

Sell-side Analyst Research and Stock Comovement*

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Abstract

We document that analysts who cover a pair of stocks expect future earnings of the stocks to be more highly correlated than do analysts who cover only one of the stocks. Such coverage-based differences in analyst research impact stock prices in a variety of ways. Returns on a pair of stocks around a recommendation or a forecast are closer when the issuing analyst covers both stocks than only one stock in the pair. Stock returns around a recommendation revision covary with returns of other stocks that the issuing analyst covers. In general, daily return correlations between stocks in a pair increase with the intensity of shared analyst coverage. Moreover, a stock's daily returns are positively correlated with daily returns of other stocks that share analyst coverage with the stock. Collectively, our evidence indicates that shared analyst coverage is a channel for information spillovers that can raise return comovement among stocks by an economically meaningful amount.

Key Words: Analyst coverage, Return correlation, Comovement, Spillover.

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1. Introduction

Researchers are debating whether sell-side analysts primarily produce stock-specific or broad (market- or industry-wide) information. Piotroski and Roulstone (2004) and Chan and Hameed (2006) document that broad stock indices explain more of the returns of stocks with higher levels of analyst coverage, suggesting that analysts convey primarily broad information. In contrast, Liu (2011) finds that analyst recommendation revisions convey primarily stock-specific information. Based on cross-sectional evidence, Crawford, Roulstone, and So (2012) show that analysts convey primarily stock-specific (broad) information for stocks that are already covered (not covered) by other analysts.

We join the debate by documenting that analysts also convey coverage-specific information, i.e., information that emphasizes commonalities among stocks in their coverage. This information, which has been overlooked by prior literature, lies within a wide spectrum whose opposite extremes are marked by stock-specific and broad information.¹ Consider analysts who concurrently cover Oracle and SAP, stocks from the enterprise software segment of the computer software industry. The analysts can produce information that is simultaneously useful in evaluating both stocks by, for example, focusing on software investments of client firms or new software releases of competitors. This information is not specific to either Oracle or SAP, yet it is more focused than information on the computer software industry or the market. Similarly, analysts covering only large oil companies such as Exxon and Chevron can focus on shared issues relating to vertical integration, issues which are largely irrelevant for small oil companies.

There are also ample opportunities for analysts to produce valuable coverage-specific information when they cover stocks from multiple industries by, for example, emphasizing the linkages between the stocks. Analysts covering both original design manufacturers (e.g., Dell) and origi-

¹We have searched for explicit coverage-specific information in analyst reports for a small set of stocks in 2010. The reports frequently contain references to other stocks analysts cover. Consistent with Franco, Hope, and Larocque (2012), most of these references are about competitors, suppliers, and customers. While consistent with the use of coverage-specific information, this evidence is not conclusive since, in many cases, analysts who do not cover competitors, suppliers, or customers also mention these stocks. However, some references strongly suggest the use of coverage-specific information. In these instances, analysts refer to other firms they cover that are not competitors, customers, or suppliers. Moreover, only these analysts appear to find these stocks relevant since other analysts do not mention these stocks. Examples of such references include one report that uses metrics for SAP and Yahoo to justify the analyst's valuation of Apple; an analysis of business ties between Discovery Communications and Mattel to justify the latter's valuation; the use of metrics on H&R Block (tax services), Republic Services (waste management) and DigitalGlobe Inc (satellite imaging) to value Cintas Corp (industrial uniforms); metrics on Arch Coal (coal mining) and Ashland Inc (chemicals) to evaluate Vulcan Materials (construction materials).

nal equipment manufacturers (e.g., Asustek) that supply components may focus on the supply chain between these companies. Similarly, analysts covering stocks from different industries but with common economic exposure, e.g., manufacturing bases in China, can highlight the effect of this exposure.

We propose that analysts convey coverage-specific information because it can help achieve an optimal balance between research costs and brokerage revenues tied to investor demand for their research. Stock-specific research is costly because it requires an analyst to gather and process information unique to each stock. To lower research cost per stock, an analyst can use coverage-specific information rather than only stock-specific information. This substitution of coverage-specific for stock-specific information will make the analyst's research less informative for the stock that is the subject of the research (stock X), but more informative for other stocks the analyst covers. Consequently, investors interested in stock X will demand less of the analyst's research on stock X . However, this fall in demand will be mitigated because the price of the research on stock X will likely fall to reflect its lower cost. Moreover, the coverage-specific content of research on stock X will attract investors interested in other stocks the analyst covers, broadening demand for the research.² In equilibrium, the lower cost and price of coverage-specific research, together with this broadening of demand, can make coverage-specific research more profitable for the analyst. Consequently, an analyst will choose to convey information that is common to stocks he covers rather than only stock-specific information when coverage-specific research significantly lowers cost or increases aggregate investor demand. At the same time, the analyst has weak incentives to only emphasize commonalities among stocks outside his coverage since he is limited to spreading costs across the stocks he covers, and can expect to be rewarded primarily for the value of his research on this limited set of stocks (Groysberg, Healy, and Maber, 2011; Krigman, Shaw, and Womack, 2001; Jackson, 2005; Ljungqvist et al., 2007).

Coverage-specific information will be used by many investors who seek cheap information that is useful to evaluate other stocks (Veldkamp, 2006). Consequently, coverage-specific information will raise average investor expectations about shared economic exposures among stocks that an analyst covers. Investor responses to their changed expectations will, in turn, result in higher

²The argument about the broadening of the investor set in response to coverage-specific information is based on Veldkamp's (2006) argument about the complementarity in information demand across different assets.

return comovement than what covariance of stock fundamentals would predict, i.e., there will be coverage-specific spillovers.³ We refer to these predictions collectively as the *Coverage-Specific Spillover Hypothesis*.

We test the different predictions of this hypothesis using all stocks at the intersection of the *CRSP/Compustat* and *I/B/E/S* databases between years 1997 and 2010. To control for stocks' shared economic exposure, our tests either employ fixed stock pairs, focus on short-term returns surrounding analyst activity, or employ a comprehensive set of controls that include correlations between stocks' past cash flows and earnings, and similarities in size, growth options, leverage, performance, stock price levels, and shared industry, location, exchange, and S&P 500 index membership. This research design is necessary to draw causal inferences about coverage-specific spillovers since shared economic exposure can affect both analysts' coverage choices and return comovement (Kini et al., 2009; Hameed et al., 2012).

We first search for direct evidence of coverage-specific information in analyst research. For each stock pair in a year, we identify analysts who cover both stocks in the pair (hereafter, pair analysts) and those who cover only one stock in the pair (hereafter, individual analysts). We then compare the correlation between the earnings forecasts for a stock pair issued by pair analysts with the correlation between earnings forecasts issued by individual analysts for the same stock pair. Any difference in the forecast correlations from pair and individual analysts for the *same* pair of stocks must only be driven by differences in shared exposure estimates between these two sets of analysts—and not by the stocks' shared economic exposure. Since both forecast correlations for a stock pair are based on the same shared economic exposure, this comparison addresses concerns about reverse causality from shared economic exposure to analyst research (Hameed et al., 2012). We find that the within-stock pair correlation between the earnings forecasts from pair analysts are both meaningfully and statistically higher than those from individual analysts. This difference indicates a stronger emphasis on shared economic exposure by pair analysts, supporting the *Coverage-Specific Spillover Hypothesis*.

Our second set of tests examines short-term price responses to analyst activity (i.e., issuance of a recommendation or a forecast) for evidence of coverage-specific information. We compare

³Investor expectations of shared economic exposure result in comovement between stock returns (Merton, 1973).

how activity from pair and individual analysts for one stock in a pair (i.e., activity stock) affects the return on the other stock (i.e., no-activity stock). Since the price responses to activity from the two groups of analysts for the *same* stock pair will be based on the *same* fundamentals, this comparison addresses concerns about reverse causality from shared exposure to analyst research and investor responses (Hameed et al., 2012). We find that returns on the activity and no-activity stocks are closer in response to activity by pair analysts than activity by individual analysts. The economic and statistical significance of this difference suggests stronger information spillovers from activity by pair analysts, supporting the *Coverage-Specific Spillover Hypothesis*.

By decomposing stock returns around recommendation revisions (Liu, 2011), we find that coverage-specific information in analyst recommendations has a price impact comparable to that of broad market- and industry-related information in the recommendations. We also find that return correlations between the recommended stock and other stocks that share coverage by the analyst making the recommendation are significantly higher than return correlations between the recommended stock and other stocks that share coverage by *inactive* analysts. This finding links coverage-specific spillovers directly to analyst activity.

In our final set of tests, we examine how shared analyst coverage affects correlation between stocks' daily returns during a year. The effect of shared coverage is apparent at the stock-pair level: Stock pairs with higher shared coverage display greater return correlation even after we introduce an exhaustive set of controls for shared economic exposure between the stocks in a pair. In fact, daily return correlation of a stock pair is directly related to the estimates of shared exposure conveyed in the earnings forecasts of pair analysts even after we control for estimates of shared exposure conveyed in the earnings forecasts of individual analysts. Furthermore, a portfolio of stocks with which a stock shares analyst coverage is a significant determinant of the stock's daily returns, and this relation is incremental to the effect of industry- and market-returns. We find corroborating evidence in return synchronicity tests. Broad stock indices better explain daily stock returns of individual stocks that share more analyst coverage with other stocks. At the same time, the increased return synchronicity due to shared analyst coverage is more concentrated on portfolios of stocks that share more analyst coverage. These results hold even after we control for the effect of shared economic exposure as well as the level of analyst coverage on return synchronicity (Piotroski and Roulstone, 2004; Chan and Hameed, 2006).

Consistent with the *Coverage-Specific Spillover Hypothesis*, all our findings indicate that analyst research conveys coverage-specific information and this information spills over across stocks that share analyst coverage. The coverage-specific spillovers are apparent even after we control for shared economic exposure between the stocks. Our findings also support the existence of broad and stock-specific information in analyst research. However, they are inconsistent with analyst research *exclusively* conveying either of broad or stock-specific information, i.e., the absence of coverage-specific information in analyst research.

Our paper contributes to the literature on the information content of analyst research. Security analysts produce value-relevant information (Givoly and Lakonishok, 1979; Bhushan, 1989; Lys and Sohn, 1990; Brennan, Jegadeesh, and Swaminathan, 1993; Francis and Soffer, 1997; Frankel, Kothari, and Weber, 2006).⁴ Based on the ability of market- and industry-indices to explain a stock's returns (return synchronicity), Piotroski and Roulstone (2004) and Chan and Hameed (2006) find that analysts primarily produce market- and industry-specific information. In contrast, Liu (2011) shows that analysts primarily produce stock-specific information. Hameed et al. (2012) reconcile these two seemingly contradictory findings by showing that prices of stocks that are followed by more analysts are more accurate and that investors use these prices to infer the values of less-researched stocks. Consequently, returns on stocks with greater analyst following covary more strongly with market- and industry indices, giving the appearance that analysts primarily produce broad information. We propose and find evidence that analysts *also* produce information that focuses on commonalities among stocks they cover. This coverage-specific information is distinct from stock-specific or broad market and industry information discussed in the prior literature. Unlike spillovers of market- or industry-wide information, spillovers of coverage-specific information raises comovement only among stocks that share analyst coverage. Moreover, coverage-specific information spillovers, as measured by increases in return comovement, are of comparable magnitude to the effect of broad market or industry information in analyst research.

Our paper also contributes to the literature on stock return comovement. Prior studies show that return comovement between stocks in a pair is determined by similarities in size and book-

⁴Analysts also influence investments of portfolio managers (Walther, 1997; Falkenstein, 1996; Barber and Odean, 2008) and small investors (Malmendier and Shanthikumar, 2007; Mikhail, Walther, and Willis, 2007).

to-market ratio (Fama and French, 1993), cash flows (Chen, Chen, and Li, 2010), price level (Green and Hwang, 2009), retail investor trading behavior (Kumar and Lee, 2006), industry membership (Kallberg and Pasquariello, 2007), and stock index membership (Barberis, Shleifer, and Wurgler, 2005).⁵ Nevertheless, Chen, Chen, and Li (2010) show that these determinants cannot collectively explain a large portion of the variation in pair-wise daily return correlations. We propose and show that, even after controlling for the determinants of return correlation highlighted in this literature, the extent of shared analyst coverage can explain economically meaningful variation in pair-wise return correlations.

The remainder of the paper is organized as follows. Section 2 develops the *Coverage-Specific Spillover Hypothesis*. Section 3 describes the sample. Section 4 documents differences in the information content of earnings forecasts issued by pair and individual analysts. Section 5 documents the short-term price effects of activity by pair and individual analysts. Section 6 describes a battery of tests linking the level of shared analyst activity to daily return comovement. Section 7 provides concluding remarks. We provide detailed variable descriptions in the Appendix.

2. Coverage-specific spillover hypothesis

Veldkamp (2006) develops a rational expectations model to explain how investor demand matches with analysts' supply of information on different assets. The model demonstrates that, when information production is costly, analysts can lower the cost of their research, and thus its price, by producing information common to multiple assets. Investors demand such research since they acquire it at a lower price and since it is informative for multiple assets. In equilibrium, investors use research common to multiple assets more heavily than research specific to individual assets. Consequently, returns on assets comove more strongly than can be justified based on the covariance of their fundamentals alone.

We extend Veldkamp's arguments to account for an important institutional feature: Each analyst covers a limited number of stocks and is rewarded primarily for the value of his research

⁵Modern asset pricing theories (CAPM and Arbitrage Pricing Theory) build on the concept of covariance risk. Moreover, uncovering the determinants of return correlation among individual assets is of great interest to both practitioners and researchers working in the areas of portfolio management (Qian, Hua, and Sorensen, 2007), risk management (Jorion, 2007), asset price dynamics (Rosenberg and Schuermann, 2006; Brooks, Henry, and Persaud, 2002), and trading strategies (Gatev, Goetzmann, and Rowenhorst, 2006; Papadakis and Wysocki, 2008).

on these stocks.⁶ From a cost perspective, an analyst can lower research costs per stock by gathering and processing information relevant to multiple stocks in his coverage and spreading the research costs accordingly. Since each analyst is limited to spreading the costs across the stocks he covers, diversifying the scope of his research to stocks outside his coverage can yield few additional savings. From a revenue perspective, the analyst can fully capture increased investor demand by using coverage-specific information to widen the scope of his research only across stocks he covers. Since the analyst cannot expect to be rewarded for increased investor activity in stocks he does not cover, widening the scope of his research to stocks outside his coverage will likely not be as profitable. Consequently, an analyst will choose to convey information that is common to stocks he covers when there are significant cost reductions as well as increased aggregate investor demand from this strategy.

If analysts produce, and investors use, coverage-specific research, then this research should spill over to stocks that share coverage from the same analysts and promote comovement between the prices of these stocks. We refer to this hypothesis as the *Coverage-Specific Spillover Hypothesis* and develop three related predictions that we elaborate below.

2.1. Coverage-specific research

According to the *Coverage-Specific Spillover Hypothesis*, analysts use information that is common to the stocks they cover. Consequently, analysts who cover both stocks in a pair (i.e., pair analysts) are likely to develop their research using information that is common to the pair. In contrast, analysts who cover one stock in a pair (i.e., individual analysts) will use information that is less likely to be common to both stocks in the pair.⁷ Since earnings forecasts for a pair of stocks will likely be more highly correlated when they are made using the same information set, the earnings forecasts for a stock pair from pair analysts will be more highly correlated than earnings forecasts from individual analysts.⁸

⁶By producing high-quality research on stocks they cover, analysts can attract new underwriting business (Krigman, Shaw, and Womack, 2001), generate brokerage income (Jackson, 2005), and earn “All-Star” recognition (Ljungqvist et al., 2007). Analysts earn higher compensation for each of these outcomes (Groysberg, Healy, and Maber, 2011).

⁷Although these analysts will also use information that is common to the stocks they cover, their research will include less information that is relevant for both stocks in the pair.

⁸Earnings forecasts issued by pair analysts may also differ from those issued by individual analysts for behavioral reasons. Because coverage choices influence analysts’ information sets, they can influence the cues that

In contrast, correlations of earnings forecasts should not differ between pair and individual analysts if their research lacks coverage-specific information, i.e., if the research *exclusively* conveys broad or stock-specific information. If both pair and individual analysts exclusively focus on broad information, they will both base their research for each stock on market information or information on the industry to which each stock belongs. Therefore, research from pair and individual analysts will convey similar information about each stock in the pair. Similarly, if analysts exclusively focus on stock-specific information, pair and individual analysts will produce research on each stock that will be uninformative about the other stock in the pair. Consequently, there should be no systematic difference between the correlations of earnings forecasts issued by pair and individual analysts.

Research Prediction: *Earnings forecasts for a pair of stocks will correlate more strongly if analysts cover both stocks than if they cover only one stock in the pair.*

2.2. Shared coverage and investor reactions

According to the *Coverage-Specific Spillover Hypothesis*, investors will react differently to research from pair and individual analysts. Forecasts and recommendations from pair analysts for one stock will be informative about both stocks in a pair, causing the price of the second stock to comove with the price of the first stock. When an individual analyst issues a forecast or recommendation for one stock in the pair, this activity will convey less information about the second stock. Therefore, the price of the second stock will comove less with the price of the first stock.

In contrast, investor reactions to research from pair and individual analysts should not differ if analyst research *exclusively* conveys broad or stock-specific information. When analysts exclusively focus on market or industry information, research on one stock from both types of analysts will be similarly informative about the second stock, and therefore should elicit similar price responses for the second stock. If analysts exclusively focus on stock-specific information, research from both types of analysts will be similarly uninformative about the second stock. Therefore,

analysts employ when estimating shared exposure between stocks. For example, analyst forecasts may be affected by cue competition whereby analysts may underutilize salient cues because they are also presented with irrelevant ones (Kruschke and Johansen, 1999; Hirshleifer, 2001). However, Chen and Jiang (2005) find that analysts' forecasts are driven by their incentives rather than behavioral biases.

the price of the second stock should not respond to research on the first stock regardless of whether it is produced by pair or individual analysts.

Investor Reaction Prediction: *Earnings forecasts or stock recommendations for one stock in a pair will influence the price of the second stock more strongly if analysts cover both stocks than if analysts cover one stock in the pair.*

2.3. Shared coverage and return comovement

Analyst activity is not limited to publicly observable actions such as the forecast and recommendation announcements. We expect that analysts' private communications with investors will also influence investor perceptions of shared economic exposure. Therefore, according to the *Coverage-Specific Spillover Hypothesis*, analyst research will spill over to stocks that share coverage from the same analysts even when the analysts are not publicly active. Such information spillovers are likely to increase with the number of analysts that cover the same stocks as this will reinforce investor perceptions of shared economic exposure. Therefore, daily returns on stocks with shared analyst coverage will covary more strongly as the level of shared coverage rises.

In contrast, shared coverage should not affect daily return comovement when analysts *exclusively* produce either broad or stock-specific information. If analysts exclusively produce industry information, spillovers from their research should be systematically related to stocks' industry membership, and if they produce market-wide information, the spillovers should be similar across all stocks. In either case, the spillovers will not be systematically related to the analysts' coverage. If analysts exclusively produce stock-specific information, their research should not convey information about other stocks.

Comovement Prediction: *A stock's return will comove more strongly with returns of other stocks with which it shares more analyst coverage.*

Prior research has demonstrated that analysts prefer to cover stocks that share economic exposure with a larger set of stocks (Hameed et al., 2012), and follow portfolios that consist of stocks with higher shared economic exposure (Kini et al., 2009). The reason for this preference is clear: It is simpler to analyze a set of similar stocks than a set of diverse stocks. This

preference alone ensures that stocks that share analyst coverage will display more correlated earnings forecasts as well as higher return correlation. The underlying cause of these relations is shared economic exposure. In contrast, the premise of our predictions is that analyst research generates information spillovers and thus return comovement. Therefore, to test the predictions of the *Coverage-Specific Spillover Hypothesis* we have to control for the effect of shared economic exposure. We take care to do so in all the tests we describe below.

3. Sample

We construct a comprehensive sample at the intersection of the *CRSP/Compustat* and *I/B/E/S* databases. For each year between 1997 and 2010, we identify stocks that satisfy the following criteria: (i) annual financials and daily returns should not have any missing observations; (ii) prices should be higher than \$1 at the end of each month; (iii) at least one *qualified* analyst should cover the stock. We define a qualified analyst as one who follows at most 40 stocks during the year (more than 99% of the *I/B/E/S* analysts), with the intent of removing analyst teams and clerical errors.

Using the stocks that survive these filters, we generate all possible pairs of stocks for each year. To find stock pairs with shared analyst coverage, we impose the following additional filter on this universe of stock pairs: At least one qualified analyst should cover both stocks in each pair by issuing a recommendation or earnings forecast for each stock in the pair. Collectively, these criteria generate the largest possible sample of stock pairs with shared analyst coverage that is relatively free of market microstructure effects. On average, this sample of stock pairs is made up of 3,518 stocks per year, representing more than 99% of the market capitalization of all U.S. public stocks.

Insert Table 1 approximately here

Table 1 presents descriptive statistics for the sample. The sample includes 1,489,895 stock pairs, which correspond to 106,421 stock pairs per year. On average, stocks in a pair are followed by 23.4 analysts, 1.9 of whom are pair analysts. On average, analysts issue 19.7 recommendations and 93.4 annual and quarterly earnings forecasts for each stock pair in a year. Pair analysts account for 8.3% of the analysts covering a stock pair and 15.1% (15.6%) of the total number

of recommendations (forecasts) for a pair. We do not find a significant difference between the *per-stock* recommendation or forecast frequencies of pair and individual analysts.

Panel A of Table 2 presents descriptive statistics for our sample stocks (49,251 stock-years). An average stock is covered by 9.2 analysts (*Coverage*) and shares analysts with an average of 60.5 other stocks. The sample stocks have total assets (*Assets*) of \$6.1 billion, equity market capitalization (*Market Cap*) of \$4.1 billion, book value of equity (*Equity*) of \$1.6 billion, and annual trading volume (*Volume*) of 202.6 million shares. Additionally, 14% of the sample stocks are included in the S&P500 index (*S&P500*). The sample average for liabilities deflated by assets (*Leverage*) is 0.54, return-on-assets (*ROA*) is 0.00, earnings-per share (*EPS*) is \$0.83, book-to-market ratio (*BM*) is 0.69, stock price (*Price*) is \$24.2, and age is 13.2 years (*Age*). In untabulated results we find that firms in our sample are perceptibly larger than the other CRSP/Compustat firms. The sample firms are also less levered, more profitable, older, and enjoy higher valuations than other firms. These differences are not surprising, because analysts are more likely to cover large and profitable firms (McNichols and O'Brien, 1997; O'Brien and Bhushan, 1990; Rajan and Servaes, 1997).

Insert Table 2 approximately here

Panel B of Table 2 presents descriptive statistics for the sample stock pairs. The pairwise return correlation (*Correlation*) averages 0.269 and displays considerable variation: The 25th percentile of *Correlation* is 0.121 while the 75th percentile is 0.393. The sample average of *Correlation* is significantly higher than that for stock pairs that have no pair coverage (0.174). Our measure of the prevalence of pair analysts, *Pair Coverage*, is the number of pair analysts divided by the total number of analysts covering either stock in the pair. *Pair Coverage* falls in the interval (0, 1], averages 0.102, and displays considerable variation: The 25th percentile of *Pair Coverage* is 0.042 while the 75th percentile is 0.125. There are a small number of pairs with *Pair Coverage* equal to one (1,786 pairs or 0.12% of the sample). More than 80% of these pairs have only one analyst covering them.

We test the *Research Prediction* by comparing the within-stock pair correlations of monthly consensus earnings forecasts issued by pair analysts and individual analysts. Using annual earnings forecasts issued by pair analysts only, we construct a times series of monthly consensus

forecasts for each stock in the pair and compute the correlation between the two consensus forecast series. We refer to this correlation as the *Pair Forecast Correlation*. We repeat this process for annual earnings forecasts issued by individual analysts, and refer to the resulting correlation as the *Individual Forecast Correlation*. We only use stock-pair-years with at least three months with consensus earnings forecasts from individual and pair analysts for both stocks. The average values of *Pair Forecast Correlation* and *Individual Forecast Correlation* are close at 0.099 and 0.100, respectively.⁹ Both sets of earnings forecast correlations are less than half the average correlation in daily stock returns.

Our research design isolates the effect of coverage-specific spillovers on return comovement between the stocks in a pair by controlling for the known determinants of return comovement such as correlated trading and shared economic exposure. Panel B of Table 2 provides descriptive statistics for these control variables. We control for the intensity of analyst coverage (Piotroski and Roulstone, 2004; Chan and Hameed, 2006) using *Coverage Intensity*, which is the ratio of the total number of analysts covering either stock in the pair to the average number of analysts covering stocks from each of the pair’s two-digit SIC industries. Average *Coverage Intensity* is 1.29, indicating that the sample stocks enjoy higher than industry-average analyst coverage.

We also use the following indicator (dummy) variables as controls: *Same Industry* indicates if pair stocks belong to the same two-digit SIC industry (Kallberg and Pasquariello, 2007); *Related Industry* indicates if the pair stocks belong to industries that consume or supply 10% of one another’s output as recorded in the Input-Output Benchmark Survey of the Bureau of Economic Analysis (Menzly and Ozbas, 2010); *Same Exchange* indicates if pair stocks are listed on the same exchange (Chen, Chen, and Li, 2010); *Same State* indicates if pair stocks are headquartered in the same state (Chen, Chen, and Li, 2010); and *S&P500 Members* indicates if pair stocks both belong in the S&P 500 index (Barberis, Shleifer, and Wurgler, 2005; Greenwood, 2008).

Same Industry and *Related Industry* average 43.4% and 18.1%, respectively. The remaining stock pairs, which belong to different and unrelated industries, make up a significant portion of the sample (38.5%), consistent with Clement (1999) and Kini et al. (2009). *Same Exchange* has

⁹Note that these observations include pairs where the two stocks’ fiscal year ends are far apart, making direct comparisons between these two correlations noisy. We compare *Pair Forecast Correlation* with *Individual Forecast Correlation* in Section 4.

an average value of 59.7%, suggesting a strong likelihood that pair stocks are listed on the same exchange. *Same State* has an average value of 13.9%, consistent with the clustering of firms in a few states. *S&P500 Members* averages 7.6%. This is higher than the case if stock pairs were formed randomly ($1.7\% = 14\% \times 14\%$), likely because more analysts cover S&P 500 stocks (Veldkamp, 2006; Jegadeesh et al., 2004).

The second set of control variables captures the effect of similarities in stock characteristics on return correlation (Chen, Chen, and Li, 2010). This set is made up of the following indicator variables that equal one (zero) if characteristics of both stocks in a pair fall (do not fall) in the same quartile of the sample stocks during a year: *Similar Asset*, *Similar BM*, *Similar Age*, *Similar Leverage*, *Similar ROA*, *Similar EPS*, and *Similar Price* capture similarities in *Assets*, *BM*, *Age*, *Leverage*, *ROA*, *EPS*, and *Price*, respectively. Average values of these indicators range between 0.32 and 0.40, suggesting that a larger percentage of the pairs are formed of stocks with similar characteristics than would be the case if pairs were formed randomly, 0.25 ($= 4 \times 0.25 \times 0.25$). The likely reason for this difference is the propensity of analysts to focus their coverage on firms with similar characteristics, especially large and visible firms (Kini et al., 2009; Hameed et al., 2012).

The third set of controls is designed to capture the effect of shared economic exposure. *ROA Correlation* is the correlation in quarterly *ROA* between years $t - 4$ and t (Chen, Chen, and Li, 2010; Allayannis and Simko, 2009). To mitigate outliers, values of *ROA* greater than 10 or less than -10 are set to 10 and -10, respectively. *Δ ROA Correlation* is the correlation in quarterly changes in *ROA* between years $t - 4$ and t . *EPS Correlation* is the correlation in quarterly *EPS* between years $t - 4$ and t , and *Δ EPS Correlation* is the correlation in quarterly changes in *EPS* between years $t - 4$ and t . The average *ROA Correlation* (*EPS Correlation*) is 0.124 (0.115) indicating that pair stocks share a limited amount of performance-related exposure. The average values of *Δ ROA Correlation* and *Δ EPS Correlation* are perceptibly lower at 0.057 (0.063).

Untabulated correlation statistics show that *Correlation* is positively associated with *Pair Coverage* (0.11) as well as all the measures of shared exposure and correlated trading. *Pair Coverage* is negatively correlated with *Coverage Intensity* (-0.33) and *Related Industry* (-0.07), but positively correlated with all other measures of shared exposure and correlated trading. *Pair Coverage* is most highly correlated with *Same Industry* (0.20).

Finally, to ensure that our tests isolate and compare the information conveyed in research of pair and individual analysts rather than the characteristics of these two groups of analysts, we control for a set of pair-wise differences in analyst characteristics. Table 2, Panel C presents these analyst characteristics. First, we control for the difference in the logarithms of average experience of pair and individual analysts covering the pair (*Diff Experience*), because analyst experience can affect both the quality of an analyst’s research as well as investor responses to the research (Mikhail, Walther, and Willis, 2003).¹⁰ On average, pair analysts have been on the *I/B/E/S* database longer (*Experience*, 7.2 versus 6.5 years). Second, we control for the difference in the average size of brokers (i.e., logarithm of the number of employed analysts) that employ pair and individual analysts covering the pair (*Diff Broker Size*), because broker size can affect the resources available to analysts and the analysts’ ability to disseminate their research (Clement, 1999). Pair analysts work for brokers that employ fewer analysts (*Broker Size*, 52.5 versus 56.5 analysts). Third, we control for the difference in the logarithms of average number of stocks covered by pair and individual analysts (*Diff Companies*), because the number of stocks covered is inversely related with research resources (Clement, 1999).¹¹ Pair analysts cover more stocks (*Companies*, 20.8 versus 16.1 stocks). Finally, we control for the difference in average forecast errors between these two analyst groups (*Diff Forecast Error*), because past forecast accuracy is related with investor perceptions about the research quality (Mikhail, Walther, and Willis, 1999). We measure each analyst’s (in)accuracy using *Forecast Error*, the median absolute forecast errors across all stocks the analyst covers during a year. Absolute forecast error is defined as the absolute difference between an annual forecast and actual earnings per share deflated by the share price at the beginning of the fiscal year. Average *Forecast Error* for pair analysts and individual analysts are 0.58% and 0.64%, respectively, suggesting that pair analysts forecast more accurately, consistent with their longer experience.

¹⁰Whenever we use logarithms of variables, we take the logarithm of one plus the variable.

¹¹We do not control for differences in pair and individual analyst activity per covered stock since there is no meaningful difference between the per stock forecast or recommendation frequency of pair and individual analysts.

4. Forecast correlations

The *Coverage-Specific Spillover Hypothesis* predicts that analysts will highlight economic exposure shared by stocks in their coverage. Consequently, earnings forecasts from analysts who cover both stocks in a pair will correlate more strongly than earnings forecasts from analysts who cover only one stock (*Research Prediction*). We test the *Research Prediction* by examining the difference between the annual correlations of monthly consensus forecasts of pair analysts and individual analysts. Since the same shared economic exposure underpins both sets of forecasts, differences between the two sets of forecasts for the same stock pair can only result from differences in the economic exposure highlighted by the two sets of analysts. Therefore, a within-stock pair comparison of the consensus forecasts issued by pair and individual analysts effectively controls for reverse causality from shared economic exposure to earnings forecasts.

Figure 1 plots (across deciles of *Pair Coverage*) average *Pair Forecast Correlation* and *Individual Forecast Correlation*, which measure the correlation between the pair and individual analysts' consensus earnings forecasts for the two stocks, respectively. The figure also plots the average pair-wise difference of the two consensus correlation measures, *Diff Forecast Correlation*. In order to obtain a meaningful forecast correlation difference, we require that both forecast correlation measures are constructed using at least eight overlapping months. This filter reduces the number of observations from 688,755 to 568,307. Untabulated tests show that this filter has no meaningful effect on our results. Both average *Pair Forecast Correlation* and *Individual Forecast Correlation* increase with *Pair Coverage*.¹² This is consistent with the evidence in Kini et al. (2009) that analysts follow portfolios of stocks with high levels of shared exposure.

As is clear from the figure, *Pair Forecast Correlation* is either similar to or larger than *Individual Forecast Correlation*. The difference between the two correlation measures monotonically increases with *Pair Coverage* until its highest decile. This difference is statistically significant when *Pair Coverage* is greater than 20%. The average difference between the two correlation measures across deciles where *Pair Coverage* is greater than 20% is 3.6%, and is economically

¹²Only in the last decile of *Pair Coverage* do we observe a decline in the forecast correlations. This is likely a result of the fact that stock pairs in this range have a small number of individual analysts (1.5) and the number of pair analysts drops dramatically from 17.5 for the previous *Pair Coverage* decile to 8.1. Since the time series of monthly consensus earnings forecasts are likely to be updated less frequently when there are fewer analysts, this drop in the number of pair and individual analysts is likely to mechanically lower the precision of the two forecast correlation estimates and bias them towards zero.

significant given that *Pair Forecast Correlation* and *Individual Forecast Correlation* average 23% over this range of *Pair Coverage*. The relatively small difference for the two lowest *Pair Coverage* deciles may arise because the consensus forecast for pair analysts changes infrequently when there are only a few pair analysts (1.8 on average), lowering the precision of the correlation estimates and biasing them downwards. Overall, this evidence is consistent with the *Research Prediction* that research from pair analysts will signal higher shared economic exposure than research from individual analysts.

Insert Figure 1 approximately here

In order to understand the cross-sectional variation in the difference between pair and individual forecast correlation, we estimate the following regression model:

$$\text{Diff Forecast Correlation}_{ij,t} = \alpha + \beta \text{Pair Coverage}_{ij,t} + \gamma X_{ij,t} + \epsilon_{ij,t}, \quad (1)$$

where X represents a vector of pair-wise controls for shared economic exposure, correlated trading, and analyst characteristics. Table 3 presents OLS estimates of Eq. (1) with t-statistics based on robust standard errors clustered by stock pair and year (Petersen, 2009). Model 1 includes controls for industry, geographical and exchange linkages, and shared membership in the S&P 500 index. Model 2 adds controls for similarities in operating and financial characteristics of the stock pairs. Model 3 adds controls for shared economic exposure as reflected in correlations between measures of operating performance. Finally, Model 4 includes controls for differences in the characteristics of pair and individual analysts.

Insert Table 3 approximately here

According to the *Research Prediction*, the earnings forecasts from pair analysts will display a higher level of correlation. As *Pair Coverage* increases, the frequency of changes in and thus the precision of the consensus earnings estimates from pair analysts should rise. These changes should mitigate the downward bias in *Pair Forecast Correlation* when *Pair Coverage* is low, which is apparent from Figure 1. Therefore, we expect a positive β in Eq. (1).

Consistent with Figure 1, the coefficient estimates on *Pair Coverage* are uniformly positive and significant at the 1% level. Moreover, the coefficient estimates on *Pair Coverage* show

only small changes ranging from 8.69 to 9.07 across the models. Economically, when *Pair Coverage* increases from the first quartile (0.042) to the third quartile (0.125) of the sample, the difference in consensus forecast correlations of pair and individual analysts widens by 0.8% ($= 9.07\% \times (0.125 - 0.042)$). This is a significant impact, given that it equals 8% of the average forecast correlation for pair and individual analysts, which is around 0.100.

Few controls have statistically significant coefficient estimates, indicating that *Diff Forecast Correlation* displays limited cross-sectional variation. The coefficient estimates on *Similar ROA*, *ROA Correlation*, and *EPS Correlation* are negative and significant, suggesting that *Diff Forecast Correlation* is smaller for pairs with greater shared economic exposure. This finding indirectly supports the *Coverage-Specific Spillover Hypothesis*, since it suggests that pair analysts' estimates are highly correlated regardless of the shared exposure of the stocks in a pair while those of individual analysts are sensitive to the shared exposure. The coefficient estimate on *Diff Forecast Error* is positive and significant, suggesting that the higher correlation in forecasts of pair analysts may be associated with higher forecast errors. This is to be expected if pair analysts rely more on coverage-specific information than stock-specific information.

These results are robust to the following changes in test specifications: using a count of pair analysts instead of *Pair Coverage*; using a count of individual analysts instead of *Coverage Intensity*; using alternative industry definitions, e.g., two-digit *I/B/E/S* S/I/G industries or two-digit GICS codes; focusing only on stock pairs from the same industry or different industries; replacing the dummy variables with continuous measures of similarities/difference in pair characteristics; switching from clustering by year and stock pair to using year and stock-pair fixed effects. We have ensured that all the subsequent results are also robust to these changes in test specifications.

5. Investor reaction to analyst activity

According to the *Investor Reaction Prediction*, pair analyst research on one stock in a pair will convey more information about the second stock than research from an individual analyst. Consequently, short-term price reactions of the stock for which a recommendation or forecast is issued (i.e., the activity stock) and the other stock in the pair (i.e., the no-activity stock) should

be closer, when a pair analyst issues the recommendation or forecast than when an individual analyst does so. In contrast, if analysts rely *exclusively* on broad information or stock-specific information, the gap in price reactions between the activity and no-activity stocks should not differ between pair and individual analysts. This is because research on the activity stock from both groups of analysts will be equally informative about the no-activity stock.

5.1. Difference-in-difference tests

In order to test the *Investor Reaction Prediction*, we benchmark the price responses to research from pair analysts against the price responses to research from individual analysts covering the *same* stock pair. Since the same shared economic exposure underpins both sets of price responses, we effectively control for reverse causality from shared economic exposure to price responses. To implement the difference-in-difference test, we first identify days on which analysts issue recommendations or forecasts for only one stock in a pair (activity stock) for each stock pair-year. We refer to these days as activity days ($N = 31,683,028$). We then drop observations where the absolute value of one-day NYSE size decile-adjusted returns on either the activity or no-activity stock are greater than 95th percentile of the population of activity-day returns (that is, 6.8%).¹³ The resulting sample includes 30,098,877 activity days from 1,292,253 pair-years.

We measure the short-term price response to analyst activity for each activity day in two ways. First, we compute the absolute value of NYSE size decile-adjusted returns of the activity stock and the no-activity stock (*Absolute Return*). Second, we filter out the variation in innate daily return volatilities of individual stocks by computing an activity-day analyst informativeness (*AI*) measure as follows (Frankel, Kothari, and Weber, 2006): For stock i in the pair ij , we compute average absolute size-adjusted returns on all no-activity trading days during the year, R_i^N , where

$$R_i^N = \frac{\sum_{T_{ij}} R_{i,t}}{\#T_{ij}}, \quad (2)$$

$R_{i,t}$ is the absolute size-adjusted return of stock i on day t , T_{ij} is the set of no-activity days for

¹³We use this filter in order to remove the effect of significant events other than analyst activity such as macroeconomic news, company news, or company disclosures. Since we are using absolute returns, we are effectively dropping observations from the two tails of the actual distribution of daily returns.

the pair ij , and $\#T_{ij}$ is the number of no-activity days. Then, on each activity day for the pair ij , we compute stock i 's AI as follows:

$$AI_{ij}^i = \frac{Absolute\ Return_i}{R_i^N}. \quad (3)$$

If analyst activity is (is not) informative, then AI should exceed (equal) one on average.

Panel A of Table 4 presents mean and median values of *Absolute Return* and AI for activity and no-activity stocks. The last two columns present differences between the two price response measures for activity and no-activity stocks. Similarly, the last two rows present differences between *Absolute Return* and AI for pair and individual analysts. The intersection of the last two rows and last two columns reports the difference-in-difference tests. Specifically, each cell in the intersection compares the difference in price reactions for the activity and no-activity stocks in response to pair analyst activity with the difference in price reactions in response to individual analyst activity. This differential price reaction between activity and no-activity stocks measures the spillover from analyst activity; a smaller difference in *Absolute Return* or AI indicates a smaller difference in the price responses and, thus, a larger spillover.

Insert Table 4 approximately here

The results in Panel A provide strong support for the *Investor Reaction Prediction*. For days during which pair analysts are active, the average *Absolute Return* (AI) is 1.73% (1.109) for the activity stock and 1.60% (0.972) for the no-activity stock. For days during which individual analysts are active, the average *Absolute Return* (AI) is 1.86% (1.175) for the activity stock and 1.56% (0.966) for the no-activity stock. As expected, for both pair and individual analysts, *Absolute Return* and AI are uniformly higher for the activity stock than the no-activity stock.¹⁴ Moreover, *Absolute Return* and AI for pair analysts are lower for the activity stock and higher for the no-activity stock. This pattern is consistent with two corollaries of the *Coverage-Specific Spillover Hypothesis*. First, pair analysts provide less stock-specific information. Second, pair analysts provide more coverage-specific information.

¹⁴The AI for the no-activity stock is lower than one in response to activity from both pair and individual analysts. One reason for this could be that investors shift their attention to the activity stock for which the analyst activity is likely to be more informative and thus dampen price movements in the no-activity stock.

The difference-in-difference tests are consistent with the existence of stronger spillovers from pair analyst activity. For pair analysts, the average pair-wise *Absolute Return (AI)* difference between the activity and no-activity stock is 0.14% (0.138). In comparison, for individual analysts, the average pair-wise *Absolute Return (AI)* difference between the activity and no-activity stock is significantly larger at 0.31% (0.208). Moreover, the difference-in-difference measures are both statistically and economically significant: The average and median difference-in-difference in stock price reactions between pair and individual analysts range between 4% to 10% of the price responses of the activity stock. We conclude that, holding everything else constant, the reaction of no-activity stocks is significantly stronger to research from pair analysts than research from individual analysts. This supports the *Investor Reaction Prediction* and directly links coverage-specific spillovers to analyst activity.¹⁵

In order to examine cross-sectional variation in price responses to research from pair and individual analysts, we also estimate the following model:

$$\begin{aligned} \text{Diff Absolute Return}_{ij,t} &= \alpha + \beta \text{Pair Coverage}_{ij,t} + \gamma X_{ij,t} + \epsilon_{ij,t}, \\ \text{Diff AI}_{ij,t} &= \alpha + \beta \text{Pair Coverage}_{ij,t} + \gamma X_{ij,t} + \epsilon_{ij,t}, \end{aligned} \quad (4)$$

where *Diff Absolute Return (Diff AI)* is the pair-wise difference-in-difference between the average *Absolute Return (AI)* of the activity and no-activity stocks across the pair and individual analysts. X represents the vector of pair-wise controls from Table 3.

Panel B of Table 4 presents OLS estimates of Eq. (4) with t-statistics based on robust standard errors clustered by stock pair and year. When the dependent variable is *Diff Absolute Return*, the coefficient estimates on *Pair Coverage* range from 0.181 to 0.286, and are significant at the 1% level. When *Pair Coverage* increases from the first quartile (0.042) to the third quartile (0.125) of the sample, *Diff Absolute Return* widens by 0.02% ($= 0.286 \times (0.125 - 0.042)$) in Model 4. This is an economically significant impact, given that average *Diff Absolute Return* is 0.17%. When the dependent variable is *Diff AI*, the coefficient estimates on *Pair Coverage* range from

¹⁵In untabulated tests, we find that the results we report are robust to the following changes: using the ratios rather than differences of the two activity day price reactions; using returns within a three day announcement window to capture price responses to analyst activity; and focusing on price responses to earnings forecasts or recommendations alone.

0.093 to 0.177, and are significant at the 1% level. When *Pair Coverage* increases from the first quartile to the third quartile of the sample, *Diff AI* widens by 0.015 ($= 0.177 \times (0.125 - 0.042)$) in the Model 4. This is an economically significant impact, given that average *Diff AI* is 0.071. The positive relation between spillovers and *Pair Coverage* may arise because increased exposure to research from pair analysts conditions investors to believe that a stock pair has greater shared exposure. This argument is supported by untabulated results which indicate that the difference between the price responses of the activity and no-activity stock to individual analyst activity are more sensitive to *Pair Coverage*.

Several control variables have statistically significant estimates, indicating that the difference in spillovers between pair and individual analysts displays some cross-sectional variation. *Same Industry*, *Related Industry*, *Diff Experience*, and *Diff Broker Size* are associated with an increase in the relative strength of spillovers from pair analyst research, while *S&P500 Members*, *Similar Asset*, *Similar Age*, *Similar ROA*, *Similar EPS*, *Similar Price*, and *Diff Companies* are associated with a reduction in the relative strength of spillovers from pair analyst research.

5.2. Decomposing price effects of analyst activity

If a recommendation revision from an analyst for one stock is informative about other stocks the analyst covers, the prices of the other stocks should also respond to the recommendation revision. Therefore, returns around an analyst's recommendation revision for a stock should be correlated with returns on other stocks that the analyst covers. To test this prediction, we build on the methodology in Liu (2011) to decompose stock returns around analyst recommendation revisions into market, industry, shared coverage, and the residual stock-specific components. Specifically, we estimate the following regression for each stock (i)-analyst (a) combination using daily (t) returns during the calendar year:

$$\begin{aligned} \text{Return}_{ia,t} &= \alpha_{ia} + \beta_{ia}^A \times \text{Analyst Portfolio}_{ia,t} \\ &+ \beta_{ia}^M \times \text{Market Portfolio}_t + \beta_{ia}^I \times \text{Industry Portfolio}_{i,t} + \epsilon_{ia,t}, \end{aligned} \quad (5)$$

where *Market Portfolio* is the daily CRSP value-weighted market return, *Industry Portfolio* is the daily value-weighted two-digit SIC industry return orthogonalized relative to *Market Portfolio*,

and *Analyst Portfolio* is the daily equal-weighted return on a portfolio of all the other stocks covered by analyst *a* orthogonalized relative to *Market Portfolio* and *Industry Portfolio*.¹⁶

We employ the estimated coefficients from Eq. (5) to compute the market, industry, analyst portfolio, and the residual stock-specific components of the three-day, -1 to 1, returns around recommendation revisions issued by analyst *a* for stock *i* as follows:

$$\begin{aligned}
\text{Analyst Portfolio Component}_{ia,[-1,1]} &= \widehat{\beta}_{ia}^A \times \text{Analyst Portfolio}_{ia,[-1,1]}, \\
\text{Market Component}_{ia,[-1,1]} &= \widehat{\beta}_{ia}^M \times \text{Market Portfolio}_{[-1,1]}, \\
\text{Industry Component}_{ia,[-1,1]} &= \widehat{\beta}_{ia}^I \times \text{Industry Portfolio}_{i,[-1,1]}, \\
\text{Stock-Specific Component}_{ia,[-1,1]} &= \text{Return}_{i,[-1,1]} - \widehat{\beta}_{ia}^A \times \text{Analyst Portfolio}_{ia,[-1,1]} \\
&\quad - \widehat{\beta}_{ia}^M \times \text{Market Portfolio}_{[-1,1]} - \widehat{\beta}_{ia}^I \times \text{Industry Portfolio}_{i,[-1,1]}.
\end{aligned} \tag{6}$$

Insert Table 5 approximately here

Panel A of Table 5 reports the results of the return decomposition around 175,522 recommendation revisions (80,315 upgrades and 95,207 downgrades) in our sample. For the upgrades, the average (median) *Analyst Portfolio Component* is 0.25% (0.07%). It is larger than the average *Market Component* of 0.16%, and similar to the average *Industry Component* of 0.25%. The average *Stock-Specific Component* is 2.74%, by far the largest of the four components. For downgrades, the average *Analyst Portfolio Component* is -0.12%. It is more prominent than the average *Market Component* of 0.01% and the average *Industry Component* of -0.05%. Once again, the average *Stock-Specific Component* is -4.66%, by far the most prominent of the four. These results suggest that there is at least as much coverage-specific information in recommendation revisions as there is market or industry information.¹⁷

We develop a second set of tests based on returns around recommendation revisions to ensure that the inferences from the above return decomposition tests are robust. We estimate the

¹⁶ *Industry Portfolio* for day *t* is computed as follows: $R_t^I - \widehat{\beta}^{IM} \times \text{Market Portfolio}_t$, where R_t^I is the day *t* return on the industry portfolio and $\widehat{\beta}^{IM}$ is a regression coefficient estimated by regressing daily industry returns on market returns for the calendar year. *Analyst Portfolio* for day *t* is estimated similarly.

¹⁷ Unlike Liu (2011), we do not use the prior year returns to estimate the coefficients in Eq. (5). Doing so requires no change in analyst coverage from the prior year and thus greatly reduces our sample size. The results are similar if we strictly adhere to Liu's specifications and use the prior year returns while ensuring that analyst coverage remains unchanged, exclude observations where other analysts revise recommendations less than ten days prior, and use three-digit SIC returns which exclude the stock and industries with fewer than three stocks.

following single-step regressions of stock returns around recommendation revisions on market, industry, and analyst portfolio returns:

$$\begin{aligned}
Return_{i,[-1,1]} &= \alpha + \beta \textit{Analyst Portfolio}_{ia,[-1,1]} + \gamma X_{i,[-1,1]} + \epsilon_{i,[-1,1]}, & (7) \\
Return_{i,[-1,1]} &= \alpha + \beta \textit{Analyst Portfolio}_{ia,[-1,1]} \\
&+ \beta^O \textit{Other Analyst Portfolio}_{ia,[-1,1]} + \gamma X_{i,[-1,1]} + \epsilon_{i,[-1,1]}, \\
Return_{i,[-1,1]} &= \alpha + \beta^S \textit{Analyst Portfolio_Same Ind.}_{ia,[-1,1]} \\
&+ \beta^D \textit{Analyst Portfolio_Different Ind.}_{ia,[-1,1]} + \gamma X_{i,[-1,1]} + \epsilon_{i,[-1,1]},
\end{aligned}$$

where *Other Analyst Portfolio* is the equal-weighted return on stocks other than those covered by analyst a that share coverage with stock i ; *Analyst Portfolio_Same Ind.* (*Analyst Portfolio_Different Ind.*) is the equal-weighted return on all stocks in the same (different) two-digit SIC industry (industries) covered by analyst a during the year. These returns are orthogonalized relative to *Market Portfolio*, *Industry Portfolio*. X represents a vector consisting of *Market Portfolio*, *Industry Portfolio*, and returns on the Fama-French value (*HML*) and size (*SMB*) portfolios, and the momentum portfolio (*UMD*).

According to the *Investor Response Prediction*, the coefficient estimates on *Analyst Portfolio*, *Analyst Portfolio_Same Ind.*, and *Analyst Portfolio_Different Ind.* should be positive. Since these returns are orthogonalized relative to *Market Portfolio* and *Industry Portfolio*, these coefficients should equal zero if analysts exclusively convey broad information. They will also be zero if analysts exclusively convey exclusively stock-specific information. The coefficient estimate on *Other Analyst Portfolio* will be positive if investors use information in the recommendation revision to update their beliefs on stocks that share coverage from other (inactive) analysts. Panel B of Table 5 presents OLS estimates of Eq. (7) with t-statistics based on robust standard errors clustered by stock and year.

In Models 1 and 2, the coefficient estimates on *Analyst Portfolio* are 1.11 and statistically significant at the 1% level. These estimates are 70% larger than the average estimates for the *Analyst Portfolio* coefficients reported in Panel A ($\hat{\beta}_{ia}^A$). One possible reason for the difference is stronger coverage-specific spillovers during the recommendation revision window relative to

days during which analysts are not active. Moreover, the announcement returns are at least as strongly related to *Analyst Portfolio* as they are to market and industry returns. Specifically, when *Analyst Portfolio* increases from its first quartile (-0.9%) to its third quartile (0.8%), the announcement return rises by $1.9\% (= 1.109 \times (0.8\% - (-0.9\%)))$ in Model 2, which equals 22% of the interquartile variation in the announcement return. In comparison, changing *Market Portfolio* from its first to third quartile raises the announcement return by $2.9\% (= 1.175 \times (1.3\% - (-1.1\%)))$ or 34% of the interquartile variation in the announcement return. Changing *Industry Portfolio* from its first to third quartile raises the announcement return by $2.0\% (= 1.213 \times (0.9\% - (-0.7\%)))$, which is nearly 23% of the interquartile variation in the announcement return. Like Panel A, these results suggest that the coverage-specific information in analysts' recommendation revisions is comparable to the amount of market or industry information the recommendation revisions convey.¹⁸

In Model 3, we introduce *Other Analyst Portfolio* as an additional explanatory variable. This captures the returns on stocks that share coverage from other analysts and thus are likely to have similar levels of shared economic exposure but are not the subject of coverage-specific information produced by the recommending analyst. Consequently, by comparing the coefficient estimates on *Other Analyst Portfolio* and *Analyst Portfolio*, we can assess the extent of coverage-specific information in the recommendation revisions. The coefficient estimate on *Analyst Portfolio* drops to 0.742 but remains statistically significant at the 1% level. The coefficient on *Other Analyst Portfolio* is 0.581 and is also statistically significant at the 1% level, indicating investors believe that the recommendations are informative for other stocks that share coverage by other analysts. At the same time, consistent with the *Coverage-Specific Spillover Hypothesis*, the coefficient estimate on *Analyst Portfolio* is significantly larger than that on *Other Analyst Portfolio* at the 10% level.

In Model 4, we partition the recommending analyst's portfolio into two groups: stocks belonging to the same industry as the stock whose recommendation has changed and other stocks.

¹⁸We find similar economic significance when we compare the R^2 improvements (partial R^2 's) from adding *Analyst Portfolio*, *Industry Portfolio*, and *Market Portfolio* individually to the regression. Moreover, we find similar results (untabulated) when we make the following changes: compute *Analyst Portfolio* using market value weights or shared analyst weights, i.e., ratio of the the number of pair analysts divided by the cumulative number of pair analysts; use activity day returns instead of three day announcement returns; and use industry and analyst portfolio returns that are not orthogonalized.

By doing so we are able to assess whether there are spillovers from the analyst’s research to stocks that do not belong to the same industry. The coefficient estimates on both *Analyst Portfolio_Same Ind.* and *Analyst Portfolio_Different Ind.* are positive and statistically significant at the 1% level, consistent with the presence of coverage-specific spillovers both within and outside of the industry of the researched stock. However, the coefficient on *Analyst Portfolio_Same Ind.* is perceptibly larger and the difference between the two coefficients is statistically significant at the 1% level, indicating that spillovers are stronger to stocks in the same industry as the recommended stock.

Overall, the findings regarding short-term price responses to analyst activity support the *Investor Reaction Prediction*. An analyst’s recommendation or forecast for a stock appears to be informative for other stocks that are covered by the same analyst, even when they belong to different industries. This effect is incremental and comparable to the effect of market- and industry-wide information conveyed by the analyst.

6. Return comovement

Analysts frequently communicate their research to clients in private. Therefore, information from analyst research will frequently spillover to other stocks in their coverage. Consequently, daily returns on stocks that share analyst coverage will comove during a calendar year (*Comovement Prediction*).

6.1. Return comovement within stock pairs

To test the *Comovement Prediction*, we examine the effect of shared coverage on return comovement between stocks in a pair. Since pair analysts are more likely to emphasize economic factors that are common to both stocks in the pair, an increase in *Pair Coverage* should increase the volume of research that ties the two stocks together and promote return comovement between them. To test these arguments, we estimate the following model:

$$\text{Correlation}_{ij,t} = \alpha + \beta \text{Pair Coverage}_{ij,t} + \gamma X_{ij,t} + \epsilon_{ij,t}, \quad (8)$$

where X represents the vector of pair-wise controls from Table 3. Table 6 presents OLS estimates of Eq. (8) with t-statistics based on robust standard errors clustered by stock pair and year.

Insert Table 6 approximately here

The first two sets of estimates are made using the universe of stock pairs ($N = 91,561,175$), i.e., all stocks pairs with or without pair analysts. In both Model 1 and 2, the coefficient estimates on *Pair Coverage* are approximately equal to 0.500 and statistically significant at the 1% level. These estimates are consistent with the *Comovement Prediction* since they imply that stock pairs with shared coverage have significantly more correlated returns. We obtain similar results if we use an indicator for the presence of pair coverage instead of *Pair Coverage*.

The coefficient estimates on *Pair Coverage* are also positive and significant across all the remaining models, which use only stock pairs with pair coverage. The coefficient drops slightly from 0.231 in Model 3 to 0.218 in Model 6 with the addition of each set of controls. When *Pair Coverage* increases from the first quartile (0.042) to the third quartile (0.125) of the sample, the daily return correlation increases by 1.8% ($= 0.218 \times (0.125 - 0.042)$) in Model 6. This indicates the presence of significant coverage-specific spillovers, given that the average *Correlation* for the sample pairs is 26.9%.¹⁹

Almost all coefficient estimates on control variables have the expected signs and are statistically significant across the models. The coefficient estimates on *Coverage Intensity* are uniformly positive and significant, consistent with analyst coverage increasing return synchronicity (Piotroski and Roulstone, 2004; Chan and Hameed, 2006; and Hameed et al., 2012). Not surprisingly, daily return correlation between stocks in a pair increases with industry, geographical, and exchange linkages as well as shared membership in the S&P 500 index. Similarities in firm size, leverage, operating performance, and *BM*, which could promote correlated trading by investors, also appear to boost return correlation.²⁰ Similarly, *ROA Correlation*, a measure of shared economic exposure, is positively related to return correlation. The coefficient estimate on *Diff Broker Size* is positive and significant as we should expect if employment with larger brokers permits pair analysts to communicate their research more effectively to investors. Only

¹⁹These results are qualitatively unchanged when we substitute the ratio of forecasts (recommendations) by pair analysts to the the number of forecasts (recommendations) by all analysts as an alternative to *Pair Coverage*.

²⁰The effect of *BM* and firm size are consistent with evidence in Fama and French (1993) and Boyer (2011).

the difference between the forecast errors of pair and individual analyst (*Diff Forecast Error*) appears to lower return correlation. The negative coefficient on *Diff Forecast Error* is consistent with the notion that pair analysts who produce lower quality research have a weaker effect on return correlation.

6.2. Return comovement and the information content of analyst research

Eq. (8) controls for many determinants of return correlation within a stock pair. However, if these controls are inadequate, the positive relation between *Correlation* and *Pair Coverage* may be driven by the positive relation between shared coverage and shared economic exposure. We address this alternative explanation by examining the relation between *Correlation* and *Pair Forecast Correlation* after controlling for *Individual Forecast Correlation*, which reflects analysts' estimates of shared economic exposure. If investors are incrementally influenced by coverage-specific information in research from pair analysts, we should expect return comovement to rise with *Pair Forecast Correlation*. Therefore, we estimate the following regression model:

$$\begin{aligned} \text{Correlation}_{ij,t} = & \alpha + \beta^P \text{Pair Forecast Correlation}_{ij,t} \\ & + \beta^I \text{Individual Forecast Correlation}_{ij,t} + \gamma X_{ij,t} + \epsilon_{ij,t}, \end{aligned} \quad (9)$$

where X represents the vector of pair-wise controls from Tables 3 and 6. Table 7 presents OLS estimates of Eq. (9) with t-statistics based on robust standard errors clustered by stock pair and year.

Insert Table 7 approximately here

The coefficient estimates on *Pair Forecast Correlation* are positive and highly statistically significant across all four models. In Model 1, the coefficient estimate is 0.014. The estimate falls monotonically with the addition of each set of controls to 0.009 in Model 4. When *Pair Forecast Correlation* increases from the first quartile (-0.582) to the third quartile (0.744) of the sample, the daily return correlation increases by 1.2% ($= 0.009 \times (0.744 - (-0.582))$) in Model 4. This is a significant impact, given that it equals 4.5% of the average *Correlation* (26.9%).

Similar to Table 6, the coefficient estimates on the control variables are positive and significant as expected, with two exceptions. The coefficient on *Diff Experience* is negative and marginally significant, suggesting that more experienced analysts supply investors with less coverage-specific information. The coefficient on *Diff Forecast Error* is negative and significant, suggesting that inaccurate pair analysts have a weaker effect on return correlation.

We have also attempted to establish causality from pair coverage to stock return comovement between a stock pair using a natural experiment. For the experiment, we identify an exogenous event: analysts leaving the profession. Analysts may leave the profession for several reasons. Unsuccessful analysts may retire, while successful ones may assume managerial positions or join buy-side firms. However, analysts are unlikely to leave the profession because of changes in the shared economic exposure of a pair of stocks. In untabulated results, we find that changes in average annual return correlation for a pair of stocks are positively related to exogenous changes in the number of pair analysts due to the analysts leaving the profession. This effect is stronger for the sample period preceding the financial crisis in 2007.

6.3. Return comovement and shared analyst coverage

Individual stocks share analyst coverage with a large number of stocks (average 61, median 42), all of which should experience coverage-specific spillovers. Therefore, we now test the *Comovement Prediction* using comovement of a stock's returns with portfolios of stocks with which it shares analyst coverage. Specifically, we estimate the following regression of a stock's daily return on the return of a portfolio of stocks with which the stock shares analyst coverage as well as market indices that are typically used to price assets:²¹

$$\begin{aligned}
 \text{Return}_{i,t} &= \alpha + \beta \text{Shared Coverage Portfolio}_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}, \\
 \text{Return}_{i,t} &= \alpha + \beta^S \text{Shared Coverage Portfolio_Same Ind.}_{i,t} \\
 &\quad + \beta^D \text{Shared Coverage Portfolio_Different Ind.}_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}, \quad (10)
 \end{aligned}$$

²¹We now identify components of *all* daily returns during the year. In Panel B of Table 5, we focus on identifying components of a stock's returns around recommendation revisions. As a result, stocks with more recommendation revisions have a greater influence on the results in Table 5.

where $Return_{i,t}$ is stock i 's return on day t , *Shared Coverage Portfolio* is the return on an equal-weighted portfolio of all stocks with which stock i shares analyst coverage orthogonalized relative to *Market Portfolio* and *Industry Portfolio*. Similarly, *Shared Coverage Portfolio_Same Ind.* (*Shared Coverage Portfolio_Different Ind.*) is the equal-weighted return on all stocks in the same (different) two-digit SIC industry (industries) with which stock i shares analyst coverage orthogonalized relative to *Market Portfolio* and *Industry Portfolio*. X represents the following vector of returns: *Market Portfolio*, *Industry Portfolio*, *HML*, *SMB*, and *UMD*. According to the *Comovement Prediction*, the coefficient estimates on *Shared Coverage Portfolio*, *Shared Coverage Portfolio_Same Ind.*, and *Shared Coverage Portfolio_Different Ind.* should be positive. These coefficients should equal zero if analysts exclusively convey broad or stock-specific information. Panel A of Table 8 presents OLS estimates of Eq. (10) with t-statistics based on robust standard errors clustered by stock and year.

Insert Table 8 approximately here

Model 1, which only includes *Market Portfolio* and *Industry Portfolio* as independent variables, serves as a benchmark for the remaining models. In Model 2, which controls for market and industry returns, the coefficient on *Shared Coverage Portfolio* is 0.450. When we add the remaining controls in Model 3, the coefficient estimate on *Shared Coverage Portfolio* is 0.384. Both coefficient estimates are significant at the 1% level. Based on Model 3, varying the return on *Shared Coverage Portfolio* between its 25th and 75th percentiles accounts for 15% of the interquartile variation in *Return*. This effect is comparable to that of *Industry Portfolio* (*Market Portfolio*), which accounts for 18% (45%) of the interquartile variation in *Return*. These estimates indicate that a stock's returns are strongly tied to the returns of stocks with which it shares coverage, consistent with the *Comovement Prediction*.²²

In Model 4, the coefficient estimate on *Shared Coverage Portfolio_Different Ind.* is half the size of the estimate on *Shared Coverage Portfolio_Same Ind.* (0.110 versus 0.218). Moreover, varying the return on *Shared Coverage Portfolio_Same Ind.*, *Shared Coverage Portfolio_Different*

²²We observe similar economic significance when we compare the R^2 improvements (partial R^2 's) from adding *Shared Coverage Portfolio* and *Industry Portfolio* individually added to the regression. In untabulated tests we find similar results when we make the following changes: compute *Shared Coverage Portfolio* using market value weights or shared analyst weights, i.e., ratio of the number of pair analysts divided by the cumulative number of pair analysts; use industry and shared coverage portfolio returns that are not orthogonalized.

Ind. and *Industry Portfolio* between their 25th and 75th percentiles accounts for 9%, 6%, and 19% of the interquartile variation in *Return*, respectively. These estimates indicate that analysts provide investors with significant information on stocks they cover in other industries. Note also that the coefficient estimate on *Shared Coverage Portfolio_Same Ind.* is positive and statistically significant despite controlling for market and industry returns. Therefore, consistent with the *Coverage-Specific Spillover Hypothesis*, it appears that analysts provide investors with value-relevant information on stocks from the same industry that is distinct from broad industry information.

6.4. Return synchronicity

One way to assess the robustness of the results in Panel A of Table 8 is to examine return synchronicity with a portfolio of stocks that share coverage. We do so by extending the synchronicity tests in Piotroski and Roulstone (2004) and Chan and Hameed (2006). Specifically, we examine the relation between the extent of a stock’s shared analyst coverage and the stock’s return synchronicity with portfolios of stocks with which it shares coverage.

Following Piotroski and Roulstone (2004), and Chan and Hameed (2006), we define a stock’s return synchronicity with the market and industry, *Sync*, as follows:

$$Sync = \text{Log} \left(\frac{R^2}{1 - R^2} \right), \quad (11)$$

where R^2 is the R-squared from a regression of the stock’s daily return during a calendar year on *Market Portfolio*, and the (unorthogonalized) industry portfolio return, and one-day lagged values of these returns. We define an augmented measure stock’s return synchronicity by also including a portfolio of stocks with which it shares coverage, *Aug. Sync*, as follows:

$$Aug. Sync = \text{Log} \left(\frac{R_S^2}{1 - R_S^2} \right), \quad (12)$$

where R_S^2 is the R-squared from a regression of the stock’s daily return during a calendar year on *Market Portfolio*, the (unorthogonalized) industry portfolio return, (unorthogonalized) return on an equal-weighted portfolio of stocks with shared coverage, and the one-day lagged values of

these returns. We present summary statistics for *Sync*, *Aug. Sync*, and their difference in Panel B of Table 8. This difference isolates the ability of the shared coverage portfolio to explain a stock’s returns.

To assess the effect of shared coverage on return synchronicity, we estimate the following models:

$$\begin{aligned}
 Sync_{i,t} &= \alpha + \beta \text{Aggregate Pair Coverage}_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}, \\
 Aug. Sync_{i,t} &= \alpha + \beta \text{Aggregate Pair Coverage}_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}, \\
 Aug. Sync_{i,t} - Sync_{i,t} &= \alpha + \beta \text{Aggregate Pair Coverage}_{i,t} + \gamma X_{i,t} + \epsilon_{i,t},
 \end{aligned} \tag{13}$$

where *Aggregate Pair Coverage* is the sum of *Pair Coverage* across all stock pairs that include stock i , and X represents a vector of controls. *Aggregate Pair Coverage* reflects both the number of stocks that share coverage with stock i and the intensity of shared coverage in a manner similar to that employed to measure connectedness in the network literature.²³ This variable has a mean (median) value of 6.18 (4.87) and an interquartile range of 6.88. We control for $\text{Log}(\text{Coverage})$, which is strongly related to return synchronicity (Crawford, Roulstone, and So, 2012; Piotroski and Roulstone, 2004; and Chan and Hameed, 2006). We also control for other determinants of return comovement across broad groups of stocks such as market capitalization ($\text{Log}(\text{Market Cap})$), book-to-market ratio (BM), and trading volume ($\text{Log}(\text{Volume})$). To control for economic exposure shared by stocks with shared coverage, we also include aggregate values of all pair-wise controls for shared economic exposure we employ in Table 6. Like *Aggregate Pair Coverage*, the aggregate value of each of these controls is its sum across all stock pairs that share coverage with stock i in a given year. For example, *Aggregate Same Industry* is the sum of the dummy variable *Same Industry* across all stock pairs that share coverage with stock i in a given year. According to the *Comovement Prediction*, the coefficient estimates on *Aggregate Pair Coverage* in all three models should be positive. These coefficients should equal zero if analysts focus exclusively on either broad or stock-specific information. Panel C of Table 8 presents OLS estimates of Eq. (13) with t-statistics based on robust standard errors clustered by stock and year.

²³In the network literature the strength of a node’s linkages to other nodes in a network is measured by the sum of its connections to all nodes to which it is connected (Diebold and Yilmaz, 2011).

The coefficient estimate on *Aggregate Pair Coverage* is positive and highly statistically significant in Model 2, where the dependent variable is *Sync*. Varying *Aggregate Pair Coverage* between its 25th and 75th percentiles accounts for 10% of the interquartile variation in *Sync*. Both the coefficient estimate on *Aggregate Pair Coverage* and its economic significance are similar in Model 3, which also includes aggregate pair-wise controls for shared economic exposure. These estimates indicate that the stock's returns covary more strongly with returns on broad indices when the extent and intensity of a stock's shared coverage increases. This result is to be expected since research on a stock spills over to more than 60 stocks on average. Based on Model 5, *Aggregate Pair Coverage* appears to have a stronger influence on *Aug. Sync*; its coefficient estimate is 0.059 which is statistically significant at the 1% level. Moreover, varying *Aggregate Pair Coverage* between its 25th and 75th percentiles accounts for 14% of the interquartile variation in *Aug. Sync*. In Model 6, which also includes aggregate pair-wise controls for shared economic exposure, the coefficient estimate on *Aggregate Pair Coverage* is even higher (0.066), consistent with stronger economic significance.

Aug. Sync - Sync isolates return synchronicity with stocks that share coverage. Therefore, controlling for the economic exposure shared by stocks with shared coverage is crucial to obtaining clear inferences regarding the *Comovement Prediction*. In Model 8, where we do not include these controls, the coefficient estimate on *Aggregate Pair Coverage* is 0.017 and is significant at the 1% level. Moreover, varying *Aggregate Pair Coverage* between its 25th and 75th percentiles accounts for 31% of the interquartile variation in *Aug. Sync - Sync*. In Model 9, where we include aggregate pair-wise controls for shared economic exposure, the coefficient estimate on *Aggregate Pair Coverage* is 0.022 and is also significant at the 1% level. Moreover, varying *Aggregate Pair Coverage* between its 25th and 75th percentiles accounts for 40% of the interquartile variation in *Aug. Sync - Sync*. This indicates that an increase in the extent and intensity of coverage linkages strengthens the return comovement with stocks with shared coverage incremental to market and industry effects.²⁴

In Model 1, which does not include *Aggregate Pair Coverage*, the coefficient estimate on

²⁴We also find that the returns on a stock comove more strongly with returns on stocks that belong with it in shared-coverage triplets than returns on stocks that do not belong in its shared-coverage triplets. A shared-coverage triplet is a group of three stocks where there is at least one analyst common to all three stocks. Tests based on return synchronicity with stocks belonging in shared-coverage triplets yield similar results.

$\text{Log}(\text{Coverage})$ is positive and statistically significant, consistent with the prior literature. In Model 2, however, the coefficient estimate on $\text{Log}(\text{Coverage})$ is not statistically different from zero. This evidence suggests that the explanatory power of $\text{Log}(\text{Coverage})$ is subsumed by *Aggregate Pair Coverage*.

The evidence in Table 8 supports the *Comovement Prediction*. A stock's returns comove more closely with the returns of other stocks, particularly ones with which it shares coverage, as the stock's level of shared coverage rises. This effect is independent of the effect of the level of analyst coverage, which the literature has viewed as a measure of the amount of market- or industry-wide information disseminated by analysts.

7. Concluding Comments

In this paper, we study whether sell-side analyst research generates information spillovers among stocks that share coverage. These spillovers arise when analysts use and convey information that is common to stocks in their coverage in addition to stock-specific or broad information. We argue that coverage-specific information achieves a balance for analysts who try to reduce research costs while possibly increasing overall brokerage revenues that are tied to investor demand for their research.

Using a comprehensive set of stocks between years 1997 and 2010, we find that analysts who cover both stocks in a pair expect future earnings of the stocks to be more highly correlated than do analysts who cover only one of the stocks, especially when the number of analysts covering both stocks are high. Consequently, research on a stock is more informative about the other stock in the pair when analysts cover both stocks. On days that analysts issue forecasts or recommendations for a stock in a pair, price reactions of both stocks are closer when the forecasts or recommendations are issued by analysts who cover both stocks. Based on the decomposition of stock returns around recommendation revisions, we find that coverage-specific information has a price impact comparable to that of broad market- or industry-level information in analyst research. Moreover, this price impact is significantly stronger than for stocks that are likely to have similar shared economic exposure but are not the subject of coverage-specific information produced by the recommending analyst. We find corroborating evidence when we examine

daily returns during a year. The daily return correlation within a stock pair increases with the intensity of coverage from analysts who cover both stocks. This is likely because of the higher correlations in earnings forecasts issued by analysts who cover both stocks in a pair. In general, stock returns are positively correlated with returns on portfolios of stocks with which they share coverage, and this correlation rises with the extent and intensity of shared coverage. The effect of coverage-specific spillovers on return comovement is incremental to the effect of shared economic factors such as comovement in cash flows and earnings; similarities in size, growth, age, leverage, performance, and price level; and common industry, location, and S&P 500 index membership.

Collectively, all our findings support the *Coverage-Specific Spillover Hypothesis*, which predicts that analyst research conveys coverage-specific information and, as a result, raises return comovement between stocks that share analyst coverage by an economically meaningful amount. This coverage-specific information spillover is distinct from the effects of stock-specific and broad information conveyed by analyst research that has so far been the focus of the literature.

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Appendix: Variable definitions

Panel A: Stock characteristics (end of fiscal year unless specified otherwise)	
<i>Assets</i>	= Total assets in million \$'s.
<i>Market Cap</i>	= Equity market capitalization in million \$'s.
<i>Equity</i>	= Book value of equity in million \$'s.
<i>Volume</i>	= Trading volume in a year in million shares.
<i>S&P500</i>	= An indicator variable that is one if the stock belongs to the S&P500 index.
<i>Coverage</i>	= The number of analysts covering a stock during the year.
<i>Aggregate Pair Coverage</i>	= The sum of <i>Pair Coverage</i> across all stocks with which the stock shares analyst coverage.
<i>Leverage</i>	= Total liabilities divided by total assets.
<i>ROA</i>	= Net income divided by total assets.
<i>EPS</i>	= Earnings excluding extraordinary items per share in \$'s.
<i>BM</i>	= Book value of assets divided by market value of assets.
<i>Price</i>	= The stock's price in \$'s.
<i>Age</i>	= The number of years since the stock first appeared in the CRSP/Compustat database (1980 is the starting year).
Panel B: Annual stock-pair characteristics	
<i>Correlation</i>	= Daily return correlation of the stocks in a pair.
<i>Pair Forecast Correlation</i>	= The correlation between monthly consensus of forecasts for the two stocks in a pair issued by pair analysts.
<i>Individual Forecast Correlation</i>	= The correlation between monthly consensus of forecasts for the two stocks in a pair issued by individual analysts.
<i>Diff Forecast Correlation</i>	= <i>Pair Forecast Correlation</i> - <i>Individual Forecast Correlation</i> . Both forecast correlation measures must have at least eight overlapping months.
<i>Pair Coverage</i>	= The ratio of pair analysts to the total number of analysts (i.e., pair and individual analysts combined) covering the stock pair.
<i>Coverage Intensity</i>	= The ratio of the total number of analysts covering the pair to the sum of the average numbers of analysts covering stocks in each of the two-digit SIC industries to which the pair stocks belong.
<i>Same Industry</i>	= An indicator variable that is one if the stocks have the same two-digit SIC code.
<i>Related Industry</i>	= An indicator variable that is one if the industries to which the stocks belong consume or supply 10% of one another's output.
<i>Same Exchange</i>	= An indicator variable that is one if the stocks are listed on the same exchange (i.e., NYSE, NASDAQ, OTC, or AMEX).
<i>Same State</i>	= An indicator variable that is one if the stocks are headquartered in the same state.
<i>S&P500 Members</i>	= An indicator variable that is one if both stocks are included in the S&P500 index.
<i>Similar Asset</i>	= An indicator variable that is one if both stocks are in the same <i>Assets</i> quartile of the sample at the end of the fiscal year.
<i>Similar BM</i>	= An indicator variable that is one if both stocks are in the same <i>BM</i> quartile of the sample at the end of the fiscal year.
<i>Similar Age</i>	= An indicator variable that is one if both stocks are in the same <i>Age</i> quartile of the sample at the end of the fiscal year.
<i>Similar Leverage</i>	= An indicator variable that is one if both stocks in the pair are in the same <i>Leverage</i> quartile at the end of the fiscal year.
<i>Similar ROA</i>	= An indicator variable that is one if both stocks are in the same <i>ROA</i> quartile of the sample during the current fiscal year.
<i>Similar EPS</i>	= An indicator variable that is one if both stocks are in the same <i>EPS</i> quartile of the sample during the current fiscal year.
<i>Similar Price</i>	= An indicator variable that is one if both stocks are in the same <i>Price</i> quartile of the sample at the end of the current year.
<i>ROA Correlation</i>	= The correlation in quarterly <i>ROA</i> for years between t-4 and t.

<i>ΔROA correlation</i>	=	The correlation in changes in quarterly <i>ROA</i> for years between t-4 and t.
<i>EPS Correlation</i>	=	The correlation in quarterly <i>EPS</i> for years between t-4 and t.
<i>ΔEPS Correlation</i>	=	The correlation in quarterly changes in <i>EPS</i> for years between t-4 and t.
<i>Diff Experience</i>	=	The difference in the logarithms of one plus the averages of <i>Experience</i> for pair and individual analysts covering the pair.
<i>Diff Broker Size</i>	=	The difference in the logarithms of one plus the averages of <i>Broker Size</i> for pair and individual analysts covering the pair.
<i>Diff Companies</i>	=	The difference in the logarithms of one plus the averages of <i>Companies</i> for pair and individual analysts covering the pair.
<i>Diff Forecast Error</i>	=	The difference in the logarithms of one plus the averages of <i>Forecast Error</i> for pair and individual analysts covering the pair.

Panel C: Annual analyst characteristics

<i>Experience</i>	=	The number of years since the analyst first appeared in the I/B/E/S database.
<i>Broker Size</i>	=	The total number of analysts employed by the analyst's employer.
<i>Companies</i>	=	The total number of stocks covered by the analyst.
<i>Forecast Error</i>	=	The median of the absolute forecast errors across all companies the analyst covers. Absolute forecast error is the absolute difference between an annual forecast and actual earnings per share deflated by share price at the beginning of the fiscal year.

Figure 1: Difference between pair and individual forecast correlation. This figure illustrates, across *Pair Coverage* deciles, average correlation of monthly consensus forecasts for a stock pair issued only by pair analysts (*Pair Forecast Correlation*) and only by individual analysts (*Individual Forecast Correlation*) and the pair-wise difference between the forecast correlations. For each stock in a pair-year, we compute monthly consensus forecasts using forecasts issued by pair and individual analysts, separately. For each pair-year, we correlate monthly consensus forecasts of the two stocks issued by pair and individual analysts, separately. In order to arrive at reliable monthly correlation estimates between the two stocks, we require that forecast correlation measures are computed using at least eight overlapping months.

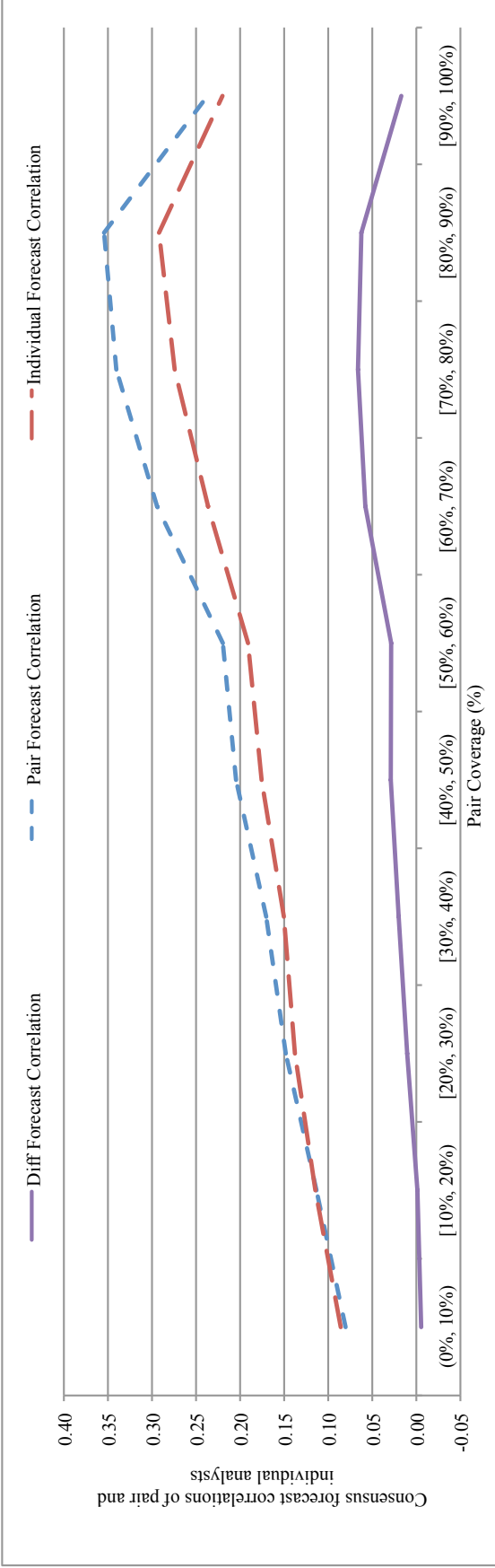


Table 1: Sample composition. This table provides an annual breakdown of our sample between years 1997 and 2010. The sample includes all pairs generated from stocks in the CRSP/Compustat database that have at least one sell-side equity analyst (from the I/B/E/S database) covering both stocks during a year. Analyst teams who have a single I/B/E/S identifier and who cover more than 40 stocks during a year are not considered. Stocks are required to have non-missing financials that are used in the subsequent tables and stock prices that are greater than \$1 on all month-ends of the year. Stocks (Stock pairs) are the number of unique stocks (stock pairs) in the sample. Pair analysts are defined as those who cover both stocks in a pair. Individual analysts are defined as those who cover only one stock in a pair. Recommendations by pair (individual) analysts show the total number of recommendations issued by pair (individual) analysts for either of the stocks in a pair. Forecasts by pair (individual) analysts show the total number of annual and quarterly earnings forecasts issued by pair (individual) analysts for either of the stocks in the pair.

Year	Stocks	Stock pairs	Pair analysts	Individual analysts	Recommendations by		Forecasts by	
					Pair analysts	Individual analysts	Pair analysts	Individual analysts
1997	4,111	130,252	1.70	19.65	2.16	13.26	10.15	59.06
1998	4,163	128,557	1.68	19.27	2.36	14.28	10.99	62.68
1999	3,901	119,308	1.77	21.28	2.40	15.60	10.47	63.39
2000	3,592	102,752	1.83	22.87	2.35	15.70	10.83	67.81
2001	3,312	91,452	1.90	22.01	2.85	17.16	13.40	76.19
2002	3,201	86,711	2.04	21.60	4.92	25.32	14.07	70.95
2003	3,267	91,505	2.04	21.90	3.85	20.40	14.55	75.92
2004	3,424	98,466	2.01	21.34	3.13	16.69	15.60	81.66
2005	3,577	105,929	1.99	20.96	2.73	14.57	15.71	80.92
2006	3,612	112,386	1.97	20.77	2.84	14.69	15.41	80.28
2007	3,533	114,541	1.98	21.19	2.69	14.51	15.71	83.07
2008	3,224	103,205	2.01	21.40	3.52	17.04	18.36	94.67
2009	3,145	102,911	2.05	22.57	3.23	18.11	18.96	102.62
2010	3,189	101,920	2.16	24.03	2.86	16.47	19.27	105.31
Average	3,518	106,421	1.94	21.49	2.99	16.70	14.53	78.89

Table 2: Descriptive statistics. Panels A, B, and C report statistics describing sample stocks, stock pairs, and characteristics of pair and individual analysts, respectively. Variable definitions are presented in the Appendix. All continuous variables are winsorized at 1% and 99%. The last two columns of Panel C report mean and median pair-wise differences between the characteristics of pair and individual analysts. These columns report results from t-tests (Wilcoxon tests) for difference in means (medians). ***, **, * indicate significance of differences at 1%, 5%, and 10%, respectively.

Panel A: Stock years (N = 49,251)						
	Mean	Minimum	25th Pctl	Median	75th Pctl	Maximum
<i>Coverage</i>	9.16	1.00	3.00	7.00	12.00	63.00
<i>Assets</i>	6,071	16	217	801	2,955	152,588
<i>Market Cap</i>	4,112	21	206	635	2,216	86,665
<i>Equity</i>	1,581	-102	99	289	969	31,726
<i>Volume</i>	202.59	1.56	16.33	52.85	163.17	3,058.50
<i>S&P500</i>	0.14	0.00	0.00	0.00	0.00	1.00
<i>Leverage</i>	0.54	0.06	0.33	0.54	0.72	1.19
<i>ROA</i>	0.00	-0.93	0.00	0.03	0.07	0.26
<i>EPS</i>	0.83	-6.98	-0.05	0.82	1.77	7.56
<i>BM</i>	0.69	0.10	0.46	0.71	0.92	1.49
<i>Price</i>	24.23	1.44	9.06	19.22	33.44	102.85
<i>Age</i>	13.23	2.00	6.00	12.00	20.00	31.00

Panel B: Stock-pair years							
	Mean	Minimum	25th Pctl	Median	75th Pctl	Maximum	N
<i>Correlation</i>	0.269	-0.661	0.121	0.239	0.393	0.98	1,489,895
<i>Pair Coverage</i>	0.102	0.009	0.042	0.067	0.125	1	1,489,895
<i>Pair Forecast Correlation</i>	0.099	-1	-0.582	0.233	0.744	1	688,755
<i>Individual Forecast Correlation</i>	0.100	-1	-0.609	0.234	0.77	1	688,755
<i>Coverage Intensity</i>	1.289	0.029	0.796	1.174	1.648	6.999	1,489,895
<i>Same Industry</i>	0.434	0	0	0	1	1	1,489,895
<i>Related Industry</i>	0.181	0	0	0	0	1	1,489,895
<i>Same Exchange</i>	0.597	0	0	1	1	1	1,489,895
<i>Same State</i>	0.139	0	0	0	0	1	1,489,895
<i>S&P500 Members</i>	0.076	0	0	0	0	1	1,489,895
<i>Similar Asset</i>	0.381	0	0	0	1	1	1,489,895
<i>Similar BM</i>	0.371	0	0	0	1	1	1,489,895
<i>Similar Age</i>	0.325	0	0	0	1	1	1,489,895
<i>Similar Leverage</i>	0.398	0	0	0	1	1	1,489,895
<i>Similar ROA</i>	0.374	0	0	0	1	1	1,489,895
<i>Similar EPS</i>	0.343	0	0	0	1	1	1,489,895
<i>Similar Price</i>	0.320	0	0	0	1	1	1,489,895
<i>ROA Correlation</i>	0.124	-1	-0.270	0.161	0.542	1	1,482,648
<i>ΔROA Correlation</i>	0.057	-1	-0.144	0.047	0.258	1	1,470,738
<i>EPS Correlation</i>	0.115	-1	-0.318	0.157	0.574	1	1,482,183
<i>ΔEPS Correlation</i>	0.063	-1	-0.167	0.054	0.296	1	1,470,069

Panel C: Pair and individual analysts (N = 1,480,417)						
	Pair analysts		Individual analysts		Pair-wise difference	
	Mean	Median	Mean	Median	Mean	Median
<i>Experience</i>	7.20	7.00	6.53	6.39	0.68***	0.47***
<i>Broker Size</i>	52.47	44.00	56.49	56.15	-3.97***	-9.60***
<i>Companies</i>	20.82	19.67	16.05	15.71	4.77***	3.79***
<i>Forecast Error</i>	0.0058	0.0038	0.0064	0.0045	-0.001***	-0.001***

Table 3: Forecast correlations. This table reports results from OLS regressions of *Diff Forecast Correlation* on *Pair Coverage* and pair-wise controls for shared economic exposure. Variable definitions are presented in the Appendix. T-statistics based on robust standard errors clustered by stock pair and year are presented in parentheses below the coefficient estimates. ***, **, * indicate significance at 1%, 5%, and 10%, respectively.

	<i>Diff Forecast Correlation (%)</i>			
	(1)	(2)	(3)	(4)
<i>Pair Coverage</i>	8.693*** (7.37)	8.717*** (7.37)	9.053*** (7.24)	9.074*** (7.06)
<i>Coverage Intensity</i>	0.025 (0.11)	0.045 (0.20)	0.052 (0.23)	0.056 (0.24)
<i>Same Industry</i>	-0.202 (-1.13)	-0.126 (-0.73)	-0.065 (-0.33)	-0.110 (-0.54)
<i>Related Industry</i>	-0.269 (-0.70)	-0.261 (-0.68)	-0.121 (-0.31)	-0.128 (-0.33)
<i>Same Exchange</i>	0.067 (0.44)	0.067 (0.42)	0.078 (0.49)	0.071 (0.46)
<i>Same State</i>	-0.172 (-1.17)	-0.166 (-1.15)	-0.109 (-0.73)	-0.102 (-0.66)
<i>S&P500 Members</i>	-0.219 (-0.90)	-0.302 (-1.01)	-0.321 (-1.09)	-0.309 (-1.02)
<i>Similar Asset</i>		0.204 (1.10)	0.202 (1.15)	0.199 (1.12)
<i>Similar BM</i>		0.005 (0.03)	0.063 (0.43)	0.066 (0.46)
<i>Similar Age</i>		0.251 (1.30)	0.230 (1.18)	0.232 (1.19)
<i>Similar Leverage</i>		-0.200 (-1.05)	-0.177 (-0.96)	-0.178 (-0.97)
<i>Similar ROA</i>		-0.409** (-2.15)	-0.322* (-1.72)	-0.321* (-1.71)
<i>Similar EPS</i>		-0.037 (-0.17)	0.065 (0.27)	0.055 (0.23)
<i>Similar Price</i>		-0.287 (-1.07)	-0.269 (-1.01)	-0.268 (-1.00)
<i>ROA Correlation</i>			-0.932*** (-2.83)	-0.933*** (-2.84)
<i>ΔROA Correlation</i>			-0.146 (-0.38)	-0.153 (-0.40)
<i>EPS Correlation</i>			-0.789** (-2.28)	-0.792** (-2.27)
<i>ΔEPS Correlation</i>			-0.189 (-0.56)	-0.191 (-0.56)
<i>Diff Experience</i>				0.018 (0.07)
<i>Diff Broker Size</i>				0.181 (1.16)
<i>Diff Companies</i>				-0.326 (-0.76)
<i>Diff Forecast Error</i>				44.214*** (4.46)
<i>Constant</i>	-0.970** (-2.24)	-0.849* (-1.78)	-0.759 (-1.62)	-0.597 (-1.11)
Adj. R ²	0.04%	0.08%	0.10%	0.10%
N	568,307	568,307	564,280	563,858

Table 4: Analyst activity returns. This table presents two measures of informativeness of analyst research for pair and individual analysts, separately. The first measure, *Absolute Return*, is the absolute value of NYSE size decile-adjusted returns for the stocks in the pair on the activity day. Activity days are defined as days in which an analyst issues forecasts or recommendations for only one stock in the pair. To reduce the effect of confounding events, we drop observations with absolute value of size-adjusted returns for either the activity or no-activity stock higher than 6.8% (95th percentile of the sample). The second measure, *Analyst Informativeness (AI)*, is the absolute value of size-adjusted activity day return for a stock divided by the average absolute value of the stock's NYSE size decile-adjusted returns on no-activity days throughout the year (Frankel et al., 2006). We compute average and median values of *Absolute Return* and *AI* for each pair-year and for pair analysts and individual analysts separately (N=1,292,253 pair-years). Panel A presents mean and median pair-year values of *Absolute Return* and *AI* for the activity and no-activity stocks as well as within-pair differences of these values. Panel B reports results from regressing the difference in *Absolute Return* and *AI* on *Pair Coverage*, *Coverage Intensity*, and pair-wise controls for shared economic exposure. Variable definitions are presented in the Appendix. T-statistics based on robust standard errors clustered by stock pair and year are presented in parentheses below the coefficient estimates.***, **, * indicate significance at 1%, 5%, and 10%, respectively.

		Activity stock		No-activity stock		Difference		
		<i>Absolute Return</i>	<i>AI</i>	<i>Absolute Return</i>	<i>AI</i>	<i>Absolute Return</i>	<i>AI</i>	
Pair analysts		Mean	1.73%	1.109	1.60%	0.972	0.14%***	0.138***
		Median	1.63%	1.081	1.48%	0.959	0.13%***	0.122***
Individual analysts		Mean	1.86%	1.175	1.56%	0.966	0.31%***	0.208***
		Median	1.66%	1.076	1.32%	0.904	0.25%***	0.163***
Pair-Individual		Mean	-0.13%***	-0.065***	0.04%***	0.005***	-0.17%***	-0.071***
		Median	-0.02%***	-0.007***	0.11%***	0.058***	-0.12%***	-0.045***

Panel B: Difference in spillovers from activity by pair analysts and individual analysts

	<i>Diff Absolute Return</i>				<i>Diff AI</i>			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
<i>Pair Coverage</i>	0.248*** (4.83)	0.183*** (3.77)	0.181*** (3.75)	0.286*** (5.82)	0.103*** (4.34)	0.095*** (4.13)	0.093*** (4.11)	0.177*** (6.60)
<i>Coverage Intensity</i>	-0.013 (-1.33)	-0.008 (-0.87)	-0.008 (-0.83)	-0.004 (-0.39)	0.002 (0.48)	0.003 (0.69)	0.003 (0.70)	0.007* (1.80)
<i>Same Industry</i>	-0.048*** (-5.22)	-0.059*** (-6.12)	-0.059*** (-6.19)	-0.050*** (-5.29)	-0.017*** (-4.39)	-0.019*** (-4.57)	-0.019*** (-4.76)	-0.012*** (-2.98)
<i>Related Industry</i>	-0.024** (-2.51)	-0.024** (-2.57)	-0.024*** (-2.65)	-0.022** (-2.39)	-0.008* (-1.73)	-0.008* (-1.74)	-0.009* (-1.73)	-0.007 (-1.46)
<i>Same Exchange</i>	0.050*** (7.77)	0.032*** (5.23)	0.032*** (5.36)	0.033*** (5.44)	-0.005 (-1.40)	-0.007** (-2.18)	-0.007** (-2.12)	-0.006* (-1.70)
<i>Same State</i>	-0.003 (-0.48)	0.000 (0.05)	-0.000 (-0.09)	-0.005 (-1.04)	0.004 (1.22)	0.004 (1.34)	0.004 (1.21)	-0.001 (-0.36)
<i>S&P500 Members</i>	0.141*** (9.33)	0.074*** (5.65)	0.074*** (5.58)	0.064*** (4.67)	0.040*** (5.18)	0.031*** (4.15)	0.031*** (4.10)	0.023*** (3.17)
<i>Similar Asset</i>		0.100*** (11.81)	0.101*** (11.72)	0.101*** (11.55)		0.015*** (6.73)	0.015*** (6.79)	0.016*** (6.52)
<i>Similar BM</i>		-0.005 (-1.45)	-0.005 (-1.50)	-0.006 (-1.63)		0.001 (0.59)	0.001 (0.63)	0.001 (0.39)
<i>Similar Age</i>		0.031*** (6.49)	0.031*** (6.66)	0.031*** (6.36)		0.007*** (2.84)	0.007*** (3.07)	0.006*** (2.72)
<i>Similar Leverage</i>		0.002 (0.48)	0.002 (0.42)	0.001 (0.31)		0.002 (0.86)	0.002 (0.79)	0.001 (0.54)
<i>Similar ROA</i>		0.026*** (5.69)	0.026*** (5.48)	0.025*** (5.23)		0.006** (2.26)	0.006** (2.24)	0.005* (1.89)
<i>Similar EPS</i>		0.019*** (7.24)	0.020*** (7.17)	0.021*** (8.06)		0.002 (0.90)	0.002 (1.03)	0.003 (1.47)
<i>Similar Price</i>		0.055*** (9.28)	0.055*** (9.39)	0.055*** (9.12)		-0.001 (-0.50)	-0.001 (-0.59)	-0.001 (-0.63)
<i>ROA Correlation</i>			0.005 (1.08)	0.006 (1.37)			0.001 (0.24)	0.001 (0.59)
<i>ΔROA Correlation</i>			-0.008 (-1.08)	-0.009 (-1.16)			-0.005 (-1.24)	-0.005 (-1.36)
<i>EPS Correlation</i>			-0.008 (-1.49)	-0.009 (-1.61)			-0.003 (-1.45)	-0.004* (-1.73)
<i>ΔEPS Correlation</i>			0.014* (1.91)	0.015** (2.16)			0.004 (0.92)	0.005 (1.28)
<i>Diff Experience</i>				-0.064*** (-5.44)				-0.042*** (-4.82)
<i>Diff Broker Size</i>				-0.044*** (-11.37)				-0.038*** (-10.80)
<i>Diff Companies</i>				0.057*** (6.91)				0.029*** (4.34)
<i>Diff Forecast Error</i>				-1.576*** (-3.75)				-0.079 (-0.35)
<i>Constant</i>	-0.195*** (-6.35)	-0.255*** (-7.59)	-0.257*** (-7.64)	-0.303*** (-9.20)	-0.076*** (-4.50)	-0.084*** (-4.79)	-0.085*** (-4.80)	-0.120*** (-6.00)
Adj. R ²	0.25%	0.43%	0.43%	0.56%	0.04%	0.05%	0.05%	0.26%
N	1,292,253	1,292,253	1,274,571	1,268,872	1,292,253	1,292,253	1,274,571	1,268,872

Table 5: Stock returns around analyst recommendation revisions. Panel A reports coefficient estimates from OLS regressions of daily stock returns on *Analyst Portfolio* ($\hat{\beta}^A$), *Market Portfolio* ($\hat{\beta}^M$), and *Industry Portfolio* ($\hat{\beta}^I$) estimated independently for each year-stock-analyst combination. *Market Portfolio* is the daily CRSP value-weighted return, *Industry Portfolio* is the daily value-weighted two-digit SIC industry return orthogonalized relative to *Market Portfolio*. *Analyst Portfolio* is the daily equal-weighted return on the portfolio of other stocks covered by the analyst orthogonalized relative to *Market Portfolio* and *Industry Portfolio*. Panel A also reports the following components of three-day stock returns around recommendation revisions, $Return_{[-1,1]}$: *Analyst Portfolio Component* ($\hat{\beta}^A \times Analyst\ Portfolio_{[-1,1]}$); *Market Component* ($\hat{\beta}^M \times Market\ Portfolio_{[-1,1]}$); *Industry Component* ($\hat{\beta}^I \times Industry\ Portfolio_{[-1,1]}$); and *Stock-Specific Component* ($Return_{[-1,1]} - Analyst\ Portfolio\ Component - Market\ Component - Industry\ Component$). The above coefficients and return components are reported separately for recommendation upgrades and downgrades. Panel B reports results from OLS regressions of $Return_{[-1,1]}$ on the following analyst coverage related portfolios in addition to *Analyst Portfolio*, *Market Portfolio*, *Industry Portfolio*, returns on the Fama-French value (*HML*) and size (*SMB*) portfolios, and the momentum (*UMD*) portfolio: *Analyst Portfolio_Same Ind.* (*Analyst Portfolio_Different Ind.*), which is the equal-weighted return on stocks in the same (different) two-digit SIC industry that share coverage from the analyst, and *Other Analyst Portfolio*, which is the equal-weighted return on stocks that share coverage with analysts other than the recommending analyst. T-statistics based on robust standard errors clustered by stock and year are presented in parentheses below the coefficient estimates. ***, **, * indicate significance at 1%, 5%, and 10%, respectively.

Panel A: Components of announcement returns					
	Mean	Std. Dev.	25th Pctl	Median	75th Pctl
<hr/>					
Three-day announcement returns around upgrades (N = 80,315)					
$\hat{\beta}^A$	0.64	0.54	0.28	0.62	0.97
$\hat{\beta}^M$	1.15	0.58	0.75	1.09	1.49
$\hat{\beta}^I$	0.81	0.67	0.33	0.76	1.20
<i>Return</i> _[-1,1]	3.41%	9.81%	-1.13%	2.29%	6.77%
<i>Analyst Portfolio Component</i>	0.25%	3.39%	-0.72%	0.07%	1.11%
<i>Market Component</i>	0.16%	3.00%	-1.02%	0.21%	1.41%
<i>Industry Component</i>	0.25%	1.95%	-0.33%	0.05%	0.67%
<i>Stock-Specific Component</i>	2.74%	8.90%	-1.18%	1.73%	5.65%
<hr/>					
Three-day announcement returns around downgrades (N = 95,207)					
$\hat{\beta}^A$	0.66	0.55	0.29	0.64	1.00
$\hat{\beta}^M$	1.14	0.61	0.72	1.06	1.47
$\hat{\beta}^I$	0.78	0.69	0.29	0.72	1.18
<i>Return</i> _[-1,1]	-4.82%	12.37%	-8.13%	-2.48%	0.99%
<i>Analyst Portfolio Component</i>	-0.12%	3.61%	-0.92%	0.01%	0.90%
<i>Market Component</i>	0.01%	3.03%	-1.03%	0.15%	1.27%
<i>Industry Component</i>	-0.05%	1.97%	-0.49%	0.00%	0.46%
<i>Stock-Specific Component</i>	-4.66%	11.68%	-7.51%	-2.38%	0.68%

Panel B: Regressions of announcement returns				
	Three-day announcement returns			
	(1)	(2)	(3)	(4)
<i>Analyst Portfolio</i>	1.112*** (25.31)	1.109*** (26.56)	0.742*** (18.87)	
<i>Analyst Portfolio_Same Ind.</i>				0.686*** (16.34)
<i>Analyst Portfolio_Different Ind.</i>				0.288*** (9.82)
<i>Other Analyst Portfolio</i>			0.581*** (8.29)	
<i>Market Portfolio</i>	1.193*** (21.36)	1.175*** (19.20)	1.167*** (18.45)	1.203*** (19.58)
<i>Industry Portfolio</i>	1.212*** (20.63)	1.213*** (20.78)	1.216*** (21.39)	1.285*** (23.46)
<i>SMB</i>		-0.005 (-0.19)	-0.025 (-0.86)	-0.003 (-0.10)
<i>HML</i>		-0.037** (-2.32)	-0.038** (-2.37)	-0.043** (-2.51)
<i>UMD</i>		-0.020*** (-2.71)	-0.018** (-2.57)	-0.021*** (-2.81)
<i>Constant</i>	-0.013*** (-5.53)	-0.012*** (-5.48)	-0.012*** (-5.50)	-0.012*** (-5.43)
t-stat (<i>An. Port. = Other An. Port.</i>)			1.79	
t-stat (<i>An. Port._Same Ind. = An. Port._Diff Ind.</i>)				6.99
Adj. R ²	12.6%	12.6%	13.0%	13.1%
N	175,522	175,522	173,623	157,070

Table 6: **Pair coverage and return correlation.** This table reports results from OLS regressions of *Correlation* on *Pair Coverage* and a set of pair-wise controls. Variable definitions are presented in the Appendix. T-statistics based on robust standard errors clustered by stock pair and year are presented in parentheses below the coefficient estimates. ***, **, * indicate significance at 1%, 5%, and 10%, respectively.

	<i>Correlation</i>					
	Pair Universe		Sample Pairs			
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Pair Coverage</i>	0.505 *** (17.93)	0.493*** (17.66)	0.231*** (10.17)	0.213*** (9.93)	0.201*** (9.34)	0.218*** (9.99)
<i>Coverage Intensity</i>	0.048 *** (9.81)	0.048 *** (9.91)	0.046*** (6.49)	0.046*** (6.33)	0.046*** (6.39)	0.046*** (6.47)
<i>Same Industry</i>	0.019 *** (3.99)	0.017 *** (3.63)	0.059*** (13.89)	0.053*** (14.19)	0.051*** (12.97)	0.048*** (12.14)
<i>Related Industry</i>	0.000 (-0.12)	-0.001 (-0.27)	0.026*** (5.43)	0.025*** (5.39)	0.022*** (5.06)	0.022*** (5.01)
<i>Same Exchange</i>	0.030 *** (7.81)	0.028 *** (6.92)	0.050*** (10.83)	0.045*** (8.83)	0.044*** (8.98)	0.044*** (8.60)
<i>Same State</i>	0.005 ** (2.39)	0.004 ** (2.19)	0.019*** (3.84)	0.019*** (3.91)	0.016*** (3.37)	0.018*** (3.61)
<i>S&P500 Members</i>	0.063 *** (6.61)	0.056*** (5.70)	0.080*** (8.54)	0.066*** (6.35)	0.066*** (6.40)	0.066*** (6.54)
<i>Similar Asset</i>		0.008 *** (7.22)		0.017*** (7.66)	0.017*** (7.64)	0.017*** (7.58)
<i>Similar BM</i>		0.003 *** (6.55)		0.006** (2.23)	0.006** (1.96)	0.006** (2.06)
<i>Similar Age</i>		0.002*** (3.76)		0.007*** (3.85)	0.008*** (4.09)	0.008*** (4.17)
<i>Similar Leverage</i>		0.002*** (2.60)		0.011*** (3.92)	0.011*** (3.55)	0.011*** (3.54)
<i>Similar ROA</i>		0.003 *** (5.50)		0.011*** (3.04)	0.008** (2.30)	0.008** (2.34)
<i>Similar EPS</i>		0.004 *** (5.15)		0.007* (1.66)	0.004 (1.03)	0.004 (0.99)
<i>Similar Price</i>		0.009 *** (17.44)		0.016*** (10.69)	0.016*** (11.16)	0.016*** (11.33)
<i>ROA Correlation</i>					0.036*** (4.07)	0.036*** (4.10)
Δ ROA Correlation					0.017*** (5.79)	0.017*** (5.78)
<i>EPS Correlation</i>					0.007 (1.35)	0.007 (1.37)
Δ EPS Correlation					0.027*** (3.30)	0.026*** (3.29)
<i>Diff Experience</i>						-0.004 (-1.64)
<i>Diff Broker Size</i>						0.011*** (4.66)
<i>Diff Companies</i>						0.002 (0.42)
<i>Diff Forecast Error</i>						-0.492*** (-2.86)
<i>Constant</i>	0.101 *** (5.16)	0.094*** (4.82)	0.117*** (3.57)	0.098*** (2.80)	0.096*** (2.82)	0.100*** (2.83)
Adj. R ²	6.3%	6.5%	10.5%	11.3%	13.5%	14.1%
N	91,561,175	91,561,175	1,489,895	1,489,895	1,470,060	1,460,819

Table 7: Return correlation and forecasts. This table reports results from OLS regressions of *Correlation* on *Pair Forecast Correlation*, *Individual Forecast Correlation* and a set of pair-wise controls. Variable definitions are presented in the Appendix. T-statistics based on robust standard errors clustered by stock pair and year are presented in parentheses below the coefficient estimates. ***, **, * indicate significance at 1%, 5%, and 10%, respectively.

	<i>Correlation</i>			
	(1)	(2)	(3)	(4)
<i>Pair Forecast Correlation</i>	0.014*** (11.28)	0.013*** (9.78)	0.009*** (9.06)	0.009*** (8.89)
<i>Individual Forecast Correlation</i>	0.015*** (4.08)	0.014*** (3.77)	0.009*** (2.78)	0.009*** (2.85)
<i>Coverage Intensity</i>	0.030*** (4.38)	0.031*** (4.32)	0.032*** (4.56)	0.032*** (4.51)
<i>Same Industry</i>	0.061*** (11.08)	0.052*** (12.68)	0.049*** (11.43)	0.046*** (10.64)
<i>Related Industry</i>	0.026*** (5.42)	0.025*** (5.31)	0.021*** (4.91)	0.021*** (4.82)
<i>Same Exchange</i>	0.050*** (7.94)	0.043*** (6.61)	0.042*** (6.74)	0.041*** (6.56)
<i>Same State</i>	0.027*** (4.73)	0.027*** (4.82)	0.023*** (4.32)	0.024*** (4.54)
<i>S&P500 Members</i>	0.113*** (15.53)	0.092*** (11.61)	0.090*** (11.52)	0.090*** (11.56)
<i>Similar Asset</i>		0.027*** (9.02)	0.027*** (8.78)	0.026*** (8.57)
<i>Similar BM</i>		0.007* (1.80)	0.006 (1.62)	0.006* (1.66)
<i>Similar Age</i>		0.009*** (4.01)	0.010*** (4.58)	0.010*** (4.61)
<i>Similar Leverage</i>		0.017*** (4.53)	0.016*** (4.14)	0.016*** (4.18)
<i>Similar ROA</i>		0.014*** (3.75)	0.011*** (2.87)	0.012*** (2.94)
<i>Similar EPS</i>		0.004 (0.83)	0.002 (0.33)	0.001 (0.30)
<i>Similar Price</i>		0.019*** (6.81)	0.018*** (7.32)	0.018*** (7.39)
<i>ROA Correlation</i>			0.045*** (4.55)	0.044*** (4.59)
Δ ROA Correlation			0.022*** (6.87)	0.022*** (6.97)
<i>EPS Correlation</i>			0.003 (0.42)	0.003 (0.45)
Δ EPS Correlation			0.036*** (4.11)	0.035*** (4.10)
<i>Diff Experience</i>				-0.007* (-1.73)
<i>Diff Broker Size</i>				0.016*** (6.85)
<i>Diff Companies</i>				-0.002 (-0.36)
<i>Diff Forecast Error</i>				-1.178*** (-5.98)
<i>Constant</i>	0.187*** (5.28)	0.160*** (4.10)	0.154*** (4.11)	0.161*** (4.22)
Adj. R ²	9.8%	11.1%	14.1%	14.8%
N	688,755	688,755	683,084	682,458

Table 8: **Pair coverage, stock returns and return synchronicity.** Panel A reports results from OLS regressions of a stock’s daily equal-weighted returns on portfolios of all other stocks that share analyst coverage with the stock (*Shared Coverage Portfolio*), stocks from the same industry that share coverage (*Shared Coverage Portfolio_Same Ind.*), and stocks from other industries that share coverage (*Shared Coverage Portfolio_Different Ind.*). All three sets of returns are orthogonalized relative to market portfolio returns (*Market Portfolio*) and industry portfolio returns. Industry portfolio returns are orthogonalized relative to the market portfolio returns (*Industry Portfolio*). Controls are *Market Portfolio*, *Industry Portfolio*, and returns on the Fama-French size and value portfolios (*SMB*, and *HML*, respectively), and momentum portfolio (*UMD*). Panel B reports summary statistics for return synchronicity (*Sync*), augmented return synchronicity (*Aug. Sync*), and the difference between these two variables. *Sync* (*Aug. Sync*) is $\text{Log}(\frac{R^2}{1-R^2})$ ($\text{Log}(\frac{R_S^2}{1-R_S^2})$), where R^2 (R_S^2) is the R-squared from the regression of a stock’s daily return on the daily market and industry returns (plus *Shared Coverage Portfolio*) and the lagged values of these regressors. Panel C presents estimates of OLS regressions of *Sync*, *Aug. Sync*, and their difference on *Aggregate Pair Coverage* for the stock and a set of controls. *Aggregate Pair Coverage* is the sum of *Pair Coverage* across stock pairs that share coverage with the stock. Other variables, whose names are preceded by “*Aggregate*”, are defined similarly and their definitions are presented in the Appendix. T-statistics based on robust standard errors clustered by stock and year are presented in parentheses below the coefficient estimates. ***, **, * indicate significance at 1%, 5%, and 10%, respectively.

Panel A: Pair coverage and stock returns				
	Return			
	(1)	(2)	(3)	(4)
<i>Shared Coverage Portfolio</i>		0.450*** (15.23)	0.384*** (13.77)	
<i>Shared Coverage Portfolio_Same Ind.</i>				0.218*** (11.05)
<i>Shared Coverage Portfolio_Different Ind.</i>				0.110*** (17.66)
<i>Market Portfolio</i>	1.040*** (21.62)	1.040*** (21.65)	1.044*** (69.49)	1.067*** (82.79)
<i>Industry Portfolio</i>	0.614*** (13.50)	0.613*** (13.48)	0.594*** (13.18)	0.655*** (15.00)
<i>SMB</i>			0.459*** (14.99)	0.461*** (16.50)
<i>HML</i>			0.196*** (7.09)	0.171*** (6.04)
<i>UMD</i>			-0.083*** (-4.50)	-0.090*** (-5.19)
<i>Constant</i>	-0.000 (-0.40)	-0.000 (-0.50)	-0.000** (-2.45)	-0.000*** (-3.50)
Adj. R ²	16.4%	18.3%	19.0%	20.0%
N	9,591,192	9,591,192	9,591,192	7,571,993

Panel B: Descriptive statistics for return synchronicity (N=49,467)						
	Mean	Minimum	25th Pctl	Median	75th Pctl	Maximum
<i>Sync</i>	-1.503	-8.440	-2.329	-1.377	-0.570	4.595
<i>Aug. Sync</i>	-1.299	-7.373	-2.162	-1.207	-0.372	4.595
<i>Aug. Sync-Sync</i>	0.204	0.000	0.027	0.099	0.253	5.956

Panel C: Aggregate pair coverage and stock return synchronicity

	<i>Sync</i>			<i>Aug. Sync</i>			<i>Aug. Sync - Sync</i>		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Agg. Pair Coverage</i>		0.042*** (3.60)	0.044*** (3.80)		0.059*** (4.96)	0.066*** (6.17)		0.017*** (6.91)	0.022*** (7.86)
<i>Log(Coverage)</i>	0.074** (2.36)	-0.027 (-0.71)	-0.138*** (-3.39)	0.098*** (3.45)	-0.044 (-1.19)	-0.146*** (-3.83)	0.024*** (2.92)	-0.017** (-2.55)	-0.008 (-1.10)
<i>Log (Market Cap)</i>	0.236*** (8.93)	0.227*** (8.35)	0.297*** (11.75)	0.268*** (11.43)	0.255*** (10.54)	0.324*** (14.17)	0.032*** (5.31)	0.028*** (4.88)	0.027*** (6.83)
<i>BM</i>	0.594*** (3.64)	0.547*** (3.40)	0.470*** (3.12)	0.655*** (4.17)	0.589*** (3.81)	0.508*** (3.61)	0.061*** (4.80)	0.042*** (3.09)	0.038*** (2.58)
<i>Log (Volume)</i>	0.227*** (4.96)	0.238*** (5.32)	0.254*** (6.30)	0.213*** (4.85)	0.229*** (5.34)	0.243*** (6.46)	-0.014** (-2.17)	-0.009 (-1.47)	-0.011 (-1.63)
<i>Agg. Same Industry</i>			0.003** (2.28)			0.001* (1.70)			-0.001** (-2.26)
<i>Agg. Related Industry</i>			-0.002* (-1.71)			-0.003*** (-3.52)			-0.001*** (-2.76)
<i>Agg. Same Exchange</i>			0.006*** (4.00)			0.006*** (4.66)			0.001** (2.17)
<i>Agg. Same State</i>			-0.002*** (-2.73)			0.000 (0.47)			0.003*** (4.67)
<i>Agg. S&P500 Members</i>			-0.017*** (-7.14)			-0.017*** (-7.76)			-0.000 (-0.26)
<i>Agg. Sim. Asset</i>			-0.007*** (-5.25)			-0.007*** (-5.22)			-0.000 (-0.28)
<i>Agg. Sim. BM</i>			-0.003* (-1.67)			-0.002** (-2.08)			0.000 (0.22)
<i>Agg. Sim. Age</i>			0.001 (0.73)			0.001 (1.38)			0.001 (1.06)
<i>Agg. Sim. Leverage</i>			0.003** (2.48)			0.003** (2.09)			-0.000 (-1.45)
<i>Agg. Sim. ROA</i>			0.003** (2.23)			0.003*** (2.58)			0.000 (0.55)
<i>Agg. Sim. EPS</i>			0.001 (0.78)			0.001 (0.29)			-0.001 (-1.57)
<i>Agg. Sim. Price</i>			-0.000 (-0.04)			-0.000 (-0.09)			-0.000 (-0.09)
<i>Agg. ROA Corr.</i>			0.009*** (6.12)			0.010*** (6.81)			0.001*** (2.83)
<i>Agg. ΔROA Corr.</i>			0.008*** (3.43)			0.006*** (2.67)			-0.002*** (-2.88)
<i>Agg. EPS Corr.</i>			-0.002 (-1.03)			-0.001 (-0.60)			0.001* (1.94)
<i>Agg. ΔEPS Corr.</i>			0.013*** (5.65)			0.013*** (5.59)			0.000 (0.15)
<i>Agg. Diff Experience</i>			-0.004*** (-3.11)			-0.002** (-2.17)			0.001*** (3.89)
<i>Agg. Diff Broker Size</i>			0.000 (0.88)			0.001** (2.27)			0.001*** (3.93)
<i>Agg. Diff Companies</i>			-0.012*** (-5.02)			-0.013*** (-5.51)			-0.001* (-1.93)
<i>Agg. Diff Forecast Err.</i>			-0.160 (-1.49)			-0.130 (-1.28)			0.029 (1.12)
<i>Constant</i>	-4.502*** (-18.81)	-4.521*** (-18.95)	-4.901*** (-21.44)	-4.540*** (-20.99)	-4.568*** (-21.15)	-4.951*** (-23.50)	-0.038 (-1.22)	-0.046 (-1.47)	-0.050* (-1.78)
Adj. R ²	49,467	49,467	48,500	49,467	49,467	48,500	49,467	49,467	48,500
N	36.1%	36.6%	44.10%	40.6%	41.5%	49.40%	3.5%	4.9%	7.20%