Crowdsourcing Forecasts: competition for sell-side analysts?

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Abstract

Recent research has begun to question the importance of forecasts to sell-side analysts. Prior research established the co-existence of longer horizon optimism and short-term pessimism in sell-side forecasts. These factors motivate us to explore a new phenomenon – crowdsourcing, as an alternative source of forecasts. We obtain revenue and earnings forecasts from estimize, an entity which crowdsources and distributes these forecasts online. We find the estimize forecasts are, on average, as accurate as the sell-side. Further, although our results show the estimize forecasts to be relatively more optimistic, on average, and particularly in short horizons, our analysis suggest it is at least partially explained by the extreme pessimism of the sell-side's final forecasts. Our market test confirms support for the superiority of estimize's short-term forecasts. Our results provide support for the value of crowdsourced forecasts.

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1. Introduction

Forecasts are fundamental to markets. Revenues, earnings, and cash flows are common forecast parameters. Sell-side analysts are one publicly available source of such forecasts for market participants and academics. Early research established analyst forecast superiority to time series models (Brown et al., 1987) and linked sell-side analyst career success to forecast accuracy (Stickel, 1992; Mikhail et al., 1999). However, there was also evidence of an optimistic bias (O'Brien, 1988; Hong and Kubik, 2003). An entire stream of literature explored whether analyst incentives were the cause for the forecast bias and, in general, found little support. Subsequent work showed that the optimism had dissipated in later samples, and, instead, longer-term optimism and short-term pessimism co-existed, perhaps to support management's effort to meet or beat expectations (Richardson et al., 2004).

Recent studies are beginning to question the importance of forecasting to sell-side analysts (Brown et al., 2013). Groysberg et al. (2011) find no relation between forecast accuracy and compensation, providing a possible explanation for its reduced importance. Johnston et al. (2012) show that a simple adjustment to enhance forecast accuracy is overlooked by analysts, thus providing direct evidence of forecasting's reduced importance. Surveys suggest that industry knowledge is increasingly important to sell-side analysts. If forecasts are becoming less important to sell-side analysts, then it seems plausible that their quality may have declined or may do so in the future, thus begging the question: are there alternative and/or better sources for forecasts? Certainly, many companies now issue their own forecasts, but it is not the norm, and such forecasts may suffer from their own biases. Time-series forecasts are a possibility, Bradshaw et al. (2012) show that in some circumstances, such as smaller or younger firms, they are superior to sell-side analyst annual forecasts. However, neither of these alternatives appear to offer a complete solution. Independent and buy-side analysts are another option, but their forecasts are rarely publicly available, and previous research, which is limited, suggests that both are less accurate than sell-side analysts and, in the case of buy-side, more optimistic as well (Groysberg et al., 2008; Gu and Xue, 2008). However, the samples for both of these studies are limited and fairly dated.

In this paper, we explore a new phenomenon, crowdsourcing of forecasts. We obtain revenue and earnings forecasts from estimize. Estimize is an open platform that collects forecasts from more than 2,000 contributors for approximately 1,400 firms. Many contributors are employed on the buy-side or at independent research firms.[1] These forecasts are available on their website as well as recently being added to Bloomberg terminals. Our primary interest is whether these forecasts are comparable to sell-side forecasts in terms of accuracy and whether, perhaps due to differing incentives, reflect less bias.

Institutional changes are another motivation to revisit prior findings of sell-side analyst forecast superiority. The operating practices of sell-side research departments were altered dramatically by various regulatory and voluntary changes that occurred in the early 2000s.[2] The research labor market has changed substantially following the Global Settlement. Many good analysts left the sell-side because of the likelihood of reduced compensation caused by the decoupling of research funding and underwriting. Further, many sell-side research departments

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[1] The company describes their contributors as follows: analysts, portfolio managers, and traders from many high-profile hedge funds, mutual funds, and asset management firms. The community also includes a large contingent of professional independent analysts, retail traders and investors, hobbyists, corporate finance professionals, industry professionals, and students. Anyone is free to join. Recently they have begun to collect affiliation data, but it is unavailable for our data. Touted benefits of participating are information sharing and creation of a track record.

[2] For example, Regulation Fair Disclosure (FD) in 2001, Self-Regulation Organization rules of NYSE and NASDAQ in 2002, and the Global Research Analyst Settlement in 2003.

were significantly downsized for the same reason.[3] This exogenous shock to the sell-side would have altered the pool of available candidates to the buy-side and independent research providers not only immediately but also thereafter. Anecdotal evidence of such is found in the following quote from a 2007 *Business Week* article.

"Demand for analysts is strong, but the landscape has shifted. More research dollars are flowing away from…, so called sell side firms that sell their research to others. Instead, buy side firms such as hedge funds and other money managers are hiring in-house research staffs, paying top dollar to keep those investing insights all to themselves."

The Global Settlement may have leveled the research playing field in another way as well. By requiring the funding of independent research for five years, the settlement may have facilitated independent research providers' ability to hire better talent and broaden their coverage. These changes could make previous findings of the sell-side's forecast superiority over buy-side and independent analysts less likely in today's environment.

To evaluate the relative quality of forecasts, we adopt a dual approach. We assess *ex post* performance by comparing accuracy and bias of both revenue and earnings forecasts for the two groups of forecasters (estimize versus sell-side). We hypothesize that estimize may be as accurate as the sell-side in smaller or less covered firms where the pay-off to the sell-side analyst and her associated brokerage firm is likely lower. Based on prior studies however, we expect, on average, estimize will be less accurate. Further with respect to bias, we expect the two groups to be similar in the longer horizons but that estimize to be more optimistic in short horizons due to sell-side incentives to curry favor with company management and facilitate meeting or beating expectations. As a measure of *ex ante* performance, we follow Gu and Xue (2008) and compare

[3] In 2004, the number of sell-side analysts had decreased 15-20% according to John McInerney, senior director Citigate Financial Intelligence. The Flight of the Sell-Side Analyst, CFO July 8, 2004.

earnings response coefficients (ERCs) for the two groups of forecasts. Forecasts that are better proxies for market expectations should have a stronger association with returns at the time the actual is announced, reflected by higher ERCs. Previous studies find that the *ex ante* and *ex post* measures do not always produce consistent results (O'Brien, 1988; Gu and Xue, 2008). We match the estimize data for quarterly periods ending in 2012 to the corresponding IBES (Institutional Brokers' Estimate System) coverage (representing the sell-side) for those firms.

Comparing the estimize forecasts to the sell-side forecasts, on average, we find no difference in forecast accuracy of either earnings or revenue. Given previous results of sell-side forecasts accuracy superiority over both buy-side and independent analysts we believe this finding is noteworthy. Testing for differential bias, we find estimize to be slightly more optimistic, consistent with prior research on the buy-side. The optimism is concentrated in short horizon forecasts. Further, in additional analysis, we attribute this result, at least in part, to the pessimism of the sell-side's last forecast, consistent with an incentive to allow firms to meet or beat expectations. Our ERC test confirms the superiority of the estimize short-term forecasts as they show a stronger association with the earnings announcement returns. Further, we partition the sample by firm size and analyst coverage to examine potential cross-sectional differences in forecast properties. We find little evidence of differences in accuracy but do find that the main revenue bias result is concentrated in low analyst coverage firms.

Our paper addresses an under-researched but promising topic related to information intermediaries, sources beyond sell-side equity analysts (Berger, 2011). It also extends prior research by exploring buy-side and independent analyst's disaggregated earnings forecasts (Ertimur et al., 2011) by examining both revenue and earnings forecasts. Previous studies limited their tests to earnings forecasts. Our results suggest that the inferences are similar for both types of forecasts, on average. The consistency of results between revenue and earnings also ameliorates concern that the two groups of analysts may be forecasting different measures of earnings, complicating the comparison. The paper also introduces a new data source that is more current than previous studies. Further, perhaps by including a broader array of forecasters, our study seems to suggest that sell-side forecast superiority no longer applies. Whether this is due to the declining importance of forecasts to the sell-side or an improvement in the talent and skills of the buy-side and independent analysts is a question that we are unable to answer with our limited time series of data. High-quality forecasts are of importance not only to market participants but also to academics who use them as proxies of market expectations. This new source of forecasts could alter the conclusions of previous studies.

Our study also has potentially broader implications. Our early results suggest that crowdsourcing is effective in creating a reliable information source. Estimize as a crowdsourcing platform represents a possible market solution to the shortcomings associated with sell-side analyst forecasts perhaps resulting from their incentives. The application of technology to enhance the information environment of firms is innovative and possibly revolutionary.

The remainder of the paper is organized as follows. Section 2 reviews prior literature and outlines our hypotheses. Section 3 details the research design. Empirical results are presented in Section 4 and Section 5 concludes.

2. Previous research and hypotheses

Sell-side equity analysts, as information intermediaries is a highly studied topic. In contrast, there is very little research on buy-side and independent analysts. Given that buy-side and independent analysts are heavy contributors to estimize, we use previous research on them to motivate our work. The difference in attention the two groups of analysts has received is most likely due to the plethora of available data for the sell-side relative to other analysts. Early research established sell-side analyst forecast superiority to time series models (Brown et al., 1987) and linked sell-side analyst career success to forecast accuracy (Stickel, 1992; Mikhail et al., 1999). However, early research also documented an optimistic bias in sell-side forecasts (O'Brien, 1988). Lim (2001) proposes and finds support for a rational trade-off of optimistic forecast bias to improve management access and hence forecast accuracy. Many studies have examined the effect of analyst incentives on their outputs, and most studies find the effect is on recommendations rather than forecasts (Lin and McNichols, 1998; Irvine, 2004). Further, more recent research finds little evidence of optimism, on average, instead suggesting that early optimism is followed by pre-announcement pessimism to facilitate firms' meeting or beating expectations (Richardson et al., 2004). Ljungqvist et al. (2007) provide evidence that institutional ownership is positively associated with sell-side forecast accuracy, rationalizing that analyst career success is often at institutions' mercy. Given the large role of institutional investors in U.S. stocks, they present a powerful counterforce to other potential incentives that sell-side analysts face. In sum, the majority of past evidence generally supports the importance of forecasting to sell-side analysts and the quality of their forecasts. Perhaps then it is not surprising that in comparison, independent and buy-side analyst earnings forecasts tend to be less accurate and more optimistically biased (Groysberg et al., 2008; Gu and Xue, 2008).

However, a few recent papers begin to question the importance of forecasts for sell-side analysts, which in turn presents the possibility that the relative quality of their forecasts may have declined or may do so in the future. For example, Johnston et al. (2012) show that a simple adjustment to enhance forecast accuracy is overlooked by analysts. Such lack of action suggests that accuracy is not of the highest importance to analysts. Further, Groysberg et al. (2011) find no relation between forecast accuracy and compensation and argue that sell-side analyst compensation is typically tied to commissions, soft-dollar revenues in the stocks they cover, their *Institutional Investor* magazine ranking, and their ability to create demand for a new issue that their firm is underwriting or distributing, but not necessarily to their forecasting ability. If forecast accuracy does not contribute to compensation, then it likely receives less attention from analysts. Brown et al. (2013) in a survey find that analysts rank forecasts last in importance. Only 24% of analysts surveyed in their study responded that the accuracy and timeliness of earnings forecasts are very important to their compensation; rather, industry knowledge is the most important determinant and the most important input to both earnings forecasts and stock recommendations.

Schipper (1991) notes that buy-side and sell-side analysts work for different types of firms and face different incentives. Whereas a sell-side analyst works for a brokerage firm and issues publicly available forecasts and recommendations, a buy-side analyst works for a mutual fund, hedge fund, or pension fund and provides forecasts and recommendations privately to the employing firm. Early papers documented that sell-side analysts are generally more competent and are compensated better (e.g., Dorfman and McGough, 1993; Williams et al., 1996). Also, buy-side firms are also more likely to retain poorly performing analysts (Groysberg et al., 2008). In addition, the number of firms covered by buy-side analysts generally exceeds the coverage of sell-side analysts, and sell-side analysts are more likely to focus on a subset of similar firms. Taken together, such factors likely explain the previously documented superiority of sell-side analysts with respect to forecast accuracy (e.g., Groysberg et al., 2008).

The role of an independent analyst is more similar to that of the sell-side analyst. Their primary role is to create research reports for clients. Prior research however suggests that independent analysts are of lower quality and have less resources relative to the sell-side which at least in part explains their less accurate forecasts (Jacob et al., 2008).

However, Groysberg et al. (2008) do acknowledge that part of the sell-side superiority was a function of their preferential access in the period prior to Regulation FD. In addition, there has been other changes in the way sell-side research operates since the Groysberg et al., (2008) and the Gu and Xue, (2008) studies were conducted, potentially further altering the relative advantage of the sell-side.[4] Moreover, buy-side analysts likely have access to most sell-side analyst reports, conduct their own independent research, and are likely aware of the historic pattern of pessimistic final forecasts by the sell-side. Despite that, what little research that does exist suggests that the sell-side is more accurate. Therefore, our first hypothesis is:

H1: Estimize's earnings forecasts are less accurate than sell-side earnings forecasts.

Prior studies find that revenue increases are often more persistent than expense decreases, and, as a consequence, investors' reaction to revenue surprises are greater than earnings surprises (e.g., Jegadeesh and Livnat, 2006; Keung, 2010; Ertimur et al., 2011). Also, Ghosh, Gu, and Jain (2005) claim that investors consider revenue growth more than earnings growth in valuing firms. These studies suggest that investors would value revenue forecasts to complement earnings forecasts. However, there is a paucity of evidence on the properties of buy-side and independent analyst revenue forecasts, let alone the relative revenue forecast accuracy between sell-side and buy-side and independent analysts. Since we are not aware of any prior research that points to a differential forecasting performance for revenues by the two types of analysts, we expect that the

[4] See FN2 and related discussion.

properties of revenue forecasts would be similar to earnings forecasts. Hence our next hypothesis:

H1A: Estimize's revenue forecasts are less accurate than sell-side revenue forecasts.

On the question of forecast bias, little is known about the incentives of buy-side and independent analysts. The evidence on sell-side analysts suggests that incentives have little effect on forecasts with the exception of a short-horizon pessimism that may be a result of managers attempting to "walk-down" earnings targets to a level that can be more easily met (Richardson et al., 2004). Given that buy-side forecasts are generally not made public, there would be little incentive for the analyst to participate in the same walk-down game as the sell-side analyst. If that is the case, the greater optimism for buy-side forecasts observed by previous studies (e.g., Groysberg et al., (2008)) is more likely to be observed for forecasts closer to the announcement date. Hence our next hypotheses:

H2: Estimize's analyst longer-horizon forecasts (earnings and revenues) are as optimistic as sell-side forecasts.

H2A: Estimize's analyst short-horizon forecasts (earnings and revenues) are more optimistic than sell-side forecasts.

It is not clear whether buy-side or independent analysts would ever have an advantage, informationally or otherwise, over the sell-side. Past studies suggest that sell-side analysts are of higher ability (Groysberg et al., 2008). One could imagine that if any analyst chose to focus on smaller or less covered firms, they could develop a relative advantage over others. Certainly, Bradshaw et al.'s (2012) results demonstrate the sell-side's relative weakness in forecasting small firms. And perhaps smaller or less-covered firms are the focus of buy-side or independent analysts to compensate for weaker coverage from the sell-side. Lys and Soo (1995) find accuracy improves with coverage, and so it would be harder for any competing analysts to show incremental superiority in the highly covered firms. Certainly, a sell-side information advantage may be more pronounced for larger and more-covered firms, where the potential payoff for information search is likely greater. For example, due to more share turnover and a higher likelihood of exposure to institutional investors. Thus as our final hypothesis we conjecture the following:

H3: Estimize analyst forecasts are as accurate as the sell-side for smaller or less-covered firms.

3. Sample and research design

3.1 Sample

Estimize was founded in 2011 and advertises itself as "the first open platform for earnings estimates." By crowdsourcing earnings and revenue estimates from contributors ranging from hedge fund and institutional professionals to independent investors, estimize provides an alternative source of forecasts. We obtain estimize's quarterly forecast data for quarterly periods ending in 2012. Table 1 outlines the sample selection. The initial data contain 18,048 earnings forecasts for 1,415 firms. After requiring IBES forecasts for the same firm quarter as well as eliminating some observations due to missing or problematic data, we are left with 17,486 earnings forecasts for 1,387 firms. For our main analysis, we want to compare these observations with IBES forecasts of similar horizon. We define forecast horizon for matching purposes as two groups, less than and equal to 30 days and greater than 30 days. Missing horizon matches result in a final sample of 15,044 earnings forecasts for 1,142 firms.[5] So the final sample reduction is the result of IBES forecasts not existing for the corresponding sample forecast horizon. We relax our matching requirement and use the larger sample for robustness testing with the caveat that inferences might be problematic.

Prior research on buy-side and independent analysts has only explored earnings forecasts. We have the benefit of revenue forecasts to extend past work. The horizon-matched revenue forecast sample (untabulated) is similar to the earnings sample detailed above with a slightly smaller number of firms (1,133) but a slightly higher number of observations (15,467). The matching IBES forecasts are discussed below. We obtain market variables from the CRSP (Center for Research in Security Prices) and accounting data from Compustat.

In Table 2, we present some exploratory analysis of the firm coverage within the estimize data. In Panel A, we compare firm size and firm market-to-book ratios relative to the IBES universe. Although estimize's data cover fewer firms, those firms are larger than IBES firms, on average, with average market capitalizations of $11 billion versus an IBES average of $5.7 billion. The sample firms are also, on average, more growth oriented than the entire IBES universe, with slightly higher market-to-book ratios, 3.9 versus 3.1, respectively. Therefore, it does not appear that the sample is limited to smaller or perhaps less-covered firms. We explore analyst coverage in Panel B.

There are, on average, 10 buy-side or independent analysts forecasting each firm, although the coverage is highly skewed as the median is much lower at three. The average for IBES coverage of the sample firms is approximately 17 analysts per firm, and the median is

[5] Although estimize's first year of operations was 2011, there are a limited number of forecasts for 2011 fiscal periods. We focus our analysis on fiscal periods ending in 2012, estimize's first full year of operations. For comparison, Groysberg et al. (2008) examine annual forecasts from 37 buy-side analysts at one top-10 money management firm. Their buy-side final sample contains 3,526 forecasts for 337 stocks. As noted earlier, estimize has over 2,000 contributors. Gu and Xue (2008) examine 6,999 quarterly forecasts related to 1,198 firms.

similar at 15. We also note some other significant differences. The forecast horizon differs dramatically; the average forecast age for estimize is 19 days versus 187 days for the sell-side. Although these are quarterly forecasts, the IBES average is high in part because analysts tend to issue a quarterly forecast for each quarter at the beginning of the year, making the horizon for latter quarters extremely high. There is also a difference in the number of forecasts per quarter. The sell-side appears to be updating their forecasts, issuing on average nearly four forecasts per quarter. In contrast, the buy-side and independents have one forecast per quarter. Finally, many of the buy-side and independents are only contributing forecasts for one firm based on a median of one, but there are some covering many more, as the average is approximately seven.

3.2 Research design

Our primary interest is the comparison of forecast properties of estimize to that of sell-side analysts. We use IBES forecasts as representatives of the sell-side. To evaluate the relative quality of forecasts, we adopt a dual approach. We assess *ex post* performance by comparing accuracy and bias of both revenue and earnings forecasts for the two groups of forecasters. As a measure of *ex ante* performance, we compare earnings response coefficients (ERCs) for the two groups of forecasts.

3.2.1 Forecast accuracy and bias

Our dependent variables are standard measures in the literature. *FERR*, our measure of accuracy, is the absolute value of forecast errors (actual less forecast) deflated by beginning-of-period stock price for earnings and market value of equity for revenue. Our bias measure (*BIAS*) is calculated in the same manner without applying the absolute value. Actuals are taken from

IBES.[6] Calculating *FERR* and *BIAS* for both revenue and earnings results in four forecast measures.

For our regression analyses, the main independent variable is *ESTIMIZE.* It is an indicator variable that is set to 1 for estimize forecasts and zero otherwise.

Our specifications are as follows:

$$Forecast\ Measure = \beta_0 + \beta_1 ESTIMIZE + \gamma\ Controls + \varepsilon \qquad (1)$$

Our multivariate analysis controls for other known determinants of forecast accuracy, such as forecast horizon, as well as company characteristics. Since information arrives over time, forecast error should decline as the earnings announcement approaches (O'Brien, 1988). *HORIZON* is the number of days from the analyst forecast date to the date of the company's earnings announcement. Brown (1999) finds that forecast errors differ between loss and profit companies, and therefore we include *LOSS* to control for forecast differences between profitable and nonprofitable quarters. *LOSS* is an indicator variable, 1 if net income is less than zero, zero otherwise. We include *FIRM SIZE* to control for differential information environments between large and small firms. *FIRM SIZE* is measured as the natural log of the market value of equity at the end of the previous period. Lys and Soo (1995) find that analysts' forecast accuracy increases with analyst following. *FOLLOWING* is the number of analysts who provide forecasts on a company during the quarter.

We include industry-fixed effects in all of our analysis to control for forecast difficulty across industries. To control for potential accuracy differences across quarters, we include quarter-fixed effects as well. All standard errors are clustered at the firm level.

[6] Gu and Xue (2008) use the same construct.

3.2.2 Market test

As a measure of *ex ante* performance, we follow Gu and Xue (2008) and compare earnings response coefficients (ERCs) for the two groups of forecasts. We run a standard ERC model shown below as Equation 2 for each forecasting group. The dependent variable is the three-day, size-adjusted buy and hold return (BHAR) around each respective earnings announcement. The main variable of interest is the consensus forecast error (FE) for the respective forecasters. The ERC, which is the α_1 coefficient on the consensus forecast error, is the basis for comparing market association. The group with the larger ERC suggests closer alignment with market expectations. We run the model both with raw measures as well as absolute value measures of returns and forecast error. Firm-specific control variables are not required, but we do control for quarter and industry effects.

$$BHAR = \alpha_0 + \alpha_1 FE + \gamma\ Controls + \varepsilon \qquad (2)$$

4. Results

4.1 Univariate analysis

In Table 3, we present the univariate analysis of forecast accuracy and bias for the two types of analysts (estimize versus sell-side). We analyze the full sample as well as partitions by forecast horizon. The first two rows examine earnings forecasts (accuracy followed by bias), and the last two rows do the same for revenue forecasts. The full sample contains the 15,044 (15,467) estimize earnings (revenue) forecasts from Table 1. The corresponding IBES sample contains 73,645 (68,089) earnings (revenue) forecasts. The larger IBES sample is a result of higher analyst firm coverage as well as more frequent forecasting by IBES analysts.

The first row examines earnings forecast accuracy. The first column presents the full sample, which is firm and forecast horizon matched, and shows that sell-side analyst earnings forecasts have larger errors on average (0.0046 versus 0.0025) compared to estimize. The inference from the median is the same. The results are similar for revenue forecasts (third row), although both the mean raw errors and the difference are larger (0.0135 versus 0.0075). This evidence of greater accuracy by the estimize analysts is surprising and counter to our first two hypotheses. The pattern of sell-side inferiority is also fairly consistent when we partition by forecast horizon (less than and equal to 30 days or greater than 30 days). However, the medians in the longer horizon, greater than 30 days, are exceptions. For earnings, the medians show no difference based on the Wilcoxon test, and for revenue, the IBES median is slightly smaller. The results using the larger non-horizon-matched robustness sample, shown in the fourth column, are comparable to the horizon matched full sample.

However, one needs to be cautious in interpreting all of these univariate results given that we know from Table 2 that the forecast horizon for the two groups differs significantly. Our multivariate tests will control for forecast horizon with greater precision. Moreover, the estimize sample in the longer-horizon window is relatively small making generalizable results more problematic. The forecast bias results are discussed next.

Both the horizon-matched full sample and the robustness sample show that sell-side forecasts are more optimistic than the estimize forecasts for earnings (second row) and revenue (fourth row), on average. Optimism is reflected by a negative sign, as the forecast is greater than the actual. The mean earnings forecast bias for IBES is -0.001 versus 0.000 for estimize. The corresponding figures for revenue forecasts are -0.0031 and -0.0007. Medians also suggest sell-side relative optimism, although the median earnings forecast error for the sell-side is zero and the estimize median is slightly pessimistic. For revenue, both medians are slightly optimistic, with the sell-side slightly more so.

The pattern of greater sell-side optimism across forecast horizon, however, is not consistent. IBES earnings and revenue forecasts are more (less) optimistically biased for longer (shorter) term forecasts. For example, in the 30-days-or-less column based on means, IBES earnings forecasts are more pessimistic than the buy-side and independents (0.0009 versus 0.0004), and the contrast is more dramatic for revenue forecasts (0.0013 versus -0.0009). This result is consistent with our H2A hypothesis. In the greater-than-30-days column, the results are similar to the full sample, perhaps not surprising given that most of the IBES observations are in that group. The sell-side's greater optimism in the longer horizon is counter to our expectation of similar bias in hypothesis H2. Again however, this comparison is limited by the small estimize long horizon sample size. The multivariate results follow.

4.2 Regression analysis: *FERR* and *BIAS*

Tables 4 through 7 present the results. Earnings forecasts are tabled first, accuracy with *FERR* as the dependent variable followed by the bias analysis. The corresponding revenue analyses follow. Table 4 presents the earnings accuracy regression results. Columns A through D correspond to the samples presented in Table 3. After controlling for the previously documented determinants of earnings forecast accuracy, the *ESTIMIZE* dummy is statistically insignificant in all four analyses, suggesting no difference in earnings forecasting performance between the two groups of analysts. This finding is in contrast to the univariate analysis, which suggests superior estimize analyst accuracy but only crudely controlled for forecast horizon. The regression analyses suggest that estimize earnings forecasts are, on average, as accurate as sell-side analyst forecasts. Nonetheless, this result is noteworthy because all previous research found buy-side and independent analysts to be less accurate than the sell-side.

The control variables, the age of forecasts (*HORIZON*), *FIRM SIZE*, and the *LOSS* dummy load consistently in the predicted directions. The *FOLLOW* variable is statistically insignificant in all specifications. The following effect is likely subsumed by the firm size variable. The adjusted r-squareds for the regressions are of reasonable magnitudes, suggesting our specification explains a reasonable amount of the variation in forecast error.

In contrast to the evidence of equivalency for accuracy, the *ESTIMIZE* variable loads negatively in three of the four earnings forecast bias regressions reported in Table 5, the exception being for longer-term forecasts (>30 days). The longer-term forecasts show no statistically significant difference between the two groups, consistent with our hypothesis H2. The other results suggest greater earnings forecast optimism for estimize analysts, particularly in shorter horizons. This is consistent with the univariate analysis and supports H2A. Finding greater optimism for the buy-side or independent analysts is consistent with prior research but seems at odds with the lack of evidence regarding a difference in forecast accuracy. This apparent puzzle will be explored further, later in the paper.

The corresponding revenue forecast regression results are reported in Tables 6 (accuracy) and 7 (bias). The tenor of the results is similar to the earnings results. The main difference is for longer horizons (greater than 30 days), the estimize revenue forecasts appear to be less accurate and more pessimistic based on positive and statistically significant coefficients on the buy-side variable in both Tables 6 and 7. Also, the robustness sample results in Table 6 differ slightly from the horizon-matched sample results. The *ESTIMIZE* variable is positive and statistically significant, suggesting less accurate estimize analysts. However, as noted earlier, this sample is potentially problematic so caution is warranted in interpreting this differing result.[7]

Taken together, the revenue and earnings forecast results suggest, in general, that estimize forecasts are as accurate as sell-side forecasts but that they are more optimistically biased, particularly in short horizons. The optimism finding is consistent with the pessimism of short-term sell-side analyst forecasts documented in prior studies, something we will explore further in Section 4.4.

4.3 Cross-sectional analysis: firm size and analyst following

Next, we present our cross-sectional analyses. We partition the observations based on firm size and analyst following using the median of the variable of interest. Given prior evidence that firm size relates to predisclosure period information environment (Atiase, 1985) and analyst coverage and forecast accuracy (Lang and Lundholm, 1996), we examine whether the performances of estimize analysts versus sell-side analysts vary with firm size and analyst following.

We present a summary of results for these tables. The columns correspond to the respective samples, which are the same as in the previous tables with the innovation being that each column is further partitioned into two groups using the median of firm size or analyst following. The rows present only the coefficients on the *ESTIMIZE* variable for each respective regression.

For both forecast accuracy and bias in Table 8, we find no statistically significant differences across the firm-size groups for either earnings or revenue forecasts. The results of

[7] To further explore the robustness of our results, we re-run our tests excluding forecasts from contributors that only contribute for one firm. Are results are similarly except for revenue FERR which is no longer statistically significant.

Table 9 also provide no evidence of accuracy differences for earnings or revenue forecasts across the coverage partitions. There is some evidence of greater optimism for estimize in low-coverage firms, at least for revenues in the short-horizon sample. Yet there is also evidence of incremental pessimism for revenue forecasts in the longer-horizon forecasts for these firms.

The main results of Table 4 found the estimize earnings forecasts to be as accurate as the sell-side. The cross-sectional analyses show that result holds in all partitions. We had expected that only for smaller or less-covered firms would the estimize analysts be as accurate (H3). The power of our cross-sectional tests may be limited by the relatively small sample size which is also somewhat skewed to larger firms.

4.4. Revisiting the accuracy and bias result

As noted earlier, we find that estimize analysts, on average, are as accurate as sell-side analysts despite the fact that they show a slight relative optimistic bias, particularly in the short-horizon window. We conjecture that a walk-down of their forecasts by sell-side analysts contributes to this result. To explore that possibility, in Table 10, we present univariate comparisons of the sell-side's most recent forecast, i.e., the one issued closest to the actual earnings announcement versus all prior forecasts. In terms of accuracy, not surprisingly, the magnitude of the forecast error declines for the most recent forecast relative to previous ones. This is true for both earnings and revenue. For example, prior earnings forecasts have a mean FERR of 0.0052 versus 0.0030 for the last forecast. The same pattern appears for revenue forecasts, that is, 0.0153 versus 0.0088 respectively. Of greater relevance are the bias measures. For both earnings and revenue, we see the mean prior forecasts are negative, supporting optimism, however, the last or most recent forecast mean is positive, suggesting pessimism. For earnings, the mean of prior forecasts is -0.0016, in contrast to the most recent mean of 0.0005. The comparison for revenue is similar. This contrast is representative of the walk-down first presented in Richardson et al. (2004).

Performing a similar analysis for estimize is problematic since many analysts only forecast once per quarter. However, Table 3 can be used as a crude proxy. For earnings, comparing across the greater-than-30-days-horizon group and the less-than-and-equal-to-30-days group, in the bias row, we also see the switch from optimism to pessimism (-0.0003 versus 0.0004), but the change is less dramatic than that of the sell-side above. For revenue forecast bias, the results are mixed. Based on means, the most recent (<30 days) buy-side revenue forecasts seem more optimistic than the prior forecasts (-0.0009 versus 0.0002). The medians suggest the opposite (-0.0000 versus -0.0002).

Both the means and medians indicate greater optimism for IBES earnings and revenue forecasts relative to estimize in the greater-than-30-days horizon. However, for the shorter horizon (<30 days), the opposite is true as the results are consistent with greater optimism in the estimize forecasts. So the sell-side represents both ends of the spectrum, the most optimistic in long horizons and the most pessimistic in short horizons.

4.5 Market test

Finally, we report the short-window ERC regression results in Table 11. We report two sets of results for earnings, one relating signed three-day size-adjusted buy and hold returns with consensus forecast bias and the other relating the absolute value of both the short-window stock returns and consensus forecast errors. Since the estimize forecasts are primarily short-term, we limit our test to forecasts issued within 30 days to allow a fairer comparison. The results show that announcement-period stock returns are more strongly associated with the signed earnings surprise calculated using estimize forecasts. The ERC based on estimize forecasts is 3.093, significantly larger than the 2.413 resulting from IBES forecasts. The difference in these two ERCs is statistically significant (p-value<0.05). In contrast, the unsigned results show little difference in magnitude or statistical significance. We interpret these results in combination with our previous findings as support for the story that although there is little difference in accuracy between the two groups, the fact that estimize forecasts are relatively less pessimistic in the short-horizon results in a better representation of market expectations, as evidenced by the stronger association with returns.

5. Conclusion

We explore a new phenomenon, crowdsourcing of forecasts. We obtain revenue and earnings forecasts from estimize. Estimize is an open platform to which all members can contribute forecasts. We compare these forecasts to those of sell-side analysts covering the same firms, found on IBES. Our results support the effectiveness of crowdsourcing. We find no difference in accuracy, on average. Although we do find relative optimism for the estimize group, especially in the short horizon, our analysis suggests it is at least in part due to the extreme pessimism of the final forecasts prior to the earnings announcement of sell-side analysts. We confirm the superiority of estimize forecasts by demonstrating a stronger association with returns around the corresponding earnings announcement.

Finally, in cross-sectional analysis, we find that the forecast accuracy equivalency holds across firm size and analyst coverage partitions. Similarly, we find no difference for earnings forecast bias across the partitions, but there is some evidence that the revenue forecast bias of the estimize analysts may be concentrated in low analyst coverage firms. We leave for future research an explanation for this finding.

Much has been written about sell-side analyst incentives and the impact on their reporting. Estimize provides a new source of forecast data for both market participants and academics that is perhaps a better reflection of market expectations because it is free of the conflicts sell-side analysts face.

However, our paper is not without caveats. Buy-side and independent analysts may face their own incentives, of which little has been written or is known, and so future research may uncover corresponding shortcomings. Further, with the relatively short life of estimize, our sample period is limited, and thus our analysis is clustered in a small window of time. Therefore, its generalizability is an open question. Finally, although it is well known that IBES does not represent all sell-side analysts, its coverage is fairly broad. Little is known about the universe of non sell-side forecasts and forecasters so it is difficult to generalize our findings to all buy-side or independent analysts.

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Table 1
Estimize Forecasts
Sample Selection

	# of Firms	# of Earnings Forecasts
Initial sample	1,415	18,048
Less:		
Missing IBES coverage	(12)	(151)
Missing other data	(14)	(383)
Observations with a forecast date after the announcement date	(2)	(28)
Final sample of firms	1,387	17,486
Less:		
Observations without an IBES forecast in the same forecast horizon	(245)	(2,442)
Final sample of firms with an IBES forecast in the same forecast horizon	**1,142**	**15,044**

This table delineates the sample selection process. We obtain the forecast data from estimize. Footnote 1 contains the company's description of their contributors. We first require firms to have a matching IBES firm. We then eliminate firms without available data necessary to compute our dependent and control variables. We next eliminate firms with a negative forecast horizon. This results in a sample of 1,387 firms and 17,486 observations. Finally, we limit our sample to those observations with an IBES forecast in the same approximate forecast horizon (within 30 days or greater than 30 days). Horizon is the number of days between the forecast date and the earnings announcement date. The time-matched sample consists of 1,142 firms and 15,044 observations.

Table 2
Comparison of the ESTIMIZE Sample and IBES

Panel A: Comparison of Firms Covered by ESTIMIZE and IBES Universe

Market Capitalization (in billions)

	Mean	Median	T-test	Wilcoxon Test
Estimize sample firms	10.97	2.72	0.0000	0.0000
IBES universe	5.67	0.79		

Market-to-Book Ratio

	Mean	Median	T-test	Wilcoxon Test
Estimize sample firms	3.93	2.31	0.0000	0.0000
IBES universe	3.14	1.75		

Panel B: Coverage of Firms by ESTIMIZE and IBES Forecasters

ESTIMIZE Forecasts

	N	Mean	Median	Std. Dev.
Forecasters per firm	1,387	10.33	3.00	29.32
Age of forecasts	17,486	18.90	2.00	61.11
Forecasts per firm per forecaster per quarter	2,805	1.00	1.00	0.00
Firms covered by forecaster	1,951	7.43	1.00	36.79

IBES Forecasts (Firm and Forecast Period matched to buy-side sample above)

	N	Mean	Median	Std. Dev.
Analysts per firm	1,387	17.17	15.00	10.13
Age of forecasts	189,866	185.08	188.00	105.39
Forecasts per firm per analyst per quarter	8,825	3.64	3.00	2.63

See Table 1 for estimize sample selection.

Table 3
Comparison of ESTIMIZE and IBES Forecast Accuracy and Bias

	Full Sample with a Matching Horizon Forecast		HORIZON<=30		HORIZON>30		Robustness Sample	
	ESTIMIZE	IBES	ESTIMIZE	IBES	ESTIMIZE	IBES	ESTIMIZE	IBES
FERR (Earnings)								
Mean	0.0025	0.0046	0.0023	0.0030	0.0038	0.0048	0.0025	0.0054
Median	0.0010	0.0016	0.0009	0.0012	0.0017	0.0016	0.0010	0.0019
N	15,044	73,645	13,005	9,170	2,039	64,475	17,486	189,866
t-test	0.0000		0.0000		0.0000		0.0000	
Wilcoxon test	0.0000		0.0000		0.9135		0.0000	
BIAS (Earnings)								
Mean	0.0003	-0.0010	0.0004	0.0009	-0.0003	-0.0013	0.0002	-0.0018
Median	0.0002	0.0000	0.0002	0.0004	0.0000	0.0000	0.0002	0.0000
N	15,044	73,645	13,005	9,170	2,039	64,475	17,486	189,866
t-test	0.0000		0.0000		0.0000		0.0000	
Wilcoxon test	0.0000		0.0000		0.0004		0.0000	
FERR (Revenue)								
Mean	0.0075	0.0135	0.0068	0.0089	0.0126	0.0142	0.0078	0.0164
Median	0.0022	0.0038	0.0020	0.0022	0.0045	0.0042	0.0023	0.0050
N	15,467	68,089	13,420	9,433	2,047	58,656	17,479	167,356
t-test	0.0000		0.0000		0.0018		0.0000	
Wilcoxon test	0.0000		0.0181		0.0475		0.0000	
BIAS (Revenue)								
Mean	-0.0007	-0.0031	-0.0009	0.0013	0.0002	-0.0038	-0.0008	-0.0044
Median	-0.0001	-0.0004	-0.0000	0.0002	-0.0002	-0.0006	-0.0000	-0.0007
N	15,467	68,089	13,420	9,433	2,047	58,656	17,479	167,356
t-test	0.0000		0.0000		0.0000		0.0000	
Wilcoxon test	0.0000		0.0000		0.0000		0.0000	

See Table 1 for buy-side sample selection. FERR is calculated as $|\text{Actual - Forecast}|$ and is scaled by the share price at the end of the previous quarter for earnings and the market value of equity at the end of the previous quarter for revenue. BIAS is calculated as Actual - Forecast and is scaled by the share price at the end of the previous quarter for earnings and the market value of equity at the end of the previous quarter for revenue. HORIZON is the number of days between the forecast date and the earnings announcement date.

Table 4
Earnings Forecast Error

DEPEDENT VARIABLE: FERR	(A) Full Sample of Firms Covered by both Estimize and IBES with a Matching Horizon Forecast	(B) Forecasts with Horizon <=30 days	(C) Forecasts with Horizon >30 days	(D) Robustness Sample of Firms Covered by Both Estimize and IBES
ESTIMIZE	-0.0000424	0.0000242	0.000417	0.000291
	(-0.23)	(0.16)	(1.36)	(1.53)
HORIZON	0.0000110***	0.0000277***	0.00000971***	0.0000122***
	(8.12)	(3.25)	(8.06)	(11.44)
FIRM SIZE	-0.000957***	-0.000577***	-0.00110***	-0.00106***
	(-3.99)	(-5.23)	(-3.75)	(-6.11)
LOSS	0.0138***	0.00706***	0.0171***	0.0162***
	(4.23)	(5.20)	(3.92)	(8.22)
FOLLOW	-0.00000593	0.00000408	-0.00000975	0.0000114
	(-0.60)	(1.13)	(-0.86)	(1.24)
INTERCEPT	0.0108***	0.00737***	0.0123***	0.0111***
	(4.11)	(5.00)	(3.87)	(5.86)
TIME AND INDUSTRY DUMMIES	YES	YES	YES	YES
N	88,689	22,175	66,514	207,352
Adj. R^2	0.229	0.187	0.255	0.310

This table contains regression results with earnings FERR as the dependent variable. See Table 1 for sample selection. FERR is calculated as │Actual - Forecast│and is scaled by the share price at the end of the previous quarter for earnings. ESTIMIZE is an indicator variable set equal to 1 if the forecast is from an estimize analyst and zero otherwise. HORIZON is the number of days between the forecast date and the earnings announcement date. FIRM SIZE is measured as the natural log of the market value of equity at the end of the previous quarter. LOSS is an indicator variable set equal to 1 if actual earnings are less than zero. FOLLOW is the total analyst coverage (buy-side and IBES) during the quarter. All continuous variables are winsorized at the 1% level. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10, 5, and 1 % level, respectively.

Table 5
Earnings Forecast Bias

DEPEDENT VARIABLE: BIAS	(A) Full Sample of Firms Covered by both Estimize and IBES with a Matching Horizon Forecast	(B) Forecasts with Horizon <=30 days	(C) Forecasts with Horizon >30 days	(D) Robustness Sample of Firms Covered by Both Estimize and IBES
ESTIMIZE	-0.000798***	-0.000550***	-0.000254	-0.00132***
	(-3.82)	(-3.78)	(-0.83)	(-5.99)
HORIZON	-0.0000123***	-0.00000832	-0.0000121***	-0.0000153***
	(-7.43)	(-1.11)	(-6.70)	(-11.68)
FIRM SIZE	0.000111	-0.0000502	0.000151	0.0000640
	(0.60)	(-0.51)	(0.65)	(0.42)
LOSS	-0.0142***	-0.00468***	-0.0188***	-0.0162***
	(-4.46)	(-4.71)	(-4.51)	(-8.30)
FOLLOW	-0.00000592	-0.00000735**	-0.00000401	-0.00000398
	(-0.93)	(-1.99)	(-0.54)	(-0.93)
INTERCEPT	0.00178	0.00138	0.00177	0.00259
	(0.74)	(0.59)	(0.61)	(1.35)
TIME AND INDUSTRY DUMMIES	YES	YES	YES	YES
N	88,689	22,175	66,514	207,352
Adj. R^2	0.174	0.077	0.221	0.247

This table contains regression results with earnings BIAS as the dependent variable. See Table 1 for sample selection. BIAS is calculated as Actual - Forecast and is scaled by the share price at the end of the previous quarter for earnings. ESTIMIZE is an indicator variable set equal to 1 if the forecast is from an estimize analyst and zero otherwise. HORIZON is the number of days between the forecast date and the announcement date. FIRM SIZE is measured as the natural log of the market value of equity at the end of the previous quarter. LOSS is an indicator variable set equal to 1 if actual earnings are less than zero. FOLLOW is the total analyst coverage (buy-side and IBES) during the quarter. All continuous variables are winsorized at the 1% level. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10, 5, and 1 % level, respectively.

Table 6
Revenue Forecast Error

DEPEDENT VARIABLE: FERR	**(A) Full Sample of Firms Covered by both Estimize and IBES with a Matching Horizon Forecast**	**(B) Forecasts with Horizon <=30 days**	**(C) Forecasts with Horizon >30 days**	**(D) Robustness Sample of Firms Covered by Both Estimize and IBES**
ESTIMIZE	0.000499	0.000314	0.00320***	0.00114**
	(0.90)	(0.66)	(2.95)	(2.01)
HORIZON	0.0000392***	0.0000967***	0.0000374***	0.0000436***
	(8.50)	(3.79)	(8.67)	(14.38)
FIRM SIZE	-0.00340***	-0.00148***	-0.00415***	-0.00410***
	(-4.12)	(-4.38)	(-3.98)	(-6.54)
FOLLOW	-0.0000165	0.00000537	-0.0000280	0.0000153
	(-0.67)	(0.63)	(-0.95)	(0.73)
INTERCEPT	0.0381***	0.0183***	0.0460***	0.0451***
	(4.37)	(4.44)	(4.17)	(6.90)
TIME AND INDUSTRY DUMMIES	YES	YES	YES	YES
N	83,556	22,853	60,703	184,835
Adj. R^2	0.178	0.164	0.192	0.186

This table contains regression results with revenue FERR as the dependent variable. See Table 1 for sample selection. FERR is calculated as |Actual - Forecast| and is scaled by the market value of equity at the end of the previous quarter for revenue. ESTIMIZE is an indicator variable set equal to 1 if the forecast is from an estimize analyst and zero otherwise. HORIZON is the number of days between the forecast date and the announcement date. FIRM SIZE is measured as the natural log of the market value of equity at the end of the previous quarter. FOLLOW is the total analyst coverage (buy-side and IBES) during the quarter. All continuous variables are winsorized at the 1% level. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10, 5, and 1 % level, respectively.

Table 7
Revenue Forecast Bias

DEPEDENT VARIABLE: BIAS	**(A) Full Sample of Firms Covered by both Estimize and IBES with a Matching Horizon Forecast**	**(B) Forecasts with Horizon <=30 days**	**(C) Forecasts with Horizon >30 days**	**(D) Robustness Sample of Firms Covered by Both Estimize and IBES**
ESTIMIZE	-0.00119**	-0.00218***	0.00240***	-0.00186***
	(-2.35)	(-4.80)	(2.80)	(-3.65)
HORIZON	-0.0000243***	-0.0000207	-0.0000243***	-0.0000304***
	(-5.26)	(-0.96)	(-4.78)	(-9.48)
FIRM SIZE	0.00134**	0.000363	0.00162**	0.00190***
	(2.18)	(1.17)	(2.09)	(3.76)
FOLLOW	-0.0000226	-0.000017**	-0.0000224	-0.0000280*
	(-1.37)	(-2.02)	(-1.11)	(-1.80)
INTERCEPT	-0.0146**	-0.00350	-0.0174*	-0.0167***
	(-2.05)	(-0.93)	(-1.92)	(-2.91)
TIME AND INDUSTRY DUMMIES	YES	YES	YES	YES
N	83,556	22,853	60,703	184,835
Adj. R^2	0.074	0.066	0.087	0.096

This table contains regression results with revenue BIAS as the dependent variable. See Table 1 for sample selection. BIAS is calculated as Actual - Forecast and is scaled by the market value of equity at end of the previous quarter for revenue. ESTIMIZE is an indicator variable set equal to 1 if the forecast is from an estimize analyst and zero otherwise. HORIZON is the number of days between the forecast date and the announcement date. FIRM SIZE is measured as the natural log of the market value of equity at the end of the previous quarter. FOLLOW is the total analyst coverage (buy-side and IBES) during the quarter. All continuous variables are winsorized at the 1% level. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10, 5, and 1 % level, respectively.

Table 8
Forecast Error and Bias for Subsamples Partitioned Based on the Median of Firm Size

	Full Sample with a Matching Horizon Forecast		Horizon<=30 Days		Horizon>30 Days		Robustness Sample	
	Small Firms	**Large Firms**	**Small Firms**	**Large Firms**	**Small Firms**	**Large Firms**	**Small Firms**	**Large Firms**
DEPENDENT VARIABLE: FERR (EPS)								
ESTIMIZE	0.0000711	0.000195	-0.0000190	-0.00000877	0.000417	0.000421**	0.0000905	0.000400***
	(0.23)	(1.48)	(-0.08)	(-0.05)	(0.84)	(2.39)	(0.24)	(2.69)
Difference in Coefficients	0.0001239		0.00001023		0.000004		0.0003095	
DEPENDENT VARIABLE: BIAS (EPS)								
ESTIMIZE	-0.00117***	-0.000731***	-0.000581**	-0.000776***	-0.000257	-0.000268	-0.00174***	-0.00101***
	(-3.06)	(-4.24)	(-2.50)	(-3.72)	(-0.42)	(-1.00)	(-4.02)	(-5.06)
Difference in Coefficients	0.000439		-0.000195		-0.000011		0.00073	
DEPENDENT VARIABLE: FERR (REVENUE)								
ESTIMIZE	0.000632	0.00108	0.000392	0.000190	0.00162	0.00333***	0.00106	0.00128**
	(0.85)	(1.45)	(0.60)	(0.27)	(1.31)	(2.94)	(1.08)	(2.10)
Difference in Coefficients	0.000448		-0.000202		0.00171		0.00022	
DEPENDENT VARIABLE: BIAS (REVENUE)								
ESTIMIZE	-0.00119*	-0.00121	-0.00215***	-0.00238***	0.00297**	0.00173	-0.00187**	-0.00167***
	(-1.76)	(-1.52)	(-3.42)	(-3.58)	(2.04)	(1.64)	(-2.10)	(-2.95)
Difference in Coefficients	-0.00002		-0.00023		-0.00124		0.00521	

This table contains regression results for subsamples partitioned based on the median of the market value of equity. See Table 1 for sample selection. FERR is calculated as |Actual - Forecast| and is scaled by the share price at the end of the previous quarter for earnings and the market value of equity at the end of the previous quarter for revenue. BIAS is calculated as Actual - Forecast and is scaled by the share price at the end of the previous quarter for earnings and the market value of equity at end of the previous quarter for revenue. ESTIMIZE is an indicator variable set equal to 1 if the forecast is from an estimize analyst and zero otherwise. *, **, and *** indicate statistical significance at the 10, 5, and 1 % level, respectively.

Table 9
Forecast Error and Bias for Subsamples Partitioned Based on the Median of Analyst Following

	Full Sample with a Matching Horizon Forecast		Horizon<=30 Days		Horizon>30 Days		Robustness Sample	
	Low Coverage	High Coverage	Low Coverage	High Coverage	Low Coverage	High Coverage	Low Coverage	High Coverage
DEPENDENT VARIABLE: FERR (EPS)								
ESTIMIZE	-0.000515	0.000195	0.000174	-0.000236	0.000251	0.000511	-0.0000152	0.000557**
	(-1.47)	(0.81)	(0.80)	(-0.95)	(0.56)	(1.45)	(-0.06)	(2.12)
Difference in Coefficients	0.00071		-0.00041		0.00026		0.000709	
DEPENDENT VARIABLE: BIAS (EPS)								
ESTIMIZE	-0.000667**	-0.000912***	-0.00064***	-0.000619***	0.000624	-0.000510	-0.00100***	-0.00172***
	(-2.43)	(-2.64)	(-3.30)	(-3.18)	(1.25)	(-1.40)	(-4.22)	(-4.78)
Difference in Coefficients	-0.000245		0.000021		-0.001134#		-0.00072#	
DEPENDENT VARIABLE: FERR (REVENUE)								
ESTIMIZE	-0.000360	0.000643	0.000297	0.000460	0.00201	0.00330**	-0.0000369	0.00137**
	(-0.43)	(0.88)	(0.40)	(0.78)	(1.62)	(2.03)	(-0.04)	(2.48)
Difference in Coefficients	0.001003		0.000163		0.00129		0.0014069	
DEPENDENT VARIABLE: BIAS (REVENUE)								
ESTIMIZE	-0.00166**	-0.000726	-0.00291***	-0.00116*	0.00443***	0.00118	-0.00231***	-0.00114**
	(-2.41)	(-0.93)	(-4.60)	(-1.86)	(2.95)	(0.97)	(-2.83)	(-2.08)
Difference in Coefficients	0.000934		0.00175##		-0.00325#		0.00117	

This table contains regression results for subsamples partitioned based on the median of analyst following (FOLLOW). See Table 1 for sample selection. FERR is calculated as │Actual - Forecast│and is scaled by the share price at the end of the previous quarter for earnings and the market value of equity at the end of the previous quarter for revenue. BIAS is calculated as Actual - Forecast and is scaled by the share price at the end of the previous quarter for earnings and the market value of equity at end of the previous quarter for revenue. ESTIMIZE is an indicator variable set equal to 1 if the forecast is from an estimize analyst and zero otherwise. *, **, and *** indicate statistical significance at the 10, 5, and 1 % level, respectively. ## indicates statistical significance at the 5% level and # indicates statistical significance at the 1% level.

Table 10
Comparison of Most Recent and Prior IBES Forecasts

FERR (EPS)	**Mean**	**Median**	**T-test**	**Wilcoxon Test**
Prior Forecasts	0.0052	0.0019	0.0000	0.0000
Most Recent Forecast	0.0030	0.0011		

BIAS (EPS)	**Mean**	**Median**	**T-test**	**Wilcoxon Test**
Prior Forecasts	-0.0016	-0.0002	0.0000	0.0000
Most Recent Forecast	0.0005	0.0005		

FERR (REVENUE)	**Mean**	**Median**	**T-test**	**Wilcoxon Test**
Prior Forecasts	0.0153	0.0046	0.0000	0.0000
Most Recent Forecast	0.0088	0.0023		

BIAS (REVENUE)	**Mean**	**Median**	**T-test**	**Wilcoxon Test**
Prior Forecasts	-0.0044	-0.0010	0.0000	0.0000
Most Recent Forecast	0.0002	0.0003		

This table provides results comparing the most recent IBES forecast to prior IBES forecasts for the sample of firms detailed in Table 1. The most recent forecast is the last forecast prior to the earnings announcement, and prior forecasts are all others. FERR is calculated as $|\text{Actual - Forecast}|$ and is scaled by the share price at the end of the previous quarter for earnings and the market value of equity at the end of the previous quarter for revenue. BIAS is calculated as Actual - Forecast and is scaled by the share price at the end of the previous quarter for earnings and the market value of equity at end of the previous quarter for revenue.

Table 11
Abnormal Stock Returns and Consensus Earnings Forecasts

DEPENDENT VARIABLE	(A) BHAR3	(B) BHAR3	(C) ABS_BHAR3	(D) ABS_BHAR3
INTERCEPT	-0.0305*	-0.0330*	0.0548***	0.0541***
BIAS_IBES	2.413***			
BIAS_ESTIMIZE		3.093***		
FERR_IBES			2.474***	
FERR_ESTIMIZE				2.494***
TIME AND INDUSTRY DUMMIES	YES	YES	YES	YES
N	1,819	1,819	1,819	1,819
Adj. R^2	0.017	0.031	0.143	0.144
Difference in Coefficients on IBES and BUY-SIDE	0.68##		0.02	

This table contains regression results with BHAR3 and ABS_BHAR3 as the dependent variables. BHAR3 is the size-adjusted buy-and-hold return during the three trading days around the earnings announcement. ABS_BHAR3 is the absolute value of BHAR3. BIAS_IBES is the consensus forecast bias for IBES forecasts made during the 30 days prior to the information release; BIAS_ESTIMIZE is the consensus forecast bias for estimize forecasts made during the 30 days prior to the information release; FERR_IBES is the consensus forecast error for IBES forecasts made during the 30 days prior to the information release; and FERR_ESTIMIZE is the consensus forecast error for estimize forecasts made during the 30 days prior to the information release. When a forecaster has more than one forecast during the period, only the most recent forecast is included. The variables are scaled by share price at the end of the previous period. All continuous variables are winsorized at the 1% level. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10, 5, and 1 % level, respectively. ## indicates statistical significance at the 5% level.