Uncovering Expected Returns: Information in Analyst Coverage Proxies

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Abstract

We show that analyst coverage proxies contain information about expected returns. We decompose analyst coverage into abnormal and expected components using a simple characteristic-based model and show that firms with abnormally high analyst coverage subsequently outperform firms with abnormally low coverage by approximately 80 basis points per month. We also show abnormal coverage rises following exogenous shocks to underpricing and predicts improvements in firms' fundamental performance, suggesting that return predictability stems from analysts more heavily covering underpriced stocks. Our findings highlight the usefulness of analysts' actions in expected return estimations, and a potential inference problem when coverage proxies are used to study information asymmetry and dissemination.

JEL Classifications: G10, G11, G12, G14, M40, M41

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1. Introduction

This study examines the implications of analysts' coverage incentives for the information content of standard analyst coverage proxies. We do so by decomposing coverage into an expected component based on observable firm-characteristics and an abnormal component, which we show has strong predictive power for returns. Our evidence adds directly to the growing literature on firm-level expected return proxies. In addition, it yields an important insight for the vast literature that uses analyst coverage to study market prices, trading, and liquidity. Specifically, we show that analyst coverage proxies – commonly used to measure information asymmetry and dissemination – also reflect firm-level expected returns.[1]

Classical economic models provide a framework for understanding the impact of expected payoffs and resource constraints on individual behavior. In many tests of these models, researchers use proxies for expected payoffs and resource constraints to study individual behavior. In this paper, we reverse the process. Specifically, we use the resource allocation behavior of individual security analysts to reverse engineer their expectations about future payoffs for the firms they choose to either cover or forgo. We then examine how these inferred expectations are related to firms' subsequent performance.

Security analysts' decision to either cover or forgo covering a firm presents a particularly interesting setting in which to study constrained resource allocation. This is because the typical security analyst: (a) specializes in providing information to the market, (b) faces non-trivial switching costs when making coverage decisions, and (c) receives a clear payoff from identifying stocks with greater potential upside.[2] Given their incentive structure and their relative sophistication about company prospects, we posit that analysts' choices of which firms to cover contain information useful in forecasting firms' future performance.

[1] Throughout, we use the term 'expected returns' to refer to all *ex ante* predictability in returns, including long-term discount rates and mispricing, although we also devise additional tests to refine this interpretation.

[2] A related literature examines whether investment managers' portfolio allocation decisions lead firms' performance but points out that managers also face strong incentives to maximize assets under management (e.g., Berk and Green (2004)), minimize idiosyncratic risk (e.g., Cohen, Polk, and Silli (2010)), and provide a liquidity service to investors (e.g., Edelen (1999)), which confounds the link between managers' expected payoffs and realized investment returns. We discuss this issue further in Section 2.

Our empirical strategy is based on the premise that when resource-constrained analysts decide how to allocate their time and attention, they will have a strong preference for better performing firms. Prior research offers some support for this view. For example, McNichols and O'Brien (1997) shows analysts drop coverage of unprofitable firms and Scherbina (2008) shows analysts are more likely to suppress negative, compared to positive, earnings news. In addition, Das, Guo, and Zhang (2006) finds that among newly-public firms, those with superior prospects receive greater attention from analysts relative to the characteristics of their initial public offering. This evidence is, in part, a reflection of analysts' incentives to generate investment banking deals, brokerage commissions, accurate earnings forecasts, and access to firms' management. As a result, resource-constrained analysts likely prefer covering firms with superior prospects because they tend to have higher valuations, greater trading volumes, more easily forecasted earnings, and a desire to share positive news.

In this study, we develop a simple characteristic-based model to extract expected return information from standard analyst coverage data. Our approach is broadly applicable in cross-sectional tests to over 4,000 firms per month, including firms without analyst coverage, and does not require conditioning on specific firm-events, such as an initial public offering. The key assumption we rely on is that analysts' coverage decisions consist of a component driven by firms' expected performance and a mechanical component summarized by observable firm-characteristics. Based on this assumption, our approach seeks to isolate the component of coverage driven by analysts' expectations over firms' future performance.

This paper proceeds in three stages. First, we implement our approach for uncovering expected performance information embedded in analyst coverage proxies and relate these expectations to the cross-section of future stock returns. Second, we examine the mechanism linking abnormal coverage and future returns, focusing on analysts' resource constraints and the role of underpricing. Finally, we study returns around firms' earnings announcements to illustrate the importance of our findings for research using analyst coverage as proxies for information asymmetry and dissemination.

We measure abnormal analyst coverage for each firm by comparing the observed level against an expected level to remove the mechanical component of coverage attributable to the firm's size, liquidity, and past performance. We do so using two main proxies for analyst coverage. The first proxy is the number of unique earnings forecasts summed across all analysts and forecasted fiscal periods (i.e., analyst/forecast pairs, where revisions are single counted), which we refer to as 'total coverage'. The second proxy is the number of unique analysts covering a firm, which we refer to as 'simple coverage'. We then calculate abnormal coverage, defined as the residuals from monthly cross-sectional regressions of the two analyst coverage proxies on three control variables: firm size, share turnover, and past returns.

We test whether abnormal coverage contains expected return information by examining its predictive power for returns. These tests hinge upon analysts' coverage decisions leading firms' performance and thus the null hypothesis reflects characterizations of analysts in prior research as marketeers or 'trend chasers' that herd toward over-valued, glamour stocks (e.g., Chung and Jo (1996), Gleason and Lee (2003), Jegadeesh et al. (2004)).

Our first main tests show abnormal coverage positively predicts firms' monthly returns. On average, firms in the highest decile of abnormal total coverage outperform the lowest decile by 80 basis points per month on a value-weighted basis (t-statistic = 3.45) and 87 basis points on an equal-weighted basis (t-statistic = 7.03). Sorting firms by abnormal simple coverage yields similar predictive power for monthly returns. These return patterns are striking in their magnitude and consistency across equal- and value-weighting, suggesting abnormal coverage is associated with an economically large source of predictable returns.

The returns associated with abnormal coverage do not appear to reverse in subsequent months. In fact, we find that abnormal coverage information predicts returns over the next three months. The persistence in return predictability mitigates concerns that our findings stem from transitory price pressure that subsequently reverses. Parallel tests show, however, that raw coverage is uncorrelated with future returns, which highlights the importance of measuring the abnormal component of coverage.

To mitigate concerns that our findings are driven by an omitted firm fixed-effect, we also show that *within-firm changes* in abnormal coverage predict returns. The predictive power of abnormal coverage for returns is also robust to controlling for firms' exposure to standard asset pricing factors and is distinct from firms' size, momentum, and book-to-market ratio, as well as return reversals, announcement premia, and post-earnings announcement drift. Related tests show the performance information in abnormal coverage is incremental to the predictive power of analyst forecast dispersion and forecasted earnings-to-price ratios. Moreover, our study is the first to establish complementarities between what analysts 'do', via their coverage decisions, and what analysts 'say', via the content of their forecasts.

In further tests, we demonstrate how our methodology can also be applied to portfolios of firms, for example, grouped by industry. These tests show how researchers can utilize the broad applicability and simple structure of our approach. In doing so, we provide novel evidence that coverage decisions serve as a leading indicator of sector-wide performance.

After establishing a robust link between abnormal coverage and returns, the second section of the paper sheds light on the underlying mechanism and, in particular, the role of resource constraints. To the extent resource constraints incentivize analysts to bias coverage toward firms with higher expected returns, we predict that higher marginal costs of providing coverage signal analysts' expectations of higher marginal benefits in the form of superior *ex post* performance for the firms in their coverage portfolio.

We provide two sets of evidence in support of this prediction. First, at the firm-level, we use coverage changes, as well as the size of analysts' coverage portfolios, to proxy for the marginal cost of providing coverage. Second, at the market-level, we use reductions (expansions) in the aggregate analyst sector to proxy for changes in analysts' resource constraints. Across both sets of tests, we find that the predictive power of the abnormal coverage is stronger when marginal costs are higher and resource constraints are more likely to bind. Together, these tests show that when analysts have fewer resources to allocate, where they choose to allocate resources is an even stronger signal about firms' future performance.

Our finding that prices predictably fall for abnormally low coverage firms, and vice versa, are potentially consistent with rational asset pricing models in which asymmetric information results in lower prices by reducing demand from uninformed investors (e.g., Admati (1985), Wang (1993), and Easley and O'Hara (2004)). Kelly and Ljungqvist (2012) empirically validates these models, showing that *exogenous* reductions in analyst coverage elicit lower market prices but are unrelated to firm's operating performance. By contrast, we show the abnormal component of analysts' coverage decisions, which are largely endogenous, positively predict both levels and changes in firms' operating performance. These results suggest that our findings are at least partially driven by analysts' incentives to cover firms with better, and improving, operating performance.

We also conduct a series of tests that rely on mutual fund redemptions as an instrument for exogenous shocks to firm-level underpricing. Prior research shows that mutual fund redemptions trigger downward price pressure, which results in sustained and economically large underpricing (e.g., Edmans, Goldstein, and Jiang (2012)). We show that analysts are significantly more likely to increase both raw and abnormal coverage of firms that experience extreme outflows, suggesting analysts increase coverage for underpriced stocks.

The broader contribution of this paper extends beyond the study of expected returns. In particular, our findings help inform the extensive literature in finance, economics, and accounting that uses analyst coverage as proxies for the extent of information intermediation. Because firms' performance influences which investors choose to trade a stock, how frequently they trade, and the market price used for trading, the expected performance component of analyst coverage can create a mechanical correlation between coverage proxies and various market outcomes – such as pricing multiples, liquidity, and ownership structure. Thus, our findings show that researchers may incorrectly attribute this mechanical correlation to the impact of analysts' role as intermediaries, when the associations are likely confounded by analysts' tendency to cover firms with superior performance prospects. In our final tests, we illustrate this point empirically in the context of firms' earnings announcements.

Our final tests examine the relation between analyst coverage and firms' returns during their earnings announcements. We focus on announcements because information asymmetry and mispricing regarding earnings news likely play a heightened role in driving asset returns. We show the expected component of coverage is negatively related to announcement returns, consistent with higher information asymmetry firms commanding higher returns. By contrast, the abnormal component of coverage is positively related to announcement returns, consistent with abnormal coverage leading increases in firms' operating performance. These two components have offsetting effects in the context of announcement returns, creating downwardly biased coefficient estimates on coverage as a proxy for information asymmetry. However, this issue is likely relevant for a variety of research contexts, and need not offset, indicating the sign and severity of the bias likely depends on the outcome of interest.

We use the earnings announcement setting, as well as Tobin's Q regressions, to show that sample selection choices and the inclusion of standard control variables in multivariate tests can actually worsen researchers' inference problems. Together, the inference problems we illustrate collectively add support for the approaches in Hong and Kacperczyk (2010) and Kelly and Ljungqvist (2012) that use exogenous shocks to analyst coverage to assess the impact of analysts on market outcomes.

In sum, this paper provides three main insights. Conceptually, this study contributes to our understanding of analysts' role as informational intermediaries by showing that analysts allocate coverage based on firms' expected returns. Practically, this study provides a simple characteristic-based model to uncover expected return information embedded in analyst coverage proxies that offers strong predictive power for firms' earnings and returns. Finally, methodologically, this study shows the use of analyst coverage in capital market settings is complicated by the fact that these proxies also reflect expected returns.

The rest of the paper is organized as follows. Section 2 surveys related studies. Section 3 details the main tests and Section 4 contains additional analyses. Section 5 details the implications for future research and Section 6 concludes.

2. Literature Review

By studying how analysts allocate coverage across firms, this paper relates to prior research examining the performance of investment managers' portfolio allocation decisions. A central topic in this literature is whether investment managers possess sufficient skill in identifying and harnessing expected return information to generate realized investment performance above their benchmarks.[3] However, several studies point out that investment managers' portfolio performance are not necessarily reflective of their expectations over future equity returns because investment managers are also compensated based on their total assets under management (Berk and Green (2004)), their ability to avoid idiosyncratic risks (e.g., Cohen, Polk, and Silli (2010), Huang, Sialm, and Zhang (2011)), and from providing a liquidity service to investors (e.g., Edelen (1999), Alexander, Cici, and Gibson (2007)).

Our approach also builds upon prior studies that use market prices to infer risk premia (e.g., Mehra and Prescott (1985)) and growth prospects (e.g., Lakonishok, Shleifer, and Vishny (1994)), fund flows to measure investor sophistication (e.g., Frazzini and Lamont (2008)), and firm-behavior to measure market sentiment (e.g., Baker and Wurgler (2006)). Our approach differs in that we infer expectations not based on market prices or firms' behavior but rather by the behavior of information intermediaries. This allows us to jointly study how analysts' incentives impact the information content of standard coverage proxies and the implications of this information content for studying market outcomes.

A substantial body of research shows that analysts facilitate market efficiency when providing coverage by reducing uncertainty over firms' value (see Beyer et al. (2010) for a recent literature review). However, related studies show analysts' employment incentives create predictable biases in their outputs and coverage decisions (e.g., Womack (1996), Bradshaw (2002), Groysberg, Healy, and Maber (2011)). For example, McNichols and O'Brien (1997)

[3]Whereas several studies find that, on average, mutual funds fail to generate excess returns (e.g., Malkiel (1995), Carhart (1997), and Rubinstein (2001)), other studies suggest that there is evidence that investment managers possess stock picking ability when looking within their portfolio allocation decisions (e.g., Wermers (2000), Cohen, Gompers, and Vuolteenaho (2002), and Kacperczyk, Sialm, and Zheng (2005)).

shows the distribution of analysts' buy/sell recommendations are positively skewed because analysts are averse to conveying negative signals and that analysts add (drop) coverage of firms that have higher (lower) levels of profitability. Our study compliments prior findings by showing analysts' coverage decisions lead *changes* in firms' performance not yet reflected in market prices and, in doing so, convey information about firms' expected returns.

Related research casts significant doubt that analysts' outputs, such as buy/sell recommendations, are useful in generating profitable investment signals (e.g., Michaely and Womack (1999), Barber et al. (2001), Bradshaw (2004), and Altinkilic, Hansen, and Ye (2015)). We explore an alternative 'wisdom-of-the-crowds' approach to extract investment signals by shifting focus away from what analysts say when providing coverage, and instead toward uncovering expected return information based on which firms analysts choose to cover. As a result, our findings relate to evidence that market prices fail to reflect low saliency signals (e.g., Gabaix et al. (2006), Hirshleifer, Lim, and Teoh (2009) and Giglio and Shue (2014)) and suggest investors may underweight abnormal coverage information due to its low saliency relative to analysts' explicit investment advice, such as buy/sell recommendations.

Our findings build upon evidence in Das, Guo, and Zhang (2006), hereafter DGZ, that initial public offerings (IPOs) with abnormally high analyst coverage tend to outperform, indicating analysts provide greater coverage to IPO firms with superior prospects. DGZ motivate their focus on IPOs by noting that they correspond to 'extreme uncertainty and information asymmetry' due to the influx of initial public disclosures such as financial statements, and periods when analysts face heightened incentivizes to support investment banking business. We show the link between coverage decisions and expected returns is quite general and extends beyond these specific settings. Additionally, DGZ measure abnormal coverage relative to the characteristics of the IPO, including the size of the offering, the extent of offer underpricing, and the composition of the underwriting team. We develop and implement a simple characteristic-based methodology, which does not require conditioning upon event- or deal-specific attributes, and thus is easily portable across research settings.

An important feature (and, we believe, contribution) of this paper is in highlighting the size, broad applicability, and robustness of the predictive link between abnormal coverage and the cross-section of returns.[4] Most prior research on the implications of analysts' coverage incentives focus on specific contexts, such as equity issuances, or relatively rare events that are more difficult for researchers to observe, such as coverage initiations or terminations. This narrower focus in prior research may help to explain the continued use of analyst coverage as a popular proxy for information intermediation, despite the proxy's high potential for noise. Our findings show that the expected return component of standard analyst coverage proxies is both widespread and economically large, rather than context-specific, and in Section 5 we illustrate how this form of noise can significantly impact researchers' inferences.

In a related study, Jung, Wong, and Zhang (2015) use conference call transcripts to show the rate of analysts' participation in firms' conference calls, relative to the level of existing analyst coverage, is positively associated with changes in firms' fundamentals and future returns. A key insight from Jung, Wong, and Zhang (2015) is that non-covering analysts are more likely to conduct due diligence on firms with superior prospects. This study offers complimentary evidence by focusing on the forecasting behavior of analysts currently providing coverage relative to firms' characteristic profile.

Our findings indicate that analysts' coverage incentives create a potential welfare transfer (via less coverage) away from firms with lower expected returns. Similarly, to the extent analysts facilitate price discovery by disseminating information, our findings suggest that coverage decisions may influence the relative speed with which good versus bad news is reflected in prices and thus relates to prior evidence that 'bad news travels slowly' (e.g., Hong, Lim, and Stein (2000)).[5] Specifically, our findings suggest bad news may travel slowly because analysts devote less effort toward covering firms with lower expected returns.

[4]Our methodology allows us to study expected return information for approximately 4,200 unique firms each calendar month, whereas Das, Guo, and Zhang (2006) use a sample of 4,082 IPOs spanning a 15 year period. We leverage the broad applicability of our approach by aggregating information within industries and providing new evidence that coverage decisions also forecast sector-wide performance.

[5]Interestingly, Hong, Lim, and Stein (2000) provide evidence that firms' returns are positively related to abnormal analyst coverage calculated relative to firm size but do not comment on this evidence.

3. Empirical Tests

3.1. Data and Methodology

The main analyses in this paper examine the link between abnormal analyst coverage and firms' future returns. Analyst coverage data comes from the IBES unadjusted detail file, which reflects a cumulative record of analysts' earnings forecasts across dates and forecasted fiscal periods. The IBES detailed forecast database begins in the late 1970's but the data is initially sparse and grows rapidly to cover a broader cross-section of firms in the early 1980's. We merge the analyst data with CRSP after eliminating firms with share codes other than 10 or 11 and firms with prices below $1. We also merge in fundamental information from Compustat using firms' most recent quarterly financial statements and requiring non-missing book values. We begin the sample in 1982, which is the first year in which there are at least 500 unique firms with earnings forecasts in the IBES unadjusted detail file.

In the initial tests, we do not require firms to have coverage in IBES to avoid unnecessarily censoring the sample against firms with abnormally low coverage. Because we do not require analyst coverage, the sample largely corresponds to the CRSP/Compustat universe subject to the listed data requirements. The final sample consists of 1,661,511 firm-months spanning the 33 year window from 1982 through 2014.

The first step in the analyses involves estimating abnormal analyst coverage for each unique firm-month. We use the notation i to index firms and m to refer to the calendar month in which we estimate firms' abnormal coverage. We estimate abnormal analyst coverage by identifying discrepancies between realized and expected levels of coverage based on observable firm-characteristics. Calculating these discrepancies requires two central inputs: proxies for analyst coverage and firm-characteristics useful in estimating expected analyst coverage. Our main tests use two proxies for analyst coverage, both of which are measured over the 90 trading days ending at the conclusion of month m. The choice of a 90-day window is intended to mimic the calculation of the IBES consensus summary file but, in doing so, reflects a tradeoff between incorporating stale information versus excluding forecasts that are not revised due to analysts' beliefs that their initial forecasts are accurate. In subsequent tests, we show that the paper's main findings are robust to alternative measures of coverage, including measures constructed from the IBES consensus summary file.

The first proxy for observed analyst coverage is the number of unique earnings forecasts summed across all analysts and forecasted fiscal periods (i.e., analyst/forecast pairs, where revisions are single counted), referred to as 'total analyst coverage' and denoted as TOT. The second proxy is the number of unique analysts covering a firm, referred to as 'simple' coverage, and denoted as COV. Both total and simple coverage are set to zero for firms without analyst coverage. To highlight the difference between TOT and COV, suppose there are two analysts covering a given firm. The first analyst issues forecasts for next-quarter and one-year-ahead earnings and the second analyst issues only a next-quarter forecast. Then, total analyst coverage would equal three and simple coverage would equal two.

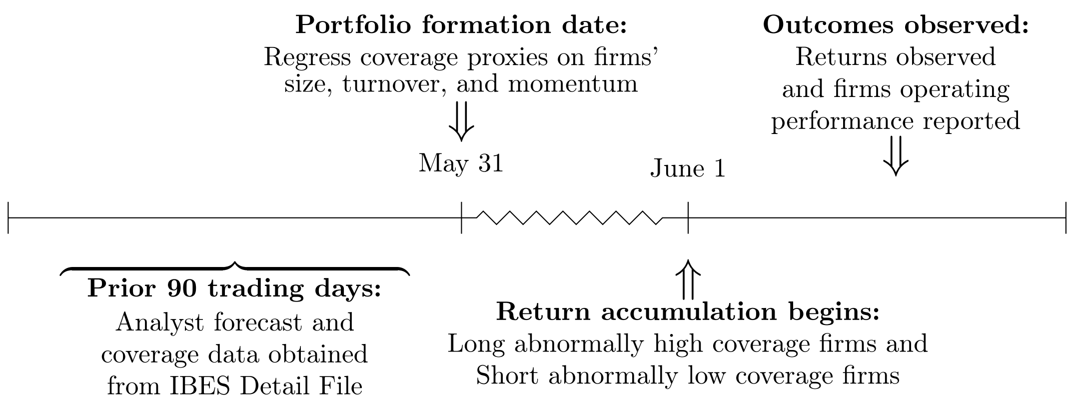
We calculate the abnormal component of analyst coverage by fitting monthly regressions of our two coverage proxies, TOT and COV, to isolate the components of coverage not attributable to firms' size, liquidity, and past performance profile. To mitigate the influence of outliers, we use the log of one plus each analyst coverage proxy when estimating abnormal coverage. More specifically, we calculate abnormal total coverage for firm i in calendar month m by estimating the following regressions:

$$Log(1 + TOT_{i,m}) = \beta_0 + \beta_1 SIZE_{i,m} + \beta_2 TO_{i,m} + \beta_3 MOMEN_{i,m} + \epsilon_{i,m} \tag{1}$$

where $SIZE_{i,m}$ is the log of market capitalization in month m, $TO_{i,m}$ is share turnover calculated as trading volume scaled by shares outstanding, and $MOMEN_{i,m}$ is the firm's cumulative market-adjusted return, where $TO_{i,m}$ and $MOMEN_{i,m}$ are measured over the 12-months leading up to month m. Under this approach, we define abnormal total coverage for each firm-month as the regression residuals (i.e., $\epsilon_{i,m}$) from estimating Eq. (1).

Abnormal simple coverage is defined analogously using the log of one plus COV as the dependent variable in Eq. (1). We use notation $ATOT$ to refer to the abnormal component of total coverage and $ACOV$ to refer to the abnormal component of simple coverage, where higher values correspond to firms that have greater analyst coverage than expected given their size, liquidity, and past performance profile.

The diagram below provides the timeline of analysis for calculating firms' abnormal coverage using the month of May as the portfolio formation month, m:



The above diagram uses a May 31 portfolio formation date as an example to emphasize that the empirical tests are constructed to avoid look ahead biases: all of the signals used for constructing abnormal analyst coverage are observable prior to May 31 and all of the outcomes being predicted are observed after June 1.

Panel A of Table 1 contains the time-series average coefficients from estimating Eq. (1). The coefficients corresponding to total and simple coverage are consistent in sign and significance, where both raw analyst coverage proxies are increasing in contemporaneous firm size (t-statistics = 75.3 and 88.8) and share turnover (t-statistics = 18.1 and 18.4). The regression results also show that both analyst coverage proxies are decreasing in firms' momentum after controlling for their size and past turnover. These findings suggest that, for a given level of market capitalization and liquidity, analysts provide greater coverage to firms following a decline in market prices, and vice versa.[6] The average R^2 values reported

[6]Untabulated results show that both coverage proxies are positively related to momentum before controlling for SIZE and TO, consistent with analysts providing greater coverage of better performing firms

in Panel A show that the three characteristics used in Eq. (1), on average, explain over 60% of the variation in analyst coverage.

The three firm-characteristics used in Eq. (1) were selected for parsimony and computational ease but may also omit other firm characteristics that drive variation in expected analyst coverage. For example, prior research shows that analysts prefer to cover glamour firms, with greater volatility, and firms with high profitability (e.g., Bhushan (1989), Jegadeesh et al. (2004)). The goal of calculating abnormal coverage is to remove the mechanical component associated with firm characteristics, suggesting that any variable included in calculating abnormal coverage should at least have incremental and statistically significant explanatory power for analyst coverage.

To shed light on this issue, Figure 1 plots the absolute t-statistics and adjusted R^2 values when iteratively adding firm characteristics to Eq. (1). Specifically, we examine firms' book-to-market (LBM), volatility (VLTY), and return-on-assets (ROA). After controlling for firm size, turnover, and momentum, Figure 1 shows that the incremental t-statistics are generally all below two in absolute value, with the exception of log book-to-market for simple coverage. Moreover, the slope of the R^2 plot sharply levels off after the three main firm-characteristics are included, suggesting book-to-market, volatility, and profitability offer little incremental explanatory power. In the tests below, we provide corroborating evidence that the addition of additional controls does not significantly impact the predictive power of abnormal coverage for future returns (See Table 4 for more details).

To study the link between abnormal coverage and future firm performance, we assign firms to deciles of $ATOT$ and $ACOV$ at the end of month m, where the higher (lower) deciles correspond to firms with abnormally high (low) coverage. Panels B and C of Table 1 contain average observation counts and firm characteristics across decile portfolios of $ATOT$ and $ACOV$. The observation counts show that there are approximately 419 firms in each decile, indicating that the two abnormal coverage proxies are observable for a broad cross-sectional sample of roughly 4,200 firms per calendar month.

Panels B and C show that both *ATOT* and *ACOV* are positively related to the raw values of total and simple coverage. Both measures of abnormal coverage are, by construction, uncorrelated with firms' size, turnover, and past performance, however Panels B and C show that firm size and turnover tend to be highest for the middle portfolios. Each panel also reports firms' VLTY, calculated as the standard deviation of monthly returns over the twelve months ending in month m; LBM calculated as the log of one plus a firm's book-to-market ratio; and SP; calculated as a firm's average relative spread over the twelve months ending in month m. Firms in the extreme deciles are somewhat more volatile, suggesting that analysts tend to provide abnormal coverage to high uncertainty firms. In the tests discussed below, we control for additional firm-characteristics not accounted for in Eq. (1) and show that the main results do not appear driven by omitted controls.

3.2. Abnormal Coverage and Future Returns

Table 2 contains the first main results of the paper. Specifically, Panels A and B contain equal- and value-weighted average monthly returns across abnormal total and simple coverage deciles, where coverage is measured in month m and returns are measured in month $m+1$. Our main tests focus on cross-sectional differences in raw returns to accommodate varying types of expected return information embedded in coverage proxies but we also show our findings are robust to the use of risk-adjusted returns in subsequent tests. The 'High-Low' columns reflect the average return from a long position in the highest decile of abnormal coverage and a short position in the lowest decile. Corresponding t-statistics, shown in parentheses, are calculated using the time-series distribution of monthly returns.

Panel A shows a striking positive relation between abnormal coverage and future returns. Firms in the highest decile of abnormal total coverage, *ATOT*, outperform those in the lowest decile by 87 basis points per month on an equal-weighted basis (t-statistic = 7.03), which corresponds to an annualized return of approximately 11%. The results also appear robust to value-weighting, where firms in the high *ATOT* decile outperform those in the lowest decile on a value-weighted basis by 80 basis points per month (t-statistic = 3.45).

Panel B shows that the return spread for abnormal simple coverage, $ACOV$, is similar in magnitude with an equal-weighted spread of 81 basis points and a value-weighted spread of 62 basis points, where both are significant at the 1% level. Together, Panels A and B show that abnormal coverage reveals an economically large source of predictable returns that holds in broad cross-sectional tests and when positions are value-weighted.

Related evidence in Figure 2 presents average monthly returns to the equal- and value-weighted $ATOT$ and $ACOV$ strategies for each year in the sample. The average strategy returns are generally positive throughout the sample window, including in the wake of Regulation FD and Global Settlement following the Internet Bubble's collapse, mitigating concerns that our results are isolated within a specific period. Moreover, the distribution of returns appears positively skewed, where the average equal-weighted (value-weighted) return is positive in 26 (24) out of the 33 year sample window from 1982 through 2014.

Panels C and D of Table 2 contain parallel return tests when ranking firms into deciles based on the raw values of total and simple analyst coverage, TOT and COV. These results show that neither measure of raw analyst coverage is significantly correlated with firms' future returns, with t-statistics ranging from 0.46 to -0.86. Panel D shows that raw simple coverage deciles have a U-shaped relation with monthly returns, where the large positive returns among the lowest decile are consistent with the well-documented size-effect in returns. The lack of a significant correlation between the raw measures and returns underscores the importance of measuring the abnormal component of coverage to study expected returns.

Table 3 examines the link between abnormal analyst coverage and firms' future returns after controlling for each portfolio's exposure to standard monthly asset pricing factors. Each panel presents portfolio alphas, factor loadings, and corresponding t-statistics across the extreme abnormal total coverage deciles as well as the long-short hedge portfolio. The reported alphas correspond to the intercept from a regression of the portfolio's raw returns minus the risk-free rate, regressed on the contemporaneous excess market return ($MKTRF$); two Fama-French factors (SMB, and HML); and the momentum factor (UMD).

Panels A and B show that the long-short $ATOT$ decile strategy has a positive loading on the market portfolio suggesting that analysts allocate abnormal coverage to firms with higher sensitivities to the market portfolio, consistent with analysts preferring to cover firms that track the broader economy. Strategy returns also load positively on the SMB factor across the equal- and value-weighted strategies but the sign and significance of the HML and UMD loadings depend on the strategy's weighting scheme. Despite abnormal coverage being correlated with firms' market beta, abnormal coverage retains strong predictive power when controlling for standard asset pricing factors. Specifically, the factor-adjusted alphas remain highly significant with an equal-weighted alpha of 80 basis points per month (t-statistic = 7.6) and a value-weighted alpha of 56 basis points (t-statistic = 3.16).

Panels B and C contain analogous results using the long-short $ACOV$ decile strategy. The $ACOV$ strategy yields similar results with an equal-weighted alpha of 75 basis points per month (t-statistic = 6.9) and a value-weighted alpha of 39 basis points (t-statistic = 2.32). For both the $ATOT$ and $ACOV$ strategies, the importance of controlling for factor-exposure depends on the portfolio weights. Comparing Tables 2 and 3 shows that the equal-weighted results are largely unchanged across the use of raw and factor-adjusted returns. The returns to the value-weighted strategies, however, attenuate when using factor-adjusted returns, but remain economically and statistically significant.

The results in Table 3 also show that factor-adjusted returns are balanced across the extreme portfolios. For example, the equal-weighted alphas for the highest $ATOT$ decile is 38 basis points (t-statistic = 3.55) and the alpha for the lowest $ATOT$ decile is -42 basis points (t-statistic = 5.14). The symmetry in the equal-weighted alphas across the extreme portfolios mitigates concerns investors can only capture the predictable pattern in returns by undertaking short positions. The value-weighted alphas, however, appear stronger among the highest decile, suggesting that analysts are more likely to provide abnormally high coverage to larger firms with higher expected returns, than abstaining from providing coverage to larger firms with lower expected returns.

3.3. Robustness and Persistence

Panel A of Table 4 contains results from Fama-MacBeth regressions of monthly raw returns on total analyst coverage, and additional controls. These tests have two motivations. First, we confirm that the predictive power of standard analyst coverage proxies for returns hinges upon controlling for variation in coverage attributable to firm size, turnover, and momentum. Second, we establish the incremental predictive power of abnormal coverage relative to other signals known to explain the cross-section of returns.

Column (1) confirms the result from Table 3 that *raw* total coverage, TOT, is not significantly related to future returns (t-statistic = 1.59) in univariate tests. However, column (2) shows that TOT becomes highly significant (t-statistic = 6.53) once we control for firms' size, share turnover and momentum. Not surprisingly, the variation in total coverage (i.e., TOT) becomes equivalent to the variation in abnormal coverage (i.e., $ATOT$) when researchers also control for size, turnover, and momentum. These tests serve as a reminder that testing the significance of abnormal coverage along side additional controls yields the same inference as when including these control variables in the estimation of $ATOT$ in Eq. (1).

Columns (3) through (4) show that the predictive power of abnormal coverage is also distinct from firms' book-to-market ratio and return volatility. The subsequent columns also control for returns in month m, denoted as RR, to differentiate the results from short-term return reversals; an earnings announcement month dummy variable, denoted EAM, to differentiate the results from earnings announcement premia; and standardized unexplained earnings, denoted SUE, and total accruals scaled by lagged total assets, denoted ACC, to differentiate the results from the accrual anomaly in Sloan (1996). Across all of these specifications, the predictive power of abnormal coverage remains highly significant with corresponding t-statistics all above five.

Column (7) of Panel A shows the abnormal component of simple coverage similarly retains incremental predictive power. Column (8) however shows that only total coverage remains significant when both coverage proxies are considered simultaneously, suggesting analysts signal expected returns not only through their decision to cover a firm but also through the extent to which they devote greater resources by forecasting earnings for a greater number of fiscal periods. As a result, the remaining analyses focus on abnormal total coverage as the main predictive signal, which we refer to as abnormal coverage for brevity.

The final three columns of Panel A control for the level of institutional ownership as well as lagged and forward changes in ownership. These tests show that lagged changes in ownership are negatively related to month $m+1$ returns, consistent with institutional price pressure reversing in subsequent months. By contrast, forward changes in ownership are positively related to month $m+1$ returns, consistent with institutional demand eliciting higher prices. Across columns (7) through (9), the abnormal component of coverage remains a positive predictor of future returns with t-statistics above five. By controlling for both lagged and forward changes in institutional holdings, these findings mitigate concerns that the positive link between abnormal coverage and returns is driven solely by institutional investors demanding coverage of firms they have or hope to acquire.

Are there complementarities between abnormal coverage and analysts' earnings forecasts? To address this question, Panel B of Table 4 examines the predictive power of abnormal coverage relative to analysts' forecasted earnings-to-price and the forecast dispersion effect documented in Diether, Malloy, and Scherbina (2002). To conduct these tests, we first limit the sample to firms with at least three analysts to ensure the availability of analyst forecast dispersion, $DISP$, measured as the standard deviation of one-year-ahead forecasts scaled by price, and the average forecast scaled by price, E/P.[7]

Column (1) of Panel B regresses monthly returns on indicators for terciles of abnormal coverage, where we omit the intercept term from these regressions to avoid multicollinearity. These tests confirm that firms' month $m+1$ returns are increasing across abnormal coverage terciles. Columns (2) and (3) interact abnormal coverage terciles with indicators for the high, mid, and low terciles of analyst forecast dispersion, $DISP$. The interaction terms show that

[7] We omit tests that condition upon analysts forecasts and forecast dispersion from Panel A because they require conditioning upon analyst coverage and reduces our sample by approximately 40 percent.

returns are highest among firms with high abnormal coverage and low forecast dispersion (i.e., low disagreement), whereas returns are lowest among firms with low abnormal coverage and high forecast dispersion(i.e., high disagreement), suggesting that abnormal coverage and the extent of agreement among analysts provide complimentary information.

Columns (4) and (5) of Panel B contain analogous tests where we interact abnormal coverage with indicators for the high, mid, and low terciles of analysts' forecasted earnings-to-price E/P. The interaction terms show that returns are highest when both abnormal coverage and E/P are high (i.e., higher expected profitability), whereas returns are lowest when both abnormal coverage and E/P are low (i.e., lower expected profitability).

Related tests in column (6) on Panel B use continuous version of each variable to show that abnormal coverage retains incremental predictive power over $DISP$ and E/P. Together, the Panel B results suggest that the expected performance component of abnormal coverage is distinct from the content of analysts' forecasts. Moreover, our study is the first to show synergies from leveraging analysts' coverage decisions along with their explicit forecasts.

Having established that abnormal coverage incrementally predicts monthly returns, our next analyses examine the persistence of this predictive relation. Figure 3 presents equal- and value-weighted returns from the abnormal total coverage strategy using up to a seven-month lag between the monthly return, measured in m+1, and the measurement of coverage (i.e., $ATOT$ measured in m-1 to m-7), where the results corresponding to month m are shown in Table 2 and omitted from the figure. Colored bars indicate the reported strategy return is statistically significant at the 5% level. The equal-weighted results show that the $ATOT$ strategy continues to predict future returns using a seven-month lag but that the returns monotonically decrease with the duration of the lag, suggesting that the information embedded in abnormal coverage is gradually incorporated into prices.

The bottom chart in Figure 3 shows that lagged values of $ATOT$ also predict value-weighted returns for up to a three-month lag (i.e., $ATOT$ measured in m-1 and m-2) but become insignificant with longer lags. These findings indicate that the persistence of the signal's predictive power depends on the portfolio weights. More importantly, the evidence in Figure 3 shows that the sign of the strategy returns do not immediately reverse when using lagged signals and thus mitigates concerns that the predictive power stems from transitory price pressure that immediately reverses in subsequent months.

To gauge the sensitivity of the main findings to alternative implementations, Table 5 verifies the predictive power of abnormal analyst coverage across alternative subsamples and data requirements. The first two rows of Panel A address the concern that the evidence of predictable returns stem from analysts more actively forecasting earnings in response to earnings announcements coinciding with month m and thus reflect a form of post-earnings announcement drift not accounted for in Table 4.

The next three sets of results in Panel A examine the sensitivity of the main findings to subsamples that differ in terms of the required level of analyst coverage. The first subsample requires at least one covering analyst. Further, to connect our findings to studies that require at least three covering analysts when calculating consensus earnings forecasts, we also examine subsamples based on the requirements of having greater than three covering analysts and that have less-than-or-equal-to three covering analysts.

The third and fourth sets of results of Panel A show our main findings hold among the positive coverage subsamples but that there is attenuation in the size of the strategy returns, suggesting that part of the main strategy returns stem from identifying firms without analyst coverage that underperform in the future (i.e., large, highly traded firms without coverage). The fifth set of results of Panel A shows abnormal coverage also predicts equal-weighted returns among the subsample of firms with three or fewer analysts covering the firm but that the value-weighted returns are no longer significant, suggesting that an upper limit on coverage reduces the informativeness of abnormal coverage among larger firms.

The final set of results in Panel A relies on estimates of total coverage from the IBES Summary File by taking the maximum number of analysts comprising a given consensus forecast for a firm, across all forecasted future fiscal periods. These tests show our results are robust to the use of the IBES Summary File, which underscores a key inference for the expansive literature that uses standard analyst coverage proxies to measure information asymmetry by showing that this data also embeds information about expected returns.

The main tests in this paper rely on measures of analyst coverage that overlap because analyst activity is summed over 90-day rolling window. Panel B of Table 5 examines the sensitivity of the paper's main findings when portfolios are implemented at lower frequencies to avoid overlapping signals. More specifically, the first set of tests in Panel B examine the returns to portfolios that are rebalanced and held for twelve months, where abnormal analyst coverage is measured three months after firms' fiscal-year end.

Table 5 shows that annual rebalancing results in an equal-weighted return of 6.4% (t-statistic = 4.01) and a value-weighted return of 4.39% (t-statistic = 2.48) per year. The magnitudes of annualized returns are lower than the returns from compounding the main monthly strategy, which dovetail nicely with the results in Figure 3 that the predictive power of abnormal coverage attenuates when forecasting returns multiple months in advance. The second set of results in Panel B presents analogous results when measuring analyst coverage three-months after a firm's fiscal quarter end and holding the corresponding long-short position for three months. The quarterly tests yields an equal-weighted three-month returns of 1.8 % (t-statistic = 4.91) and value-weighted return of 2.44 % (t-statistic = 4.41).

Related tests in Panel C of Table 5 show that our main tests are robust to using two alternative implementations based on *within-firm* changes. Specifically, the top rows present returns sorted by changes in abnormal coverage from month $m-3$ to m. Similarly, the bottom rows present month $m+1$ returns when sorting firms based on the abnormal component changes in total coverage after controlling for firms' size, momentum, and turnover (i.e., replacing levels of coverage in Eq. (1) with changes).

The results in Panel C of Table 5 show that the positive link between abnormal coverage and returns holds for both level- and change-based specifications. Moreover, the change-based specification in Table 6 mitigates concerns that the positive link between abnormal coverage levels and returns are driven by an omitted firm-fixed effect that is not controlled for in our model of abnormal coverage or multivariate tests. For an omitted factor, such as risk, to explain our findings, the factor would need to not only be omitted from our control variables but also change over time in parallel with changes in abnormal coverage.

A key feature of the methodology we develop in this paper is that it is broadly applicable to many firms because it does not require positive analyst coverage or conditioning upon firm-specific events, such as an initial public offering. To underscore this feature, we show our approach can be also aggregated across several firms to predict *industry-level* returns. These tests examine whether analysts collectively identify and gravitate toward promising sectors of the economy that they expect to outperform.

Specifically, Panel D of Table 5 contains monthly industry-average returns after sorting industries into decile portfolios on the basis of abnormal industry coverage. Each month, we group firms using the Fama-French 48-industry classification and estimate abnormal industry coverage again using Eq. (1), as in our main tests, but when replacing the firm-level variables with value-weighted industry averages. Each decile portfolio consists of approximately three-and-a-half industries per month and 110 firms per industry-month, where one-month-ahead returns are value-weighted across all firms in a given industry.[8] Our portfolio tests sorted by abnormal industry coverage yield a return spread of approximately 50 basis points per month (t-statistic = 2.69) when industries are equal-weighted and 47 basis points (t-statistic = 2.24) when industries are value-weighted based on the average market capitalization of firms in a given industry. Together, these tests provide novel evidence that analysts' coverage decisions serve as a leading indicator of sector-wide, in addition to firm-specific, performance.

Together, the results in Tables 5 show the paper's main findings are largely robust to alternative implementations and subsamples. In the next section, we extend these results by shedding light on the source of return predictability and, in particular, the role of analysts' resource constraints and firms' fundamental performance.

[8]We require that an industry to have at least 20 firms to be included in the Panel D analysis although our results do not appear highly sensitive to this requirement.

4. Additional Analyses

This section provides details on extensions of the main results that explore the influence of analysts' resource constraints as well as the information content of abnormal coverage.

4.1. Analyst Resource Constraints

In this subsection, we explore the hypothesis that resource constraints motivate analysts to selectively allocate coverage toward firms with superior prospects. To the extent that our hypothesis holds, we expect that the resources analysts expend to provide coverage to be informative of their marginal benefits. More specifically, we predict that higher marginal costs of providing coverage signal analysts' expectations of higher marginal benefits in the form of superior *ex post* performance for the firms in their coverage portfolio.

In the tests below, we use three different approaches to capture variation in the marginal costs of coverage: one based on the size of analysts' coverage portfolios, a second based on market-level changes in the analyst sector, and a third based on changes in abnormal coverage. Although each marginal cost proxy is imperfect, the consistency in results across the three proxies supports the idea that analysts allocate coverage by equating the marginal costs of coverage to their expected marginal benefits.

Our first tests examine whether the return results predictably vary with characteristics of the analysts who are currently providing coverage, which we refer to as 'current analysts'. In Panel A of Table 6, we examine the predictive power of abnormal analyst coverage when conditioning on the share of resources current analysts allocate to a given firm. To capture variation in analysts' resource allocation, we use the size of analysts' coverage portfolios to proxy for cross-sectional variation in their resource constraints.

Specifically, we measure current analysts' selectivity, referred to as $SELC$, as the inverse of the number of distinct firms analysts are currently following, where we require that a firm has non-zero coverage. Higher values of $SELC$ indicate current analysts are covering few other firms and thus proxies for the relative *share* of resources allocated to a given firm.

Under the assumption that, all else equal, analysts prefer to cover a greater number of firms, the construction of $SELC$ is designed to capture variation in analysts' total resources that may be driven by their employer and/or professional experience.

Panel A shows that returns are largest when abnormally high coverage stems from highly selective analysts. Specifically, average returns for firms within the highest decile of abnormal coverage and highest tercile of $SELC$ is 2.56% basis points; the highest return of all other portfolio combinations. By contrast, average returns for firms in the lowest decile of abnormal coverage and lowest tercile of $SELC$ is 0.17%; the lowest return of all other portfolio combinations. These results suggest that coverage is most indicative of underpricing when a firm has abnormally high coverage *despite* current analysts being highly selective. Conversely, the results suggest that coverage is most indicative of overpricing when a firm has abnormally low coverage perhaps only *because* current analysts are not being selective.

Related evidence in Figure 4 takes a market-level view to study the role of resource constraints in driving the paper's main results. The figure plots average equal- and value-weighted monthly returns from the abnormal total coverage strategy when the sample window is partitioned into three equal-sized groups based on annual market-level changes in analyst coverage. Each year, we calculate the total number of unique analyst-firm pairs as well as the percentage change from the prior year. The 'Reductions' group consists of the eleven years with the largest decreases in unique analyst-firm pairs and the 'Expansions' group consists of the eleven years with the largest increases in unique analyst-firm pairs.

Figure 4 shows that average strategy returns are higher in years of market-level coverage reductions and lower in years of market-level coverage expansions. These results are consistent with analysts' resource constraints becoming more binding in years of coverage reductions and less binding in years of coverage expansions. The evidence that abnormal coverage strategy returns are highest in years of reductions is consistent with analysts having to become more selective when allocating coverage and, in doing so, allocating coverage to firms with the strongest future prospects.

Panel B of Table 6 uses within-firm *changes* in analyst coverage as an alternative proxy for analysts' marginal costs. Because analysts likely incur greater costs from initiating compared to sustaining coverage, we predict that abnormal coverage is most likely to reflect higher (lower) expected returns when it stems from increases (decreases) in coverage. To test this prediction, Panel B presents equal- and value-weighted average monthly raw returns across abnormal coverage deciles when partitioning the sample based on whether coverage increased (i.e., ΔCOV>0), remain unchanged (i.e., ΔCOV=0), or decreased (i.e., ΔCOV<0) from month $m-3$ to m. Consistent with our prediction, Panel B of Table 6 shows that returns are larger when abnormally high coverage corresponds to contemporaneous increases in coverage and smaller when abnormally low corresponds to contemporaneous decreases in coverage. These findings are consistent with analysts revealing their views of firms' future prospects when incurring higher marginal costs for providing coverage.

Together, the three sets of results in Table 6 and Figure 4 show that when analysts have fewer resources to allocate, where they choose to allocate those resources is a stronger signal of firms' performance prospects. As a result, variation in analysts' resource constraints elicits predictable variation in the predictive power of abnormal coverage for future returns.

4.2. Fundamental Performance

To shed light on the source of the predictable pattern in returns, Table 7 examines the link between abnormal coverage and firms' subsequently reported fundamental performance. We measure fundamental performance using the $FSCORE$ from Piotroski (2000) and Piotroski and So (2012), which sums nine binary signals that award higher values for improvements in firms' profitability, financial leverage, and operating efficiency relative to the prior year.

To examine the link between abnormal coverage and firms' $FSCORE$, we measure abnormal coverage at the end of each calendar quarter and examine its ability to predict firms' $FSCORE$s corresponding to the next four fiscal periods (i.e., Q1 through Q4). Table 7 contains results from regressions of both levels and changes in firms' $FSCORE$, where changes are defined as the log of a firm's $FSCORE$ from a future fiscal period scaled by its

$FSCORE$ from the same fiscal quarter in the prior year. Panels A and B of Table 7 show that firms' abnormal coverage positively predicts both levels and changes in their operating performance, which suggests analysts uncover mispricing by anticipating firms' profitability and allocating greater resources to ascending firms. In doing so, analysts convey information about firm-level expected returns through their allocation of coverage.

4.3. Identifying Mispricing through Mutual Fund Flows

A central inference from this paper is that analyst coverage data embeds expected return information because analysts allocate abnormal coverage to underpriced firms. To sharpen this inference, we use quarterly mutual fund outflow data from Edmans, Goldstein, and Jiang (2012) as an instrument for exogenous shocks to firm-level mispricing. Several studies including Coval and Stafford (2007) and Edmans, Goldstein, and Jiang (2012), show that mutual funds sell firms' shares roughly in proportion to index weights when needing cash to pay for investor redemptions. This selling behavior results in significant downward price pressure that takes multiple months to reverse, which results in sustained underpricing.

In Panel A of Table 8, we examine changes in analyst coverage following fund outflows. We measure changes in coverage for each firm-quarter by comparing coverage immediately after versus before the quarter of the fund flows. The fund flow data is as described in Edmans, Goldstein, and Jiang (2012), which only reflects fund outflows, and results in a sample of 53,046 firm-quarters spanning 1982 through 2007.

The first column of Panel A shows that the first (fifth) quintile corresponds to the largest (smallest) outflows. Using changes in both abnormal and raw levels of analyst coverage, we find that analysts are significantly more likely to increase coverage for firms that experience extreme outflows. Related evidence in Panel B shows that the significant negative relation between fund flows and changes in coverage is robust to controlling for firms' size, glamour status, and past returns. By using mutual fund outflows to identify firm-level underpricing, these findings provide strong support for the idea that analysts allocate greater resources toward covering firms with greater underpricing.

4.4. Understanding the Mechanism

Our central findings are consistent with the idea that analysts (or their employers) conduct due diligence to identify firms with superior performance prospects and in doing so uncover firm value not yet reflected in market prices. However, there are several alternative and non-mutually-exclusive channels that could give rise to the positive link between abnormal analyst coverage and firms' returns.

One potential channel linking coverage to firm performance is that institutional investors request that analysts cover firms that they have, or hope to, invest in. However, Table 4 shows the positive link between abnormal coverage and returns holds after controlling for the level of, and changes in, institutional ownership, suggesting our findings are unlikely to be solely driven by institutional demand.

Another potential channel is that firms implicitly buy coverage by increasing disclosure (e.g., issuing earnings forecasts) when they believe they are undervalued to reduce the costs thats analysts incur in providing coverage. In untabulated tests, we find no changes in our inferences when conditioning upon firms' use of earnings guidance and 'firm-initiated' press releases, mitigating concerns that abnormal coverage is simply a response to increased disclosures by undervalued firms. Finally, analyst coverage could potentially *create* firm value by serving a governance role and monitoring firms' behavior (e.g., Moyer, Chatfield, and Sisneros (1989)). To explore this potential channel, we conducted analogous tests using the subsample of firms with strong governance as indicated by firms having an above median G-Index from Gompers, Ishii, and Metrick (2003). We find that the predictive power of *ATOT* holds among the subsample with strong governance, which mitigates concerns that our findings are driven solely by analysts creating value by monitoring the firm.

Collectively, these results suggest that our main inferences are unlikely to be solely driven by these alternative explanations. However, an important caveat is that we can not directly observe these alternative channels and must rely on noisy proxies, suggesting that multiple channels may be at play at the same time.

5. Implications for Future Research

A central takeaway from this paper is that standard analyst coverage proxies reflect variation in: (1) the information intermediation role performed by analysts and (2) expected performance information related to firms' earnings news. To illustrate how the dual-content of coverage proxies can elicit measurement error and impact researchers' inferences, consider a basic regression of the following form (we also later add control variables below):

$$\text{Market Outcomes} = \alpha + \delta \text{Analyst Coverage} + \psi \tag{2}$$

where the dependent variable could reflect, among other outcomes, asset returns, pricing multiples, liquidity, and/or trade behavior.

By substituting the expected and abnormal components of analyst coverage into Eq. (2), we see that the above regression is equivalent to:

$$\text{Market Outcomes} = \alpha + \gamma_1 \text{Expected Coverage} + \gamma_2 \text{Abnormal Coverage} + \psi \tag{3}$$

where the expected component equals the fitted value from estimating Eq. (1) and abnormal coverage reflects the corresponding regression error term. This simple transformation illustrates that when researchers study the relation between market outcomes and analyst coverage, the sign and magnitude of the δ coefficient in Eq. (2) depends on the relative influence of the effects represented by γ_1 vs. γ_2 in Eq. (3). Specifically, the inference that researchers draw from estimating Eq. (2) depends on the influence of informational intermediation performed by analysts, which is more likely reflected in the expected component, versus the influence of expected returns, as reflected in the abnormal component.

To illustrate how measurement error in analyst coverage proxies can affect researchers' inferences, we examine the relation between raw coverage and firms' returns during earnings announcement months in Table 9. We focus specifically on firms' earnings announcements because information asymmetry and mispricing regarding earnings information likely play a first-order role in driving asset returns.

Mimicking the structure of Eq. (2), columns (1) and (4) of Panel A show that raw analyst coverage proxies are insignificantly related to announcement returns. To shed light on the insignificant relation, we decompose raw coverage into expected and abnormal components. Mimicking the structure of Eq. (3), columns (2) and (5) of Panel A show the expected component is *negatively* related to returns, consistent with higher information asymmetry (i.e., low coverage) firms earning higher announcement returns. By contrast, columns (3) and (6) show that the abnormal component is *positively* related to announcement returns, consistent with the earlier evidence that abnormal coverage predicts firms' earnings news. Together, these two offsetting effects create the insignificant relation between raw coverage and announcement returns and thus demonstrates that the relation between analyst coverage and market outcomes depends on the relative influence of the two sub-components.

In cases where the two components of coverage offset, such as earnings announcement returns, the coefficient estimates on analyst coverage as a proxy for information intermediation are likely understated and biased toward zero. Conversely, in cases where the two components have the same sign, the estimated impact of analysts' intermediation is likely overstated. Thus, our findings highlight that the expected return component of coverage is not only likely relevant for a variety of research contexts but also that the sign and magnitude of the measurement problem depends on which dependent variable is being studied.

Sample selection criteria are also relevant because they influence the extent to which expected performance information is relevant for researchers' dependent variable of interest. To illustrate this point, Panels B and C of Table 9 present analogous tests when partitioning the sample based on terciles of firm size. Panel B shows raw coverage has an insignificant relation with announcement returns among smaller firms but a significantly positive relation among larger firms. To the extent that information asymmetry commands higher returns around firms' announcements, these results are counter-intuitive (and potentially puzzling) because analysts are commonly characterized as resolving information asymmetry, which should yield a significant negative effect concentrated among smaller firms.

Panel C helps understand the source of the Panel B findings. Specifically, we show that the insignificant relation between raw coverage and announcement returns among small firms is driven by two simultaneous effects. The first is a large negative relation between the expected component of coverage and returns, consistent with the intuition that analysts play a larger role in mitigating information asymmetry for smaller firms. The second effect is a large positive relation between abnormal coverage and returns, consistent with analysts uncovering greater mispricing among smaller firms. Together, these tests show that both components of coverage have larger effects among small firms but that the two effects cancel each other out when researchers conduct tests using raw analyst coverage.

Panel C also shows the coefficients on the expected component decrease in magnitude with firm size but are only significant among small firms, consistent with the intuition that information intermediation matters more when information asymmetry is high. Additionally, the abnormal component results remain significant across sample partitions but attenuate with firm size. Thus, a broader takeaway is that sample selection also matters by influencing both the importance of information intermediation and the potential for mispricing.

As a corollary, we also illustrate how and why the coefficient estimates on coverage proxies are highly sensitive to researchers' choice of controls in multivariate tests. Moreover, we show that commonly used control variables can actually *worsen* the inference problem by making the incremental variation in raw coverage proxies more closely aligned with the abnormal component. To see this more precisely, consider the following regression:

$$\text{Market Outcomes} = \alpha + \tau \text{Analyst Coverage} + \sum_{i=1}^{K} \lambda_i \cdot Z_i + \psi \tag{4}$$

where Z_i denotes the researchers' control variables. When firms' size, turnover, and momentum are included as controls, the incremental variation in raw coverage (i.e., the portion not explained by Z_i) is identical to the variation in abnormal coverage and thus the τ coefficient from Eq. (4) becomes equivalent to the θ coefficient from the following regression:

$$\text{Market Outcomes} = \alpha + \theta \text{Abnormal Coverage} + \psi. \tag{5}$$

Thus, researchers running a regression of the form in Eq. (4) may interpret the τ coefficient as reflecting the effect of analysts' information dissemination when it is likely confounded by the relation between the market outcome and expected returns (i.e., θ from Eq. (5)).

To further illustrate this final point, Table 10 presents a simple regression of firms' Tobin Q on total analyst coverage, where Q is measured as the sum of the market value of assets and the book value of common stock scaled by the book value of assets. Column (1) shows a strong, positive univariate relation between Q and analyst coverage (t- statistic = 6.01), which may cause researchers to interpret the magnitude and significance of coefficient estimate as the impact of analyst coverage on firm valuation. Chung and Jo (1996) and Chen and Steiner (2000) document a similar positive relation between coverage and Q, inferring that analysts increase firm value by serving a marketing function. Columns (2) through (4), however, demonstrate the sensitivity of this interpretation to additional controls.

Columns (2) and (3) show the link between Q and coverage remains largely unchanged when controlling for momentum but that the coefficient estimate shrinks dramatically and becomes insignificant when controlling for share turnover. Moreover, column (4) shows that the link between Q and coverage remains statistically significant when controlling for firm size but actually flips signs relative to column (1), becoming significantly negative.

Column (5) of Table 10 contains controls for size, turnover, and momentum, such that the incremental variation in total coverage corresponds to abnormal coverage. When all three controls are included, the coefficient corresponding to total coverage is significantly negative (t- statistic = -6.22), which may be initially puzzling in the context of prior evidence that analysts preserve value by serving a marketing role. However, this evidence aligns well with our earlier evidence that analysts provide abnormal coverage to undervalued firms. More broadly, the instability in both the sign and significance of the coefficient estimates in Table 10 highlights the sensitivity of regressions involving analyst coverage to researchers' choices of controls, which can cause the incremental variation in analyst coverage proxies to align with analysts' incentives to cover firms with superior prospects.

Collectively, the simple examples illustrated in Tables 9 and 10 show that the estimated relations between standard analyst coverage proxies and various market outcomes depend on (i) the relevance of expected performance information, (ii) sample selection criteria, and (iii) researchers' selection of control variables. These inferences apply to virtually any setting where researchers rely on analyst coverage proxies, particularly when controls for expected future performance are not appropriate or attainable. As a result, the broader inference problems we illustrate add support for the approaches in Hong and Kacperczyk (2010) and Kelly and Ljungqvist (2012) that use of exogenous shocks to analyst coverage to assess the impact of analysts on capital market outcomes.

6. Conclusion

In this paper, we examine expected return information obtained by studying how market participants allocate limited resources and attention. Specifically, we use the behavior of security analysts to reverse engineer their expectations over future payoffs and then study the implications of these expectations for our understanding of market outcomes.

We develop and implement a simple approach for decomposing analyst coverage proxies into abnormal and expected components that is both broadly applicable and easily portable across research settings. We show that abnormal coverage offers strong predictive power for firms' future returns and fundamental performance, suggesting that analysts convey expected return information by providing greater coverage to underpriced firms. As a corollary, we illustrate how and why the use of analyst coverage proxies in capital market settings is complicated by the fact that these proxies also reflect expected performance information. Together, our findings highlight both the promise of using resource allocation decisions to study expected returns, and the potential inference problems from using analyst coverage proxies to study information asymmetry and dissemination.

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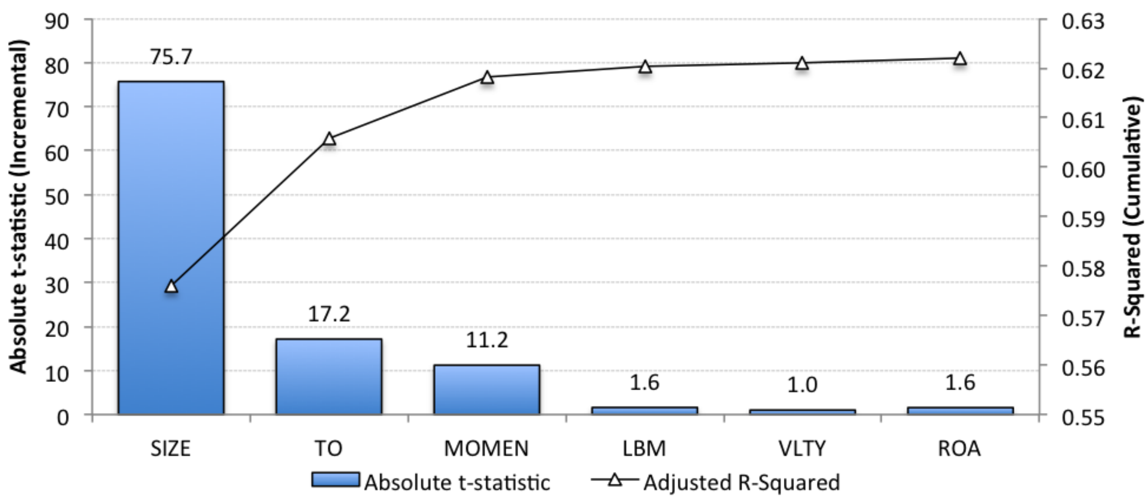
Figure 1. Analyst Coverage and Firm-Characteristics

The charts below contain cumulative adjusted R-squared values and multivariate t-statistics across regressions of analyst coverage that iteratively added firm characteristics. The top (bottom) plot contains results from regressing total (simple) analyst coverage on firm characteristics. Reported values reflect time-series averages of monthly regression results. The report R-squared values reflect the explained variation in analyst coverage after cumulatively adding the variables listed along the y-axis, such that the first value reflects the R-squared when only including firm size and where the last value reflects the R-squared from including all six listed firm characteristics. Similarly, the reported t-statistics reflect regression results from iteratively adding the firm-characteristics listed along the Y-axis. Total analyst coverage is defined as the number of unique analyst-forecast pairings measured over the 90 days ending at the conclusion of month m. When an analyst revises a given forecast within the measurement window, only the most recent forecast is included in the calculation of total analyst coverage. The bottom chart is defined analogously using the abnormal simple coverage strategy, where abnormal simple coverage is the residual from a monthly regression of log of one plus the number of unique analysts covering a firm over the 90 days ending at the conclusion of month m. In each plot, the coverage proxy is regressed on firm's contemporaneous log market capitalization (SIZE), and lagged twelve-month share turnover (TO), momentum (MOMEN), log book-to-market (LBM), return volatility (VLTY), and return on assets (ROA). The sample for this analysis consists of 1,661,511 firm-month observations spanning 1982 through 2014.



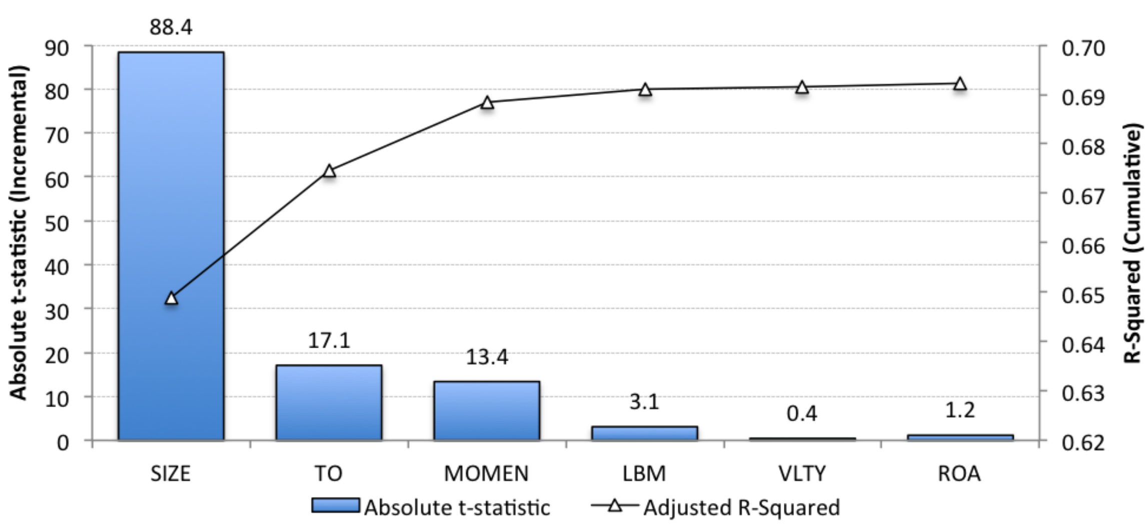
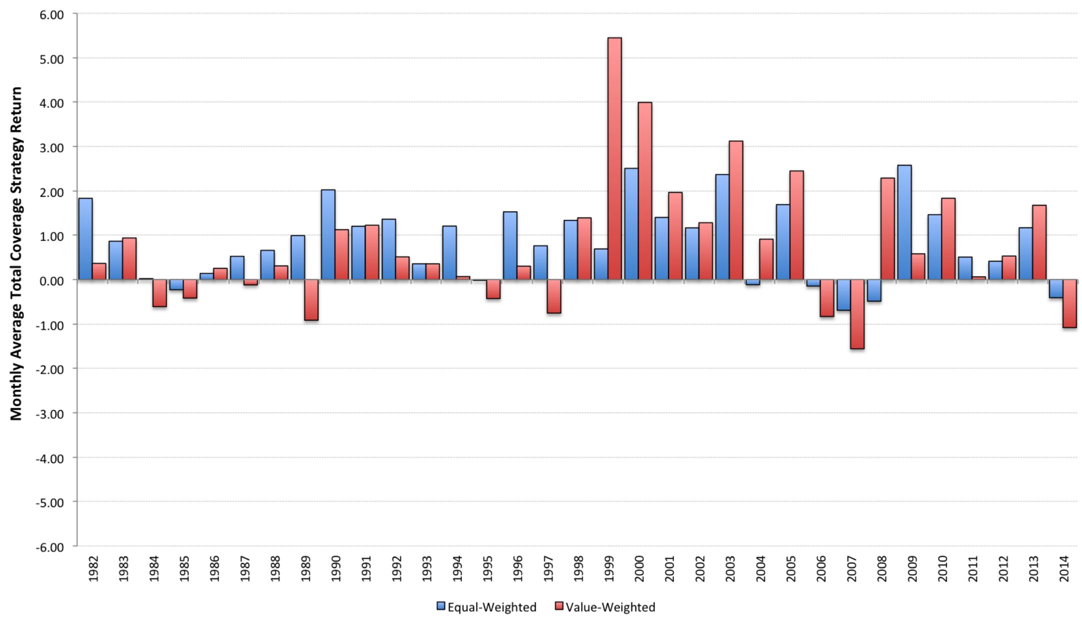


Figure 2. Average Annual Strategy Returns

The top chart plots average monthly returns within each year from the abnormal total coverage strategy. Abnormal total coverage is the residual from a monthly regression of log one plus total analyst coverage measured in month m regressed on firm's contemporaneous log market capitalization, and lagged twelve-month share turnover and momentum. Total analyst coverage is defined as the number of unique analyst-forecast pairings measured over the 90 days ending at the conclusion of month m. When an analyst revises a given forecast within the measurement window, only the most recent forecast is included in the calculation of total analyst coverage. The strategy is implemented at the end of each calendar month m and held in month m+1 by ranking firms into deciles of abnormal total coverage and taking a long (short) position in firms within the highest (lowest) decile. The bottom chart is defined analogously using the abnormal simple coverage strategy, where abnormal simple coverage is the residual from a monthly regression of log of one plus the number of unique analysts covering a firm over the 90 days ending at the conclusion of month m. The sample for this analysis consists of 1,661,511 firm-month observations spanning 1982 through 2014.



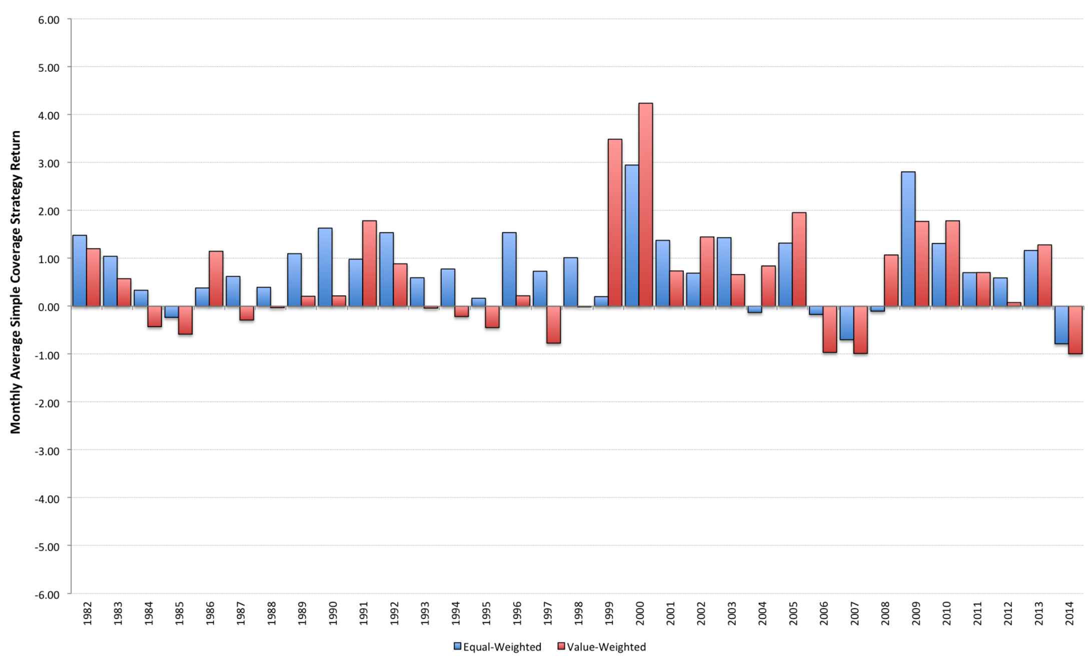
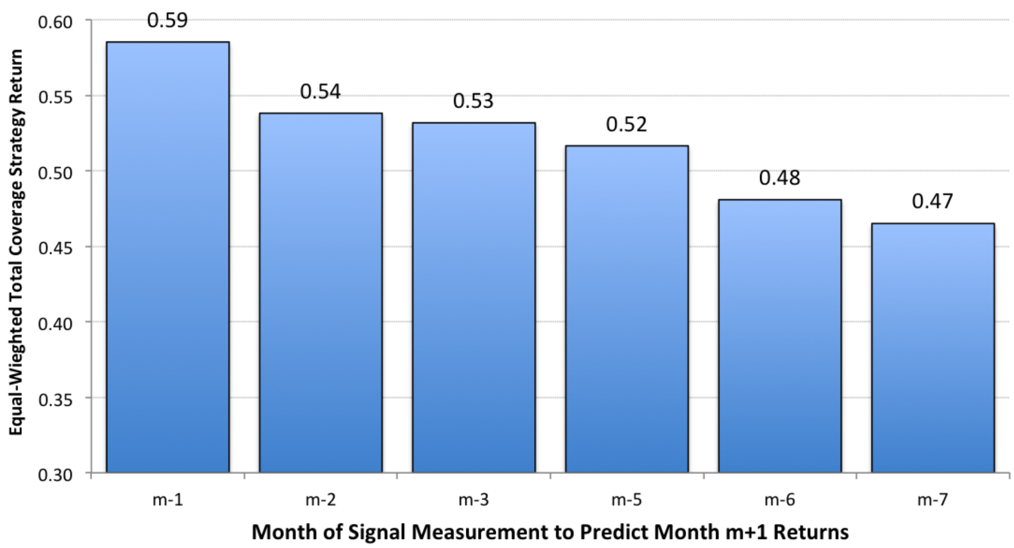


Figure 3. Returns to Lagged Coverage Signal

The top (bottom) chart plots cumulative equal-weighted (value-weighted) returns from the abnormal total coverage strategy using multiple lags between the measurement of coverage and the monthly return. Abnormal total coverage is the residual from a monthly regression of log one plus total analyst coverage measured in month m regressed on firm's contemporaneous log market capitalization, and lagged twelve-month share turnover and momentum. Returns are measured in month m+1, the figure illustrates decile strategy returns measuring abnormal coverage in months m-1 to m-7. Total analyst coverage is defined as the number of unique analyst-forecast pairings measured over the 90 days ending at the conclusion of month m. When an analyst revises a given forecast within the measurement window, only the most recent forecast is included in the calculation of total analyst coverage. The strategy is implemented at the end of each calendar month m and held starting in month m+1 by ranking firms into deciles of abnormal total coverage and taking a long (short) position in firms within the highest (lowest) decile. Colored bars indicate that the reported strategy return is significant at the 5% level. The sample for this analysis consists of 1,661,511 firm-month observations spanning 1982 through 2014.



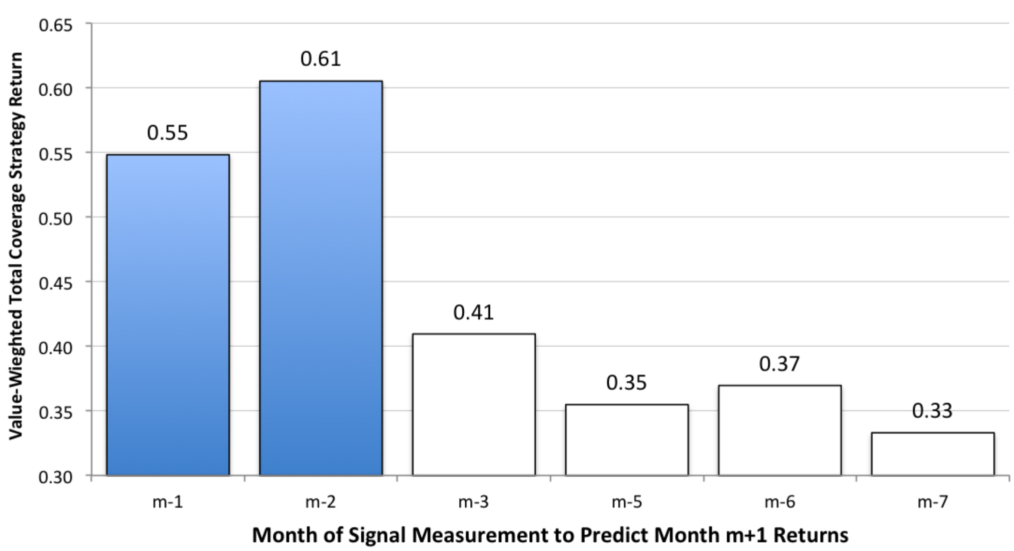


Figure 4. Market-Level Coverage Expansions vs. Contractions

This chart plots average equal- and value-weighted monthly returns from the abnormal total coverage strategy when the sample window is partitioned into three equal-sized groups based on annual market-level changes in analyst coverage. Each year, we calculate the total number of unique analyst-firm pairs and calculate the percentage change from the prior year. The 'Reductions' group consists of the eleven years with the largest decreases in unique analyst-firm pairs, the 'Expansions' group consists of the eleven years with the largest increases in unique analyst-firm pairs, the remaining eleven years are shown in the 'Mid' group. Abnormal total coverage is the residual from a monthly regression of log one plus total analyst coverage measured in month m regressed on firm's contemporaneous log market capitalization, and lagged twelve-month share turnover and momentum. Total analyst coverage is defined as the number of unique analyst-forecast pairings measured over the 90 days ending at the conclusion of month m. When an analyst revises a given forecast within the measurement window, only the most recent forecast is included in the calculation of total analyst coverage. The strategy is implemented at the end of each calendar month m and held in month $m+1$ by ranking firms into deciles of abnormal total coverage and taking a long (short) position in firms within the highest (lowest) decile. The sample for this analysis consists of 1,661,511 firm-month observations spanning 1982 through 2014.

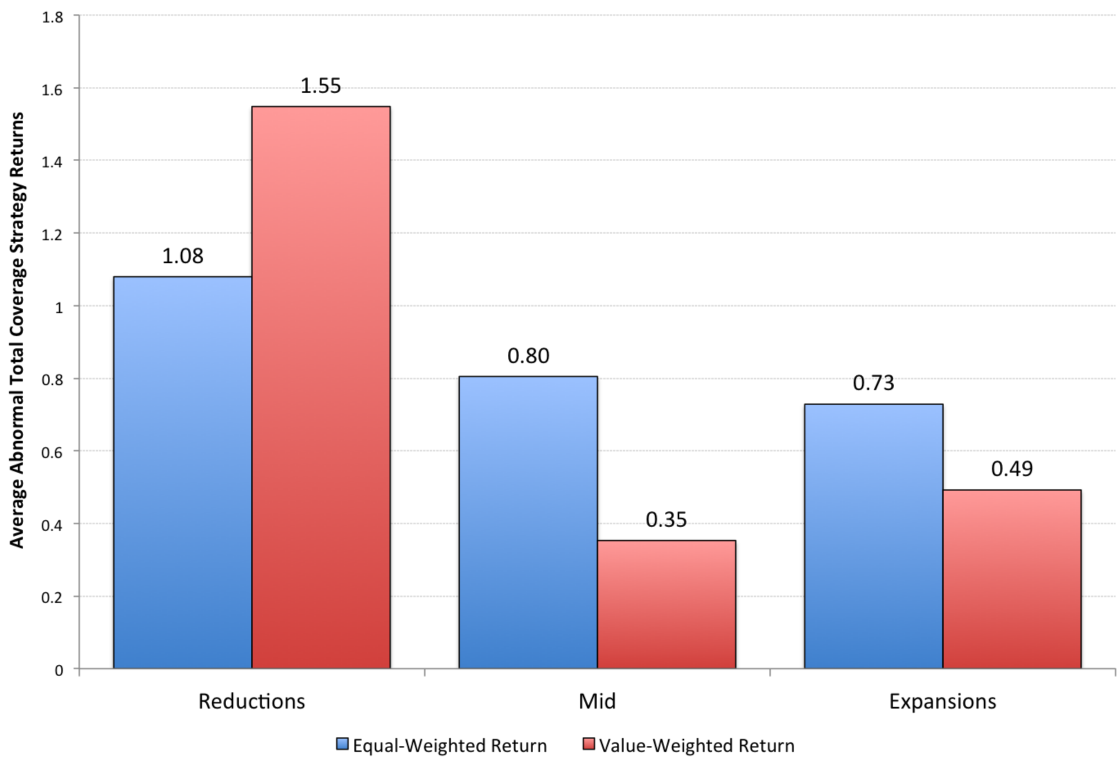


Table 1. Descriptive Statistics

Panel A contains time-series average coefficients from regressing total and simple analyst coverage measured in month m regressed on firm's contemporaneous log market capitalization (SIZE), and lagged twelve-month share turnover (TO) and momentum (MOMEN). Total analyst coverage, TOT, is defined as the number of unique analyst-forecast pairings measured over the 90 days ending at the conclusion of month m. Simple analyst coverage, COV, is defined as the log of one plus the number of unique analysts covering a firm over the 90 days ending at the conclusion of month m. Panels B and C present time-series averages across abnormal total and abnormal simple coverage deciles. Abnormal total coverage is the residual from a monthly regression of log one plus total analyst coverage measured in month m regressed on firm's contemporaneous log market capitalization, and lagged twelve-month share turnover and momentum. Abnormal simple coverage is defined analogously as the residual from a monthly regression of log of one plus the number of unique analysts covering a firm over the 90 days ending at the conclusion of month m. VLTY is defined as the standard deviation of monthly returns over the twelve months ending in month m. SP is a firm's average relative spread over the twelve months ending in month m. LBM is the log of one plus a firm's book-to-market ratio. The sample for this analysis consists of 1,661,511 firm-month observations spanning 1982 through 2014.

Panel A: Average Regression Coefficients

	Total Coverage		Simple Coverage	
	Mean	t-statistic	Mean	t-statistic
INT	-5.526	-55.984	-4.074	-69.077
SIZE	0.618	75.311	0.433	88.805
TO	0.270	18.082	0.167	18.351
MOMEN	-0.317	-11.225	-0.219	-13.390
R^2	0.618		0.688	

Panel B: Descriptive Statistics by Abnormal Total Coverage Deciles

	1 (Low)	2	3	4	5	6	7	8	9	10 (High)
OBS	419	420	420	420	420	420	420	420	420	419
TOT	3.861	12.777	25.506	33.792	38.390	40.909	42.669	43.566	44.019	45.814
COV	0.765	2.308	4.449	5.924	6.735	7.239	7.542	7.614	7.420	7.096
SIZE	12.122	11.585	12.035	12.366	12.506	12.559	12.543	12.405	12.143	11.602
TO	1.133	0.871	1.033	1.146	1.203	1.232	1.236	1.211	1.167	1.063
GP	0.069	0.082	0.085	0.088	0.088	0.089	0.090	0.091	0.091	0.093
MOM	0.057	0.033	0.034	0.034	0.038	0.045	0.044	0.044	0.029	0.032
VLTY	0.134	0.131	0.126	0.122	0.119	0.119	0.119	0.121	0.125	0.136
SP	0.013	0.018	0.018	0.017	0.016	0.014	0.012	0.011	0.012	0.014
LBM	0.490	0.516	0.501	0.487	0.480	0.477	0.478	0.482	0.496	0.556

Panel C: Descriptive Statistics by Abnormal Simple Coverage Deciles

	1 (Low)	2	3	4	5	6	7	8	9	10 (High)
OBS	419	420	420	420	420	420	420	420	420	419
TOT	6.012	12.012	19.164	26.686	32.641	38.055	42.139	46.088	50.607	57.911
COV	0.852	1.860	3.091	4.421	5.569	6.541	7.366	8.175	9.009	10.210
SIZE	12.357	11.770	11.884	12.093	12.257	12.359	12.391	12.394	12.341	12.022
TO	1.240	0.936	0.988	1.036	1.091	1.153	1.181	1.205	1.226	1.240
GP	0.069	0.081	0.086	0.089	0.090	0.090	0.090	0.091	0.090	0.090
MOM	0.052	0.040	0.043	0.038	0.041	0.043	0.038	0.036	0.024	0.037
VLTY	0.130	0.129	0.128	0.124	0.122	0.121	0.121	0.121	0.123	0.132
SP	0.012	0.016	0.017	0.016	0.016	0.015	0.014	0.013	0.013	0.013
LBM	0.477	0.497	0.493	0.491	0.489	0.487	0.491	0.493	0.499	0.548

Table 2. Monthly Average Returns

Panels A and B present equal- and value-weighted average monthly raw returns across abnormal total and abnormal simple coverage deciles. Returns are measured in month $m+1$, where abnormal total and abnormal simple coverage are calculated and assigned to deciles in month m. Abnormal total coverage is the residual from a monthly regression of log one plus total analyst coverage measured in month m regressed on firm's contemporaneous log market capitalization, and lagged twelve-month share turnover and momentum. Abnormal simple coverage is defined analogously as the residual from a monthly regression of log of one plus the number of unique analysts covering a firm over the 90 days ending at the conclusion of month m. OBS indicates the monthly average number of observations for each portfolio. Corresponding t-statistics, shown in parentheses, are calculated using the monthly time-series distribution. Panels C and D present analogous results using raw total and simple analyst coverage. The sample for this analysis consists of 1,661,511 firm-month observations spanning 1982 through 2014.

Panel A: Average Returns Across Abnormal Total Coverage Deciles

Weights:	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low
Equal	0.552	0.830	1.012	1.067	1.127	1.236	1.258	1.234	1.284	1.423	0.871
	(2.07)	(3.30)	(3.99)	(4.09)	(4.27)	(4.55)	(4.48)	(4.23)	(4.21)	(4.30)	(7.03)
Value	0.799	0.944	1.043	1.055	1.081	1.166	1.159	1.282	1.279	1.597	0.798
	(3.42)	(4.17)	(4.76)	(4.52)	(4.50)	(4.73)	(4.50)	(4.71)	(4.48)	(4.75)	(3.45)

Panel B: Average Returns Across Abnormal Simple Coverage Deciles

Weights:	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low
Equal	0.578	0.801	0.993	1.049	1.129	1.225	1.197	1.336	1.324	1.388	0.809
	(2.14)	(3.13)	(3.78)	(3.93)	(4.20)	(4.54)	(4.36)	(4.76)	(4.51)	(4.28)	(6.49)
Value	0.784	0.911	1.075	1.052	1.089	1.067	1.097	1.230	1.194	1.405	0.621
	(3.31)	(3.98)	(4.62)	(4.63)	(4.77)	(4.52)	(4.50)	(5.14)	(4.65)	(4.76)	(3.38)

Panel C: Average Returns Across Raw Total Coverage Deciles

Weights:	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low
Equal	1.424	1.490	1.476	1.838	1.719	1.716	1.793	1.688	1.611	1.568	0.144
	(3.09)	(2.38)	(2.53)	(2.93)	(2.58)	(2.52)	(2.76)	(2.79)	(2.72)	(2.55)	(0.42)
Value	1.620	1.319	1.533	1.384	1.496	1.702	1.710	1.578	1.448	1.440	-0.181
	(3.29)	(2.17)	(3.11)	(2.58)	(2.74)	(3.38)	(3.24)	(3.43)	(3.43)	(2.95)	-(0.80)

Panel D: Average Returns Across Raw Simple Coverage Deciles

Weights:	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low
Equal	1.427	0.761	1.487	1.672	1.758	1.775	1.720	1.765	1.646	1.573	0.146
	(3.09)	(1.23)	(2.59)	(2.48)	(2.64)	(2.59)	(2.58)	(2.89)	(2.82)	(2.70)	(0.46)
Value	1.623	0.446	1.589	1.517	1.269	1.667	1.756	1.756	1.467	1.432	-0.191
	(3.30)	(0.64)	(3.13)	(2.84)	(2.35)	(2.86)	(3.01)	(3.57)	(3.28)	(3.06)	-(0.86)

Table 3. Factor-Adjusted Portfolio Alphas

This table presents equal- and value-weighted portfolio alphas and corresponding t-statistics across abnormal total coverage deciles. Returns are measured in month $m+1$, where abnormal total coverage are calculated and assigned to deciles in month m. Alpha is the intercept from a regression of raw returns minus the risk-free rate, regressed on the contemporaneous excess market return (MKTRF); two Fama-French factors (SMB, and HML); and the momentum factor (UMD). Abnormal total coverage, $ATOT$, is the residual from a monthly regression of log one plus total analyst coverage measured in month m regressed on firm's contemporaneous log market capitalization, and lagged twelve-month share turnover and momentum. Abnormal simple coverage is defined analogously as the residual from a monthly regression of log of one plus the number of unique analysts covering a firm over the 90 days ending at the conclusion of month m. The sample for this analysis consists of 1,661,511 firm-month observations spanning 1982 through 2014.

Panel A: Equal-Weighted Alphas for Total Coverage

	Alpha	*MKTRF*	*SMB*	*HML*	*UMD*
High	0.376	1.082	0.925	0.179	-0.304
	(3.55)	(43.47)	(26.22)	(4.73)	-(13.00)
Low	-0.419	0.869	0.811	0.057	-0.109
	-(5.14)	(45.29)	(29.81)	(1.94)	-(6.06)
High-Low	0.795	0.213	0.114	0.122	-0.195
	(7.60)	(8.65)	(3.27)	(3.27)	-(8.43)

Panel B: Value-Weighted Alphas for Total Coverage

	Alpha	*MKTRF*	*SMB*	*HML*	*UMD*
High	0.388	1.162	0.744	0.027	-0.017
	(2.69)	(34.24)	(15.46)	(0.52)	-(0.53)
Low	-0.171	0.966	-0.155	0.071	-0.056
	-(1.72)	(41.28)	-(4.67)	(2.00)	-(2.55)
High-Low	0.560	0.195	0.899	-0.044	0.039
	(3.16)	(4.68)	(15.19)	-(0.70)	(1.00)

Panel C: Equal-Weighted Alphas for Simple Coverage

	Alpha	*MKTRF*	*SMB*	*HML*	*UMD*
High	0.321	1.106	0.830	0.231	-0.308
	(3.25)	(47.74)	(25.25)	(6.56)	-(14.11)
Low	-0.428	0.904	0.822	0.098	-0.112
	-(6.00)	(53.87)	(34.55)	(3.86)	-(7.07)
High-Low	0.749	0.202	0.007	0.133	-0.196
	(6.90)	(7.92)	(0.21)	(3.42)	-(8.17)

Panel D: Value-Weighted Alphas for Simple Coverage

	Alpha	*MKTRF*	*SMB*	*HML*	*UMD*
High	0.198	1.136	0.444	0.168	-0.005
	(1.60)	(39.01)	(10.76)	(3.79)	-(0.20)
Low	-0.192	0.975	-0.085	0.008	-0.037
	-(1.96)	(42.22)	-(2.58)	(0.23)	-(1.71)
High-Low	0.390	0.160	0.529	0.159	0.032
	(2.32)	(4.06)	(9.44)	(2.66)	(0.85)

Table 4. Fama-MacBeth Regressions

This table presents results from monthly Fama-MacBeth regressions of raw returns on abnormal total and abnormal simple analyst coverage, and additional controls. Returns are measured in month m+1. Total analyst coverage, TOT, is defined as the number of unique analyst-forecast pairings measured over the 90 days ending at the conclusion of month m. Simple analyst coverage, COV, is defined as the log of one plus the number of unique analysts covering a firm over the 90 days ending at the conclusion of month m. The regressions control for firm's contemporaneous log market capitalization (SIZE), and lagged twelve-month share turnover (TO) and momentum (MOMEN). VLTY is defined as the standard deviation of monthly returns over the twelve months ending in month m. LBM is the log of one plus a firm's book-to-market ratio. RR is the firm's raw return in month m. EAM is a dummy variable that equals one when a given firm announces earnings. SUE is a firm's standardized unexplained earnings, defined as the realized EPS minus EPS from four quarters prior, divided by the standard deviation of this difference over the prior eight quarters. ACC is the difference between net income and cash flows from operations scaled by lagged total assets. INST denotes firms' institutional ownership as a fraction of shares outstanding, $\Delta INST(LAG)$ equals the change in institutional ownership in month m relative to $m-3$, and $\Delta INST(FUT)$ equals the change in institutional ownership in month $m+3$ relative to month m. The sample for Panel A consists of 1,661,511 firm-month observations spanning 1982 through 2014. Panel B presents results monthly Fama-MacBeth regressions using a sample of 1,002,315 firm-months with at least three analysts providing coverage. *High* (*Low*) *ATOT* is a dummy variable that equals one for firms in the upper (lower) tercile of abnormal coverage for month m, where *MidATOT* reflects the remainder. The intercept term is omitted from Panel B to avoid multicollinearity. Columns (2) and (3) interact the abnormal coverage dummies with indicators for the high, mid, and low terciles of analyst forecast dispersion, $DISP$, measured as the standard deviation of one-year-ahead forecasts scaled by price. Columns (4) and (5) present analogous tests for analysts' average one-year-ahead forecasts scaled by price, E/P. Column (6) contains controls for the continuos versions of the signals. The parentheses contain t-statistics from the Fama-MacBeth regressions after Newey-West adjustments for autocorrelation up to 10 lags. The notations ***, **, and * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively.

Panel A: Full Sample Cross-Sectional Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log(1+TOT)	0.063	0.263***	0.233***	0.220***	–	0.179***	0.207***	0.234***	0.209***
	(1.59)	(6.53)	(5.91)	(5.46)	–	(2.71)	(5.14)	(5.68)	(5.36)
Log(1+COV)	–	–	–	–	0.331***	0.068	–	–	–
	–	–	–	–	(5.76)	(0.68)	–	–	–
SIZE	–	-0.154***	-0.169***	-0.176***	-0.192***	-0.181***	-0.182***	-0.164***	-0.171***
	–	(-2.89)	(-3.83)	(-3.99)	(-4.33)	(-4.26)	(-4.17)	(-3.80)	(-3.84)
TO	–	-0.425***	-0.293***	-0.272***	-0.270***	-0.274***	-0.280***	-0.226***	-0.226***
	–	(-4.31)	(-3.97)	(-3.75)	(-3.71)	(-3.80)	(-3.87)	(-3.09)	(-3.13)
MOMEN	–	0.637***	0.985***	0.783***	0.785***	0.787***	0.781***	0.805***	0.752***
	–	(3.82)	(5.55)	(4.48)	(4.54)	(4.55)	(4.43)	(4.50)	(4.15)
LBM	–	–	0.633***	0.643***	0.630***	0.643***	0.654***	0.645***	0.675***
	–	–	(3.49)	(3.57)	(3.50)	(3.58)	(3.70)	(3.63)	(3.83)
VLTY	–	–	-3.322***	-2.897***	-2.905***	-2.891***	-2.771***	-2.810***	-2.623***
	–	–	(-3.46)	(-3.06)	(-3.08)	(-3.06)	(-2.96)	(-2.86)	(-2.66)
RR	–	–	-0.036***	-0.038***	-0.038***	-0.038***	-0.038***	-0.039***	-0.039***
	–	–	(-9.40)	(-9.98)	(-10.03)	(-9.93)	(-10.03)	(-10.30)	(-10.27)
EAM	–	–	0.116***	0.088**	0.090**	0.097**	0.094**	0.036	0.033
	–	–	(2.75)	(2.08)	(2.18)	(2.26)	(2.25)	(0.74)	(0.68)
SUE	–	–	–	0.076***	0.076***	0.076***	0.076***	0.081***	0.080***
	–	–	–	(13.46)	(13.48)	(13.47)	(13.47)	(13.60)	(13.50)
ACC	–	–	–	-1.852**	-1.865**	-1.849**	-1.858**	-2.093**	-2.098**
	–	–	–	(-2.18)	(-2.20)	(-2.17)	(-2.24)	(-2.43)	(-2.47)
INST	–	–	–	–	–	–	0.257	-0.190	0.070
	–	–	–	–	–	–	(1.64)	(-1.04)	(0.37)
Δ*INST(LAG)*	–	–	–	–	–	–	–	-1.923***	–
	–	–	–	–	–	–	–	(-7.20)	–
Δ*INST(FUT)*	–	–	–	–	–	–	–	–	3.582***
	–	–	–	–	–	–	–	–	(7.23)
Intercept	0.974***	2.767***	2.908***	2.905***	3.109***	2.968***	2.905***	2.850***	2.822***
	(3.07)	(3.46)	(4.51)	(4.58)	(4.89)	(4.84)	(4.60)	(4.64)	(4.55)
R^2 (%)	0.687	3.126	4.517	4.860	4.812	4.977	4.970	5.181	5.288

Table 4: [Continued] Fama-MacBeth Regressions

Panel B: Combining Coverage and Forecast Signals						
	(1)	(2)	(3)	(4)	(5)	(6)
High ATOT	1.276***	0.904**	1.939***	1.666***	2.517***	–
	(4.20)	(2.45)	(3.15)	(5.59)	(4.35)	–
*High ATOT * Low Signal*	–	0.828***	0.702***	-0.660**	-0.412*	–
	–	(4.03)	(5.11)	(-2.06)	(-1.76)	–
*High ATOT * Mid Signal*	–	0.468***	0.386***	-0.433***	-0.326***	–
	–	(3.03)	(3.63)	(-2.96)	(-3.34)	–
Mid ATOT	1.106***	1.081***	2.108***	1.068***	2.068***	–
	(4.18)	(4.31)	(3.60)	(4.62)	(3.66)	–
*Mid ATOT * Low Signal*	–	0.356***	0.341***	-0.346	-0.192	–
	–	(4.32)	(5.96)	(-1.29)	(-1.04)	–
*Mid ATOT * High Signal*	–	-0.360**	-0.284***	0.393***	0.277***	–
	–	(-2.13)	(-2.80)	(3.26)	(3.29)	–
Low ATOT	0.888***	1.246***	2.315***	0.395	1.674***	–
	(3.30)	(5.02)	(3.96)	(1.05)	(2.82)	–
*Low ATOT * Mid Signal*	–	-0.325***	-0.362***	0.541**	0.268**	–
	–	(-3.24)	(-4.43)	(2.46)	(2.04)	–
*Low ATOT * High Signal*	–	-0.845***	-0.730***	0.830***	0.443***	–
	–	(-3.33)	(-4.62)	(3.20)	(2.63)	–
ATOT	–	–	–	–	–	0.278***
	–	–	–	–	–	(5.06)
DISP	–	–	–	–	–	-0.080***
	–	–	–	–	–	(-5.56)
E/P	–	–	–	–	–	-0.221
	–	–	–	–	–	(-0.20)
R^2	0.131	0.142	0.186	0.148	0.189	0.189
Interaction Signal:	N/A	DISP	DISP	E/P	E/P	N/A
Controls?	N	N	Y	N	Y	Y

Table 5. Alternative Implementations

Panel A presents equal- and value-weighted average monthly raw returns across alternative calculations of abnormal total coverage and the implementations of their corresponding strategies. The description of each sample requirement is shown in the first column. Returns are measured in month $m+1$, where abnormal total coverage is calculated and assigned to deciles in month m. Abnormal total coverage is the residual from a monthly regression of log one plus total analyst coverage measured in month m regressed on firm's contemporaneous log market capitalization, and lagged twelve-month share turnover and momentum. Analyst Coverage is defined as the number of unique analysts providing an earnings forecast for a firm over the 90 days ending at the conclusion of month m. The second to bottom row of Panel A contains an estimate of total coverage constructed from the IBES Summary File by taking the maximum number of analysts comprising a given consensus forecast, across all possible earnings forecasts for a given firm. The bottom row of Panel A examines the subsample of firms that have been in the CRSP database at least five years. Corresponding t-statistics, shown in parentheses, are calculated using the monthly time-series distribution. Panel B contains alternative implementations of the abnormal total coverage decile strategy. The top row represents the return from rebalancing the portfolio three-months after a firm's fiscal year end and held for twelve months. The bottom row represents the return from rebalancing the portfolio three-months after a firm's fiscal quarter end and held for three months. Panel C contains analyses based on within-firm changes in coverage. The top rows of Panel C present returns sorted by changes in abnormal coverage from month $m-3$ to m. The bottom rows of Panel C present month $m+1$ returns when sorting firms based on the abnormal component changes in total coverage after controlling for firms' size, momentum, and turnover (i.e., replacing levels of coverage in Eq. (1) with changes). Panel D presents equal- and value-weighted industry average monthly raw returns across deciles of industry-average abnormal total coverage, where industries are defined using the Fama-French 48-industry classification. Abnormal total coverage is the residual from a monthly regression of log one plus the industry average of total analyst coverage measured in month m regressed on the industry averages of contemporaneous log market capitalization, and lagged twelve-month share turnover and momentum. The bottom two rows of Panel D present the time-series average number of industries per month in each decile and the average number of unique firms per industry-month. The main sample for this analysis before imposing the specified data requirements consists of 1,661,511 firm-month observations spanning 1982 through 2014.

Panel A: Monthly Returns across Alternative Implementations

Description:	Equal-Weighted			Value-Weighted		
	High	Low	High-Low	High	Low	High-Low
Non-Announcement Months	1.300	0.452	0.848	1.528	0.852	0.675
	(3.90)	(1.66)	(6.22)	(4.41)	(3.53)	(2.72)
Announcement Months	1.420	0.624	0.796	1.650	0.668	0.981
	(4.23)	(2.22)	(5.18)	(4.86)	(2.51)	(3.86)
Analyst Coverage > 0	1.434	0.805	0.629	1.578	0.900	0.678
	(4.22)	(2.90)	(4.87)	(5.06)	(3.88)	(3.18)
Analyst Coverage > 3	1.406	0.900	0.505	1.485	0.914	0.571
	(4.11)	(3.19)	(3.91)	(4.79)	(3.93)	(2.77)
Analyst Coverage <= 3	1.350	0.570	0.780	0.895	0.948	-0.053
	(4.57)	(2.12)	(4.52)	(3.35)	(3.99)	-(0.31)
Constructed from IBES Summary	1.415	0.549	0.866	1.455	0.781	0.673
	(4.33)	(2.07)	(7.17)	(4.65)	(3.32)	(3.17)

Panel B: Lower Frequency Rebalancing

Description:	Equal-Weighted			Value-Weighted		
	High	Low	High-Low	High	Low	High-Low
Annual Rebalance; 12-Month Holding	2.799	-3.563	6.361	1.900	-2.494	4.394
	(2.21)	-(3.37)	(4.01)	(1.35)	-(2.03)	(2.48)
Quarterly Rebalance; 3-Month Holding	0.649	-1.153	1.802	1.042	-1.394	2.435
	(2.13)	-(4.83)	(4.91)	(2.76)	-(2.99)	(4.41)

Table 5: [Continued] Alternative Implementations

Panel C: Within-Firm Changes in Abnormal Coverage Proxies						
Description:	Equal-Weighted			Value-Weighted		
	High	Low	High-Low	High	Low	High-Low
Changes in ATOT	1.344	0.742	0.602	1.168	0.846	0.322
	(4.36)	(2.56)	(7.20)	(4.35)	(3.16)	(2.14)
Abnormal ΔTOT	1.295	0.977	0.318	1.100	0.887	0.214
	(4.44)	(3.35)	(3.92)	(4.74)	(3.82)	(2.28)

Panel D: Predicting Industry-Level Returns										
Weights:	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low
Equal	0.835	0.914	1.060	1.210	1.011	1.047	1.232	1.197	1.050	1.333	0.498
	(3.03)	(3.60)	(4.17)	(4.38)	(3.86)	(4.23)	(4.76)	(4.75)	(4.16)	(4.79)	(2.69)
Value	0.885	0.923	1.014	1.224	1.037	1.075	1.146	1.122	0.978	1.355	0.471
	(3.49)	(3.69)	(4.06)	(4.65)	(3.99)	(4.48)	(4.40)	(4.39)	(3.88)	(4.93)	(2.24)
#Ind	3.04	3.89	3.74	3.81	3.66	3.89	3.90	3.65	3.97	3.14	
#Firm/Ind	71.80	85.58	76.41	80.33	95.56	105.00	114.17	136.00	158.83	178.33	

Table 6. Estimating the Role of Resource Constraint

Panel A presents equal- and value-weighted average monthly raw returns across portfolios independently sorted by deciles of abnormal total coverage and terciles of analysts' selectivity, *SELC*. *SELC* is a proxy for analysts' selectivity, measured as the inverse of the average number of unique firms in the portfolio of covering analysts, where an analyst is deemed a covering analyst when he/she issues at least one earnings forecast. Returns are measured in month m+1, where abnormal total coverage is calculated and use to construct deciles in month m. Abnormal total coverage is the residual from a monthly regression of log one plus total analyst coverage measured in month m regressed on firm's contemporaneous log market capitalization (SIZE), and lagged twelve-month share turnover (TO) and momentum (MOMEN). Total coverage denotes the total number of unique analyst-forecast pairings over the 90-days ending at the conclusion of month m. Panel B presents analogous tests by partitioning the sample based on whether coverage increased (i.e., ΔCOV>0), remain unchanged (i.e., ΔCOV=0), or decreased (i.e., ΔCOV<0) from month $m-3$ to m. The sample for this analysis consists of 1,661,511 firm-month observations spanning 1982 through 2014.

Panel A: Conditioning Upon Analyst Selectivity (SELC)

	Equal-Weighted			Value-Weighted		
	High SELC	Mid	Low SELC	High SELC	Mid	Low SELC
10 (High)	2.561	1.644	1.207	2.764	2.015	1.299
9	1.495	1.365	1.162	1.233	1.580	1.122
8	1.568	1.321	1.071	1.485	1.503	1.147
7	1.777	1.322	1.021	1.588	1.375	1.086
6	1.643	1.327	1.009	1.341	1.482	1.039
5	0.956	1.183	1.158	1.122	1.469	1.042
4	1.170	1.042	1.073	1.421	1.307	1.056
3	1.156	0.985	1.069	0.994	1.290	1.044
2	0.892	1.005	0.799	1.279	1.205	0.914
1 (Low)	0.553	0.842	0.170	1.026	1.001	0.517
High-Low	2.009	0.771	0.864	1.738	0.809	0.721

Panel B: Conditioning Upon Changes in Coverage

	Equal-Weighted			Value-Weighted		
	ΔCOV>0	ΔCOV=0	ΔCOV<0	ΔCOV>0	ΔCOV=0	ΔCOV<0
10 (High)	1.595	1.454	1.322	1.812	1.527	1.417
9	1.259	1.468	1.074	1.216	1.398	1.275
8	1.258	1.245	1.257	1.271	1.307	1.340
7	1.114	1.316	1.315	1.013	1.245	1.361
6	1.235	1.270	1.104	1.099	1.222	1.183
5	1.021	1.176	1.132	0.997	1.162	1.221
4	1.077	1.087	0.999	1.042	1.051	1.072
3	0.874	1.015	1.069	0.880	1.077	1.172
2	0.583	0.860	0.817	0.815	0.771	1.095
1 (Low)	0.684	0.598	0.366	0.925	0.620	0.841
High-Low	0.911	0.856	0.956	0.887	0.906	0.576

Table 7. Predicting Fundamental Performance

This table contains results from firm-quarter regressions where the dependent variables are future levels and changes in firms' fundamental performance. Fundamental performance is measured by the FSCORE composite measure constructed in Piotroski (2000), which is a summary of nine binary signals each indicating improvements in fundamental performance. Q1 through Q4 denote firms' one- through four-quarters ahead FSCORE. Panel A uses levels as the dependent variable and Panel B uses changes in fiscal-quarter matched percentage changes in FSCORE. Abnormal total coverage, *ATOT*, is the abnormal from a monthly regression of log one plus total analyst coverage measured in month m regressed on firm's contemporaneous log market capitalization (SIZE), and lagged twelve-month share turnover (TO) and momentum (MOMEN). Total coverage denotes the total number of unique analyst-forecast pairings over the 90-days ending at the conclusion of month m. LBM is the log of one plus a firm's book-to-market ratio. VLTY is defined as the standard deviation of monthly returns over the twelve months ending in month m. Year fixed-effects are included throughout and reported t-statistics are based on two-way cluster robust standard errors, clustered by firm and quarter. The notations ***, **, and * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively. The sample for this analysis consists of 552,617 firm-quarter observations spanning 1982 through 2014.

Panel A: Regressions of Future FSCORE Levels

Quarter:	Q+1	Q+2	Q+3	Q+4
	(1)	(2)	(3)	(4)
ATOT	0.116***	0.121***	0.110***	0.109***
	(14.47)	(15.43)	(13.81)	(13.53)
SIZE	0.128***	0.133***	0.126***	0.123***
	(15.88)	(16.09)	(15.11)	(14.48)
MOMEN	0.078***	0.063***	0.048***	0.047***
	(6.27)	(5.52)	(4.37)	(4.24)
LBM	-0.360***	-0.338***	-0.347***	-0.331***
	(-9.21)	(-8.64)	(-8.76)	(-8.46)
VLTY	-0.831***	-0.904***	-0.838***	-0.912***
	(-5.44)	(-5.72)	(-5.47)	(-5.91)
R^2 (%)	4.103	3.967	3.560	3.367

Panel B: Regressions of Future FSCORE Changes

Quarter:	Q+1	Q+2	Q+3	Q+4
	(1)	(2)	(3)	(4)
ATOT	0.360***	0.505***	0.307***	0.267***
	(7.27)	(7.69)	(4.28)	(3.15)
SIZE	-0.082	0.069	-0.059	-0.125
	(-1.32)	(0.90)	(-0.59)	(-1.16)
MOMEN	-1.157***	-1.383***	-1.623***	-1.637***
	(-6.97)	(-6.46)	(-8.01)	(-7.24)
LBM	0.124	0.497	0.202	0.575
	(0.39)	(1.25)	(0.53)	(1.22)
VLTY	3.771**	1.564	2.713	0.923
	(2.25)	(0.78)	(1.39)	(0.36)
R^2 (%)	0.063	0.079	0.111	0.101

Table 8. Identifying Mispricing using Mutual Fund Outflows

Panel A contains descriptive statistics of changes in analyst coverage across quintiles of quarterly mutual fund outflows, denoted $Outflows$, as calculated in Edmans, Goldstein, and Jiang (2012). Abnormal total coverage, $ATOT$, is the abnormal from a monthly regression of log one plus total analyst coverage, denoted TOT, measured in month m regressed on firm's contemporaneous log market capitalization (SIZE), and lagged twelve-month share turnover (TO) and momentum (MOMEN). TOT is defined the total number of unique analyst-forecast pairings over the 90-days ending at the conclusion of month m. $\Delta ATOT$ and ΔTOT equal the within-firm change in $ATOT$ and TOT from the prior calendar quarter. Panel B contains analogous results of regressions of changes in analyst coverage on fund flows and additional firm characteristics. Year fixed-effects are included throughout and reported t-statistics are based on two-way cluster robust standard errors, clustered by firm and quarter. The notations ***, **, and * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively. The sample for this analysis consists of 53,046 firm-quarters observations spanning 1982 through 2007.

Panel A: Averages Across Fund Outflow Quintiles

	Outflows	$\Delta ATOT$	ΔTOT
Q1 (Large Outflows)	-2.189	0.394	9.491
Q2	-0.392	1.538	14.021
Q3	-0.154	0.851	13.977
Q4	-0.050	-1.983	10.655
Q5 (Small Outflows)	-0.003	-3.244	2.274
Q1-Q5	-2.186	3.638	7.217
p-value	(0.00)	(0.01)	(0.00)

Panel B: Regressions of Coverage on Outflows

	$\Delta ATOT$		ΔTOT	
	(1)	(2)	(3)	(4)
Outflows	-0.800***	-0.966***	-1.657***	-0.911***
	(-3.35)	(-3.94)	(-4.87)	(-3.43)
SIZE	–	-0.270	–	1.567***
	–	(-1.49)	–	(5.06)
LBM	–	1.902	–	-5.923***
	–	(1.51)	–	(-4.32)
MOMEN	–	1.059	–	7.403***
	–	(1.32)	–	(10.54)
R^2 (%)	0.038	0.067	0.169	1.438

Table 9. Announcement Month Returns

Panel A contains results from firm-quarter regressions where the dependent variable equals firms' returns during the months of their quarterly earnings announcements. Raw analyst is decomposed into two parts: the expected component based on fitted values from Eq. (1) and the abnormal component based on the residual from Eq. (1). Abnormal total coverage, $ATOT$, is the abnormal from a monthly regression of log one plus total analyst coverage measured in month m regressed on firm's contemporaneous log market capitalization (SIZE), and lagged twelve-month share turnover (TO) and momentum (MOMEN). Total coverage denotes the total number of unique analyst-forecast pairings over the 90-days ending at the conclusion of month m. Simple coverage is defined analogously using the total number of unique analysts providing coverage over the 90-days ending at the conclusion of month m. Panels B and C present analogous results when partitioning the sample in terciles of firm's log market capitalization, where tercile portfolios are formed each calendar quarter. Year fixed-effects are included throughout and reported t-statistics are based on two-way cluster robust standard errors, clustered by firm and quarter. The notations ***, **, and * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively. The sample for this analysis consists of 552,617 firm-quarter observations spanning 1982 through 2014.

Panel A: Components of Coverage

Coverage Measure:	Total Coverage			Simple Coverage		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Raw Coverage)	0.012	–	–	0.004	–	–
	(0.18)	–	–	(0.04)	–	–
Expected Component	–	-0.159*	-0.158*	–	-0.237*	-0.242*
	–	(-1.76)	(-1.75)	–	(-1.78)	(-1.82)
Abnormal Component	–	–	0.307***	–	–	0.573***
	–	–	(4.81)	–	–	(5.97)
R^2	0.000	0.016	0.050	0.000	0.016	0.056

Panel B: Firm Size Partitions

Coverage Measure:	Total Coverage			Simple Coverage		
Size Partition:	Small	Mid	Large	Small	Mid	Large
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Raw Coverage)	0.009	0.162*	0.221***	0.006	0.236	0.209*
	(0.08)	(1.81)	(2.65)	(0.03)	(1.64)	(1.95)
R^2	0.000	0.015	0.034	0.000	0.012	0.017

Panel C: Components of Coverage Partitioned

Coverage Measure:	Total Coverage			Simple Coverage		
Size Partition:	Small	Mid	Large	Small	Mid	Large
	(1)	(2)	(3)	(4)	(5)	(6)
Expected Component	-1.112***	-0.375	0.204	-2.455***	-0.602	0.152
	(-4.45)	(-1.38)	(1.14)	(-4.77)	(-1.59)	(0.80)
Abnormal Component	0.401***	0.313***	0.231***	0.838***	0.521***	0.255***
	(4.12)	(4.83)	(3.36)	(4.39)	(4.92)	(2.59)
R^2	0.129	0.064	0.034	0.145	0.062	0.018

Table 10. Tobin's Q Regressions

This table contains results from firm-month regressions where the dependent variable equals firms' month m Tobin's Q ratio, measured as the sum of the market value of assets and the book value of common stock scaled by the book value of assets. Total coverage denotes the total number of unique analyst-forecast pairings over the 90-days ending at the conclusion of month m. The regressions also include controls for contemporaneous log market capitalization (SIZE), and lagged twelve-month share turnover (TO) and momentum (MOMEN). Year fixed-effects are included throughout and reported t-statistics are based on two-way cluster robust standard errors, clustered by firm and quarter. The notations ***, **, and * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively. The sample for this analysis consists of 552,617 firm-quarter observations spanning 1982 through 2014.

	(1)	(2)	(3)	(4)	(5)
Log(1+TOT)	0.072***	0.072***	0.011	-0.071***	-0.103***
	(6.01)	(6.04)	(1.15)	(-3.91)	(-6.22)
MOMEN	–	0.524***	–	–	0.438***
	–	(12.90)	–	–	(12.19)
TO	–	–	0.232***	–	0.210***
	–	–	(10.33)	–	(10.37)
SIZE	–	–	–	0.161***	0.134***
	–	–	–	(11.51)	(10.83)
R^2	0.002	0.023	0.017	0.007	0.038