



Uncovering expected returns: Information in analyst coverage proxies[☆]



Charles M.C. Lee^a, Eric C. So^{b,*}

^aStanford University Graduate School of Business, Stanford Graduate School of Business, 655 Knight Way, Stanford, CA 94305, USA

^bMassachusetts Institute of Technology Sloan School of Management, MIT Sloan School of Management, 100 Main Street, Cambridge, MA 02142, USA

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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.

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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

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* Corresponding author.

E-mail addresses: Clee8@stanford.edu (C.M.C. Lee), eso@mit.edu (E.C. So).

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.

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 covering. 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 nontrivial 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.

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 \(1997\)](#) show 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 et al. \(2006\)](#) find 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.

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 proxy for total analyst coverage as the number of unique earnings forecasts summed across all analysts and forecasted fiscal periods (i.e., analyst/forecast pairs, where revisions are single counted). We then calculate abnormal coverage, defined as the residuals from monthly cross-sectional regressions of total analyst coverage on three control variables: firm size, share turnover, and past returns.

Given analysts' role in forecasting firms' earnings, we hypothesize that analysts identify firms' with higher expected returns by forecasting their subsequently reported fundamental performance. We provide support for this hypothesis by showing that abnormal coverage offers strong predictive power for both levels and changes in firms' fundamental performance. These tests suggest analysts anticipate firms' subsequently reported performance and allocate abnormally high coverage to ascending firms.

We next 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 overvalued, glamour stocks (e.g., [Chung and Jo, 1996](#); [Gleason and Lee, 2003](#); [Jegadeesh et al., 2004](#)).

Our findings 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). 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.

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

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 et al., 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](#).

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.

To help contextualize our results, we document a value-weighted factor-adjusted alpha corresponding to abnormal coverage of 56 basis points per month (t -statistic = 3.16), which is roughly on par with the monthly book-to-market and momentum premiums of approximately 45 to 60 basis points documented in [Fama and French \(2012\)](#). An important caveat is that our main portfolio tests rely on monthly rebalancing, whereas book-to-market and momentum strategies can be rebalanced annually, suggesting the amount of capital deployable toward abnormal coverage is likely lower than these other well-known anomalies.

Our finding that prices predictably fall for abnormally low coverage firms, and vice versa, is 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](#); [Easley and O’Hara, 2004](#); [Kelly and Ljungqvist, 2012](#)). However, because we focus on abnormal analyst coverage as an investment signal, rather than more salient analyst-based signals such as their buy/sell recommendations or target prices, our findings are also potentially consistent with prior evidence that market prices fail to reflect low saliency information (e.g., [Hirshleifer et al., 2009](#); [Giglio and Shue, 2014](#)).

To shed further light on the sources of return predictability, we also use mutual fund redemptions as an exogenous shock to firm-level underpricing. We show analysts respond to the downward price pressure triggered by fund outflows by increasing both raw and abnormal coverage, suggesting that part of the return predictability we document is driven by analysts gravitating toward firms whose prices are pushed below fundamental value.

Taken together, our findings on the responsiveness of abnormal coverage to mutual fund flows, as well as our evidence on its ability to forecast firms’ operating performance, suggest that analysts are providing abnormal coverage to underpriced firms. These findings are much more difficult to reconcile with risk-based explanations. Instead, our collective evidence appears more consistent with abnormal coverage signaling mispricing and investors underweighting abnormal coverage information due to its low saliency relative to analysts’ explicit investment advice.

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 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](#) 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 is 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 et al., 2010](#); [Huang et al., 2011](#)), and from providing a liquidity service to investors (e.g., [Edelen, 1999](#); [Alexander et al., 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 et al., 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.

³ Whereas several studies find that, on average, mutual funds fail to generate excess returns (e.g., [Malkiel, 1995](#); [Carhart, 1997](#); [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 et al., 2002](#); [Kacperczyk et al., 2005](#)).

A substantial body of research shows that analysts facilitate market efficiency when providing coverage by reducing uncertainty over firms' value [see [Kothari et al. \(2016\)](#) 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 et al., 2011](#)). For example, [McNichols and O'Brien \(1997\)](#) show 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 complements 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](#); [Altinkılıç et al., 2016](#)). 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. Because abnormal coverage is likely less likely to register as an investment signal compared to analysts' explicit investment advice, our findings are consistent with evidence in prior research that market prices fail to respond to low saliency signals (e.g., [Gabaix et al., 2006](#)) and information that is more difficult to acquire (e.g., [Cohen and Lou, 2012](#)).

Our findings build upon evidence in [Das et al. \(2006\)](#), 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 incentives 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 re-

search 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. Together, the inference problems we highlight 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 a related study, [Jung et al. \(2015\)](#) 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 et al. \(2015\)](#) is that non-covering analysts are more likely to conduct due diligence on firms with superior prospects. This study offers complementary 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 et al., 2000](#)).⁵ Specifically, our findings suggest bad news may travel slowly because analysts devote less effort toward covering firms with lower expected returns.

3. Empirical tests

This section contains details of our sample selection and the results of our main 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 come from the Institutional Brokers Estimates System (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 1970s but the data are initially sparse and grow rapidly to cover a broader cross-section of firms in the early 1980's. We merge the analyst data with Center for Research in Security Prices (CRSP) data 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

⁴ Our methodology allows us to study expected return information for approximately 4,200 unique firms each calendar month, whereas [Das et al. \(2006\)](#) 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 et al. \(2000\)](#) provide evidence that firms' returns are positively related to abnormal analyst coverage calculated relative to firm size but do not comment on this evidence.

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 measure analyst coverage 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.

We measure analyst coverage as 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 . This approach not only captures analysts' decision to cover a firm but also the extent to which they devote greater resources by forecasting earnings for a greater number of fiscal periods.⁶

We calculate the abnormal component of analyst coverage by fitting monthly regressions of total coverage, TOT , 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 total analyst coverage when estimating firms' abnormal coverage. More specifically, we calculate abnormal total coverage for firm i in calendar month m by estimating the following regressions:

$$\begin{aligned} \text{Log}(1 + TOT_{i,m}) = & \beta_0 + \beta_1 \text{SIZE}_{i,m} + \beta_2 \text{TO}_{i,m} \\ & + \beta_3 \text{MOMEN}_{i,m} + \epsilon_{i,m}, \end{aligned} \quad (1)$$

where $\text{SIZE}_{i,m}$ is the log of market capitalization in month m , $\text{TO}_{i,m}$ is share turnover calculated as trading volume scaled by shares outstanding, and $\text{MOMEN}_{i,m}$ is the firm's cumulative market-adjusted return, where $\text{TO}_{i,m}$ and

$\text{MOMEN}_{i,m}$ 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). We use the notation $ATOT$ to refer to the abnormal component of total coverage, where higher values correspond to firms that have greater analyst coverage than expected given their size, liquidity, and past performance profile.

Fig. 1 provides the timeline of analysis for calculating firms' abnormal coverage using the month of May as the portfolio formation month, m . The timeline 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 show that total analyst coverage is increasing in contemporaneous firm size (t -statistic = 75.3) and share turnover (t -statistic = 18.1). The regression results also show that total coverage is 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.⁷ The average R^2 values reported 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, Fig. 2 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, Fig. 2 shows that the incremental t -statistics are generally all below two in absolute value. 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 further controls does not significantly impact the predictive power of abnormal coverage for future returns (see Table 6 for more details).

⁶ In Table 9 and our online Appendix, we show that our results are qualitatively similar throughout our main tests when using 'simple' analyst coverage, defined as the number of unique analysts covering a firm.

⁷ Untabulated results show that total coverage is positively related to momentum before controlling for SIZE and TO, consistent with analysts providing greater coverage of better performing firms.

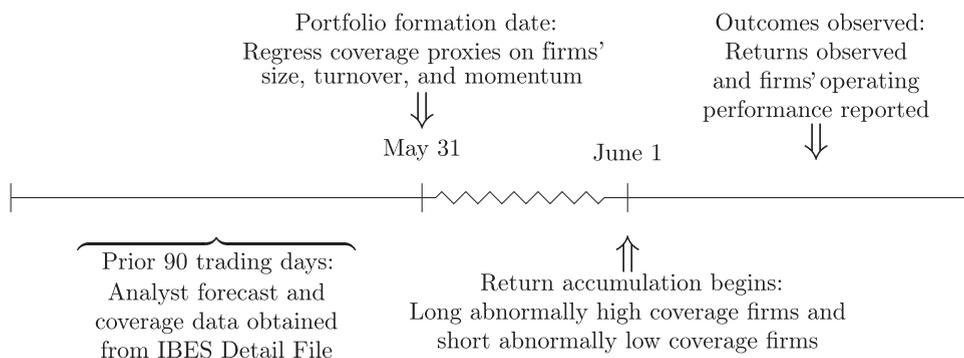


Fig. 1. Timeline of analysis. The figure provides the timeline of analysis for calculating firms' abnormal coverage using the month of May as the portfolio formation month, m . The timeline uses a May 31 portfolio formation date as an example to emphasize that the empirical tests are constructed to avoid 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.

Table 1

Descriptive statistics.

Panel A contains time-series average coefficients from regressing total analyst coverage measured in month m regressed on firms' contemporaneous log market capitalization (SIZE), and lagged 12-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 . Panel B presents time-series averages across abnormal total deciles. Abnormal total coverage is the residual from a monthly regression of log one plus total analyst coverage measured in month m regressed on firms' contemporaneous log market capitalization, and lagged 12-month share turnover and momentum. COV is the number of analysts covering a firm. VLTY is defined as the standard deviation of monthly returns over the 12 months ending in month m . SP is a firm's average relative spread over the 12 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 coefficients

	Mean	t-statistic
INT	-5.526	-55.984
SIZE	0.618	75.311
TO	0.270	18.082
MOMEN	-0.317	-11.225
R ²	0.618	

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

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

Panel B shows that $ATOT$ is positively related to the raw values of total coverage as well as the number of analysts

covering the firm (COV). Abnormal coverage is, by construction, uncorrelated with firms' size, turnover, and past performance, however, Panel B shows 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 12 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 12 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.

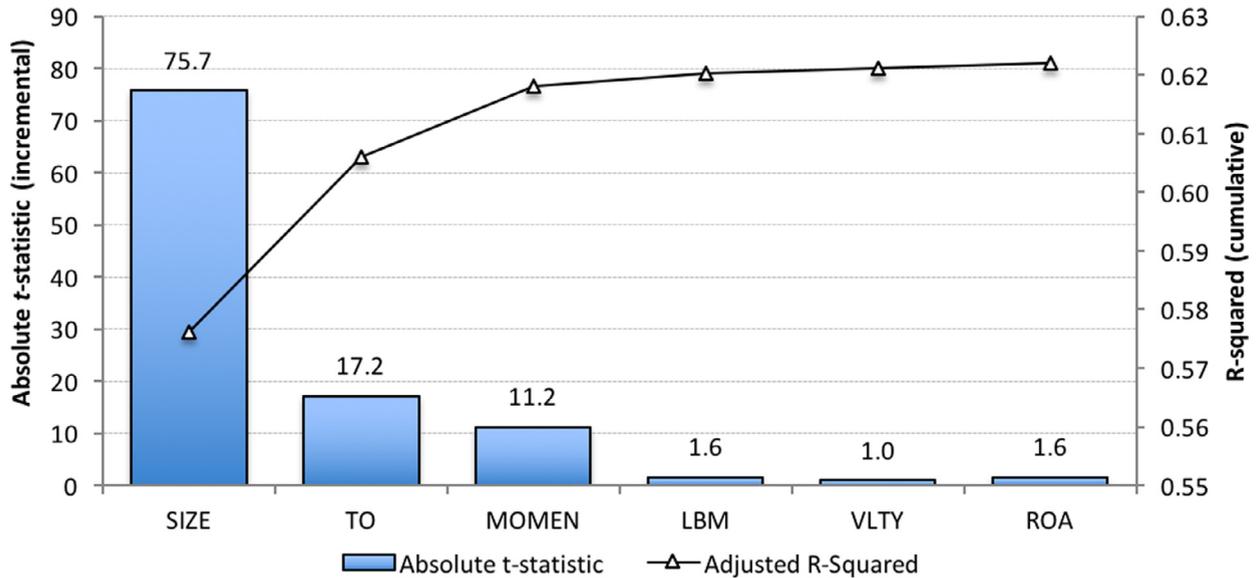


Fig. 2. Analyst coverage and firm characteristics. The charts below contain cumulative adjusted R -squared values and multivariate t -statistics across regressions of analyst coverage that iteratively add firm characteristics. The top plot contains results from regressing total analyst coverage on firm 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 total coverage proxy is regressed on firms' contemporaneous log market capitalization (SIZE), and lagged 12-month share turnover (TO), momentum (MOMEN), log book-to-market (LBM), return volatility (VLTY), and return on assets (ROA). See Table 1 for descriptive statistics for the main sample. The sample for this analysis consists of 1,661,511 firm-month observations spanning 1982 through 2014.

3.2. Fundamental performance

In our first tests, we examine the link between abnormal coverage and firms' subsequently announced fundamental performance. Given analysts' role in predicting firms' earnings, we hypothesize that analysts identify firms' with higher expected returns by forecasting their subsequently reported fundamental performance. To test this hypothesis, we proxy for firms' fundamental performance using the $FSCORE$ measure from Piotroski (2000) and Piotroski and So (2012), which sums nine binary signals that award higher values for superior levels of, as well as improvements in, firms' profitability, financial leverage, and operating efficiency relative to the prior year. We initially focus on this composite measure, rather than a specific focus on earnings, to capture longer-horizon fundamental performance and risks, but also separately consider the composite measure's individual components.⁸

Table 2 contains the time-series average of firms' future $FSCORE$ and its individual components, where $FSCORE$ is measured at the next earnings announcement follow-

ing month m . We match firms' quarterly fundamentals to monthly abnormal total coverage deciles to match the structure of our monthly return tests, however, the results are qualitatively identical if we measure abnormal coverage only at the end of each calendar quarter. The first row of Table 2 shows that $FSCORE$ is increasing across abnormal coverage deciles. The difference across high and low $ATOT$ deciles is 0.271 (t -statistic = 21.47), which corresponds to an approximate 5.2% increase in $FSCORE$ relative to the mean value of 5.3. These findings are consistent with analysts allocating greater abnormal coverage to firms that subsequently announce stronger, and ascending, fundamental performance.

To provide insight into the specific types of fundamental information analysts are forecasting, the subsequent rows of Table 2 present averages of the nine binary signals used to construct $FSCORE$: $CFO > 0$, indicating the firm reports positive cash flow from operations; $ACC < 0$, indicating the firm reports income-decreasing accruals; $NI > 0$, indicating the firm reports positive net income; $\Delta NI > 0$, indicating the firm reports an increase in net income relative to the prior year; $\Delta LEV < 0$, indicating the firm reports decreased leverage; $\Delta LIQ > 0$, indicating the firm reports an increase in the ratio of current assets to current liabilities; $\Delta SL = 0$, indicating the firm reports did sell equity; $\Delta MRG > 0$, indicating the firm reports an increase in gross margin; $\Delta TO > 0$, indicating the firm reports an increase in its asset turnover ratio.

⁸ Our main tests focus on firms' fundamental performance rather than revisions in analysts' forecasts because many firms in our sample do not have analyst coverage. Additionally, in Section 3.5, we show that the predictive power of abnormal coverage for future returns is most pronounced when analysts' forecasted earnings-to-price is high, suggesting that analysts' earnings forecasts already reflect the strong fundamental performance that motivates their coverage decision.

Table 2

Predicting fundamental performance.

This table contains average summary fundamental analysis scores, FSCORE, and its components across abnormal total coverage deciles. Fundamental performance is measured at the earnings announcement subsequent to the measurement of analyst coverage. FSCORE is the sum of nine binary signals: $CFO > 0$, which equals one if the firm reports positive cash flow from operations; $ACC < 0$, which equals one if the firm reports income-decreasing accruals; $NI > 0$, which equals one if the firm reports positive net income; $\Delta NI > 0$, which equals one if the firm reports an increase in net income relative to the prior year; $\Delta LEV < 0$, which equals one if the firm reports a decrease in leverage; $\Delta LIQ > 0$, which equals one if the firm reports an increase in the ratio of current assets to current liabilities; $\Delta SL = 0$, which equals one if the firm reports selling equity in the fiscal quarter; $\Delta MRG > 0$, which equals one if the firm reports an increase in gross margin; $\Delta TO > 0$, which equals one if the firm reports an increase in asset turnover ratio. Abnormal total coverage is the residual from a monthly regression of log one plus total analyst coverage measured in month m regressed on a firm's contemporaneous log market capitalization, and lagged 12-month share turnover and momentum. Corresponding t -statistics, shown in parentheses, are calculated using the monthly time-series distribution. The sample for this analysis consists of 1,661,511 firm-month observations spanning 1982 through 2014.

	Abnormal total coverage deciles										High-Low	t -stat.
	1 (Low)	2	3	4	5	6	7	8	9	10 (High)		
FSCORE	4.923	4.955	5.076	5.166	5.215	5.240	5.248	5.264	5.253	5.193	0.271	(21.47)
$CFO > 0$	0.597	0.603	0.634	0.650	0.655	0.658	0.656	0.653	0.646	0.627	0.030	6.754
$ACC < 0$	0.502	0.505	0.515	0.520	0.527	0.529	0.533	0.535	0.529	0.524	0.022	8.122
$NI > 0$	0.695	0.707	0.734	0.754	0.759	0.764	0.757	0.742	0.709	0.649	-0.047	-8.316
$\Delta NI > 0$	0.601	0.608	0.630	0.641	0.641	0.643	0.645	0.646	0.649	0.651	0.050	14.028
$\Delta LEV < 0$	0.659	0.656	0.652	0.654	0.656	0.660	0.659	0.660	0.659	0.655	-0.005	-1.761
$\Delta LIQ > 0$	0.370	0.379	0.400	0.414	0.412	0.410	0.406	0.403	0.402	0.404	0.034	11.289
$\Delta SL = 0$	0.566	0.551	0.562	0.581	0.600	0.613	0.631	0.655	0.677	0.667	0.101	27.158
$\Delta MRG > 0$	0.467	0.477	0.483	0.482	0.484	0.491	0.490	0.490	0.486	0.484	0.017	6.428
$\Delta TO > 0$	0.500	0.506	0.516	0.512	0.515	0.513	0.514	0.512	0.512	0.521	0.022	8.177

By decomposing FSCORE into its components, Table 2 shows that analysts allocate greater coverage to firms that subsequently report stronger cash flows from operations (i.e., $CFO > 0$) but also firms with greater income-decreasing accruals (i.e., $ACC < 0$). Additionally, the results corresponding to $NI > 0$ and $\Delta NI > 0$ show that high ATOT firms are more likely to report negative but increasing income relative to the same quarter in the prior year. Together, these findings suggest that analysts may identify firms that are more likely to be underpriced due to transitory income-decreasing accruals that subsequently translate into higher net income. Among the four income measures considered (i.e., $CFO > 0$, $ACC < 0$, $NI > 0$, and $\Delta NI > 0$), abnormal coverage is most strongly related to subsequently announced changes in net income. The high-low spread of 0.05 (t -statistic = 14.03) for $\Delta NI > 0$, suggests high abnormal coverage firms are 5% more likely, relative to a mean of 0.64, to report increases in net income compared to low abnormal coverage firms.

The next three rows of Table 2 show that higher abnormal coverage firms are more likely to subsequently report decreasing leverage and increasing financial liquidity as measured by their current ratio. High abnormal coverage firms are also less likely to access capital via the equity market, suggesting a superior ability to generate sufficient internal cash flows. Similarly, related evidence in the bottom two rows of Table 2 shows that firms with higher abnormal coverage are more likely to subsequently report improvements in its gross margins and asset turnover, suggesting that analysts identify and provide abnormal coverage to firms with improving operational efficiency.

In Table 3, we extend the univariate link between abnormal coverage and fundamentals by examining levels and changes in firms' FSCOREs corresponding to the next four fiscal periods (i.e., Q1 through Q4). To facilitate inter-

pretation, all variables in Panels A and B of Table 3 are standardized each month to have a zero mean and unit standard deviation.

Panel A of Table 3 shows that abnormal coverage positively predicts firms' FSCOREs over the four subsequent fiscal quarters. Because all variables are standardized, the average ATOT coefficient indicates that a two-standard deviation increase in abnormal coverage is associated with an approximate 0.12 ($=0.06 \times 2$) higher standard deviation in FSCORE over each of the next four fiscal quarters. The persistence of this relation suggests abnormal coverage predicts longer-term trends in firms' operating performance. In terms of economic magnitude, the ATOT and MOMEN coefficients suggest that abnormal coverage and lagged returns have comparable predictive power for firms' future FSCORE.

To mitigate concerns that the link between ATOT and FSCOREs is driven by analysts covering firms with persistently high profitability, Panel B of Table 3 examines the predictive link between abnormal coverage and forward changes in firms' FSCOREs. These tests show that abnormal coverage predicts changes in firms' subsequently reported FSCOREs, which is consistent with analysts identifying trends in firms' performance that gradually manifest in reported financial statements. Comparing the coefficient magnitudes across Panels A and B indicate, however, that abnormal coverage has stronger power for subsequently reported FSCORE levels than changes in FSCORE.

Together, the evidence in Table 3 shows that abnormal coverage offers robust predictive power for both levels and changes in firms' fundamental performance. These results suggest that analysts anticipate firms' profitability and allocate greater resources to ascending firms. To the extent that investors only gradually respond to the performance information embedded in analyst coverage, abnormal

Table 3

Regressions of future fundamental performance.

This table contains results from monthly Fama-MacBeth regressions where the dependent variables are future levels and changes in firms' fundamental performance. To facilitate interpretation, all variables in this regression are standardized each month to have a zero mean and unit standard deviation. 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 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 12-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 12 months ending in month *m*. The notations ***, **, and * indicate the coefficient is significant at the 1%, 5%, and 10% level, respectively. The sample for this analysis consists of 1,661,511 firm-month 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)
<i>ATOT</i>	0.062*** (17.57)	0.065*** (17.61)	0.058*** (13.85)	0.059*** (14.09)
<i>SIZE</i>	0.118*** (9.50)	0.119*** (9.96)	0.116*** (9.99)	0.113*** (10.31)
<i>MOMEN</i>	0.081*** (13.88)	0.066*** (11.46)	0.054*** (9.51)	0.051*** (9.00)
<i>LBM</i>	-0.070*** (-7.11)	-0.065*** (-6.85)	-0.064*** (-6.93)	-0.063*** (-6.89)
<i>VLTY</i>	-0.077*** (-7.45)	-0.083*** (-8.23)	-0.077*** (-7.58)	-0.084*** (-8.40)
<i>R</i> ² (%)	6.455	6.138	5.615	5.435

Panel B: Regressions of future FSCORE changes				
Quarter:	Q+1	Q+2	Q+3	Q+4
	(1)	(2)	(3)	(4)
<i>ATOT</i>	0.009*** (5.28)	0.013*** (6.11)	0.008*** (3.77)	0.008*** (4.00)
<i>SIZE</i>	-0.006* (-1.86)	-0.000 (-0.03)	-0.002 (-0.40)	-0.003 (-0.81)
<i>MOMEN</i>	-0.031*** (-12.80)	-0.039*** (-14.12)	-0.051*** (-16.78)	-0.048*** (-15.88)
<i>LBM</i>	-0.006*** (-2.58)	-0.005 (-1.60)	-0.004 (-1.11)	-0.003 (-0.80)
<i>VLTY</i>	0.012*** (3.65)	0.002 (0.46)	0.007 (1.44)	0.001 (0.26)
<i>R</i> ² (%)	0.658	0.757	0.826	0.843

coverage may also convey information about expected returns. We explore this issue in the next section by examining the predictive link between abnormal analyst coverage and future firm-level returns.

3.3. Abnormal coverage and future returns

Table 4 examines the predictive link between abnormal coverage and future returns. Specifically, Panels A and B contain equal- and value-weighted average monthly returns across abnormal 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. We calculate corresponding *t*-statistics, shown in parentheses, 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). These tests 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 Fig. 3 presents average monthly returns to the equal- and value-weighted *ATOT* strategies for each year in the sample. The average strategy returns are generally positive throughout the sample window, including in the wake of Regulation Fair Disclosure (Reg 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) years out of the 33-year sample window from 1982 through 2014.

Panel B of Table 4 contains parallel return tests when ranking firms into deciles based on the raw values of total analyst coverage, *TOT*. These results show that raw analyst coverage is significantly correlated with firms' future returns, with equal- and value-weighted *t*-statistics of 0.42 and -0.80. 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.

Having established that abnormal coverage predicts one-month-ahead returns, our next analyses examine the persistence of this predictive relation. Fig. 4 presents 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 4 and omitted from the figure. Shaded bars indicate the reported strategy return is statistically significant at the 5% level.

Fig. 4 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 show that the sign of the strategy returns do not immediately reverse when using lagged signals and thus mitigate concerns that the predictive power stems from transitory price pressure that immediately reverses in subsequent months.

Table 4

Monthly average returns Panels A and B present equal- and value-weighted average monthly raw returns across abnormal total and raw coverage deciles, respectively. 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 firms' contemporaneous log market capitalization, and lagged 12-month share turnover and momentum. Corresponding t -statistics, shown in parentheses, are calculated using the monthly time-series distribution. 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 (2.07)	0.830 (3.30)	1.012 (3.99)	1.067 (4.09)	1.127 (4.27)	1.236 (4.55)	1.258 (4.48)	1.234 (4.23)	1.284 (4.21)	1.423 (4.30)	0.871 (7.03)
Value	0.799 (3.42)	0.944 (4.17)	1.043 (4.76)	1.055 (4.52)	1.081 (4.50)	1.166 (4.73)	1.159 (4.50)	1.282 (4.71)	1.279 (4.48)	1.597 (4.75)	0.798 (3.45)

Panel B: 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 (3.09)	1.490 (2.38)	1.476 (2.53)	1.838 (2.93)	1.719 (2.58)	1.716 (2.52)	1.793 (2.76)	1.688 (2.79)	1.611 (2.72)	1.568 (2.55)	0.144 (0.42)
Value	1.620 (3.29)	1.319 (2.17)	1.533 (3.11)	1.384 (2.58)	1.496 (2.74)	1.702 (3.38)	1.710 (3.24)	1.578 (3.43)	1.448 (3.43)	1.440 (2.95)	-0.181 (-0.80)

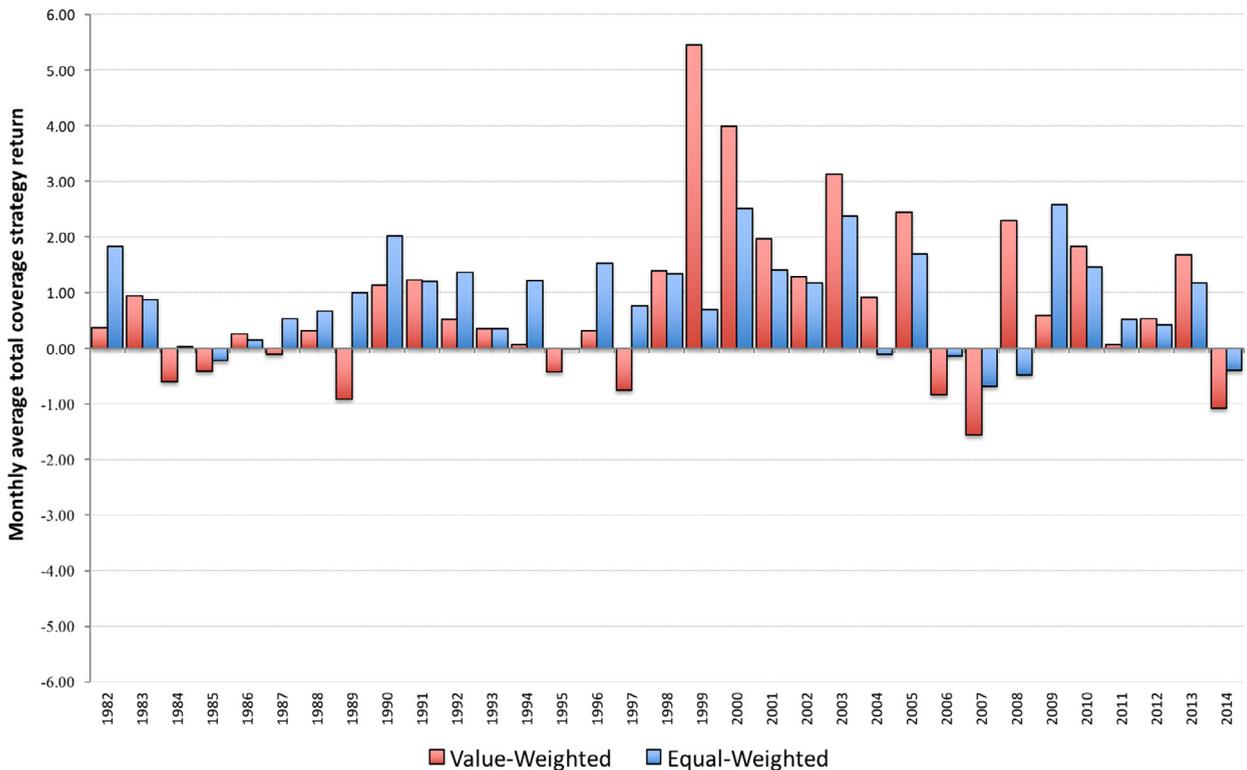


Fig. 3. Average annual strategy returns. The figure plots average monthly returns within each year from the abnormal total coverage strategy. Abnormal total coverage is the residual from a monthly regression of log one plus total analyst coverage measured in month m regressed on firms' contemporaneous log market capitalization, and lagged 12-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. See Table 1 for descriptive statistics for the main sample. The sample for this analysis consists of 1,661,511 firm-month observations spanning 1982 through 2014.

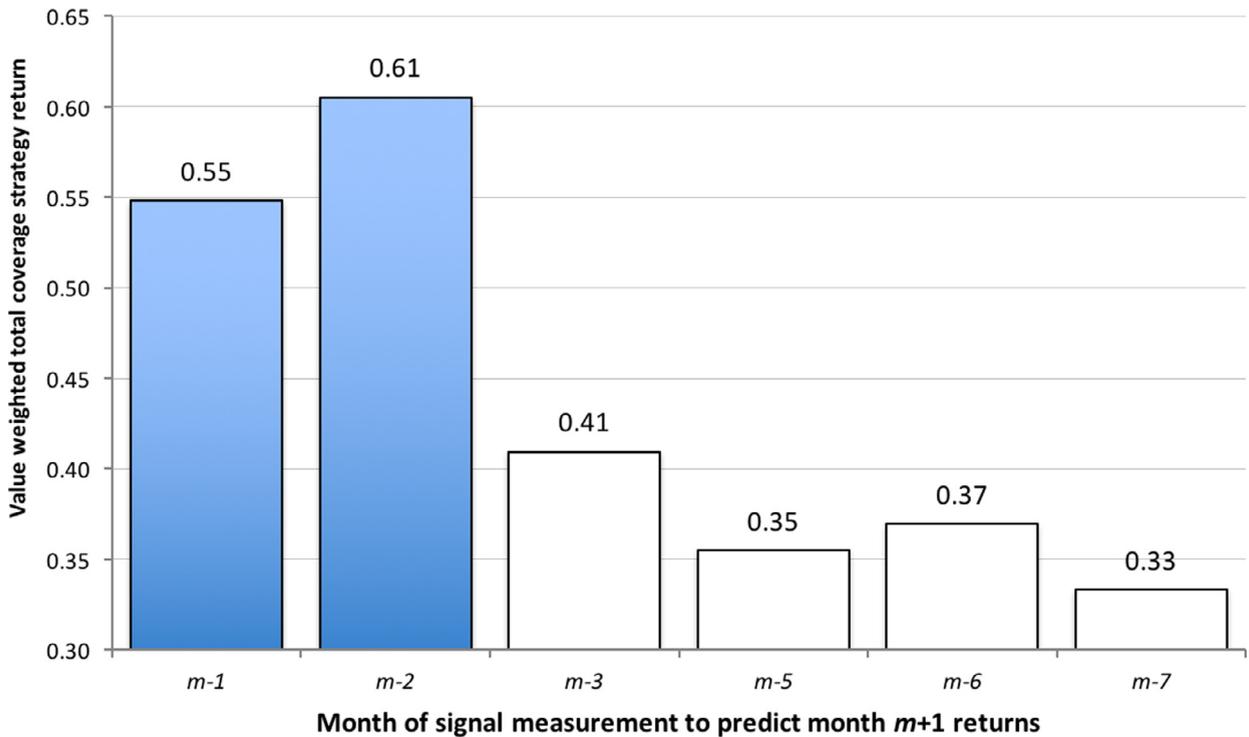


Fig. 4. Returns to lagged coverage signal. The figure plots cumulative value-weighted returns from the abnormal total coverage strategy using multiple lags between the measurement of coverage and the monthly return. Abnormal total coverage is the residual from a monthly regression of log one plus total analyst coverage measured in month m regressed on firms' contemporaneous log market capitalization, and lagged 12-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. Shaded bars indicate that the reported strategy return is significant at the 5% level. See Table 1 for descriptive statistics for the main sample. The sample for this analysis consists of 1,661,511 firm-month observations spanning 1982 through 2014.

Table 5 examines the link between abnormal analyst coverage and firms' future returns after controlling for each portfolio's exposure to standard monthly asset pricing factors. The table presents portfolio alphas and factor loadings across 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 (Small-Minus-Big (*SMB*), and High-Minus-Low (*HML*)); and the momentum factor (Up-Minus-Down (*UMD*)).

Table 5 shows 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. 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 a value-weighted alpha of 56 basis points (t -statistic = 3.16).

Table 5

Factor-adjusted portfolio alphas This table presents value-weighted portfolio alphas and corresponding t -statistics across abnormal total coverage deciles. Returns are measured in month $m+1$, where abnormal total coverage is 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 a firm's contemporaneous log market capitalization, and lagged 12-month share turnover and momentum. The sample for this analysis consists of 1,661,511 firm-month observations spanning 1982 through 2014.

	<i>Alpha</i>	<i>MKTRF</i>	<i>SMB</i>	<i>HML</i>	<i>UMD</i>
10 (High <i>ATOT</i>)	0.388	1.162	0.744	0.027	-0.017
9	0.072	1.099	0.606	0.165	0.008
8	0.128	1.081	0.460	0.124	-0.015
7	0.039	1.060	0.332	0.137	-0.032
6	0.067	1.051	0.172	0.089	-0.003
5	-0.006	1.047	0.066	0.090	0.000
4	0.028	1.022	-0.058	0.035	-0.024
3	0.033	0.963	-0.142	-0.022	0.057
2	0.024	0.957	-0.254	-0.077	-0.038
1 (Low <i>ATOT</i>)	-0.171	0.966	-0.155	0.071	-0.056
High-Low <i>ATOT</i>	0.560	0.195	0.899	-0.044	0.039
(t -statistic)	(3.16)	(4.68)	(15.19)	-(0.70)	(1.00)

Table 6

Fama-MacBeth regressions This table presents results from monthly Fama-MacBeth regressions of raw returns on abnormal total analyst coverage, and additional controls. To facilitate interpretation, all independent variables in this regression are standardized each month to have a zero mean and unit standard deviation. Returns are measured in month $m+1$ and are non-standardized. 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 . The regressions control for a firm's contemporaneous log market capitalization ($SIZE$), and lagged 12-month share turnover (TO) and momentum ($MOMEN$). $VLTY$ is defined as the standard deviation of monthly returns over the 12 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 earnings Per Share (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 consists of 1,661,511 firm-month observations spanning 1982 through 2014. 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Log(1 + TOT)</i>	0.087 (1.53)	0.394*** (6.77)	0.343*** (6.22)	0.321*** (5.77)	0.299*** (5.35)	0.342*** (6.18)	0.284*** (5.58)
<i>SIZE</i>	-	-0.306*** (-2.95)	-0.334*** (-3.88)	-0.347*** (-4.04)	-0.359*** (-4.24)	-0.324*** (-3.86)	-0.346*** (-3.97)
<i>TO</i>	-	-0.373*** (-4.21)	-0.270*** (-4.15)	-0.254*** (-3.96)	-0.265*** (-4.20)	-0.207*** (-3.08)	-0.208*** (-3.11)
<i>MOMEN</i>	-	0.384*** (4.76)	0.575*** (7.12)	0.456*** (5.73)	0.454*** (5.68)	0.478*** (5.75)	0.432*** (5.09)
<i>LBM</i>	-	-	0.193*** (3.09)	0.196*** (3.16)	0.200*** (3.29)	0.197*** (3.30)	0.212*** (3.59)
<i>VLTY</i>	-	-	-0.216*** (-2.65)	-0.186** (-2.34)	-0.177** (-2.25)	-0.187** (-2.23)	-0.165** (-1.98)
<i>RR</i>	-	-	-0.539*** (-9.10)	-0.564*** (-9.52)	-0.567*** (-9.57)	-0.595*** (-9.79)	-0.605*** (-9.88)
<i>EAM</i>	-	-	0.064*** (3.95)	0.052*** (3.18)	0.054*** (3.34)	0.032* (1.71)	0.031 (1.62)
<i>SUE</i>	-	-	-	0.405*** (14.85)	0.405*** (14.88)	0.430*** (14.89)	0.423*** (14.65)
<i>ACC</i>	-	-	-	-0.260*** (-6.05)	-0.258*** (-6.08)	-0.288*** (-6.19)	-0.284*** (-6.18)
<i>INST</i>	-	-	-	-	0.073* (1.66)	-0.052 (-1.04)	0.075 (1.37)
$\Delta INST(LAG)$	-	-	-	-	-	-1.937*** (-7.26)	-
$\Delta INST(FUT)$	-	-	-	-	-	-	0.516*** (8.10)
<i>Intercept</i>	1.102*** (3.82)	1.102*** (3.82)	1.104*** (3.83)	1.122*** (3.90)	1.121*** (3.90)	1.214*** (4.25)	1.167*** (4.11)
<i>R</i> ² (%)	0.687	3.126	4.517	4.860	4.969	5.181	5.367

Comparing Tables 4 and 5 shows that the value-weighted strategies attenuate from 80 to 56 basis points when using factor-adjusted returns, but remain economically and statistically significant. For context, the monthly alpha of 56 basis points implies an average annualized alpha of 6.9%, making the magnitude comparable to the 60 basis point earnings announcement premium strategy return documented in Barber et al. (2013).

3.4. Multivariate tests

Table 6 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.

To facilitate interpretation, all of the independent variables in Table 6 (but not returns) are standardized each month to have a zero mean and unit standard deviation. Column 1 confirms the result from Table 5 that raw total coverage, TOT , is not significantly related to future returns (t -statistic = 1.53) in univariate tests. However, column 2 shows that TOT becomes highly significant (t -statistic = 6.77) 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 alongside additional controls yields the same inference

as when including these control variables in the estimation of *ATOT* in Eq. (1).

Columns 3 and 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, however, the R^2 values indicate that explanatory power for the cross-section of returns remains low throughout.

In terms of economic magnitude, column 4 indicates that a two-standard deviation change in abnormal coverage corresponds to an approximate 64 ($= 0.32 \times 2$) basis point spread on monthly returns, even when controlling for other well-known cross-sectional return prediction variables. Further, because all independent variables are standardized, we can compare the coefficient magnitudes to gauge economic magnitudes. Column 4 suggests that the incremental return spread associated with abnormal coverage compares favorably to other well-known accounting anomalies, falling in between post-earnings announcement drift (*SUE* coefficient = 0.41) and the accrual anomaly (*ACC* coefficient = -0.26).

The final three columns of Table 6 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 5 through 7, 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.

3.5. Synergies between abnormal coverage and analysts' forecasts

Are there complementarities between abnormal coverage and analysts' earnings forecasts? To address this question, Table 7 examines the predictive power of abnormal coverage relative to analysts' forecasted earnings-to-price and the forecast dispersion effect documented in Diether et al. (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*.

Column 1 of Table 7 contains results from regressing 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, where the return spread across high and low terciles is approximately 40 basis points per month.

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 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).

Because the interaction effects are based on binary variables, the coefficients are interpretable as average monthly returns. For example, column 3 indicates that the average return of firms with high abnormal coverage and low forecast dispersion is approximately 264 basis points ($= 1.94 + 0.7$), whereas the average return of firms with low abnormal coverage and high forecast dispersion is approximately 159 basis points ($= 2.32 - 0.73$), indicating that abnormal coverage and the extent of agreement among analysts provide complementary information about future returns.

Columns 4 and 5 of Table 7 contain analogous tests where we interact abnormal coverage with indicators for the high, mid, and low terciles of analysts' forecasted *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). These results suggest that our main findings tend to be driven by cases where analysts provide high (low) abnormal coverage at the same time as forecasting strong (weak) fundamental performance.⁹

In terms of economic magnitude, column 5 indicates that the average return of firms with high abnormal coverage and high *E/P* is approximately 252 basis points, whereas the average return of firms with low abnormal coverage and high forecast dispersion is approximately 167 basis points. The 85 basis point difference ($= 252 - 167$) is more than double the univariate spread of 40 basis points shown in column 1, which attests to synergies achieved when leveraging the two signals of firm value.

Additionally, column 6 of Table 7 uses continuous versions of each variable to show that abnormal coverage retains incremental predictive power over *DISP* and *E/P*, indicating that our main findings are distinct from the earnings-to-price and forecast dispersion effects documented in prior research. Collectively, the findings in Table 7 provide novel evidence of complementarities be-

⁹ In untabulated results, we find that although the earnings forecasts of abnormally high coverage firms tend to be more accurate, these analysts also tend to be positively surprised at earnings announcements, suggesting that analysts use anticipated performance information to motivate their coverage decisions but also tend to revise their expectations in the direction of abnormal coverage at the time earnings are announced.

Table 7

Interaction effects This table presents results from monthly Fama-MacBeth regressions using a sample of 1,002,315 firm-months with at least three analysts providing coverage. 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 . Abnormal total coverage, ATOT, is the residual from a monthly regression of log one plus total analyst coverage measured in month m regressed on a firm's contemporaneous log market capitalization (SIZE), and lagged 12-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 . 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 this regression 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 continuous 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.

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

tween what analysts 'do,' via their coverage decisions, and what analysts 'say,' via the content of their forecasts.

3.6. Identifying mispricing through mutual fund flows

A key inference from this paper is that analyst coverage data embed expected return information because analysts allocate abnormal coverage based on firm-level mispricing. In a broader sense, mispricing encompasses the separation of market prices from firms' fundamental value. As a result, there are at least two possible, non-mutually exclusive, channels through which analysts can identify mispricing. The first channel occurs when analysts forecast information about a firm's fundamental performance that is not yet reflected in its current market price. A second channel occurs when analysts identify mispricing by observing changes in market prices, while holding constant a firm's fundamental value. Whereas Tables 2, 3, and 7 highlight the first channel, we also explore the second channel in Table 8.

A key challenge in testing this second channel is the need to identify non-fundamental-based changes in mar-

ket prices. To do so, we use quarterly mutual fund outflow data from Edmans et al. (2012) as an instrument for exogenous shocks to firm-level mispricing. Several studies, including Coval and Stafford (2007) and Edmans et al. (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 results in sustained underpricing but is unrelated to firms' fundamentals and takes multiple months to reverse.

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. More specifically, we measure quarterly changes in abnormal and the log of raw coverage, and multiply the difference by 100. The fund flow data are as described in Edmans et al. (2012), which only reflect fund outflows expressed as a percentage of firms' shares outstanding, and results in a sample of 53,046 firm-quarters spanning 1982 through 2007.

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 et al. (2012). Abnormal total coverage, *ATOT*, is the residual from a monthly regression of log one plus total analyst coverage, denoted *TOT*, measured in month *m* regressed on a firm's contemporaneous log market capitalization (*SIZE*), and lagged 12-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, multiplied by 100. 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-quarter observations spanning 1982 through 2007.

Panel A: Averages across fund outflow quintiles				
	<i>Outflows</i>	$\Delta ATOT$	ΔTOT	
Q1 (Large <i>Outflows</i>)	-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 <i>Outflows</i>)	-0.003	-3.244	2.274	
Q1-Q5	-2.186	3.638	7.217	
<i>p</i> -value	(0.00)	(0.01)	(0.00)	

Panel B: Regressions of coverage on outflows				
	$\Delta ATOT$		ΔTOT	
	(1)	(2)	(3)	(4)
<i>Outflows</i>	-0.800*** (-3.35)	-0.966*** (-3.94)	-1.657*** (-4.87)	-0.911*** (-3.43)
<i>SIZE</i>	-	-0.270 (-1.49)	-	1.567*** (5.06)
<i>LBM</i>	-	1.902 (1.51)	-	-5.923*** (-4.32)
<i>MOMEN</i>	-	1.059 (1.32)	-	7.403*** (10.54)
<i>R</i> ² (%)	0.038	0.067	0.169	1.438

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. In terms of economic significance, the difference in ΔTOT implies that firms in the highest outflow quintile receive approximately 3.5 more analysts' forecasts in the post- versus pre-outflow quarter, compared to firms in the lowest outflow quintile. Related evidence in Panel B of Table 8 shows that the negative relation between fund flows and changes in coverage is robust to controlling for firms' size, glamour status, and past returns, suggesting our findings are more likely attributable to variation in underpricing.

By using mutual fund outflows to identify firm-level mispricing, these tests suggest that part of the return predictability we document is driven by analysts increasing abnormal coverage in response to exogenous sources of underpricing. More broadly, the findings in Table 8 suggest that analysts' coverage decisions convey expected return information, not only because they reflect analysts' expectations of future fundamentals, but also because they are

motivated by deviations of market prices from firms' fundamental values.

4. Robustness

In our final analyses, Table 9 explores the sensitivity of the main findings to alternative implementations, subsamples, and data requirements. The first two rows of Panel A address the concern that return predictability stems from analysts more actively forecasting earnings in response to earnings announcements and thus that our results reflect a form of post-earnings announcement drift not accounted for in our multivariate tests.

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.

Table 9

Alternative implementations Panel A presents 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 a firm's contemporaneous log market capitalization, and lagged 12-month share turnover and momentum. 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. 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 12 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 row of Panel C presents returns sorted by changes in abnormal coverage from month $m-3$ to m . The bottom row of Panel C presents 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 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 12-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: Returns across alternative implementations

Description:	Abnormal coverage deciles		
	High	Low	High-Low
Non-announcement months	1.528 (4.41)	0.852 (3.53)	0.675 (2.72)
Announcement months	1.650 (4.86)	0.668 (2.51)	0.981 (3.86)
Analyst coverage > 0	1.578 (5.06)	0.900 (3.88)	0.678 (3.18)
Analyst coverage > 3	1.485 (4.79)	0.914 (3.93)	0.571 (2.77)
Simple coverage	1.405 (4.76)	0.784 (3.31)	0.621 (3.38)
Constructed from IBES Summary	1.455 (4.65)	0.781 (3.32)	0.673 (3.17)

Panel B: Lower frequency rebalancing

Description:	Abnormal coverage deciles		
	High	Low	High-Low
Annual rebalance; 12-month holding	1.900 (1.35)	-2.494 (-2.03)	4.394 (2.48)
Quarterly rebalance; 3-month holding	1.042 (2.76)	-1.394 (-2.99)	2.435 (4.41)

Panel C: Within-firm changes

Description:	Abnormal coverage deciles		
	High	Low	High-Low
Changes in ATOT	1.168 (4.35)	0.846 (3.16)	0.322 (2.14)
Abnormal Δ TOT	1.100 (4.74)	0.887 (3.82)	0.214 (2.28)

Panel D: Predicting industry-level returns

	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High-Low
VW>Returns:	0.885 (3.49)	0.923 (3.69)	1.014 (4.06)	1.224 (4.65)	1.037 (3.99)	1.075 (4.48)	1.146 (4.40)	1.122 (4.39)	0.978 (3.88)	1.355 (4.93)	0.471 (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	

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 examines strategy returns based on the abnormal component of simple analyst coverage, measured as the number of analysts providing coverage, regardless of the number of fiscal periods that they are forecasting. This abnormal simple coverage strategy yields an average return of 62 basis points (t -statistic = 3.38), which is economically significant but smaller than the returns to the abnormal total coverage strategy. This attenuation suggests analysts convey expected return information 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.

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 that standard analyst coverage proxies embed 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 windows. Panel B of Table 9 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 examines the returns to portfolios that are rebalanced and held for 12 months, where abnormal analyst coverage is measured three months after firms' fiscal-year end.

Table 9 shows that annual rebalancing results in 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 Fig. 4 that return predictability 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 position for three months, which yields a value-weighted return of 2.44% (t -statistic = 4.41).

Related tests in Panel C of Table 9 examine two alternative implementations based on *within-firm* changes. Specifically, the top rows rely on changes in abnormal coverage from month $m - 3$ to m and the bottom rows rely 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 in coverage).

Panel C of Table 9 shows the positive link between abnormal coverage and returns holds for change-based specifications, which mitigates concerns that the positive link between abnormal coverage levels and returns is driven by an omitted firm-fixed effect not controlled

for in our model of abnormal coverage or multivariate tests. The monthly returns remain statistically significant but strongly attenuate relative to the levels-based measures of abnormal coverage, suggesting analysts convey expected return information not only through their decision to drop coverage but also through their decision to abstain from coverage despite a firm appearing attractive given its size, liquidity, and past performance profile.

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, Panel D of Table 9 shows 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 9 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.

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.

5. 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' fundamental performance and future returns, suggesting that analysts convey expected return information by providing greater coverage to underpriced firms. As a corollary, our findings illustrate 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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