Sell-side Analyst Research and Stock Comovement*

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Abstract

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Key Words: Analyst Coverage, Return Correlation, Comovement, Spillover, Earnings Forecast, Stock Recommendation, Event Study.

1. Introduction

This study examines whether sell-side analyst research generates stock comovements through *coverage-specific* information spillovers. Coverage-specific spillovers can arise when analysts balance the costs of producing high quality research against the potential rewards from producing it.[1] To economize on information generation and processing costs, analysts will limit their use of stock-specific information. At the same time, analysts will eschew heavy reliance on general information that is relevant to a broad set of stocks to improve the quality of their research. We hypothesize that analysts' incentive structure will induce them to achieve a balance between cost and quality by producing research that emphasizes information common to the stocks in their coverage (coverage-specific information). By doing so, individual analysts will overstate—and raise investor expectations about—the economic exposure shared by the stocks in their coverage. This emphasis on coverage-specific information will induce excess return comovement among these stocks, i.e., their comovement will be higher than it would have been if it were based on complete information about the stocks' fundamentals.[2]

To test our hypothesis linking analyst coverage to excess return comovement, each year between 1997 and 2006, we form pairs of U.S. stocks. For each stock pair in a year, we identify analysts who cover both stocks in the pair (analysts with common coverage) and those who cover only one stock in the pair (analysts with individual coverage). If analysts emphasize coverage-specific information we should expect the research of analysts with common coverage to generate information spillovers and increase return comovement for the pair. In contrast, if analyst research emphasizes firm-specific information, there should not be significant spillovers between a pair stocks, even among pairs that share coverage from the same analysts. Similarly, there should be little difference between the spillovers from research produced by analysts with common and individual coverage if analyst research emphasizes broadly-relevant information. In this case, all analyst research should spill over to a large set of stocks and thus, return

[1] Veldkamp (2006) models the cost-quality tradeoff faced by rational analysts who produce research for rational investors. Her model demonstrates how, in equilibrium, analysts' attempts to economize on the cost of information can lead them to produce research that overstates the comovement between asset returns, resulting in "excess" return comovement relative to a world where analysts are not constrained by information costs.

[2] Comovement between stock returns is a consequence of investors' expectations of shared economic exposure (Merton, 1973). Brown and Mohammad (2010) and Hameed et al. (2010) provide evidence suggesting that investors use research on one firm to update their value of other firms.

comovement between a pair of stocks should not increase because of shared coverage.

We subject our hypothesis to several sets of tests. First, we investigate whether earnings forecasts issued by analysts with common coverage suggest a higher degree of shared exposure between stocks in a pair than do forecasts issued by analysts with individual coverage. For each stock in a pair, we compute a monthly series of consensus forecasts using only forecasts issued by analysts with common coverage. Then we estimate the correlation between the two time-series of consensus forecasts. We repeat the process using only forecasts made by analysts with individual coverage. We find that the correlation between the monthly consensus forecasts from analysts with common coverage is systematically higher than the correlation estimated from forecasts of analysts with individual coverage. This difference suggests that analysts generate research that emphasizes coverage-specific information.

Second, we test whether investors respond differently to activity (i.e., issuance of a recommendation or a forecast) by analysts with common coverage than they do to activity by analysts with individual coverage. Specifically, we examine how activity by each of these two groups of analysts for one stock in a pair (i.e., activity stock) affects the return on the other stock (i.e., no-activity stock). We find that the returns on activity and no-activity stocks are significantly closer around days on which analysts with common coverage are active than on days on which analysts with individual coverage are active. This finding suggests that research produced by analysts with common coverage generates stronger spillovers, supporting the existence of coverage-specific spillovers.

Third, we examine the relation between the daily return correlation between stocks in a pair and three measures of activity by analysts with common coverage. The first two measures capture the activity level of analysts with common coverage: the ratio of analysts with common coverage to the total number of analysts covering either stock in the pair during the year (the level of common coverage), and the ratio of the number of earnings forecasts issued by analysts with common coverage to the total number of earnings forecasts issued by analysts covering either stock in the pair during the year. The third measure captures the information content of their activity: the time-series correlation between the monthly consensus forecasts of the stocks in the pair issued by analysts with common coverage. If analysts' coverage-specific emphasis raises investor expectations of shared economic exposures, then stock prices of the pair will react similarly to a broad range of news throughout the year, even on days on which there is no analyst activity. Consistent with this prediction, we find that the daily return correlation between stocks in a pair increases with each measure of activity by analysts with common coverage, after controlling for factors known to cause return correlation such as correlations in cash flows and earnings, and similarities in size, book-to-market ratio, industry membership, and S&P 500 index membership. These results are robust to corrections for reverse causality from a stock pair's shared economic exposure to activity by analysts with common coverage as well as potential omitted variable bias (endogeneity) arising from inadequate controls for shared economic exposure that could drive both the level of activity by analysts with common coverage and return correlation (Kini et al., 2009).

We also employ a natural experiment to further address concerns about reverse causality. We isolate changes the in the level of common coverage of stock pairs arising solely due to analysts quitting the profession and stopping to cover stocks altogether. Given the nature of these changes in the level of common coverage, it is unlikely that they result from changes in the economic exposure shared by the pair of stocks and thus, can be viewed as exogenous. We continue to find that the return correlation rises significantly as a result of these exogenous increases in the level of common coverage as well as increases in the intensity of earning forecasts by analysts with common coverage resulting from these exogenous coverage changes. Thus, our results support the existence of coverage-specific spillovers generating excess return comovements.

In this study, we contribute to and connect research on return comovement and research on information intermediaries. Prior studies on information intermediaries assume that the level of coverage, which is generally measured as the number of analysts covering a firm, represents resources devoted to the firm-specific information generation and processing, potentially increasing the informativeness of the asset prices (Bhushan, 1989; Frankel, Kothari and Weber, 2006). However, Piotroski and Roulstone (2004), and Chan and Hameed (2006) find that the ability of industry- and market-indices to explain a stock's returns (return synchronicity) increases with its level of coverage, and attribute this relation to analysts' focus on producing industry- and market-specific information rather than firm-specific information. Crawford, Roulstone, and So (2009) find that coverage-initiating analysts produce market-specific (firm-specific) information in the absence (existence) of coverage by other analysts. Our analysis differs from this literature because we examine the possibility that analysts produce coverage-specific information rather than restricting themselves to producing either firm-specific or broad market information. Moreover, we focus on the effect analyst research has on comovement between returns on stock pairs rather than comovement between stocks and broad indices. This approach allows us to devise simple tests based on analyst forecasts and stock returns to effectively control for reverse causality from shared exposure to common coverage. Our evidence complements the evidence in these studies as it shows that analyst research produces within-coverage information spillovers, and not necessarily only industry- or market-specific information spillovers. Moreover, it indicates that, even when a pair of stocks does not belong to the same industry, coverage-specific spillovers can increase comovement between the stocks' returns.

Our research is also related to the literature on the determinants of return comovement. These determinants include similarities in size and book-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). Chen, Chen, and Li (2010) show that these determinants cannot significantly explain daily pairwise return correlations. We complement the return comovement studies by providing evidence that common coverage by analysts can explain an economically meaningful fraction of the variation in pairwise return correlations.

The remainder of the paper is organized as follows. Section 2 provides arguments linking analyst research to stock comovement. Section 3 describes the sample and key variables. Section 4 documents differences in the information content of earnings forecasts issued by analysts with common and individual coverage. Section 5 documents the short-term price effects of analyst activity on other stocks in their coverage. Section 6 describes tests linking the level of analyst activity to stock comovement. Section 7 provides concluding remarks.

2. Linking analysts with security comovement

Security analysts play a critical role in financial markets. In recognition of their importance, researchers have extensively studied their effect on asset prices (Givoly and Lakonishok, 1979; Lys and Sohn, 1990; Francis and Soffer, 1997), investment decisions of portfolio managers (Walther, 1997; Falkenstein, 1996; Barber and Odean, 2008), investor behavior (Malmendier and Shanthikumar, 2007; Mikhail, Walther, and Willis, 2007), and the rate at which information is impounded in asset prices (Brennan, Jegadeesh, and Swaminathan, 1993). However, there is little research on how security analysts impact return comovement.[3] The paucity of empirical research linking security analysts and asset return comovement is surprising because the comovement between asset returns is of central importance to investors.[4] Moreover, there are convincing theoretical models demonstrating that analysts can influence return comovement.

In particular, Veldkamp (2006) develops a model in which analysts compete and maximize their profits from producing research while incurring information gathering and processing costs. In equilibrium, analysts maximize their profits by producing research from a single information set that is useful in evaluating a large set of assets rather than individual assets. While the resulting research is not very informative about any individual asset, investors buy this research because of its low price and its relevance for a large set of assets. Moreover, research on one asset spills over to a broad set of assets, because investors use research on one asset to form opinions about other assets. As a result, the return comovement between a broad set of assets is higher than what it would be if investors only reacted to analyst research on individual assets and ignored information spillovers.

Veldkamp's (2006) model, however, does not include an institutional feature that plays a central role in sell-side analysts' research: Individual analysts are rewarded based on the value of their research for a small number of stocks they cover.[5] Faced with such incentives, individual analysts will focus on balancing the cost and quality of their research, and pay less attention to stocks outside their coverage. Therefore, based on an argument similar to that in Veldkamp

[3]The few empirical investigations on this subject have focused on the effect of analysts on the comovement between stock return and market indices (Piotroski and Roulstone, 2004; and Chan and Hameed, 2006). A recent paper by Hameed et al. (2010) examines the link between the level of analyst coverage and comovement in stock returns.

[4]Modern asset pricing theories build on the concept of covariance risk introduced by the CAPM. 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, Sorensen, 2007), risk management (Jorion, 2007), asset price dynamics (Rosenberg and Schuermann, 2006; Brooks, Henry, and Persand, 2002), and trading strategies (Gatev, Goetzamann, and Rowenhorst, 2006; Papadakis and Wysocki, 2008).

[5]By producing high quality research on the stocks they cover, analysts can attract new underwriting business (Krigman et al., 2001), generate brokerage income (Jackson, 2005), and earn rankings from organizations such as Institutional Investor Magazine (Ljungqvist et al., 2007). Groysberg et al. (2011) document a positive association between each of these outcomes and analyst compensation.

(2006), we predict that, analysts will build their research from information that is relevant primarily for stocks in their coverage as opposed to information that is stock-specific. At the same time, because they will not be rewarded for producing research that is informative about stocks outside their coverage, individual analysts will not use broad information that is relevant for stocks outside their coverage.[6] Consequently, we expect information spillovers to occur primarily between stocks within an analyst's coverage and thus, we predict excess return comovement among stocks in an analyst's coverage. We refer to this prediction as the *coverage-specific spillover hypothesis*.

The coverage-specific spillover hypothesis can be tested by grouping analysts covering a stock pair into two groups—analysts covering both stocks (analysts with common coverage) and those covering only one stock (analysts with individual coverage). If analysts base their research primarily on coverage-specific information, then analysts with common coverage will base their research on economic factors that are common to both stocks in the pair. Consequently, research from analysts with common coverage will tend to overstate the economic exposure shared by the pair of stocks. Analysts with individual coverage will also focus their research on factors that are common to the stocks they cover. However, since they cover only one stock in the pair, their research is less likely to be based on factors that are common to both the stocks in the pair. Therefore, estimates of shared economic exposure based on research from analysts with individual coverage are likely to be lower than estimates based on research from analysts with common coverage.

In contrast, we should not observe systematic differences between research from analysts with common and individual coverage if they rely primarily on either broadly-relevant or stock-specific information. If analysts use broadly-relevant information, both analysts with common and individual coverage will base their research on similar sets of information. Similarly, if analysts utilize stock-specific information, research from both groups of analysts on one stock in a pair will not be informative about the second stock.

[6] Analysts can also reduce the cost of research by covering stocks with high shared economic exposure (Kini et al., 2009). In order to ensure that our inferences are not driven by analysts' coverage choices, we control for the effect of shared economic exposures in our tests. Whenever possible, we control for the effect of shared economic exposures by developing tests based on differences between the research of analysts with common and individual coverage for the same stock pair. When such a test is not possible, we use a variety of controls for shared economic exposures.

Hypothesis 1: *Research from analysts with common coverage of a stock pair will signal a higher level of shared exposure between the stocks than research from analysts with individual coverage.*

This prediction can be tested by examining analysts' forecasts. Because research from analysts with common coverage will overstate economic exposures shared by a pair of stocks, we expect that earnings forecasts for a pair of stocks from analysts with common coverage to be more highly correlated than those issued by analysts with individual coverage, especially when analysts with common coverage are more active.[7] In contrast, we should not expect to see a systematic difference between the earnings forecast correlations of the two sets of analysts if analysts base their research predominantly broad-based information or stock-specific information.

Under the coverage-specific spillovers hypothesis, investors should respond differently to research from analysts with common coverage and analysts with individual coverage. When an analyst with common coverage issues a forecast or recommendation for one stock in a pair, this activity will inform investors about the second stock and cause its price to move in line with the first stock. When an analyst with individual coverage issues a forecast or recommendation for one stock in the pair, this activity is less likely to convey information about the second stock and therefore, the price of the second stock is less likely to move in line with the first stock. In contrast, if both sets of analysts rely predominantly on broad-based or stock-specific information, we do not expect to observe any differential price reactions on the second stock in response to activity for the first stock by analysts with common and individual coverage. This prediction can be tested by comparing the price responses of pair of stocks to activity by analysts with common coverage and analysts with individual coverage.

Hypothesis 2: *Analyst activity (i.e., earnings forecasts or stock recommendations) for one stock in a pair will have a stronger influence on the price of the second stock around the time of the activity if the analyst covers both stocks than if the analyst covers one stock in the pair.*

If analysts with common coverage raise investor perceptions of economic exposures shared by a pair of stocks sufficiently, the pair's prices will respond similarly to a broad range of news

[7]Earnings forecasts issued by analysts with common coverage may also differ from those issued by analysts with individual coverage for behavioral reasons. Because coverage choices influence analysts' information sets, they can influence the cues that analysts employ when estimating shared exposures between stocks. For example, individual analysts' correlation estimates are subject to biases resulting from *cue competition* whereby individuals may underutilize *salient* cues because they are also presented with irrelevant ones (Kruschke and Johansen, 1999; Hirshleifer, 2001). However, consistent with our approach, Chen and Jiang (2005) find that analysts make biased forecasts as a result of their incentives rather than behavioral biases.

throughout a year, and the predicted comovement of stock prices around the time of analyst activity will carry over to days with no analyst activity. Therefore, we expect higher daily return comovement when analysts with common coverage are more active. In contrast, if both sets of analysts rely predominantly on either broad-based or stock-specific information, as argued earlier, there will be little difference between the research produced by analysts with individual and common coverage. Therefore, the relative activity level of analysts with common coverage will not affect return comovement.

The activity level of analysts with common coverage can be proxied by i) the ratio of analysts with common coverage to the total number of analysts covering the pair, and ii) the ratio of earnings forecasts issued by analysts with common coverage to the total number of forecasts for the pair. The extent to which analysts with common coverage influence investors' expectations about shared economic exposures can also be measured by the time-series correlation in their consensus earnings forecasts.

Hypothesis 3: *The daily returns on a pair of stocks will comove more strongly when analysts with common coverage are more active and when analysts with common coverage issue more highly correlated earnings forecasts for the firm pair.*

We make predictions regarding the direction in which spillovers from analyst research affect return comovement. However, from a theoretical perspective, it is also possible for causality to run the other way around, i.e., return comovement affecting analyst research. For example, to achieve economies of scale to reduce costs of research, analysts may choose to cover stocks with similar characteristics and thus, high return comovement. Each of our tests is designed to take into account this possibility. Detailed approaches are discussed below when we develop each test.

3. Sample

For each year between 1997 to 2006, we identify stocks from the *CRSP* and *I/B/E/S* databases that satisfy the following criteria: (i) the stocks are traded without discontinuity during the year, (ii) the stock prices are higher than $5 throughout the year, (iii) there are three years of past return data, (iv) the stocks are followed by at least ten analysts during the year.[8] The first three criteria ensure that our estimates of daily stock returns are free from market microstructure effects and that we have sufficient data on control variables. The last filter ensures that our results are not driven by small-firm effects and that we find a reasonable fraction of pairs with common analyst coverage. Each year, we use the stocks that survive these filters to construct our universe of stock pairs. We construct two samples derived from this universe of stock pairs to test our predictions.

Insert Table 1 approximately here

The first sample, the common coverage sample, consists of all stock pairs where at least one analyst follows both stocks in the pair.[9] Panel A of Table 1 presents descriptive statistics on the common coverage sample. On average, each year, this sample includes 22,741 stock pairs comprised of 878 unique stocks. Each pair is followed by 41.3 analysts, 3.2 of which cover both stocks in the pair. On average, analysts issue 302.2 annual and quarterly earnings forecasts for each pair, implying that an analyst issues approximately seven forecasts for each stock pair in a year. Analysts with common coverage are more active; they account for approximately 15% of the forecasts but only 8% of the analysts covering the pair. For each year, we estimate correlations ($Corr$) between the daily returns of the stocks in the pairs. The average return correlation ranges between 17.3% and 42.4% in a given year. Consistent with the coverage-specific spillover hypothesis, these correlation estimates are generally higher than those for the universe of stock pairs.

We build a second sample, the forecast correlation sample, by imposing the following two filters on the common coverage sample: (i) the fiscal year ends of both firms in the pair have to be between October 1 of the year in question and March 31 of the succeeding year, (ii) at least one analyst with common coverage and one analyst with individual coverage revise their annual earnings forecasts during every set of three consecutive months in the year. The first

[8]We consider an analyst to be covering a stock in a given year if the analyst issues either a recommendation, an annual earnings forecast, or a quarterly earnings forecast for the stock during the year.

[9]This definition is geared towards increasing the power of our tests and filters out all pairs without common analysts, which comprise 97% of the universe of stock pairs. The empirical results are qualitatively unchanged from those reported when we use the universe of stock pairs. For brevity, we have chosen not to report results of tests using the universe of stock pairs.

filter ensures that we have a minimum of eight monthly observations in each year with which to estimate the correlation between the monthly consensus forecasts for a pair of stocks. The second filter ensures we obtain meaningful consensus forecasts by eliminating pairs with stale earnings forecasts and pairs with no earnings forecasts.

Panel B of Table 1 presents data on the forecast correlation sample. On average, this sample consists of 10,830 stock pairs consisting of 730 unique companies in each year, representing 50% attrition from the common coverage sample. The average number of analysts following each pair is 40.0, close to that of the common coverage sample. Yet, the average number of analysts with common coverage as well as the average stock return correlation is higher in the forecast correlation sample (4.3 vs. 3.2 and 35.5 vs. 28.9, respectively). The higher return correlation in the forecast correlation sample is consistent with the coverage-specific spillover hypothesis, because analysts in this sample are more active than those in the common coverage sample (see Table 2 below).

Our first measure of the activity of analysts with common coverage is the ratio of the number of analysts with common coverage to the total number of analysts covering a stock pair ($CoCvg$), i.e.,

$$CoCvg_{ijt} = \frac{AI_{ijt}}{AU_{ijt}}, \tag{1}$$

where AI_{ijt} and AU_{ijt} represent the number of analysts in the intersection and the union of the sets of analysts covering stocks i and j in year t, respectively. We refer to $CoCvg$ as the *level of common coverage*. The second activity measure, $CoFst$, is the relative intensity of the forecasting activity of analysts with common coverage of a stock pair, where

$$CoFst_{ijt} = \frac{CFst_{ijt}}{Fst_{ijt}}, \tag{2}$$

$CFst_{ijt}$ is the number of quarterly and fiscal year earnings forecasts made by analysts with common coverage for the stock pair i and j in year t, and Fst_{ijt} is the total number of quarterly and fiscal year earnings forecasts for the pair of stocks in year t. We refer to $CoFst$ as the *level of common forecasts*. Both $CoCvg$ and $CoFst$ capture the level of activity of analysts with common coverage and thus, act as a measures of the strength of coverage-specific spillovers.

Using the forecast correlation sample, we construct a series of monthly consensus forecasts for each stock in a pair using forecasts from analysts with common coverage. We then compute the correlation between these two consensus forecasts series, $CFstCor$. We refer to this estimate as the *common coverage forecast correlation.* We repeat this process using forecasts from analysts with individual coverage to compute the earnings forecast correlation estimate $IFstCor$. We refer to this estimate as the *individual coverage forecast correlation.* $CFstCor$ and $IFstCor$ have similar average values of around 12.5%.

Table 2 presents summary statistics for key variables in the universe of stock pairs (N=7,580,032), common coverage sample (N=227,407), and forecast correlation sample (N=108,300). Table 3 presents Spearman correlations between these variables derived from the forecast correlation sample. The two measures of activity by analysts with common coverage (i.e., $CoCvg$ and $CoFst$) exhibit large standard deviations, indicating significant cross-sectional variation in the level of common coverage and common forecasts. Because firm pairs with higher levels of common coverage make up the forecast correlation sample, the average values of $CoCvg$ and $CoFst$ are larger in this sample (12.4 vs. 9.1, and 20.6 vs. 14.7, respectively). The common forecast correlation, $CFstCor$, also displays a large standard deviation. Consistent with *Hypothesis 3*, $CoCvg$, $CoFst$, $CFstCor$ are positively and highly statistically significantly correlated with stock return correlation. The correlation between $CoCvg$ and $CoFst$ is 0.965, indicating that they capture similar information. In order to avoid multicollinearity, our regression models do not use these two variables simultaneously as independent variables.

The evidence in Piotroski and Roulstone (2004), Chan and Hameed (2006), and Hameed et al. (2010) suggests that a higher level of analyst coverage strengthens spillovers across a broad set of stocks and raises return comovement. Therefore, we use the industry-adjusted level of analyst coverage of a firm pair, $Covg$, to control for broad spillovers, where

$$Covg_{ijt} = \frac{AU_{ijt}}{A_{indy_i,t} + A_{indy_j,t}} \tag{3}$$

and $A_{indy_k,t}$ is the average number of analysts following firms belonging to the Fama-French industry to which firm k belongs in year t. $Covg$ is only weakly correlated with return correlation and, contrary to the prior literature, the direction of this relation suggests that higher coverage is associated with lower return comovement. Our focus on stocks that are covered by at least ten analysts may explain this difference.

Insert Tables 2 and 3 approximately here

The level of economic exposure shared by companies in a pair is a key determinant of the correlation between their stock returns. We employ five variables to control for the level of shared exposure. Four of these variables are constructed from companies' quarterly financial statements during the four-year period that starts one year before and ends two years after the year of the observation.[10] Specifically, we compute (i) correlation in industry-adjusted quarterly EPS before extraordinary items (ρ^{EPS}), (ii) correlation in industry-adjusted quarterly cash flows deflated by shareholders' equity and winsorized at + 1 and - 1 (ρ^{CF}), (iii) correlation of quarterly changes in EPS as computed in (i) ($\rho^{\Delta EPS}$), and (iv) correlation of quarterly changes in cash flows as computed in (ii) ($\rho^{\Delta CF}$). Each of these variables is positively and statistically significantly related to stock return correlation, supporting their use as controls in our analysis. Consistent with our predictions, the average values of each of these four variables in both the common coverage and forecast correlation samples is perceptibly larger than their average values for the universe of stock pairs. Our fifth control variable for the level of shared economic exposure is the individual coverage forecast correlation, $IFstCor$, which captures the correlation in earnings forecasts issued by analysts with individual coverage. $IFstCor$ is positively and significantly correlated with stock return correlation.

We also use four variables to control for return correlations arising from other firm characteristics. First, D_{Indy} takes the value of 1 if both stocks in a pair belong to the same Fama-French industry, and 0 otherwise. D_{Indy} is strongly correlated with stock return correlation. Approximately 35% of the common coverage sample and 46% of the forecast correlation sample are drawn from the same Fama-French industry. The relatively high incidence of common coverage for firm pairs belonging to different industries is consistent with the evidence in Clement (1999) and Kini et al. (2009). Second, D_{Ix} takes the value of 1 if both stocks are included in

[10] See Allayannis and Simko (2009), who also use quarterly financial information for four years.

the $S\&P$ 500 index and 0 otherwise.[11] D_{Ix} is positively and significantly correlated with stock return correlation. Given that we restrict our attention to relatively large firms, 26% and 23% of the common coverage and forecast correlation samples consist of pairs where both stocks are included in the S&P 500 index. Furthermore, D_{Ix} is positively correlated with both $Covg$ and $CoCvg$, because analysts prefer to cover more visible stocks (Veldkamp, 2006; Jegadeesh et al., 2004). Third, D_{Size} takes the value of 1 if the stock market capitalizations of both firms in the pair exceed the median stock market capitalization of firms in the common coverage sample and 0 otherwise. Consistent with Fama and French (1993), D_{Size} is positively and highly statistically significantly related to stock return correlation. Fourth, $D_{B/M}$ takes the value of 1 if both stocks in a pair have book-to-market ratios lower than the median book-to-market ratio (Fama and French, 1993; Boyer, 2008). There is a negative correlation between $D_{B/M}$ and stock return correlation. Across the common coverage sample, about 44% and 34% of the pairs consist of large stocks and growth stocks, respectively. The fraction of pairs that consist of large stocks and growth stocks in the forecast correlation sample are 43% and 30%, respectively. For both samples, these ratios are higher than their respective ratios in the stock pair universe. These differences and the correlations of D_{Size} and $D_{B/M}$ with $Covg$ suggest that analysts with common coverage focus on large firms (Veldkamp, 2006) and growth firms (Jegadeesh et al., 2004) that are favored by many investors.

4. Forecast correlations

The coverage spillover hypothesis is based on the premise that individual analysts will overstate the economic exposures shared by firms they cover (*Hypothesis 1*). We test *Hypothesis 1* by examining, for a stock pair, the difference between the common coverage forecast correlation ($CFstCor$) and individual coverage forecast correlation ($IFstCor$), which measures the differential earnings correlation expectations of analysts with common and individual coverage. By employing a within stock-pair comparison of the forecasts issued by analysts with common and individual coverage, we ensure that both estimates are based on the same underlying shared

[11] Barberis, Shleifer, and Wurgler (2005) find evidence that inclusion in S&P 500 index can affect return comovement between stocks. Greenwood (2008) documents a relation between return comovement and weighting in the Nikkei 255 index.

economic exposure. Therefore, variations between the two sets of estimates cannot be caused by variations in underlying shared economic exposure, which lies as the root of any concerns about reverse causality.[12] We expect $CFstCor$ to be systematically larger than $IFstCor$ if analysts base their forecasts on coverage-specific information.

Figure 1 illustrates the difference between $CFstCor$ and $IFstCor$. To construct the figure, for each pair-year, we estimate the difference between the common coverage forecast correlation and the individual coverage forecast correlation. The figure presents the averages of these pairwise differences for 16 groups of observations, each group consisting of observations with a given number of analysts with common coverage (x axis). The first group contains observations where only one analyst covers both stocks in the pair. Subsequent groups include observations where the number of analysts with common coverage is increased by one until the number of analysts with common coverage reaches 15. The last group contains all observations with 16 or more analysts with common coverage. The number of observations declines monotonically from $77,427$ for group 1 to $1,682$ for group 15. There are $7,308$ observations in group 16. The figure also plots the 95% confidence band for the estimate of the difference.

Insert Figure 1 Approximately Here

Both averages of common and individual coverage forecast correlations increase with the number of analysts with common coverage. [13] This is consistent with the evidence in Kini et al. (2009) that analysts construct portfolios of stocks with high levels of shared exposure. As is clear from the figure, $CFstCor$ is either similar to or larger than $IFstCor$ across the groups. The difference between $CFstCor$ and $IFstCor$ monotonically increases with the number of analysts with common coverage and is statistically significant when six or more analysts maintain common coverage of a pair. The statistical insignificance of the difference for the groups with a small number of analysts with common coverage may arise because the consensus forecast for analysts with common coverage changes infrequently when there are only a few of these analysts, dampening the correlation estimates. Overall, this evidence is consistent with *Hypothesis 1*,

[12] Note, however, that two sets of analysts' perceptions of the economic exposure shared by a firm pair may differ. In fact, this variation in perceptions is the basis of the coverage-specific spillover hypothesis.

[13] We obtain similar results when we use the ratio of analysts with common coverage, $CoCvg$, instead of the number of analysts with common coverage to divide the sample into groups.

which predicts that research from analysts with common coverage will signal higher shared economic exposure than research from other analysts.

5. Price effects of analyst activity

The coverage specific spillover hypothesis can only be valid if research from analysts with common coverage influences investors differently than research from analysts with individual coverage (*Hypothesis 2*). To test *Hypothesis 2* we examine the price change of a stock within a short window around the issuance of a recommendation or forecast for the second stock in a pair. We focus on the difference between the price effects of research from analysts with common and individual coverage for the same stock pair. Therefore, we ensure that both sets of price change estimates are based on the same underlying shared economic exposure and thus, are not the result of variations in underlying shared exposure on investor or analyst behavior.

We first identify days on which analysts issue recommendations or forecasts for stocks belonging to a pair in the common coverage sample. We refer to these days as activity days ($N = 44,156,324$). We then apply the following three filters to eliminate activity days where price movements may be attributable to confounding factors: (i) there cannot be analyst activity for both stocks in a pair, (ii) either analysts with common or individual coverage are active but not analysts of both types, (iii) the absolute one-day size-adjusted return on either stock in the pair cannot exceed the 95^{th} percentile of the population of activity-day returns (that is, 6.5%). The first filter eliminates more observations of analysts with common coverage (37%) than with individual coverage (25%), because analysts with common coverage are more active. The second filter enables a clear comparison between the spillover effects of research from analysts with common and individual coverage. The third filter eliminates observations where events other than the analyst activity, such as company earnings announcements, company filings, and macroeconomic events, affect returns (Altinkilic and Hansen, 2009). These filters collectively eliminate approximately 35% of the observations in the initial sample.[14] The resulting sample includes 28,359,895 activity days, of which 3,084,697 are attributable to analysts with common coverage and 25,275,198 to analysts with individual coverage.

[14] We obtain similar results when we remove the filters and study the initial sample.

For each activity day, we compute the price reaction of the stock for which a recommendation or forecast is issued (activity stock) and the price reaction of the second stock in the pair (no-activity stock). In order to filter out the variation in innate daily market volatilities of individual stocks, we follow Frankel, Kothari and Weber (2006) and compute an activity-day analyst informativeness (AI) measure for each stock in a pair using the absolute value of its NYSE-size-decile-adjusted return as follows: First, for stock i in the pair ij, we compute average size-adjusted absolute return on all no-activity trading days during the year, $R_{N,i}$, where

$$R_{N,i} = \frac{\sum_{T_{ij}} R_{t,i}}{\#T_{ij}}, \tag{4}$$

$R_{t,i}$ is the size-adjusted absolute return of stock i on date t, T_{ij} is the set of no-activity days for the pair ij, and $\#T_{ij}$ is the number of days in the set T_{ij}. Then on each activity day for the pair ij, we compute stock i's AI as follows:

$$AI_{ij}^{i} = \frac{R_{t,i}}{R_{N,i}}. \tag{5}$$

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

Table 4 presents AI and average absolute returns for the activity and no-activity firms in two subsamples. The first subsample contains observations in which analysts with common coverage are active and the second contains observations in which analysts with individual coverage are active.[15] We use a difference-in-difference test to control for systematic differences in the information content of analyst activity. Specifically, for each pair-year, we compare the average difference in the price impact on the activity and no-activity stocks in response to activity from analysts with common coverage with that in response to activity from analysts with individual coverage.[16] The difference in the price impact of activity and no-activity stocks measures the relative informativeness of analyst activity; a smaller difference of AI or absolute return indicates

[15] A straightforward comparison of the effects of activity by analysts with common and individual coverage on the price of the no-activity stock may be inappropriate. For example, our screens eliminate a disproportionately large number of activity days for analysts with common coverage during which analysts with common coverage likely convey important information on both stocks. Therefore, the resulting sample may contain observations with systematically different information effects for activity by analysts with common and individual coverage.

[16] In untabulated tests, we use the ratio of the two activity day price reactions to measure spillovers. The results are virtually identical but are not reported to simplify exposition.

a smaller difference in the relevance of the activity to the two stocks and, thus, a larger spillover. In Panel A, we present these measures for all analyst activities (i.e., recommendations and forecasts) and in Panel B we present these measures for days on which analysts only issued forecasts. For the sake of brevity, we only discuss results in Panel A; the results in Panel B are similar.

Insert Table 4 approximately here

Table 4 provides strong support for *Hypothesis 2*. All differences between average and median values presented in Table 4 are statistically and economically significant. For days during which analysts with common coverage are active, the average AI (absolute activity day return) is 1.1442 (1.565%) for the activity stock and 1.0430 (1.480%) for the no-activity stock. For days during which analysts with individual coverage are active, the average AI (absolute activity day return) is 1.1733 (1.606%) for the activity stock and 1.0185 (1.470%) for the no-activity stock.[17] As expected, for both analysts with common and individual coverage, AI and absolute returns are uniformly higher for the activity stock than the no-activity stock. Moreover, consistent with the existence of coverage-specific spillovers, average AI for analysts with common coverage exceeds one for no-activity stocks. Average AI for analysts with individual coverage also exceeds one for no-activity stocks, supporting the existence of broad research spillovers.

For the analysts with common coverage, the average pairwise AI (absolute return) difference between the activity and no-activity stock is 0.1012 (0.085%). In comparison, for analysts with individual coverage, the average pairwise AI (absolute return) difference between the activity and no-activity stock is significantly larger, 0.1548 (0.136%). Therefore, our results support *Hypothesis 2* and the existence of coverage-specific spillovers on days with analyst activity. Moreover, they suggest that, while broad spillovers exist, they are significantly weaker than coverage-specific spillovers.

[17]The price reactions, both AI and absolute stock returns, for the activity company to activity by an analyst with individual coverage is greater than the reaction to activity by an analyst with common coverage. This finding can be explained by the greater activity of analysts with common coverage in general. Untabulated results show that analysts with common coverage are, on average, active on 2.517 days per year for a stock pair, whereas analysts with individual coverage are only active on 1.646 days. That is, the market's reaction to activity by analysts with common coverage is spread out over a larger number of days during which these analysts are active, potentially reducing the market reaction per activity day.

6. Stock return comovement

In this section, we test *Hypothesis 3*, which links activity by analysts with common coverage to daily stock return comovement during the year. All tests and regression estimates that employ (do not employ) forecast correlations are based on the forecast correlation sample (the common coverage sample).

6.1. Two-way sort

We present average daily stock return correlations between pairs of stocks in double-sorted into quintiles along two dimensions. Panel A of Table 5 sorts the pairs according to common coverage ($CoCvg$) and coverage ($Covg$). Panel B sorts the pairs according to the level of common forecasts ($CoFst$) and coverage ($Covg$). Panel C sorts the pairs according to common coverage forecast correlation ($CFstCor$) and individual coverage forecast correlation ($IFstCor$).

To control for the influence of shared economic exposure on return correlations, we first orthogonalize the return correlations with respect to the four measures of cash flow and earnings correlations. Each year, we estimate the following regression for the cross section of stock pairs in our sample

$$Corr_{ij,t} = \gamma_t + \gamma_{E,t}\ \rho_{ij,t}^{EPS} + \gamma_{C,t}\ \rho_{ij,t}^{CF} + \gamma_{\Delta E,t}\ \rho_{ij,t}^{\Delta EPS} + \gamma_{\Delta C,t}\ \rho_{ij,t}^{\Delta CF} + \eta_{ij,t}, \tag{6}$$

where i and j represent two stocks in the pair in year t. Then, we construct the transformed value of return correlation $TCorr_{ij,t}$ as follows:

$$TCorr_{ij,t} = \gamma_t + \eta_{ij,t}, \tag{7}$$

where γ_t captures the component of return correlation that is common to the entire cross-section of stock pairs in year t, and $\eta_{ij,t}$ captures the pair-specific return correlation. These transformed estimates reflect return correlation that cannot be attributed to shared economic exposure as proxied by our cash flow and earning measures. We use these transformed values of return correlations in all the regressions in this section.[18]

[18]By using the transformed correlation measures in the regressions that follow, we bias the tests against our

Insert Table 5 approximately here

In Panel A, the average return correlation is 24.8% for the lowest common coverage quintile and 40.4% for the highest common coverage quintile. Moreover, for every quintile of $Covg$, the difference between correlations for the lowest and highest quintiles of common coverage ($CoCvg$) is highly statistically significant. Both pieces of evidence support *Hypothesis 3*, and suggest that activity by analysts with common coverage has a large and economically significant influence on stock return comovement. The differences in the return correlations for stock pairs in the highest and lowest quintiles of $CoCvg$ vary inversely with the level of coverage, $Covg$, ranging from 9.8% for the highest quintile of $Covg$ to 19.6% for the lowest quintile of $Covg$. This pattern is to be expected if the level of residual uncertainty about stocks falls with the level of analyst coverage, making it more difficult for analysts with common coverage to influence investor beliefs and, thus, stock returns.

Panel B contains stronger evidence supporting the existence of coverage-specific spillovers. The average return correlation for stock pairs in the lowest quintile of forecasting intensity for analysts with common coverage ($CoFst$) is 23.0% and rises monotonically to 40.4% for pairs in the highest quintile. This monotonic relation between return correlation and $CoFst$ is evident for every quintile of $Covg$. Moreover, for every quintile of $Covg$, the difference in average return correlations between the highest and lowest quintiles of $CoFst$ is highly statistically significant and large. These differences range from 13.6% for the highest quintile of $Covg$ to 20.5% for pairs in the lowest quintile of $Covg$. Similar to Panel A, Panel B suggests that coverage-specific spillovers weaken as the level of analyst coverage of the pair increases.

In both Panels A and B, average return correlation remains around 29.0% across all quintiles of $Covg$. For stock pairs with low levels of common coverage, the return correlation in the highest quintile of $Covg$ is significantly larger than that in the lowest quintile. However, this relation reverses for high levels of common coverage. Therefore, the evidence supports the existence of some broad spillovers for stock pairs with low common coverage but not for stock pairs with high common coverage. Overall, Panels A and B provide strong support for the existence of coverage-specific spillovers but limited support for broad spillovers.

predictions. Results are stronger, in general, when we use raw correlations in all our tests.

The evidence in Panel C also supports the coverage-specific spillover hypothesis; investors respond differently to information in the forecasts made by analysts with common coverage and individual coverage. The average return correlation for the lowest quintile of $CFstCor$ is 30.0% compared with 34.6% for the higher quintile. Controlling for the individual coverage forecast correlation ($IFstCor$), the return correlation difference between the first and fifth quintiles of $CFstCor$ ranges from 0.0% to 10.2%. When sorted on individual coverage forecast correlation, the average return correlation rises from 28.2% for the lowest quintile to 36.9% for the highest quintile of $IFstCor$, indicating that return correlation is also significantly related to the forecasts of analysts with individual coverage. This evidence justifies our use of $IFstCor$ as a control variable in the following regression analysis.

6.2. Panel regressions

We now test for coverage-specific spillovers using multivariate regression models to control for factors that influence return correlation. Our regression estimates are derived for variants of the following model:

$$TCorr_{ij,t} = \alpha + \beta_C\ CoAct_{ij,t} + \beta_B\ Covg_{ij,t} + \beta_{IFC}\ IFstCor_{ij,t} + \beta_x\ X_{ij,t} + \epsilon_{ij,t}, \tag{8}$$

where $CoAct$ measures activity by analysts with common coverage ($CoCovg$ or $CoFst$), and X represents a vector of controls, D_{Indy}, D_{Ix}, D_{Size}, and $D_{B/M}$. The variable $IFstCor$ controls for shared economic exposures, while $Covg$ controls for broad spillovers.

Table 6 presents OLS and $2SLS$ estimates of each model. In each case, we present standard errors that are corrected for pair level clustering.[19] We present $2SLS$ estimates for each model, because our controls for shared economic exposure may be inadequate. If so, our OLS estimates may be biased, because shared economic exposure may drive both return correlations and analysts' coverage portfolios (Kini et al., 2009). For each $2SLS$ estimate, we use the one-year lagged value of $CoAct$ as an instrumental variable. These instruments are likely to covary strongly with

[19] Researchers typically use a fixed-effects specification to control for cross-sectional heterogeneity. However, Wooldridge (2002) shows that fixed-effects models tend to remove much of the cross-sectional variation that we wish to examine here. Therefore, we follow an alternative approach by using standard errors that are adjusted for clustering effects as advocated by Petersen (2009). Later, in Table 7, we present estimates using changes in each variable. This is equivalent to using a fixed effects specification.

our proxies for activity by analysts with common coverage, because analyst coverage tends to be relatively stable.[20] F-tests for each first stage-regression support this conjecture as they indicate that the instruments are highly relevant, i.e., the F-statistics for each instrument are well in excess of 10. Because the models are fully identified, we cannot test the validity of the instruments.[21] Hausman tests for each 2SLS estimate in Table 6 support our conjecture that the OLS estimates are biased because of an omitted latent variable. However, all coefficient estimates in Table 6 are insensitive to the estimation method we use, indicating that any bias in the OLS estimates is inconsequential.

Insert Table 6 approximately here

The results in Table 6 strongly support *Hypothesis 3*. The coefficient estimates for $CoCvg$ are above 0.40 and highly statistically significant in all the models. Similarly, the coefficient estimates for $CoFst$ range between 0.31 and 0.36 in all the models and are highly statistically significant. These estimates are relatively insensitive to the sample and the set of control variables. The R^2s of the OLS estimates range from 14.2% to 20.6%, indicating that they explain an economically significant amount of the variation in return correlation either cross-sectionally and/or over time. Consistent with the evidence in Table 5, the R^2s are typically higher when $CoFst$ is employed to proxy for coverage-specific spillovers.

The coefficient estimates for $Covg$ are all positive and highly statistically significant, consistent with the existence of broad spillovers. The coefficient estimates for $IFstCor$ are all positive and highly statistically significant indicating that the transformation of the return correlation may not have been sufficient to completely eliminate the effect of shared economic exposures. The coefficient estimates for the remaining controls are also statistically significant and consis-

[20]Clement (1999) provides early evidence that analysts develop firm-specific experience by following individual firms for several years. Recently, Brown and Mohammed (2010) document that analysts who are active between 1983 and 2005 maintained their coverage of individual firms for an average of 3.2 years. The evidence suggests significant stability in analyst coverage.

[21]To test instrument validity we need an overidentified model (Stock and Watson, 2011). To develop such a model, we examine several instrumental variable candidates, for example, various measures of "industry level" common coverage. However, these variables are either highly correlated with some of our controls, such as D_{Indy}, or do not survive tests for instrument validity such as the Hansen J test. The instruments we use will be valid if shared exposure is not persistent. When shared exposure is extremely persistent, a stock-pair fixed-effects estimate is appropriate. We present fixed-effect estimates in Table 7. To account for intermediate levels of persistence in shared exposure, we also reperform our regressions by including a one-year lagged value of $TCorr$ as a control. This modification did not result in qualitatively different estimates. We do not present these results in Table 6 for brevity.

tent with past research. For example, return comovement is higher when both stocks in a pair share industry membership. Consistent with Barberis, Shleifer, and Wurgler (2005) and Greenwood (2008), shared membership in the S&P 500 index also boosts return correlation. Moreover, consistent with Fama and French (1993) and Boyer (2008), return correlation is related to size and book-to-market ratios. The returns of large stocks and high book-to-market stocks are more highly correlated.

6.3. *Changes in common coverage*

To address concerns about potential omitted variable bias resulting from inadequate controls for shared economic exposure, we test *Hypothesis 3* using changes-in-changes analysis. We ask whether increases (decreases) in coverage-specific spillovers are associated with contemporaneous increases (decreases) in return correlation. Each set of estimates can be viewed as an event study where the event is a change in coverage-specific spillovers. For this test, we estimate variants of the following model that relates changes in $TCorr$ to contemporaneous changes in our proxies for coverage-specific spillovers, broad spillovers, and shared economic exposure ($IFstCor$):

$$\Delta TCorr_{ij,t} = \alpha + \beta_C \ \Delta CoAct_{ij,t} + \beta_B \ \Delta Covg_{ij,t} + \beta_{IFC} \ \Delta IFstCor_{ij,t} + \beta_x \ X_{ij,t} + \epsilon_{ij,t}, \quad (9)$$

where the term Δ indicates change between year $t-1$ and t. We use $CoCvg$ and $CoFst$, measures of activity by analysts with common coverage, as alternative proxies for coverage-specific spillovers. We derive one set of estimates while controlling for the levels of our control variables in year t.[22] Our second set of estimates is made after controlling for contemporaneous changes in these control variables. The latter set of estimates is equivalent to the estimates from a stock-pair fixed-effects model, which is appropriate if economic exposure is constant over time and is not adequately accounted for by our control variables.

Insert Table 7 approximately here

[22] Estimating a dynamic panel model is another alternative. In order to eliminate bias in estimates of a dynamic panel model, we need to use lagged difference variables as instruments. This results in the loss of three year of data. We have estimated such a model and obtain qualitatively similar results. For brevity, we do not report the dynamic panel estimates.

Table 7 presents estimates of models based on (9). All the reported estimates are computed using the OLS method and the standard errors are corrected for pair level clustering. Once again, the positive, stable, and statistically significant coefficient estimates for the proxies of coverage-specific spillovers provide strong support for *Hypothesis 3*. The three coefficient estimates for $\Delta CoCvg$ derived from the common coverage sample are 0.072 regardless of the set of controls we employ. The two estimates based on the forecast correlation sample are higher at 0.091. Similarly, the three coefficient estimates for $\Delta CoFst$ derived from the common coverage sample are 0.043 and the two estimates from the forecast correlation sample are 0.068. The coefficient estimates from the forecast correlation sample may be systematically larger due to the fact that analysts with common coverage issue more forecasts and thus generate stronger coverage-specific spillovers. The R^2s for all the models in Table 7 are lower than for the models in Table 6, suggesting that much of the power of the models in Table 6 is a result of their ability to explain cross-sectional variation in return correlation. However, the results in Table 7 demonstrate that the time-series variation in return correlation can also be explained by coverage-specific spillovers.

Table 7 also provides support for the existence of broad spillovers. The coefficient estimates for $\Delta Covg$ are positive. However, they are only consistently statistically significant after we include $\Delta IFstCor$ as a control variable, indicating that broad spillovers may also be stronger in the forecast correlation sample. The coefficients for $\Delta IFstCor$ are consistently positive and highly statistically significant. The coefficients for the remaining variables, indicators for common membership in industry and S&P 500 index, and similar size and book-to-market ratios, are significant when we employ their levels, but not their annual changes, as control variables. The loss of significance with the changes is likely due to reduced power because of infrequent changes in these indicator variables.

6.4. Comovement and the information content of analyst research

We predict that investors' expectations regarding the economic exposures shared by stock pairs are influenced upwards by inflated estimates of shared exposures from analysts with common coverage (*Hypothesis 3*). To test this prediction, we regress return comovement on common forecast correlation. We estimate models based on (8) and (9). Moreover, as we did in Table 6, we provide two estimates for every model based on (8); the first is an OLS estimate and the second a $2SLS$ estimate where we instrument $CFstCor$ using its lagged value. This instrument is relevant and Hausman tests indicate that the OLS estimate is subject to bias, possibly from inadequate controls for shared economic exposures. All the reported estimates are based on the forecast correlation sample.

Insert Table 8 approximately here

Table 8 presents the coefficient estimates. The coefficient estimates for $CFstCor$ are positive and highly statistically significant for all models based on (8) (Panel A). The OLS estimates vary from 0.047 when $CFstCor$ is the only independent variable to 0.028 when we include all our control variables. The 2SLS estimates range from 0.065 when $CFstCor$ is the only independent variable to 0.562 when we use all our control variables. The coefficient estimates for $\Delta CFstCor$ in Panels B and C, which are derived from models based on (9), are all positive and highly statistically significant. Across all three panels, the estimated coefficients for $CFstCor$ and $\Delta CFstCor$ decline when $IFstCor$ or $\Delta IFstCor$ is introduced as control variables. However, the coefficient estimates for $CFstCor$ and $\Delta CFstCor$ remain positive and statistically significant. Overall, the results support *Hypothesis 3*.

6.5. A natural experiment: Exogenous changes in common coverage

We attempt to establish causality from common coverage to stock return comovement by using a natural experiment. We identify an event where our measures of analyst activity vary, not because of changes in shared economic exposures, but because of exogenous events: analysts leaving the profession. Analysts may quit for several reasons. For example, unsuccessful analysts may retire, and successful analysts may assume managerial positions or join buy-side firms. In both cases, analysts' departures are unlikely to be driven by changes in the shared economic exposures of a pair of stocks. Therefore, we test the coverage-specific spillover hypothesis using observations for stock pairs that experience a change in the level of common coverage that is solely the result of analysts leaving the profession. The change in the level of common coverage can be positive or negative, depending on whether analysts with common coverage or individual coverage quit.

We first identify stock pairs where the only change in analyst coverage between two consecutive years is the result of analysts who cease to appear on the *I/B/E/S* database.[23] To ensure our test have sufficient power, we filter out observations where the change in the level of common coverage is less than 10%. After applying this screen, we have 2,493 and 1,335 stock pairs in the common coverage and forecast correlation samples, respectively. Using these observations, we estimate variants of the following model:

$$\Delta TCorr_{ij,t} = \alpha + \beta_C \ \Delta CoAct_{ij,t} + \beta_B \ \Delta Covg_{ij,t} + \beta_{IFC} \ \Delta IFstCor_{ij,t} + \beta_x \ X_{ij,t} + \epsilon_{ij,t}, \quad (10)$$

Insert Table 9 approximately here

Table 9 presents estimates of models based on (10). The reported standard errors are corrected for pair level clustering. The positive and statistically significant estimates for $\Delta CoCvg$ and $\Delta CoFst$ support *Hypothesis 3* and the coverage-specific spillover hypothesis. The coefficient estimates for $\Delta CoCvg$ are 0.25 when the common coverage sample is used and 0.47 when the forecast correlation sample is used. Similarly, the coefficient estimate for $\Delta CoFst$ almost doubles when the forecast correlation sample is used. This suggests, once again, that coverage-specific spillovers are stronger in the forecast correlation sample, possibly because this sample is more likely to contain observations where analysts with common coverage are more active.

The coefficient estimates for $\Delta Covg$ are uniformly negative. This could be due to the fact that there is not much change in the total coverage surrounding the events. The coefficient estimates for $\Delta IFstCor$ are both statistically significant and positive, once again justifying our use of this variable to control for shared exposure. The coefficient estimates for the remaining controls are uniformly statistically insignificant.

[23] In some instances, *I/B/E/S* may change an analyst's identification number when she switches from one broker to another, resulting in us classifying the analyst as having left the profession. Because we focus on events where an analyst ceases covering a stock pair and no new analysts begin covering the stock pair, our results are likely not driven by *I/B/E/S* changing analyst identification numbers.

7. Concluding Comments

In this paper, we study coverage-specific spillovers from sell-side analyst research. These spillovers arise when analysts build their research using information that is common to stocks in their coverage rather than stock-specific or broad-based information. We examine the effect of these spillovers on excess return comovement between pairs of stocks between 1997 and 2006.

We find that research on one stock is more informative about another when the analyst covers both stocks in a pair. Analysts who cover both stocks in a pair expect earnings of the stocks in the pair to be more correlated. On days that analysts issue forecasts and recommendations for only one stock in a pair, the price reactions for the two stocks are closer when the recommendations and forecasts are issued by analysts who cover both stocks in the pair. We also find a strong positive relation between the daily return correlation throughout the year and the level of common coverage, as measured by the fraction of analysts covering both stocks and their relative forecasting intensity. Moreover, higher correlations in earnings forecasts issued by analysts who cover both stocks in a pair are reflected in higher correlation between the stock returns. The effect of coverage-specific spillovers on return comovement is incremental to the effect of economic factors such as cash flow comovement, similarities in size and growth opportunities, and common industry and index membership. These results collectively support our hypothesis that sell-side analyst research generates coverage-specific spillovers that raise return comovement between stocks. That is, analyst activity on one stock is informative not only for the stock in question but also for other stocks covered by an analyst, and this effect is distinct from other broad-based spillovers described in the literature (Piotroski and Roulstone, 2004).

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Table 1: **Firm and coverage statistics**

This table provides an annual breakdown of our sample. Panel A presents data on stock pairs where each stock in the pair survives the following filters: (i) the stocks are traded without discontinuity during the year, (ii) the stock price is higher than $5, (iii) there are at least three years of past return data for the stock, (iv) the stock is followed by at least ten analysts during the year, and (v) at least one analyst follows both stocks in the pair. Panel B presents data on stock pairs that survive the following two additional filters: (vi) the fiscal year ends of both companies in the pair have to be between October 1 of the year in question and March 31 of the succeeding year, (vii) on each month-end, at least one analyst covering both firms and one analyst covering only one firm in the pair revises her annual earnings forecast within the past 90 days. The sixth (seventh) column in Panel B presents the average correlation between monthly consensus forecasts issued by analysts covering only one firm (both firms) in the pair.

Panel A: Common coverage sample

Year	Number of firms	Number of firm pairs	All analysts	Analysts following both firms	All forecasts	Forecasts by common analysts	Return correlation (%)
1997	684	19,449	41.87	2.91	257.22	32.50	24.43
1998	780	22,980	40.77	2.77	276.77	34.72	26.66
1999	883	27,666	42.49	2.80	272.59	33.98	17.29
2000	875	26,313	43.78	2.85	265.65	33.35	23.24
2001	882	21,181	41.85	3.10	316.80	46.41	34.63
2002	917	18,649	39.91	3.82	280.94	53.56	42.35
2003	942	25,541	42.29	3.20	326.32	46.28	33.31
2004	1,008	26,182	40.94	3.28	337.11	52.38	31.92
2005	941	20,749	39.54	3.70	345.85	63.59	29.87
2006	864	18,697	39.91	3.73	343.02	62.48	30.30
Average	878	22,741	41.34	3.22	302.23	45.93	28.91

Panel B: Forecast correlation sample

Year	Number of firms	Number of firm pairs	All analysts	Analysts following both firms	Indv. covg. forecast correlation	Comm. covg. forecast correlation	Return correlation (%)
1997	560	8,856	41.08	3.98	3.93	4.67	26.01
1998	640	10,392	40.34	3.85	20.91	19.23	28.92
1999	693	11,055	41.38	3.99	6.70	8.19	20.48
2000	732	12,298	42.32	3.91	2.22	-1.15	26.73
2001	735	9,387	39.72	4.40	37.42	34.84	39.34
2002	772	9,367	38.75	5.12	14.52	14.87	45.27
2003	768	10,298	39.67	4.74	10.56	10.39	38.18
2004	862	13,317	38.57	4.30	14.27	13.82	35.50
2005	802	12,147	38.81	4.41	13.42	15.58	33.26
2006	737	11,183	39.44	4.38	5.87	7.28	33.33
Average	730	10,830	40.01	4.31	12.63	12.42	32.52

Table 2: **Descriptive statistics for stock pairs**

This table presents descriptive statistics for our samples of stock pairs. Statistics for all stock pairs, including pairs that do not have analysts with common coverage, appear under the heading *Stock pair universe*. Statistics for the common coverage sample and forecast correlation sample appear under the headings *Common coverage sample* and *Forecast correlation sample*, respectively. These samples have 7,580,032, 227,407, and 108,300 pairs, respectively. *Return correlation* is the daily return correlation between pairs of stocks. These correlations are computed over one calendar year. *Common coverage* is the ratio of the number of analysts covering both stocks in a pair to the number of analysts covering the pair in the year. *Common forecast* is the ratio of the number of forecasts issued by analysts covering both stocks in a pair during the year to the total number of forecasts for the pair in the year. *Common forecast correlation* is the correlation between the monthly consensus forecasts for the two stocks issued by analysts who cover both the stocks. *Coverage* is the ratio of the number of analysts covering the stock pair divided by the sum of the average number of analysts covering firms in the industries to which the firms belong. Earnings per share (EPS) and cash flow correlations are computed using 16 quarters of data that starts with the year before the year to which the observation belongs and ends two years after the year of the observation. The correlations of EPS changes and cash flow changes are computed using quarterly changes in these variables over the same estimation periods we use to estimate the correlation in EPS and cash flows. *Individual forecast correlation* is the correlation between the monthly consensus forecasts for the pair of stocks issued by analysts covering only one stock in the pair. *Common industry* is an indicator that equals 1 if both firms in a pair belong to the same Fama-French industry. *Common index* is an indicator that equals 1 if both stocks in a pair belong to the S&P 500 Index. *Large firms* is an indicator that equals 1 if both stocks in a pair have equity market capitalizations that exceed the median equity market capitalization. *Small B/M* is an indicator that equals 1 if both stocks in the pair have book-to-market ratios lower than the median book-to-market ratio.

		Stock pair universe		Common coverage sample		Forecast corr. sample	
Variable	Symbol	Mean (%)	Std Dev (%)	Mean (%)	Std Dev (%)	Mean (%)	Std Dev (%)
Return correlation	$Corr$	19.13	12.81	28.91	17.42	32.52	18.19
Common coverage	$CoCvg$	0.53	3.80	9.09	13.01	12.42	15.17
Common forecast	$CoFst$	0.86	5.76	14.72	19.05	20.63	21.37
Common forecast corr.	$CFstCor$					12.42	68.49
Coverage	$Covg$	1.00	27.80	1.06	31.47	1.02	29.43
EPS correlation	ρ^{EPS}	3.74	38.26	9.43	40.59	13.67	41.14
Cash flow correlation	ρ^{CF}	1.68	41.96	3.02	42.48	3.66	42.34
Corr. of EPS change	$\rho^{\Delta EPS}$	1.46	42.88	4.62	43.33	6.85	43.98
Corr. of cash flow change	$\rho^{\Delta CF}$	0.22	51.12	0.94	51.02	1.12	51.07
Individual forecast corr.	$IFstCor$					12.62	71.19
Common industry	D_{Indy}	4.83	21.44	34.91	47.67	45.89	49.83
Common index	D_{Ix}	15.24	35.94	26.04	43.88	23.29	42.27
Large firms	D_{Size}	31.19	46.33	43.69	49.60	43.32	49.55
Small B/M	$D_{B/M}$	26.80	44.29	34.06	47.39	29.95	45.80

Table 3: **Correlations between variables**

This table presents Spearman correlation coefficients between variables in the forecast correlation sample. $Corr$ is the daily return correlation between the returns on pairs of stocks computed over one calendar year. $CoCvg$ is the ratio of the number of analysts covering both stocks in a pair to the total number of analysts covering the pair. $CoFst$ is the ratio of the quarterly and annual forecasts issued by analysts covering both stocks in a pair to the total number of forecasts for the pair. $CFstCor$ is the correlation between the monthly consensus forecasts for two stocks issued by analysts who cover both stocks. $Covg$ is the ratio of the total number of analysts covering either stock in the pair divided by the sum of the average number of analysts covering firms in the industries to which the firms belong. $IFstCor$ is the correlation between the monthly consensus forecasts for the pair of stocks issued by analysts covering only one stock in the pair. D_{Indy} is an indicator that equals 1 if both firms belong to the same Fama-French industry. D_{Ix} is an indicator that equals 1 if both stocks are included in the S&P 500 index during the year. D_{Size} is an indicator that equals 1 if both stocks have market capitalizations that exceed the median stock market capitalization. $D_{B/M}$ is an indicator that equals 1 if both stocks have book-to-market ratios lower than the median book-to-market ratio. ρ^{EPS} (ρ^{CF}) is the correlation between the stocks' earnings per share (EPS) (cash flows) computed using 20 quarters of data starting one year before the year to which the observation belongs. $\rho^{\Delta EPS}$ ($\rho^{\Delta CF}$) is the correlation between the change in stocks' earnings per share (EPS) (cash flows) computed using 20 quarters of data starting one year before the year to which the observation belongs.

	$CoCvg$	$CoFst$	$CFstCor$	$Covg$	$IFstCor$	D_{Indy}	D_{Ix}	D_{Size}	$D_{B/M}$	ρ^{EPS}	ρ^{CF}	$\rho^{\Delta EPS}$	$\rho^{\Delta CF}$
$Corr$	0.380	0.388	0.163	-0.010	0.158	0.237	0.082	0.117	-0.036	0.160	0.015	0.096	0.011
$CoCvg$		0.965	0.099	-0.321	0.074	0.250	0.045	0.048	-0.051	0.132	0.015	0.067	0.005
$CoFst$			0.105	-0.355	0.080	0.276	0.010	0.009	-0.052	0.138	0.017	0.071	0.005
$CFstCor$				-0.044	0.705	0.059	-0.006	-0.012	-0.027	0.083	0.003	0.077	0.001
$Covg$					-0.033	-0.054	0.214	0.326	0.121	-0.045	-0.014	-0.027	-0.005
$IFstCor$						0.054	-0.006	-0.006	-0.030	0.079	0.006	0.076	0.003
D_{Indy}							-0.114	-0.069	0.001	0.139	0.006	0.056	-0.001
D_{Ix}								0.471	0.082	-0.011	0.014	-0.014	0.000
D_{Size}									0.135	-0.027	-0.008	-0.013	-0.004
$D_{B/M}$										-0.036	0.001	-0.039	-0.001
ρ^{EPS}											0.029	0.475	0.004
$\rho^{\Delta EPS}$												0.006	0.695
$\rho^{\Delta CF}$													0.010

Table 4: **A direct test of spillovers**

This table presents, for the common coverage sample (N=227,407), returns for stocks in a pair on days that analysts are active, i.e., when they issue a forecast or recommendation, for only one stock in the pair. Each activity day, we compute the NYSE decile size-adjusted absolute returns separately for the activity stock, the stock for which analysts issue recommendations/forecasts, and the no-activity stock. For each pair-year, we then use these returns to compute measures of the informativeness of analyst research for the activity and no-activity stocks as well as analysts with common and individual coverage separately. The first measure of informativeness is the average ratio of size-adjusted absolute return on the activity day divided by the average size-adjusted absolute daily return for the stock on days with no analyst activity during the year (*AI per activity day*). The second measure is the average size-adjusted absolute stock return on activity days (*Activity day return*). The table presents mean and median values of the pair-year differences between each information measure for analysts with common and individual coverage for both the activity and no-activity stocks. With the exception of the differences indicated by $**$, which is significant at the 95% confidence level, all the differences reported in the table are significant at the 99% confidence level.

		Activity stock		No-activity stock		Activity - No-activity	
		AI per activity day	Activity day return	AI per activity day	Activity day return	AI per activity day	Activity day return
Panel A: All analyst activity							
Common coverage	mean	1.1442	1.565%	1.0430	1.480%	0.1012	0.085%
	median	1.0918	1.400%	1.0107	1.306%	0.0844	0.079%
Individual coverage	mean	1.1733	1.606%	1.0185	1.470%	0.1548	0.136%
	median	1.1389	1.544%	1.0116	1.405%	0.1302	0.138%
Common -Individual	mean	-0.0290	-0.040%	0.0246	0.010%	-0.0536	-0.051%
	median	-0.0471	-0.145%	-0.0009**	-0.100%	-0.0458	-0.059%
Panel B: Earnings forecasts only							
Common coverage	mean	1.1165	1.542%	1.0394	1.479%	0.0771	0.063%
	median	1.0666	1.367%	1.0027	1.298%	0.0641	0.057%
Individual coverage	mean	1.1497	1.585%	1.0150	1.469%	0.1346	0.116%
	median	1.1206	1.521%	1.0082	1.403%	0.1142	0.118%
Common -Individual	mean	-0.0332	-0.043%	0.0244	0.009%	-0.0576	-0.053%
	median	-0.0540	-0.154%	-0.0055	-0.105%	-0.0501	-0.061%

Table 5: **Return correlation, common forecasts, and common forecast correlations**

This table reports average return correlations ($TCorr$) for stock pairs sorted along two dimensions. Panel A first sorts pairs into quintiles by the level of analyst coverage ($Covg$), and then, within each quintile group, by common coverage ($CoCvg$). Panel B first sorts pairs into quintiles by the level of analyst coverage ($Covg$), and then, within each quintile group, by the forecasting intensity of analysts with common coverage ($CoFst$). Both Panels A and B use the common coverage sample (N=227,407). Panel C, which uses the forecast correlation sample (N=108,300), first sorts pairs by individual forecast correlation ($IFstCor$), and then by common forecast correlations ($CFstCor$). $***$ denotes significance of the differences at 99% level.

Panel A: Common coverage versus coverage

Portfolio	$CoCvg_{Low}$	$CoCvg_{Q2}$	$CoCvg_{Q3}$	$CoCvg_{Q4}$	$CoCvg_{High}$	Mean $Covg$	Mean $Corr$	$High - Low$
$Covg_{Low}$	0.2333	0.2238	0.2659	0.3421	0.4292	0.6706	0.2991	0.1959***
$Covg_{Q2}$	0.2390	0.2228	0.2495	0.3094	0.4187	0.8663	0.2881	0.1797***
$Covg_{Q3}$	0.2459	0.2277	0.2526	0.2987	0.4159	1.0166	0.2883	0.1700***
$Covg_{Q4}$	0.2504	0.2339	0.2457	0.2958	0.3838	1.1879	0.2821	0.1334***
$Covg_{High}$	0.2721	0.2493	0.2449	0.3132	0.3705	1.5212	0.2901	0.0984***
Mean $CoCvg$	0.0193	0.0448	0.0775	0.1622	0.4332			
Mean $Corr$	0.2481	0.2315	0.2517	0.3118	0.4036			
$High - Low$	0.0388***	0.0255***	-0.0211	-0.0289***	-0.0587***			

Panel B: Forecasting intensity of analysts with common coverage versus coverage

Portfolio	$CoFst_{Low}$	$CoFst_{Q2}$	$CoFst_{Q3}$	$CoFst_{Q4}$	$CoFst_{High}$	Mean $Covg$	Mean $Corr$	$High - Low$
$Covg_{Low}$	0.2212	0.2373	0.2675	0.3426	0.4258	0.6706	0.2991	0.2046***
$Covg_{Q2}$	0.2224	0.2312	0.2568	0.3094	0.4197	0.8663	0.2881	0.1973***
$Covg_{Q3}$	0.2301	0.2346	0.2579	0.3027	0.4154	1.0166	0.2883	0.1853***
$Covg_{Q4}$	0.2367	0.2395	0.2560	0.2937	0.3836	1.1879	0.2821	0.1469***
$Covg_{High}$	0.2374	0.2578	0.2768	0.3048	0.3732	1.5212	0.2901	0.1358***
Mean $CoFst$	0.0193	0.0448	0.0775	0.1622	0.4332			
Mean $Corr$	0.2296	0.2401	0.2630	0.3106	0.4035			
$High - Low$	0.0163***	0.0204***	0.0093	-0.0378***	-0.0525***			

Panel C: Common forecast correlation versus Individual forecast correlation

Portfolio	$CFstCor_{Low}$	$CFstCor_{Q2}$	$CFstCor_{Q3}$	$CFstCor_{Q4}$	$CFstCor_{High}$	Mean $IFstCor$	Mean $Corr$	$High - Low$
$IFstCor_{Low}$	0.2803	0.2832	0.2808	0.2732	0.2839	-0.8722	0.2802	0.0036
$IFstCor_{Q2}$	0.2945	0.3087	0.3136	0.3234	0.3112	-0.4806	0.3102	0.0167***
$IFstCor_{Q3}$	0.3019	0.3327	0.3307	0.3361	0.3427	0.2857	0.3287	0.0408***
$IFstCor_{Q4}$	0.3117	0.3219	0.3341	0.3503	0.3771	0.7593	0.3389	0.0654***
$IFstCor_{High}$	0.3110	0.3372	0.3709	0.4137	0.4131	0.9358	0.3691	0.1020***
Mean $CFstCor$	-0.5378	-0.0707	0.1440	0.3518	0.7259			
Mean $Corr$	0.2999	0.3168	0.3260	0.3393	0.3456			
$High - Low$	0.0308***	0.0540***	0.0901***	0.1405***	0.1292***			

Table 6: **Return correlation and coverage-specific spillovers**

This table reports estimates from regressing return correlations on proxies for coverage-specific spillovers and sets of controls. It presents two sets of coefficient estimates for every model. The first set is estimated using OLS and second set is estimated using 2SLS. Each 2SLS estimate is made using the lagged value of the key variable of interest as its instrument. In each model, the dependent variable is $TCorr$, the return correlation for firms pairs after it is orthogonalized relative to four variables capturing the correlation between the cash flows and earnings of the pair. The key variables of interest are the level of common coverage ($CoCvg$) and the intensity of forecasting by analysts with common coverage ($CoFst$). The control variables include the industry-adjusted level of coverage ($Covg$) and the level of individual forecast correlation ($IFstCor$). The remaining independent variables are D_{Indy}, D_{Ix}, D_{Size}, $D_{B/M}$, indicators that equal one when the two stocks belong to the same industry, belong to the $S\&P500$ index, have market capitalizations larger than the median, and have book-to-market ratios lower than the median, respectively. All models that do not include $IFstCor$ are estimated using the common coverage sample (N=227,407). The remaining estimates are made using the forecast correlation sample (N=108,300). Standard errors adjusted for pair level clustering are presented in parentheses immediately below the estimates.

Model	$Const$	$CoCvg$	$CoFst$	$Covg$	$IFstCor$	D_{Indy}	D_{Ix}	D_{Size}	$D_{B/M}$	$R^2(\%)$
Ia	0.2509	0.4777								14.22
	(.0009)	(.0066)								
Ib	0.2496	0.4900								
	(.0010)	(.0072)								
IIa	0.2429		0.3438							15.34
	(.0009)		(.0044)							
IIb	0.2411		0.3550							
	(.0010)		(.0048)							
IIIa	0.1727	0.4354		0.0430		0.0668	0.0111	0.0277	-0.0140	18.64
	(.0029)	(.0074)		(.0026)		(.0017)	(.0019)	(.0016)	(.0014)	
IIIb	0.1697	0.4487		0.0452		0.0657	0.0108	0.0272	-0.0139	
	(.0030)	(.0083)		(.0027)		(.0017)	(.0020)	(.0016)	(.0014)	
IVa	0.1571		0.3229	0.0506		0.0602	0.0129	0.0294	-0.0147	19.67
	(.0029)		(.0050)	(.0026)		(.0017)	(.0019)	(.0016)	(.0014)	
IVb	0.1515		0.3391	0.0545		0.0581	0.0124	0.0287	-0.0147	
	(.0031)		(.0056)	(.0027)		(.0018)	(.0019)	(.0016)	(.0014)	
Va	0.1797	0.4061		0.0551	0.0339	0.0532	0.0147	0.0260	-0.0159	19.64
	(.0044)	(.0085)		(.0040)	(.0010)	(.0023)	(.0029)	(.0022)	(.0020)	
Vb	0.1782	0.4107		0.0562	0.0348	0.0527	0.0145	0.0258	-0.0158	
	(.0046)	(.0097)		(.0042)	(.0011)	(.0023)	(.0029)	(.0022)	(.0021)	
VIa	0.1562		0.3103	0.0654	0.0332	0.0482	0.0169	0.0276	-0.0168	20.59
	(.0045)		(.0061)	(.0040)	(.0010)	(.0023)	(.0028)	(.0022)	(.0020)	
VIb	0.1521		0.3187	0.0681	0.0343	0.0472	0.0166	0.0270	-0.0167	
	(.0048)		(.0070)	(.0042)	(.0010)	(.0023)	(.0029)	(.0022)	(.0021)	

Table 7: **The effect of changes in analyst coverage on changes in return correlations**

This table reports the results of regressing changes in return correlations on changes in common coverage and changes in the intensity of forecasting by analysts with common coverage. In each regression, the dependent variable is $\Delta TCorr$, the annual change in the return correlation for a stock pair after orthogonalizing it relative to estimates of correlation between the cash flows and earnings of the pair. The independent variables include the annual change in the level of common coverage ($\Delta CoCvg$) and the annual change in the level of common forecasts ($\Delta CoFst$). The control variables include annual changes in the industry-adjusted level of coverage ($\Delta Covg$) and the change in the level of individual forecast correlation ($\Delta IFstCor$). Panel A uses as control variables D_{Indy}, D_{Ix}, D_{Size}, $D_{B/M}$, indicators that equal one when the two stocks belong to the same industry, belong to the $S\&P500$ index, have market capitalizations larger than the median, and have book-to-market ratios lower than the median, respectively. Panel B uses as control variables annual changes in the indicator variables. All models that do not include $\Delta IFstCor$ are estimated using the common coverage sample (N=227,407). The remaining estimates are made using the forecast correlation sample (N=108,300). Standard errors adjusted for pair level clustering are presented in parentheses immediately below the estimates.

Panel A: Estimates based on first differences for all but indicator variables

Model	$Const$	$\Delta CoCvg$	$\Delta CoFst$	$\Delta Covg$	$\Delta IFstCor$	D_{Indy}	D_{Ix}	D_{Size}	$D_{B/M}$	$R^2(\%)$
I	0.0048	0.0723								0.05
	(.0003)	(.0084)								
II	0.0049		0.0434							0.04
	(.0003)		(.0058)							
III	0.0030	0.0717		0.0088		0.0094	0.0016	-0.0035	-0.0026	0.20
	(.0005)	(.0085)		(.0029)		(.0005)	(.0007)	(.0007)	(.0007)	
IV	0.0030		0.0421	0.0074		0.0095	0.0016	-0.0034	-0.0026	0.19
	(.0005)		(.0058)	(.0029)		(.0005)	(.0007)	(.0007)	(.0007)	
V	0.0066	0.0914		0.0234	0.0095	0.0082	0.0015	-0.0079	-0.0058	0.82
	(.0007)	(.0107)		(.0043)	(.0006)	(.0008)	(.0010)	(.0010)	(.0010)	
VI	0.0066		0.0682	0.0219	0.0095	0.0083	0.0016	-0.0079	-0.0057	0.80
	(.0007)		(.0078)	(.0043)	(.0006)	(.0008)	(.0010)	(.0010)	(.0010)	

Panel B: Estimates based on first differences of all variables

Model	Const	$\Delta CoCvg$	$\Delta CoFst$	$\Delta Covg$	$\Delta IFstCor$	ΔD_{Indy}	ΔD_{Ix}	ΔD_{Size}	$\Delta D_{B/M}$	R^2
I	0.0046	0.0726		0.0056		0.0063	-0.0166	0.0214	0.0047	0.41
	(.0003)	(.0084)		(.0028)		(.0023)	(.0069)	(.0011)	(.0009)	
II	0.0046		0.0426	0.0042		0.0065	-0.0167	0.0215	0.0047	0.40
	(.0003)		(.0058)	(.0028)		(.0023)	(.0069)	(.0011)	(.0009)	
III	0.0060	0.0906		0.0201	0.0098	-0.0018	-0.0127	0.0160	0.0110	0.92
	(.0004)	(.0107)		(.0043)	(.0006)	(.0031)	(.0086)	(.0015)	(.0013)	
IV	0.0061		0.0674	0.0185	0.0098	-0.0017	-0.0129	0.0160	0.0110	0.92
	(.0004)		(.0078)	(.0042)	(.0006)	(.0031)	(.0087)	(.0016)	(.0013)	

Table 8: **Return comovement and estimates of correlation in earnings**

This table reports estimates from regressing return correlations on estimates of correlations in earnings derived from consensus forecasts of analysts with common coverage and sets of controls. Panel A presents two sets of coefficient estimates for every model. The first set is estimated using OLS after adjusting standard errors for stock-pair level clustering. The second set is estimated using 2SLS after adjusting standard errors for stock-pair level clustering. Each 2SLS estimate is made using the lagged value of the key variable of interest as its instrument. In each model, the dependent variable is $TCorr$, the return correlation for firms pairs after it is orthogonalized relative to four variables capturing the correlation between the cash flows and earnings of the pair. The independent variables of interest are the correlation in the consensus earnings forecasts of the pair of stocks issued by analysts covering both stocks ($CFstCor$). The control variables include the industry-adjusted level of coverage ($Covg$) and the level of individual forecast correlation ($IFstCor$). The remaining independent variables are D_{Indy}, D_{Ix}, D_{Size}, $D_{B/M}$, indicators that equal one when the two stocks belong to the same industry, belong to the $S\&P500$ index, have market capitalizations larger than the median, and have book-to-market ratios lower than the median, respectively. Panel B presents OLS estimates from regressing changes in return correlation on changes in the above variables except the indicator variables. Panel C presents OLS estimates from regressing changes in return correlation on changes in all variables. All the models are estimated using the forecast correlation sample (N=108,300). Standard errors adjusted for pair level clustering are presented in parentheses immediately below the estimates.

Panel A: Estimates based on levels

Model	$Const$	$CFstCor$	$Covg$	$IFstCor$	D_{Indy}	D_{Ix}	D_{Size}	$D_{B/M}$	$R^2(\%)$
Ia	0.3285	0.0470							2.96
	(.0012)	(.0013)							
Ib	0.3260	0.0654							
	(.0012)	(.0012)							
IIa	0.2979	0.0426	-0.0318		0.0847	0.0289	0.0459	-0.0193	10.05
	(.0043)	(.0012)	(.0040)		(.0023)	(.0032)	(.0024)	(.0022)	
IIb	0.2949	0.0571	-0.0303		0.0835	0.0287	0.0457	-0.0186	
	(.0043)	(.0016)	(.0041)		(.0023)	(.0032)	(.0024)	(.0022)	
IIIa	0.2973	0.0283	-0.0318	0.0191	0.0844	0.0288	0.0458	-0.0189	10.30
	(.0043)	(.0017)	(.0040)	(.0016)	(.0023)	(.0032)	(.0024)	(.0022)	
IIIb	0.1829	0.5619	0.0233	0.0368	0.0397	0.0221	0.0474	0.0083	
	(.0055)	(.0183)	(.0044)	(.0011)	(.0028)	(.0032)	(.0024)	(.0023)	

Panel B: Estimates based on first differences for all but indicator variables

Model	Const	$\Delta CFstCor$	$\Delta Covg$	$\Delta IFstCor$	D_{Indy}	D_{Ix}	D_{Size}	$D_{B/M}$	R^2
IV	0.0065	0.0098							0.45
	(.0004)	(.0006)							
V	0.0068	0.0099	0.0171		0.0087	0.0014	-0.0080	-0.0055	0.71
	(.0007)	(.0006)	(.0042)		(.0008)	(.0010)	(.0010)	(.0010)	
VI	0.0069	0.0058	0.0173	0.0055	0.0087	0.0014	-0.0080	-0.0054	0.78
	(.0007)	(.0009)	(.0042)	(.0008)	(.0008)	(.0010)	(.0010)	(.0010)	

Table 9: **A natural experiment**

This table reports the results of an event study, i.e., a 10% or larger change in the level of common coverage resulting solely from the departure of analysts from the industry. The estimates are the result of regressing changes in return correlations on the changes in coverage and changes in common forecasts. In each regression, the dependent variable is $\Delta TCorr$, the annual change in the return correlation for a stock pair after orthogonalizing it relative to estimates of correlation between the cash flows and earnings of the pair. The independent variables include the change in a measure of the intensity of forecasting by analysts with common coverage ($\Delta CoFst$) and the change in the level of common coverage ($\Delta CoCvg$). The control variables include the change in the industry-adjusted level of coverage ($\Delta Covg$) and the change in the level of individual forecast correlation ($\Delta IFstCor$). The remaining independent variables are D_{Indy}, D_{Ix}, D_{Size}, $D_{B/M}$, indicators that equal one when the two stocks belong to the same industry, belong to the $S\&P500$ index, have market capitalizations larger than the median, and have book-to-market ratios lower than the median, respectively. All models that do not include $\Delta IFstCor$ are estimated using the common coverage sample (N=227,407). The remaining estimates are made using the forecast correlation sample (N=108,300). Standard errors adjusted for pair level clustering are presented in parentheses immediately below the estimates.

Model	$Const$	$\Delta CoCvg$	$\Delta CoFst$	$\Delta Covg$	$\Delta IFstCor$	D_{Indy}	D_{Ix}	D_{Size}	$D_{B/M}$	$R^2(\%)$
I	0.0127	0.2558								0.50
	(.0049)	(.0719)								
II	0.0056		0.1414							0.30
	(.0038)		(.0478)							
III	0.0110	0.2482		-0.0604		0.0027	-0.0039	0.0005	0.0077	1.00
	(.0075)	(.0726)		(.0183)		(.0067)	(.0080)	(.0080)	(.0072)	
IV	0.0048		0.1342	-0.0603		0.0005	-0.0036	0.0001	0.0088	0.80
	(.0069)		(.0479)	(.0184)		(.0067)	(.0080)	(.0080)	(.0072)	
V	0.0334	0.4741		-0.0607	0.0185	0.0061	-0.0094	-0.0066	-0.0121	3.50
	(.0106)	(.1017)		(.0280)	(.0047)	(.0093)	(.0107)	(.0105)	(.0104)	
VI	0.0198		0.2314	-0.0635	0.0187	0.0027	-0.0077	-0.0092	-0.0093	2.80
	(.0098)		(.0651)	(.0281)	(.0047)	(.0093)	(.0108)	(.0106)	(.0104)	

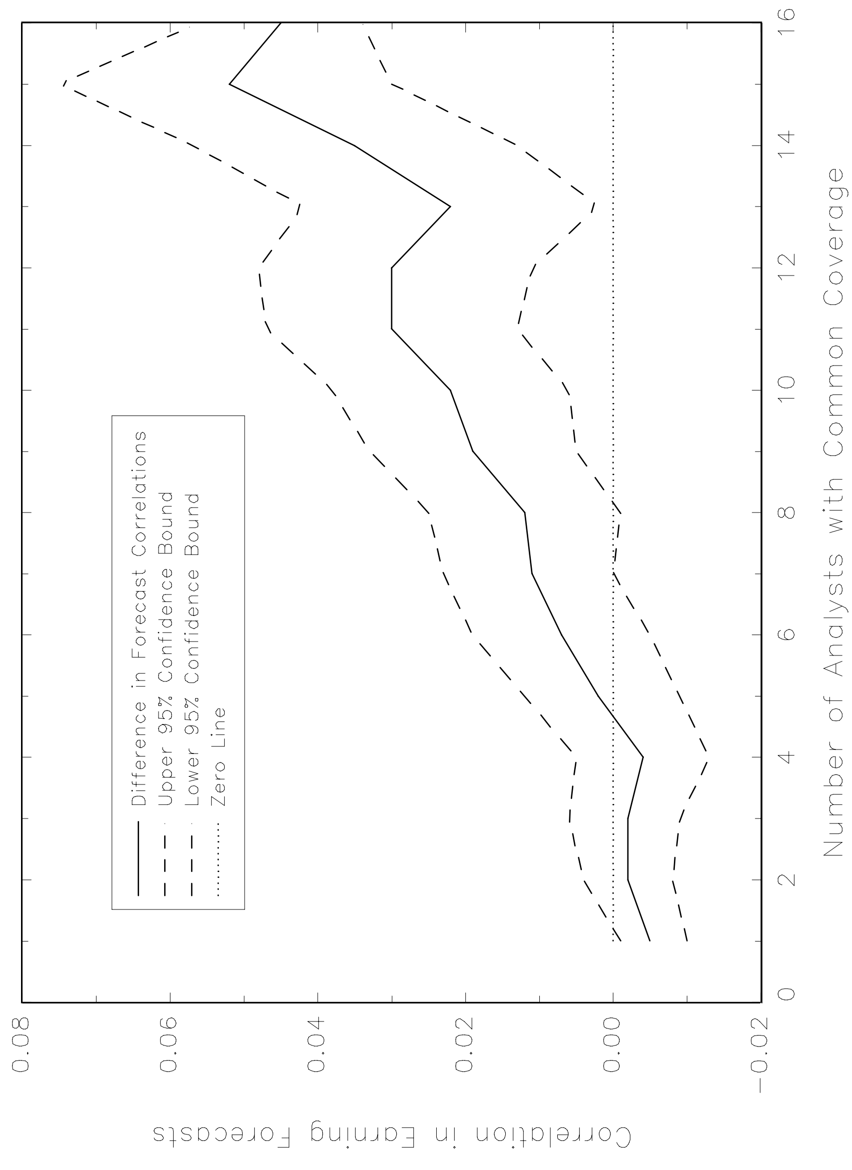

Figure 1: Difference between common and individual forecast correlation.
This figure illustrates how the level of common coverage relates to average differences in correlations of monthly consensus forecasts provided by analysts with common and individual coverage.