of Financial Economics*, Vol. 79, 257-292.

Lang, Mark H., and Russell J. Lundholm, 1996, "Corporate disclosure policy and analyst behavior," *The Accounting Review*, Vol. 71, 467-492.

Merton, Robert C., 1987, "A simple model of capital market equilibrium with incomplete information," *Journal of Finance*, Vol. 42, 483-510.

Morck, Randall, Bernard Yeung, and Wayne Yu, 2000, "The information content of stock markets: why do emerging markets have synchronous stock price movements?" *Journal of Financial Economics*, Vol. 59, 215-260.

Petersen, Mitchell A., 2007, "Estimating standard errors in finance panel data sets: comparing approaches," *Review of Financial Studies*, forthcoming.

Piotroski, Joseph D., and Darren T Roulstone, 2004, "The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices," *The Account Review*, Vol. 79, 1119-1151.

Ramnath, Sundaresh, 2002, "Investor and analyst reactions to earnings announcements of related firms: an empirical analysis," *Journal of Accounting Research*, Vol. 40, 1351-1376.

Roll, Richard, 1988, "R^2", *Journal of Finance*, Vol. 43, 541-566.

Shleifer, Andrei, and Robert W. Vishny, 1997, "The limits of arbitrage," *Journal of Finance*, Vol. 52, 35-55.

Veldkamp, Laura L., 2005, "Slow boom, sudden crash," *Journal of Economic Theory*, Vol. 124, 230-257.

Veldkamp, Laura L., 2006a, "Information markets and the comovement of asset prices," *Review of Economic Studies*, Vol. 73, 823-845.

Veldkamp, Laura L., 2006b, "Media frenzies in markets for financial information," *American Economic Review*, Vol. 96, 577-601.

Figure 1: Stocks returns and earnings forecast revisions of bellwether firms: event study

This figure plots the average cumulative abnormal return (*CAR*) of zero or low analyst firms in the same industry around the window (-1, +20) surrounding the analyst forecast revisions of bellwether firms. Abnormal return is defined as either ret in excess of value-weighted market return or ret in excess of value-weighted return of corresponding size deciles, which is expressed in basis points. CAR_0_POSFR (CAR_0_NEGFR) is the average *CAR* of zero analyst firms associated with the positive (negative) analyst forecast revisions of bellwether firms, and CAR_1_POSFR (CAR_1_NEGFR) is the average *CAR* of low analyst firms associated with the positive (negative) analyst forecast revisions of bellwether firms.

Figure 1.A Size-adjusted CAR

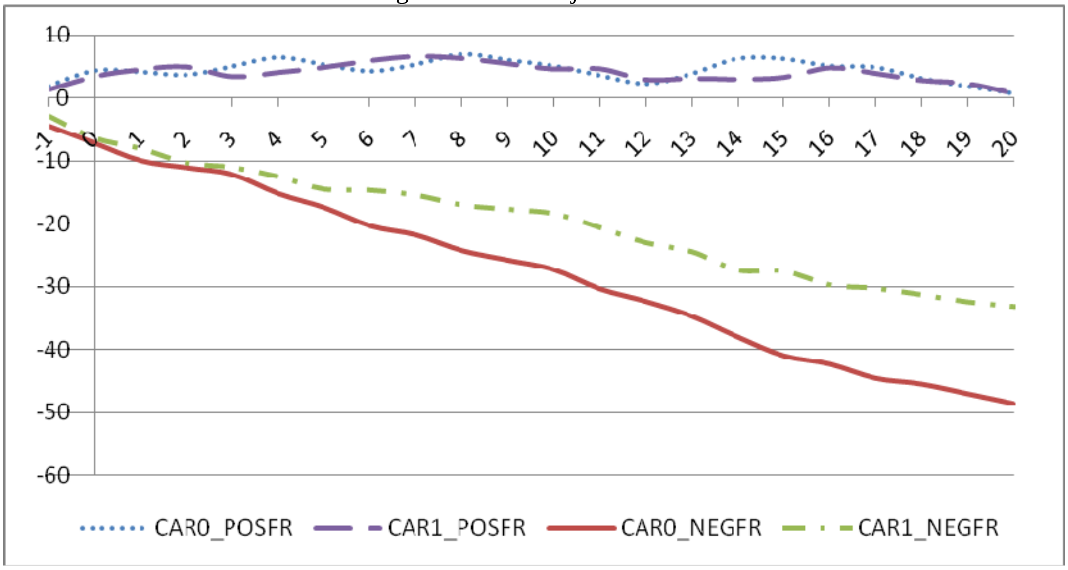

Figure 1.B Market-adjusted CAR

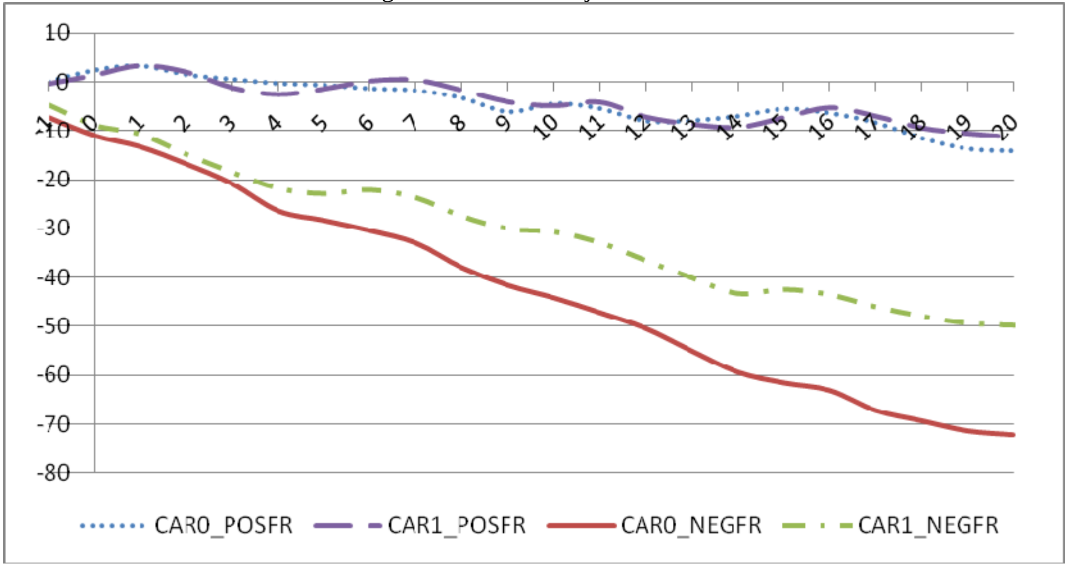

Table 1: Number of firms in the sample

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 IBES. The final sample consists of firms in CRSP-COMPUSTAT merged sample in which firms not covered by IBES are treated as firms with zero analyst coverage.

Year	CRSP sample	CRSP, COMPUSTAT merged Sample	CRSP, COMPUSTAT and IBES merged sample
1984	6968	3207	2220
1985	7099	3058	2292
1986	7544	3110	2366
1987	7896	3251	2508
1988	7865	2963	2309
1989	7613	3085	2444
1990	7411	3108	2477
1991	7430	2730	2183
1992	7760	3161	2488
1993	8262	3692	2931
1994	8837	4185	3267
1995	9243	4150	3301
1996	9821	4536	3678
1997	10080	4760	3998
1998	9984	4655	3887
1999	9690	4068	3390
2000	9362	4180	3314
2001	8678	3541	2821
2002	7945	3450	2750
2003	7507	3062	2443
2004	7347	3434	2762
2005	7365	3452	2808
2006	7431	3377	2763
2007	7677	3319	2728
Total number of firm-years	196815	85534	68128
Total number of firms	22872	12231	10198

Table 2: Summary Statistics

This table presents the summary statistics of the firm specific variables. $PCORR_k$ 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:

$$r_{iw} = a_i + b_i r^k_{Mw} + c_i r^k_{Iw} + e_{iw}, \quad (1)$$

where r_{iw} is the return on firm *i* in week w, and r^k_{Mw} and r^k_{Iw} 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:

$$r_{iw} = a_i + b_i r^k_{Mw} + c_i r^k_{Iw} + d_i r_{kw} + e_{iw}. \quad (2)$$

The r-squares from equations (1) and (2) are denoted as $R^2_{i,excl.k}$ and $R^2_{i,incl.k}$ respectively. The partial correlation of firm k with each other firm *i* [$PCORR_{k,i} = (\frac{R^2_{i,incl.k} - R^2_{i,excl.k}}{1 - R^2_{i,excl.k}})$] is averaged across all firms in the industry. 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* in the 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 thirtiles based on analyst following each year within each industry. Group zero refers to stocks with zero coverage while groups 1 to 3 have increasing coverage. T-statistics of the tests for the null hypothesis of equality for high and low (or zero) analyst coverage groups are provided in the last two columns. Panel C presents the Pearson and Spearman (reported in lower-left bloc in *Italic*) correlation coefficients.

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	40.599	27.402
$PCORR\_ROA_k$ (%)	10.720	11.013	11.119	10.669	-0.759	-5.916
$SIZE_k$ ($billion)	0.316	0.265	0.738	6.357	43.639	44.140
$TURNOVER_k$ (%)	0.313	0.474	0.606	0.676	41.014	28.142
$HERF\_SALES_k$	0.827	0.848	0.829	0.768	-20.078	-30.692
$STDRET_k$ (%)	5.306	6.077	5.890	5.240	-2.453	-32.526

Panel C: Correlation coefficients

Variable	*PCORR*$_k$	*ANALYST*$_k$	*PCORR_ROA*$_k$	*SIZE*$_k$	*TURNOVER*$_k$	*HERF_SALES*$_k$	*STDRET*$_k$
PCORR$_k$(%)		0.161***	0.025***	0.068***	0.112***	-0.012***	0.069***
ANALYST$_k$	*0.184****		-0.009**	0.339***	0.142***	-0.134***	-0.072***
PCORR_ROA$_k$(%)	*0.014****	*0.014****		-0.035***	-0.041***	0.109***	-0.073***
SIZE$_k$($billion)	*0.219****	*0.750****	*-0.056****		0.005	-0.130***	-0.077***
TURNOVER$_k$ (%)	*0.173****	*0.390****	*-0.038****	*0.305****		0.098***	0.408***
HERF_SALES$_k$	*-0.018****	*-0.105****	*0.126****	*-0.266****	*0.129****		0.194***
STDRET$_k$(%)	*0.052****	*-0.027****	*-0.030****	*-0.154****	*0.517****	*0.235****	

*, **, and *** indicate that the coefficient is statistically significant at 10%, 5% and 1% level respectively.

Table 3: Determinants of analyst coverage

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

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. Robust *t-test* statistics (based on standard errors clustered by firm and year) are provided below in *Italic*.

	Sample Period				
Indep. Var.	1984 - 2007	1984 - 1989	1990 - 1995	1996 - 2001	2002 - 2007
Intercept	1.399	2.500	1.920	1.406	1.113
	13.661	*15.400*	*17.256*	*8.369*	*7.170*
$LPCORR\_ROA_{k,t}$	0.048	0.025	0.027	0.054	0.055
	4.303	*2.075*	*1.319*	*4.521*	*2.971*
$ln(SIZE_{k,t})$	0.494	0.575	0.491	0.450	0.459
	39.077	*36.715*	*74.788*	*77.357*	*42.404*
$TURNOVER_{k,t}$	0.114	0.620	0.356	0.134	0.070
	2.854	*12.089*	*14.982*	*2.734*	*1.714*
$HERF\_SALES_{k,t}$	0.264	0.271	0.328	0.233	0.214
	7.448	*3.963*	*7.080*	*4.937*	*4.199*
$ln(STDRET_{k,t})$	0.231	0.075	0.094	0.205	0.337
	6.591	*1.314*	*2.272*	*4.849*	*7.596*
Adj. Rsq	0.631	0.700	0.674	0.624	0.600

Table 4: Return co-movement and analyst coverage

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

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. Robust *t-test* statistics (based on standard errors clustered by firm and year) are provided below in *Italic*.

	Sample Period				
Indep. Var.	1984 - 2007	1984 - 1989	1990 - 1995	1996 - 2001	2002 - 2007
Intercept	-3.431	-3.532	-3.833	-3.499	-3.261
	-16.571	*-11.996*	*-12.450*	*-21.347*	*-25.100*
$ln(1+ANALYST_{k,t})$	0.020	0.012	0.021	0.029	0.037
	5.307	*2.179*	*6.214*	*3.771*	*9.823*
$LPCORR\_ROA_{k,t}$	0.023	0.008	0.007	0.029	0.049
	3.534	*3.260*	*0.719*	*2.941*	*5.932*
$ln(SIZE_{k,t})$	0.021	0.008	0.019	0.015	0.030
	6.399	*1.174*	*6.015*	*3.216*	*5.498*
$TURNOVER_{k,t}$	0.023	0.034	0.012	0.029	0.011
	3.068	*3.280*	*1.707*	*10.042*	*2.122*
$HERF\_SALES_{k,t}$	0.043	0.042	0.044	0.033	0.038
	4.879	*3.366*	*3.173*	*2.247*	*2.203*
$ln(STDRET_{k,t})$	0.025	-0.012	0.029	0.026	0.027
	3.206	*-1.032*	*2.765*	*2.836*	*2.923*
Adj. Rsq	0.169	0.170	0.128	0.204	0.193

Table 5: Return co-movement, analyst coverage and concentration

$$LPCORR_{k,t} = a_0 + a_1 \ln(1+ANALYST_{k,t}) + b_1 \ln(1+ANALYST_{k,t}) * HERF\_ANALYST_{I,t} + a_2 LPCORR\_ROA_{k,t}$$

$$+a_3 \ln(SIZE_{k,t}) + a_4 TURNOVER_{k,t} + a_5 \ln(HERF\_SALE_{k,t}) + a_6 \ln(STDRET_{k,t}) + \sum_{I=1}^{68} d_I INDDUM_{I,t} + \sum_{y=1984}^{2006} c_y YEARDUM_y + e_{k,t}$$

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. Robust *t-test* statistics (based on standard errors clustered by firm and year) are provided below in *Italic*.

	Sample Period				
Indep. Var.	1984 - 2007	1984 - 1989	1990 - 1995	1996 - 2001	2002 - 2007
Intercept	-3.536	-3.757	-4.007	-3.827	-3.239
	-8.733	*-57.531*	*-47.723*	*-69.855*	*-64.580*
$\ln(1+ANALYST_{k,t})$	0.028	0.022	0.032	0.038	0.043
	5.954	*3.530*	*4.472*	*4.389*	*8.476*
$\ln(1+ANALYST_{k,t})*$ $HERF\_ANALYST_{I,t}$	0.323	0.308	0.424	0.521	0.211
	4.307	*4.167*	*2.982*	*4.007*	*1.191*
$LPCORR\_ROA_{k,t}$	0.023	0.007	0.018	0.034	0.036
	4.966	*5.071*	*2.364*	*3.503*	*4.276*
$\ln(SIZE_{k,t})$	0.019	0.006	0.017	0.016	0.028
	6.016	*0.837*	*5.190*	*3.630*	*4.747*
$TURNOVER_{k,t}$	0.023	0.028	0.014	0.029	0.012
	3.121	*3.029*	*1.810*	*9.112*	*2.252*
$HERF\_SALES_{k,t}$	0.044	0.037	0.046	0.031	0.044
	5.338	*2.845*	*3.364*	*2.562*	*2.849*
$\ln(STDRET_{k,t})$	0.026	-0.007	0.028	0.032	0.025
	3.145	*-0.624*	*2.936*	*3.239*	*1.585*
Adj. Rsq	0.180	0.186	0.120	0.212	0.205

Table 6: Stocks returns and earnings forecast revisions

$$R_{k,t} = a_0 + \sum_{j=1}^{3} a_j \, FR_{j,t} + b_1 \, FR_{k,t} + c_1 \, R_{m,t} + c_2 \, R_{k,t-1} + c_3 \, R_{k,t-2,t-7} + c_4 \ln(SIZE_{k,t}) + c_5 \ln(BM_{k,t}) + c_6 \, TURNOVER_{k,t} + e_{k,t}$$

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; $FR_{j,t}$ is the value-weighted average of revisions in earnings forecasts for firms in analyst thirtile 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 based on analyst coverage. Robust *t-test* statistics (based on standard errors clustered by industry and year) are provided in *Italic*.

	Analyst Coverage Groups				
Independent Variables	*Zero Coverage*	*Low Coverage*	*Medium Coverage*	*High Coverage*	*All Firms*
Intercept	0.204	0.778	2.043	1.706	0.311
	0.460	*1.518*	*3.767*	*3.067*	*0.689*
$FR_{1(low)}$	0.422	0.321	-0.006	-0.085	0.134
	2.538	*2.260*	*-0.070*	*-0.823*	*1.458*
$FR_{2(medium)}$	1.552	0.867	0.303	0.169	0.626
	5.513	*2.041*	*1.050*	*0.514*	*2.006*
$FR_{3(high)}$	0.821	1.508	1.337	0.810	1.086
	3.453	*4.253*	*4.109*	*3.323*	*4.687*
FR_k		1.247	2.046	2.095	1.641
		7.752	*7.846*	*4.453*	*7.610*
$R_{m,t}$	0.750	1.012	1.122	1.135	1.025
	8.019	*12.362*	*12.729*	*15.350*	*12.862*
$R_{k,t-1}$	0.002	-0.007	-0.014	-0.022	-0.010
	0.279	*-0.771*	*-1.715*	*-3.025*	*-1.657*
$R_{k,t-2,t-7}$	0.005	0.000	-0.001	-0.002	0.000
	1.545	*0.130*	*-0.353*	*-0.598*	*0.047*
$ln(SIZE_k)$	0.063	-0.076	-0.265	-0.168	0.022
	1.287	*-0.949*	*-3.691*	*-3.102*	*0.517*
$ln(BM_{k,})$	0.448	0.240	0.137	0.214	0.249
	6.278	*3.023*	*1.639*	*2.737*	*3.521*
$TURNOVER_k$	-0.143	-0.117	0.067	0.085	0.042
	-0.981	*-0.591*	*0.498*	*0.474*	*0.291*
Adj. Rsq (%)	6.270	10.820	15.040	18.410	12.520

Table 7: Stocks returns, earnings forecast revisions, and dispersion in revisions

$$R_{k,t} = a_0 + \sum_{j=1}^{3} a_j\, FR_{j,t} + b_1\, FR_{3,t} * DISP_{3,t} + c_1\, FR_{k,t} + c_2\, R_{m,t} + c_3\, R_{k,t-1} + c_4\, R_{k,t-2,t-7} + c_5 \ln(SIZE_{k,t})$$

$$+ c_6 \ln(BM_{k,t}) + c_7\, TURNOVER_{k,t} + e_{k,t}$$

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; $FR_{j,t}$ is the value-weighted average of revisions in earnings forecasts for firms in analyst thirtile j (within the same industry); *DISP* is the standard deviation of revision in earnings forecast among analysts; $R_{m,t}$ 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. Robust *t-test* statistics (based on standard errors clustered by industry and year) are provided in *Italic*.

	Analyst Coverage Groups				
Independent Variables	*Zero*	*Low*	*Medium*	*High*	*All*
Intercept	0.214	0.869	2.146	1.777	0.347
	0.484	*1.703*	*4.013*	*3.171*	*0.770*
$FR_{1(low)}$	0.399	0.296	-0.023	-0.103	0.111
	2.444	*2.127*	*-0.242*	*-0.982*	*1.194*
$FR_{2(medium)}$	1.521	0.906	0.336	0.158	0.624
	5.425	*2.466*	*1.399*	*0.509*	*2.229*
$FR_{3(high)}$	1.564	2.621	2.294	1.485	1.896
	6.494	*4.665*	*4.229*	*3.983*	*4.666*
FR_3*DISP_3	-0.797	-1.306	-1.210	-0.701	-0.912
	-4.157	*-4.209*	*-3.259*	*-3.232*	*-3.643*
FR_k		1.252	2.047	2.089	1.642
		7.786	*7.869*	*4.442*	*7.593*
$R_{m,t}$	0.751	1.012	1.123	1.135	1.026
	7.971	*12.326*	*12.689*	*15.369*	*12.830*
$R_{k,t-1}$	0.002	-0.007	-0.013	-0.022	-0.010
	0.271	*-0.766*	*-1.681*	*-3.062*	*-1.659*
$R_{k,t-2,t-7}$	0.005	0.000	-0.001	-0.002	0.000
	1.536	*0.102*	*-0.416*	*-0.633*	*-0.018*
$ln(SIZE_k)$	0.063	-0.087	-0.275	-0.174	0.020
	1.320	*-1.106*	*-3.895*	*-3.181*	*0.478*
$ln(BM_{k,})$	0.444	0.240	0.141	0.220	0.250
	6.362	*3.035*	*1.694*	*2.792*	*3.537*
$TURNOVER_k$	-0.149	-0.129	0.059	0.081	0.036
	-1.006	*-0.648*	*0.440*	*0.451*	*0.251*
Adj. Rsq (%)	6.282	10.830	15.050	18.440	12.540

Table 8: Stocks returns and earnings forecast revisions of bellwether firms

$$R_{k,t} = a_0 + a_1 FR_{BW,t} + b_1\ FR_{k,t} + c_1\ R_{m,t} + c_2\ R_{k,t-1} + c_3 R_{k,t-2,t-7} + c_4 \ln(SIZE_{k,t}) + c_5 \ln(BM_{k,t}) + c_6\ TURNOVER_{k,t} + e_{k,t}$$

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; $FR_{BW,t}$ is the revisions in earnings forecasts for the top three firms with the largest analyst coverage (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. The equation is estimated for all firms and separately for each group of firms based on analyst coverage. Robust *t-test* statistics (based on standard errors clustered by industry and year) are provided in *Italic*.

	Analyst Coverage Groups				
Independent Variables	*Zero Coverage*	*Low Coverage*	*Medium Coverage*	*High Coverage*	*All Firms*
Intercept	-0.155	0.479	1.950	1.955	0.175
	-0.343	*0.935*	*3.491*	*3.753*	*0.392*
FR_{BW}	0.726	1.175	0.829	0.726	0.857
	3.812	*5.833*	*3.540*	*2.880*	*4.208*
FR_k		1.270	2.062	2.045	1.643
		7.821	*7.945*	*4.296*	*7.754*
$R_{m,t}$	0.755	1.015	1.126	1.153	1.027
	7.959	*12.283*	*12.762*	*14.445*	*12.471*
$R_{k,t-1}$	0.004	-0.006	-0.013	-0.022	-0.009
	0.485	*-0.680*	*-1.664*	*-2.997*	*-1.522*
$R_{k,t-2,t-7}$	0.005	0.000	-0.001	-0.002	0.000
	1.609	*0.109*	*-0.410*	*-0.659*	*0.075*
$ln(SIZE_k)$	0.098	-0.040	-0.256	-0.208	0.032
	1.876	*-0.506*	*-3.489*	*-3.337*	*0.704*
$ln(BM_{k,})$	0.466	0.230	0.123	0.211	0.245
	6.073	*2.899*	*1.440*	*2.379*	*3.308*
$TURNOVER_k$	-0.157	-0.112	0.072	0.061	0.028
	-1.054	*-0.570*	*0.535*	*0.370*	*0.199*
Adj. Rsq (%)	6.144	10.740	15.040	17.940	12.220

Table 9: Stocks returns, earnings forecast revisions of bellwether firms, and dispersion in revisions

$$R_{k,t} = a_0 + a_1 FR_{BW,t} + a_2 FR_{BW,t} * DISP_{BW,t} + c_1\ FR_{k,t} + c_2\ R_{m,t} + c_3\ R_{k,t-1} + c_4\ R_{k,t-2,t-7} + c_5 \ln(SIZE_{k,t})$$
$$+c_6 \ln(BM_{k,t}) + c_7\ TURNOVER_{k,t} + e_{k,t}$$

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; $FR_{BW,t}$ is the revisions in earnings forecasts for the top three firms with the largest analyst coverage (within the same industry); *DISP* is the standard deviation of revision in earnings forecast among analysts; $R_{m,t}$ 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. Robust *t-test* statistics (based on standard errors clustered by industry and year) are provided in *Italic*.

	Analyst Coverage Groups				
Independent Variables	*Zero Coverage*	*Low Coverage*	*Medium Coverage*	*High Coverage*	*All Firms*
Intercept	-0.129	0.516	2.004	2.017	0.207
	-0.288	*1.026*	*3.638*	*3.983*	*0.469*
FR_{BW}	1.101	1.533	1.253	1.264	1.270
	6.176	*6.571*	*4.157*	*4.788*	*5.855*
$FR_{BW}*DISP_{BW}$	-0.160	-0.154	-0.182	-0.234	-0.179
	-4.219	*-2.306*	*-3.021*	*-3.486*	*-3.652*
FR_k		1.269	2.059	2.038	1.640
		7.796	*7.925*	*4.273*	*7.718*
$R_{m,t}$	0.755	1.014	1.126	1.153	1.027
	7.967	*12.281*	*12.764*	*14.456*	*12.474*
$R_{k,t-1}$	0.004	-0.006	-0.014	-0.022	-0.010
	0.472	*-0.686*	*-1.679*	*-3.034*	*-1.542*
$R_{k,t-2,t-7}$	0.005	0.000	-0.001	-0.002	0.000
	1.603	*0.102*	*-0.423*	*-0.693*	*0.050*
$ln(SIZE_k)$	0.096	-0.044	-0.262	-0.213	0.030
	1.852	*-0.567*	*-3.604*	*-3.486*	*0.660*
$ln(BM_{k,})$	0.464	0.230	0.124	0.211	0.244
	6.011	*2.907*	*1.451*	*2.379*	*3.296*
$TURNOVER_k$	-0.157	-0.114	0.069	0.060	0.027
	-1.057	*-0.579*	*0.516*	*0.363*	*0.192*
Adj. Rsq (%)	6.156	10.750	15.050	17.960	12.230

Table 10: Stocks returns and earnings forecast revisions of bellwether firms: event study

This table presents the average cumulative abnormal return (*CAR*) of zero or low analyst firms in the same industry in response to the analyst forecast revisions of bellwether firms. *CAR* is defined as either ret in excess of value-weighted market return or ret in excess of value-weighted return of corresponding size deciles over the (-1, +1) window surrounding the forecast revision. FR_{BW} is the revisions in earnings forecasts for the firm with largest number of analysts coverage (within the same industry); CAR_{BW} is the 3-day cumulative abnormal return of bellwether firms; CAR_0 and CAR_1 are the 3-day cumulative abnormal returns of zero-analyst firms and low-analyst firms in the same industry respectively. All variables are expressed in basis points. The average value across forecast revision events and its T-statistics (in *Italic*) are reported.

	Positive Forecast Revisions (N = 23180)		Negative Forecast Revisions (N = 31611)	
	Market-adjusted Return	*Size-adjusted Return*	*Market-adjusted Return*	*Size-adjusted Return*
FR_{BW}	40.337		-68.815	
	79.772		*-77.328*	
CAR_{BW}	34.970	34.595	-30.073	-30.814
	15.574	*15.306*	*-14.053*	*-14.345*
CAR_0	3.160	4.172	-13.427	-9.947
	1.678	*2.232*	*-8.206*	*-6.180*
CAR_1	3.257	4.567	-10.750	-8.051
	2.277	*3.166*	*-8.833*	*-6.603*

Table 11: Stocks returns and earnings forecast revisions of bellwether firms: event study controlling analysts' forecasting capability

This table presents the average cumulative abnormal return (*CAR*) of zero or low analyst firms in the same industry in response to the analyst forecast revisions of bellwether firms and the analyst forecast revisions of low- or medium-analyst firms. *CAR* is defined as either ret in excess of value-weighted market return or ret in excess of value-weighted return of corresponding size deciles over the (-1, +1) window surrounding the forecast revision. Only forecast revisions of analysts covering both bellwether firms and low or medium analyst firms within an industry are used for event study. We first average the CARs associated with an analyst's positive (or negative) revisions of earnings forecasts of bellwether firms and non-bellwether firms respectively. Then we obtained the average CARs associated with positive (or negative) revisions of earnings forecasts of bellwether firms and non-bellwether firms across analysts. *FR* is the revisions in earnings forecasts; CAR_{FR} is the 3-day cumulative abnormal return of forecast revision firms; CAR_0 and CAR_1 are the 3-day cumulative abnormal returns of zero-analyst firms and low-analyst firms in the same industry respectively. All variables are expressed in basis points. The average value across forecast revision events and its T-statistics (in *Italic*) are reported.

	Positive Forecast Revisions			Negative Forecast Revisions		
	BW Firms	*Non-BW Firms*	*DIF (BW – Non-BW)*	*BW Firms*	*Non-BW Firms*	*DIF (BW – Non-BW)*
N. of analysts		9164			10272	
FR	40.045	92.191	-52.146	-59.727	-201.390	141.663
	26.681	*32.149*	*-16.111*	*-62.527*	*-36.467*	*25.276*
			Panel A: Size-adjusted CAR			
CAR_{FR}	80.008	121.901	-41.892	-105.176	-117.765	12.589
	21.373	*28.369*	*-7.351*	*-28.344*	*-29.848*	*2.324*
CAR_0	11.067	2.492	8.575	-12.850	-5.243	-7.607
	4.556	*1.162*	*2.647*	*-5.687*	*-2.673*	*-2.542*
CAR_1	5.104	3.195	1.910	-16.841	-2.748	-14.092
	2.677	*1.924*	*0.755*	*-10.187*	*-1.866*	*-6.365*
			Panel B: Market-adjusted CAR			
CAR_{FR}	81.545	117.478	-35.933	-104.254	-116.771	12.517
	21.820	*27.871*	*-6.379*	*-27.968*	*-30.012*	*2.323*
CAR_0	9.108	-0.346	9.454	-18.429	-6.933	-11.496
	3.691	*-0.159*	*2.873*	*-8.121*	*-3.526*	*-3.829*
CAR_1	2.946	1.092	1.855	-16.002	-4.886	-11.117
	1.540	*0.679*	*0.742*	*-9.891*	*-3.379*	*-5.124*