Does Crowdsourced Research Discipline Sell-Side Analysts?

Russell Jame, Stanimir Markov, and Michael Wolfe*

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Abstract

We examine whether increased competition stemming from technological innovation disciplines sell-side analysts. We document a decline in short-term forecast bias for firms added to Estimize, an open platform that crowdsources short-term earnings forecasts, relative to matched control firms; this decline is greater when (1) existing sell-side competition is smaller, (2) earnings uncertainty is higher, and (3) Estimize coverage is less biased and more accurate. We also document an increase in short-term forecast accuracy and representativeness. Finally, we find no change in bias for longer-horizon forecasts or recommendations, suggesting competition from Estimize rather than broad economic forces drives our results.

* Jame is from the Gatton College of Business and Economics, University of Kentucky, russell.jame@uky.edu. Markov is from the Cox School of Business, Southern Methodist University, smarkov@mail.smu.edu. Wolfe is from the Pamplin College of Business, Virginia Tech, mcwolfe@vt.edu. We thank Julian Kolev, Michael Chin, and seminar participants at Arizona State University, Rutgers University, the Southern Methodist University, University of Kentucky, University of South Florida, and University of West Virginia for helpful comments, and Leigh Drogen and Josh Dulberger from Estimize for providing the data and answering our questions.

1. Introduction

The role of sell-side equity analysts as a key information intermediary in capital markets is well documented. Analyst earnings forecasts are generally superior to time-series forecasts, and a well-accepted measure of the market expectation (Brown and Rozeff, 1978; Kothari, 2001); analyst stock recommendations tend to be profitable (e.g., Womack, 1996; Jegadeesh, Kim, Krische, and Lee, 2004); and stocks covered by more analysts tend to enjoy lower cost of capital and greater liquidity (e.g., Kelly and Ljungqvist, 2012). At the same time, the sell-side research industry is fraught with conflicts of interest. Dependent on managers for information and subsidized by investment banking revenues, analysts have incentives to bias their research to please managers and facilitate investment banking activities. A vast literature concludes analyst research is biased, in some cases even distorting market prices and harming less sophisticated investors. For instance, naïve fixation on optimistic long-term forecasts explains at least partially the higher returns to contrarian investment strategies (Dechow and Sloan, 1997), whereas naïve fixation on pessimistic short-term forecasts unduly increases the valuation of firms that consistently meet analyst expectations (Kasznik and McNichols, 2002). Large investors appropriately interpret a Hold recommendation as a Sell, but small investors do not (Malmendier and Shantikumar, 2007).[1] With biased research impacting capital market prices and investor welfare, there is much interest in understanding the forces constraining sell-side bias.

Our study investigates whether increased competition stemming from technological and institutional innovations has a disciplining effect on sell-side analysts. In recent years investors have become more reliant on social media sites for information (e.g., blogs, message boards, and

[1] See Mehran and Stulz (2007) for a survey of the literature on conflicts of industry in the investment industry.

chat rooms). Seeking to capitalize on this trend and harness the wisdom of crowds, two recent entrants in the investment research industry, Seeking Alpha and Estimize, offer investors help in picking stocks and forecasting corporate earnings, respectively. Early evidence suggests that both Seeking Alpha and Estimize are useful supplementary sources of new information in capital markets (see Chen et al., 2014; and Jame et al., 2016, respectively). Further, consistent with Estimize contributors lacking incentives to cozy up to corporate management or help generate investment banking revenues, Jame et al. (2016) finds robust evidence that Estimize forecasts are less biased than sell-side forecasts. Our hypothesis is that crowdsourced research, which is informative, prone to fewer conflicts of interest, and readily available, can make it easier for investors to unravel sell-side biases, and therefore exert a disciplining effect on the sell-side.

Our study focuses on Estimize for several reasons. By freely providing investors with a clear benchmark forecast, Estimize helps investors unravel sell-side bias; in contrast, other prominent sources of investment research with crowdsourcing features freely provide research commentaries which must be further processed to obtain a benchmark recommendation or forecast (e.g., Seeking Alpha and StockTwits) or selectively provide recommendations to registered users (SumZero).[2] Second, a unique feature of Estimize is the collocation of crowdsourced forecasts and sell-side forecasts, further facilitating their comparison. Finally, since the overwhelming majority of Estimize forecasts are short-term (one-quarter ahead) forecasts, the setting affords a sharp prediction about the effect of competition on sell-side forecasting behavior: in particular, we expect Estimize to weaken sell-side analysts' propensity to issue low, easy to beat quarterly earnings forecasts (hereafter: short-term pessimism).

[2] Section 2.2.2 of Jame et al., (2016) and Chapter 5 of Egger (2014) survey key sources of crowdsourced investment research.

To test this prediction, we follow a standard difference-in-difference approach: Our treatment sample includes firms added to the Estimize platform in 2012. Our outcome variable is the difference between short-term pessimism over the three year “after” period (2013-2015) and short-term pessimism in the three year “before” period (2009-2011). We measure pessimism as actual earnings minus the average of all IBES one-quarter ahead forecasts issued within 120 days of the earning announcement, scaled by stock price at the end of the prior year. For each treated firm, we select a control firm matched on size, book-to-market, and short-term pessimism (measured over the pre-event period).

We find that treated firms have positive forecast errors of 13.8% in the “before” period, and 5.1% in the “after” period: an economically and statistically significant 8.7 percentage point (or 63%) drop in forecast pessimism. In contrast, the control firms experience a statistically insignificant 0.2 percentage point increase in pessimism. Furthermore, the difference-in-difference estimate of 8.9% is highly significant. We find similar results when we control for firm characteristics that influence sell-side bias, implement the propensity score matching method in selecting control firms, or use alternative measures of pessimism (e.g., meet or beat indicator). Furthermore, we document a leftward shift in the entire distribution of forecast pessimism, suggesting the decline in pessimism is widespread.

Accuracy and representativeness, defined as the ability to measure the market expectation, are basic forecast attributes that increased competition likely enhances. Using the same difference-in-difference design, we document that treated firms experience a statistically and economically significant decline in absolute forecast errors relative to control firms. Similarly, the relation between sell-side consensus forecast errors and earnings announcement returns strengthens for treated firms relative to control firms, consistent with Estimize making the sell-side consensus a more accurate proxy for the market expectation.

We conduct a series of tests to strengthen our inference of a causal relation between the arrival of a new competitor, Estimize, and the decline in short-term pessimism. First, we confirm that treated and control firms do not experience significant differences in pessimism in the three years preceding the introduction of Estimize, suggesting that pre-trends are unlikely to explain our results. We also find that the difference-in-difference is significantly negative in all three years of the post-event window, suggesting the decline in pessimism is permanent rather than temporary.

Second, we demonstrate that our results are stronger in circumstances where theory suggests a greater role for Estimize as a disciplining device. Specifically, consistent with the intuition that changes in competition are more important when existing competition is low, the difference-in-difference estimate is a statistically significant -15% for firms in the bottom quartile of sell-side coverage and a statistically insignificant -4% for firms in the top quartile. Furthermore, consistent with the view that the value of an external benchmark is greater when high information uncertainty makes it difficult for investors to unravel sell-side bias alone, we find the largest decline in pessimism for firms in the top quartile of forecast dispersion (or market-to-book) and no decline in pessimism for firms in the bottom quartile. Finally, we confirm the intuition that a more unbiased and accurate benchmark is a more effective benchmark. A sort on prior quarter Estimize consensus bias (accuracy) reveals a decline in pessimism of about -11% (-10%) when Estimize coverage is most unbiased (accurate) and no change in pessimism when Estimize coverage is least unbiased (accurate).

Our last set of tests addresses the concern that Estimize coverage is correlated with broad unobservable forces that steer sell-side analysts toward providing less biased research (e.g., by increasing reputation costs or reducing dependence on management for information). This explanation predicts less short-term forecast pessimism as well as less long-term forecast optimism (O'Brien, 1988) and less favorable stock recommendations (Michaely and Womack, 1999). In contrast, our hypothesis predicts only a reduction in short-term forecast pessimism, as long-term forecasts are rare and stock recommendations non-existent on the Estimize platform. Consistent with our hypothesis, we find no evidence that stocks added to Estimize experience a decline in optimism for longer-horizon earnings forecasts or investment recommendations relative to matched control firms.

Our primary contribution is toward understanding the market forces that constrain sell-side conflicts of interest. While prior literature focuses on reputational considerations (e.g., Fang and Yasuda, 2009), competition among sell-side analysts (e.g., Hong and Kacperczyk, 2010; Merkley, Michaely, and Pacelli, 2016), and regulation (e.g., Barber et al., 2006; Kadan et al., 2009), our results point to competition from new entrants as a force upending the investment research industry and disciplining the sell-side. The arrival of Estimize can be viewed as the culmination of a decades-long trend of technology empowering investors to bypass traditional sell-side research and decades-long investor criticism of conflicts of interest in the investment research industry.

Our study fits well in a broader literature that examines the effect of competition on bias in other markets. In particular, Becker and Milbourn (2011), Doherty et al. (2012), and Xia (2014) examine entrants in the highly regulated and non-competitive credit rating market, Fitch, S&P, and Egan Jones, respectively, whose organization and practices largely mirror those of the incumbents, whereas we study a market that is less regulated and more competitive, and an entrant, Estimize, whose business model and practices dramatically differ from those of the incumbents, the sell-side. Genztkow and Shapiro (2008) and Gentzkow, Glaeser and Goldin (2006) focus on the market for news. Our study's result that technology-engendered competition to sell-side research suppliers reduces sell-side bias echoes Gentzkow, Glaeser and Goldin's (2006) result that technology-engendered competition among newspapers in the 19th century reduces newspaper bias.

Finally, our study helps paint a more complete picture of the role of crowdsourced research in capital markets. Prior literature documents the emergence of crowdsourced research as a supplemental source of information in capital markets. For example, Chen et al. (2014) show that the tone of commentaries posted on *Seeking Alpha* predicts stock returns, and Jame et al. (2016) find that Estimize forecast revisions have a distinct effect on stock prices.[3] Building on these studies, we show that crowdsourced research reduces sell-side bias and increases sell-side accuracy. More broadly, our results illustrate that empowering retail investors to produce and disseminate valuable information can disrupt the traditional Wall Street information ecosystem (Costa, 2010).

2. Background and Hypothesis Development

2.1 Analyst Bias and the Moderating Role of Competition

Managers generally desire favorable sell-side coverage and they can shape analyst incentives by rewarding optimistic analysts with investment banking business, as well as private access and information. Consistent with the sell-side succumbing to management pressures, there is much evidence that analysts issue optimistic long-term earnings forecasts and recommendations, and that this optimism is explained by incentives to acquire investment banking deals (e.g., Lin

[3] Other studies that explore the impact of crowdsourced research on market prices include Crawford et al. (2014), Bliss et al. (2016), and Da and Huang (2016).

and McNichols, 1998; Michaely and Womack, 1999), and obtain valuable information (e.g., Francis and Philbrick, 1993; Das, Levine, and Sivaramakrishnan 1998).

At the same time, managers believe the market unduly rewards firms that meet or beat the sell-side consensus, measured in the days immediately prior to earnings announcements. As a consequence, managers desire a low, beatable earnings benchmark,[4] potentially creating incentives for analysts to reduce their forecasts. Extensive evidence suggests that analysts switch from long-term optimism to short-term pessimism, and that this forecasting behavior is rewarded by management (e.g., Ke and Yu, 2006, and Feng and McVay, 2010).

Factors that moderate the adverse impact of analyst conflicts of interest include regulation, reputational concerns, and competition. We briefly discuss the moderating role of regulation and expound on the moderating roles of reputation and competition with a view to developing our hypothesis that technology-induced competition can also reduce sell-side bias.

The extent to which analysts bias research to attract investment banking business largely depends on the investment bankers' ability to influence research department budgets and research analyst compensation. A string of recent reforms aim to increase analyst independence from investment bankers (e.g., NASD Rule 2711, NYSE Rule 472, and the Global Settlement), and evidence suggests these reforms have reduced but not fully eliminated analyst propensity to issue biased research (Barber et al. 2006; Kadan et al., 2009).

Sell-side research is an "experience" good purchased by investors in a multi-period setting, creating a role for reputation as a disciplining device. As discussed in Fang and Yasuda, (2009), publishing biased research creates a fundamental trade-off for all analysts: a reputation loss and

[4] See Graham et al. (2005) for survey evidence that CFOs guide sell-side analyst forecasts down to increase the likelihood of meeting the consensus, and Kasznik and McNichols (2002) and Bartov et al. (2002) for archival evidence that meeting or beating is rewarded by the market.

worsened long-term career prospects or an increase in investment banking-driven compensation. Since analysts with better reputation stand more to lose from biasing their research than other analysts do, theory predicts they will bias their research less. Consistent with this hypothesis, analysts rated "All-Stars" are less likely to issue biased research when conflicts of interest are more severe (Fang and Yasuda, 2009), and analyst bias is weaker for stocks heavily owned by institutional investors, who are more likely to discern bias and impose a reputational penalty (Ljundqvist et al., 2007).

Hong and Kacperczyk, (2010) argue that competition can reduce analyst bias through at least two channels. First, from the firm's perspective, the cost of influencing analyst coverage is increasing in the number of analysts covering the firm. Intuitively, the supply of management time and transactions requiring investment banking services is largely fixed. As the total number of analysts covering the firm increases, a firm's ability to influence coverage is weakened. Second, greater competition can increase the diversity of incentives among suppliers, making it more likely that at least one analyst will be incentivized to remain independent and provide an unbiased forecast. Access to one or more unbiased forecasts allows investors to more easily unravel biases in forecasts issued by other analysts, resulting in reputation loss and worsened career outcomes.[5] In short, competition reduces bias by exposing and penalizing biased analysts.[6]

[5] Research in psychology suggests competition can discipline the sell side even in the absence of a reputational penalty. According to Kunda's (1970) theory of motivated reasoning, individuals motivated to arrive at a particular conclusion try to justify their conclusion to a dispassionate observer; and they draw the desired conclusion only if they can muster up the evidence necessary to support it (pp. 482-482). Sell-side analysts are motivated to issue pessimistic, easy-to-beat forecasts; widely available, accurate, and substantially less biased, Estimize forecasts make justifying biased sell-side forecasts to investors more difficult, thus causing a decline in sell-side bias.

[6] The general idea that competition can resolve conflict of interest problems between the provider of an experience good and a customer by encouraging reputation building behavior is developed in Horner (2002). In his model, greater competition strengthens reputation incentives by making the threat that a dissatisfied customer will terminate the relationship with the seller more credible.

An implicit assumption in the arguments that underlie the second channel is that investors cannot fully unravel analyst bias by themselves. This is a plausible assumption. First, to fully unravel analyst bias, investors would need to know the exact nature of the optimization problem solved by every analyst; even the most sophisticated institutional investors are unlikely to possess such knowledge.[7] Second, there is ample empirical evidence consistent with investor inability to fully unravel analyst bias. For instance, Dechow and Sloan (1997) find that much of the profitability of value-oriented strategies can be explained by investors naively following biased analyst forecasts. Several studies document retail investor's inability to unravel bias. Malmendier and Shanthikumar (2007) show that while large traders (presumably institutional investors) tend to discount buy recommendation of affiliated analysts, small traders (presumably retail investors) tend to interpret the buy recommendations literally. Analyzing a small sample of stocks where analysts were found to have issued misleading research, De Franco, Lu, and Vasvari (2007) find pronounced differences in trading behavior between large and small investors; by their estimates, individual investors lost "$2.2 billion, an amount that is approximately two and a half times the amount that institutions lose." (p. 72).

Empirical evidence on the role of competition in disciplining equity analysts is limited. Using broker mergers to identify exogenous changes in analyst competition, Hong and Kacperczyk (2010) find that a decline in competition results in greater optimism in longer-term earnings forecasts. An earlier study by Gu and Xue (2008) finds that non-independent analysts who cover firms covered by independent analysts issue more accurate and less biased earnings forecasts than other non-independent analysts, consistent with non-independent analysts disciplining independent analysts.

[7] Fischer and Verrecchia (2000) make this point eloquently in the context of earnings management.

In recent years, technological and institutional innovations have given rise to new competing sources of investment research. In this study, we propose that competition from Estimize, a provider of crowdsourced earnings forecasts, has a disciplining effect on sell-side analysts. We discuss key attributes of Estimize in Section 2.2 and argue these attributes generally satisfy the conditions under which competition reduces bias in Section 2.3.

2.2 Estimize

Estimize is an open platform which crowdsources earnings forecasts from a diverse set of contributors. Estimize has received significant public acclaim and is frequently listed among the top FinTech companies. [8] As of December 2015, Estimize has attracted forecasts from over 15,000 contributors, covering more than 2000 firms.[9] Estimize forecasts tend to be short-term focused; during our sample period of 2013 to 2015 more than 90% of all estimates are forecasts of current quarter (i.e., one-quarter ahead) earnings. Contributors to the platform include buy-side and sell-side analysts, portfolio managers, retail investors, corporate finance professionals, industry experts, and students. Estimize forecasts are available on Bloomberg and several other financial research platforms and are regularly referenced in prominent financial media sources including Forbes, Barron's, The Wall Street Journal, Investors' Business Daily, and Business Week. Estimize is often featured on CNBC and has signed a data-sharing agreement which allows its estimates to be presented across all CNBC platforms. Estimize also sells a feed of all estimates made on the platform though an API in real time to buy-side clients.

Estimize was founded by Leigh Drogen, a former hedge fund analyst, with the objective of "disrupting the whole sell-side analyst regime".[10] Drogen's view is that crowdsourcing estimates

[8] See for example https://www.benzinga.com/news/15/04/5395774/the-2015-benzinga-fintech-award-winners
[9] Estimize has experienced dramatic growth since the end of our sample period. As of December 2016, Estimize has over 40,000 unique contributors.
[10] http://www.businessinsider.com/estimize-interview-leigh-drogan-2011-12

from a diverse community should lead to a superior consensus for two reasons. First, by capturing the collective wisdom of a large and diverse group, the consensus can convey new information to the market. Second, by encouraging participation from individuals with varied backgrounds, Estimize contributors are more likely to be free from many of the conflicts of interest that bias the research of sell-side analysts.[11] Jame et al. (2016) find evidence that is largely consistent with these predictions. In particular, they document that quarterly forecasts provided by Estimize are significantly less pessimistic than sell-side forecasts. They also find that Estimize forecasts are more representative of the market's expectation of earnings and incrementally useful in forecasting earnings.

2.3 Hypothesis Development

Recall that the first mechanism through which competition reduces bias relates to the *cost of influence*. Estimize entry is likely to increase the firm's cost of influencing coverage more than the entry of a typical sell-side research provider because Estimize contributors are numerous, often anonymous, and do not depend on management for information: that is, they cannot be "bribed" by managers with information, private meetings for clients, and underwriting/advisory business.

The second channel through which competition reduces bias is to increase the likelihood that one or more competitors issue unbiased forecasts, thus helping investors identify and penalize biased analysts. Estimize handily meets this condition: Estimize contributors do not depend on management for information and their forecasts are significantly less biased than sell-side forecasts (Jame et al., 2016). Furthermore, the usefulness of Estimize forecasts as a benchmarking device is likely enhanced by their high accuracy. Intuitively, an unbiased, accurate benchmark forecast is more useful in debiasing the sell-side forecast than an unbiased, inaccurate benchmark forecast.

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[11] In particular, Drogen highlights his dissatisfaction with the sell-side's "tendency to skew estimates in favor of higher earnings beat rates for the companies they cover," https://www.estimize.com/beliefs

Finally, the process of unraveling sell-side bias is likely facilitated by the collocation of crowdsourced forecasts and sell-side forecasts on the Estimize website, in the financial media (e.g., Bloomberg and CNBC), and in datasets sold to quantitative investors. In a world of limited attention, the task of debiasing the sell-side consensus is simplified when the consensus and the benchmark forecast are in close proximity.[12]

The above arguments suggest that competition from Estimize can reduce sell-side analyst's bias. We predict a decline in one-quarter ahead sell-side forecast pessimism for stocks covered by Estimize because the majority of Estimize forecasts concern one quarter ahead earnings. We use the absence of longer-horizon forecasts and investment recommendations on the Estimize platform to conduct "placebo" tests of whether sell-side optimism also declines.

Several factors may attenuate and, perhaps, even eliminate the disciplining effect of Estimize. First, retail investors, who are least likely to unravel sell-side bias and most likely to benefit from Estimize arrival, may be unable to impose sufficiently large penalties to discipline sell-side analysts. While large institutional investors do have the ability to discipline sell-side analysts, they may already unravel analyst bias, or they may tolerate analyst bias if it helps them obtain private information and access to management. Second, firms may counter the creation of new sources of investment research by investing more resources to influence traditional sell-side research providers as well as their competitors. Finally, if sell-side analysts view Estimize as a fad and predict its quick demise, they may feel no need to change their forecasting behavior.

3. Data and Descriptive Statistics

[12] The potential value of Estimize as a debiasing tool has been recognized in the financial press: "*Adjusting for bias in short-term forecasts is harder. It is tempting simply to accept the errors--after all, they tend to be off by just a little… An alternative is to look at crowdsourcing websites such as Estimize. There punters--some amateur, and some professional--are shown Wall Street consensus estimates and asked to make their own forecasts. Estimize users beat Wall Street estimates two-thirds of time.*" (*The Economist*, 3 Dec. 2016, p. 64)

3.1 Sample Selection and Summary Statistics

So that we can reliably measure the change in sell-side bias around the introduction of Estimize in 2012, we require continuous sell-side coverage from 2009 to 2015, as reported by IBES. We also require that firms have non-missing book value of equity and stock price above $5 in the year prior to the introduction of Estimize. Our final sample includes 1,842 firms.

We obtain Estimize forecasts of earnings announced from January 2012 through December 2015.[13] For each forecast, the dataset contains the forecasted earnings per share, the date of the forecast, the actual earnings per share, the date of the earnings announcement, a unique id for each contributor, and the ticker symbol of the firm. Table 1 provides summary statistics regarding the breadth and depth of Estimize coverage. Of the 1,842 firms in our sample, 1,391 firms have at least one Estimize forecast during the sample period. Collectively, there are 172,566 forecasts made by 11,167 unique contributors. The mean (median) Estimize firm is covered by 9.1 (4.0) different contributors during a quarter. Estimize's coverage and contributor base have significantly grown over time. For example, the number of firm-quarters with forecasts has increased from 1,694 in 2012 to 5,011 in 2015, while the number of contributors has increased from 1,370 to 7,555 over the same period.

Panel B of Table 1 examines the characteristics of firms partitioned based on when the firm is first added to Estimize.[14] We observe that firms added in 2012 are larger, have greater sell-side coverage, and are more growth oriented (i.e., lower book-to-market ratios) than firms added in subsequent years. These firms also attract greater Estimize coverage: 11.7 contributors per quarter compared to less than 2.5 contributors for later Estimize additions.

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[13] Other studies that examine Estimize forecasts include Jame et al. (2016), Bliss et al. (2016), Da and Huang (2016), and Ertan et al. (2016).
[14] A firm is "added to Estimize" when it receives its first Estimize forecast.

3.2 The Properties of Estimize and IBES Quarterly Forecasts

In this section we compare the properties of Estimize and IBES quarterly earnings forecasts. We limit the sample to 772 firms added to Estimize in 2012 (see Panel B of Table 1) and we report forecast properties over the 2013-2015 sample period.[15] We consider only forecasts issued within 120 days of the earnings announcement date, i.e., one-quarter ahead forecasts, which account for approximately 93% of all forecasts, and we exclude Estimize forecasts flagged as unreliable (roughly 1% of the sample). The resulting sample includes 8,265 firm-quarters with at least one Estimize and one IBES forecast.

For each firm-quarter, we compute five forecast characteristics: *Forecasters per Stock*, *Forecast Age*, *Bias* (i.e., forecast error), Absolute Forecast Error (*AbsFE),* and *Representativeness*. *Forecasters per Stock* is defined as the number of unique contributors or analysts issuing a forecast, and *Forecast Age* is defined as the number of calendar days between the forecast issue date and the earnings announcement date.

Our primary measure of forecast bias for firm *j* in quarter *t* is:

$$Bias\,/\,Prc_{j,t} = \frac{Actual_{j,t} - Consensus_{j,t}}{Price_{j,t\text{-}1}} * 100\,, \tag{1}$$

where *Actual* is reported earnings, *Consensus* is the mean Estimize (or IBES) forecast, and *Price* is closing price at the end of the prior year. In computing *Consensus*, we use only the most recent forecast by a contributor or an analyst. We winsorize *Bias/Prc* at 2.5% and 97.5%. As a robustness check, we consider two alternative measures of bias: *Bias/AbsConsensus*, which uses the absolute value of *Consensus* as an alternative scaling factor, and *MBE*, a Meet-or-Beat Earnings indicator

[15] The sample selection foreshadows subsequent analyses in which we define firms added to Estimize in 2012 as “treated firms” and define the 2013-2015 sample as the “post-event window”.

equal to 1 if *Actual* is greater than or equal to *Consensus*, and 0 otherwise. *AbsFE*, a measure of forecast accuracy, is defined as the absolute value of *Bias/Prc*.

Our measure of the degree to which the consensus forecast is representative of the market expectation (*Representativeness*) relies on the intuition that a superior measure of the market expectation exhibits a stronger association with returns at the time of the earnings announcement: that is, a higher Earnings Response Coefficient (ERC) (Brown, Hagerman, Griffin, and Zmijewski, 1987). For each firm with at least six quarters of Estimize forecasts, we estimate the time-series regression

$$CAR_{j,t} = \alpha + \beta\left(UE_{jt}\right) + \varepsilon_t, \qquad (2)$$

where *CAR* is the cumulative market-adjusted return in the three trading days around the earnings announcement date and *UE* is unexpected earnings (i.e., actual earnings less forecasted earnings), scaled by price. The slope coefficient, β, is the ERC, and our measure of representativeness. We standardize *UE* to have mean 0 and variance 1 for each firm; thus β reflects the abnormal return associated with a one-standard deviation change in unexpected earnings. We winsorize β at the 1^{st} and 99^{th} percentile.

Table 2 reports the results. On average, a stock is covered by 12.6 Estimize contributors and 14.8 IBES analysts[16]; and Estimize (IBES) forecasts are issued 9.7 days (63.8 days) prior to earnings announcements. Estimize forecasts have similar accuracy (absolute forecast errors of 17.2% versus 15.9%) and representativeness (ERCs of 4.7% versus 5.4%), but much lower bias: For instance, the average *Bias/Prc* for Estimize forecasts is 0.26% compared to 5.81% for IBES

[16] We note that the number of Estimize contributors is slightly larger than the Table 1 estimate of 11.7 because Table 2 reports the average conditional on there being at least one Estimize contributor. In contrast, the number of sell-side analysts reported in Table 2 is smaller than Table 1, because in Table 2 we exclude forecasts issued more than 120 days prior to the earnings announcement.

forecasts, and Estimize forecasts are more pessimistic than IBES forecasts in only 19.18% of all firm-quarters. The results using *Bias/Consensus* or *MBE* yield similar conclusions. The dramatic difference in bias, however measured, is consistent with sell-side analysts having greater incentives to issue pessimistic forecasts that managers can easily beat (Richardson, Teoh, and Wysocki, 2004).

4. Empirical Design

Our central prediction is that Estimize forecasts, which are easily accessible, reasonably accurate, and substantially less biased, can exert a disciplining effect on sell-side analysts' tendency to issue pessimistic forecasts of quarterly earnings. To test this prediction, we follow a standard difference-in-difference approach, which compares changes in bias for treatment and control firms around an event window.

We define treated firms as firms that are first added to Estimize in 2012. Firms added in 2012 experience significantly greater activity on the Estimize platform than firms added in later years (see Table 1). To the extent that greater Estimize activity places more pressure on sell-side analysts, this subgroup presents a more powerful setting for documenting the disciplining effect of Estimize. Candidate control firms consist of firms that have not been added to Estimize as of 2015.

We define the pre-event period as the three years prior to the introduction of Estimize (2009 to 2011) and the post-event period as the three years after Estimize (2013 to 2015).[17] We favor a long post-event window because it may take time for an upstart to prove its viability and begin to influence incumbents, and to reduce the error with which bias is measured; but in robustness tests we also analyze changes in bias at an annual frequency.

[17] Estimize was founded in 2011. 2011 earnings forecasts are not included in our dataset, but a review of historical earnings forecasts on Estimize.com indicates that earnings forecasts prior to 2012 are extremely sparse.

The exclusion restriction is that the change in bias of the treatment firms relative to control firms around the introduction of Estimize is not due to factors other than the introduction of Estimize. A natural concern is that treated firms have different characteristics from control firms, and that these differences influence the time-series behavior of *Bias/Prc*, biasing our difference-in-difference estimate. To minimize this potential bias, we match each treated firm to a control firm using either portfolio matching or propensity score matching.

Our portfolio approach matches along three characteristics: size, book-to-market, and pre-event period *Bias/Prc.* Specifically, we require that candidate control firms be in the same size quintile and book-to-market quintile, based on breakpoints estimated at the end of 2011, and then select the candidate control firm that has the smallest difference in pre-event period *Bias/Prc* (averaged across all 12 quarters in the pre-event window).[18] We match along size and book-to-market because 1) treated firms and controls firms tend to differ significantly along both dimensions (see Table 1) and 2) the magnitude of short-term pessimism tends to vary with both characteristics (see, e.g., Richardson, Teoh, and Wysocki, 2004); we match on pre-event bias to control for mean reversion.[19]

We obtain propensity scores from a logistic regression where the dependent variable is a dummy variable equal to one for treated firms and zero for control firms, and the independent variables include four firm characteristics: Log *(Size*), *Book-to-Market*, Log (*Turnover*), and Log (*Coverage*), and two forecast characteristics: *Bias/Prc* and *AbsFE*. We measure firm characteristics at the end of 2011 and forecast characteristics as quarterly averages over the period

[18] More generally, we match on the outcome variable of interest. For example, when examining *AbsFE* or *Representativeness* we match on their pre-event values.

[19]We match on only three characteristics because the pool of candidate control firms for some characteristics is quite limited. The propensity score matching approach allows us to match on more characteristics and test for the validity of the common support assumption.

2009-2011. For each treated firm, we select the control firm with the closest propensity score (i.e., nearest neighbor matching).[20]

5. Main Results

5.1 Changes in Bias – Baseline Results

Panel A of Table 3 reports the results from our tests of changes in *Bias/Prc* for treated firms and for portfolio-matched control firms after the introduction of Estimize. In the case of treated firms, the average *Bias/Prc* is 13.81% in the pre-event period and 5.08% in the post-event period. The difference of 8.73 percentage points (or 63%) is statistically significant based on standard errors double clustered by firm and quarter. In contrast, the portfolio-matched control firms experience a statistically insignificant 0.17 percentage point increase in *Bias/Prc* around the event. The difference-in-difference of -8.89 percentage points is not only statistically significant but also economically large. Specifically, the cross-sectional standard deviation of *Bias/Prc* for treated firms is 25.03%; thus, the decline of 8.89 percentage points corresponds to roughly 35% of the standard deviation of *Bias/Prc*. For reference, Hong and Kacperzyk (2010) document that the change in long-term bias associated with losing one analyst due to a broker merger is roughly 5% of the standard deviation of long term bias.[21]

To control for additional firm characteristics that influence bias, we purge *Bias/Prc* from the effects of Log (*Size*), *Book-to-Market*, Log (*Coverage)*, Log (*Turnover*), Log (*Volatility*), *Returns*, *Forecast Age*, *Guidance*, and industry and time factors by estimating the panel regression:

[20] We find that the likelihood of being included in the treated sample increases with *Size*, *Turnover*, *Coverage*, and *Bias/Prc*, and decreases with *Book-to-Market*, and *AbsFE*.
[21] In particular, Table 5 of Hong and Kacperzyk (2010) reports a mean difference-in-difference in bias ranging from 0.11 to 0.16 percentage points, while their Table 1 reports a cross-sectional standard deviation of 3.10%.

$$BIAS / Prc_{jt} = \alpha + \boldsymbol{\beta}\mathbf{X_j} + IND_j + QTR_t + \varepsilon_{jt}, \tag{3}$$

where **X** is the vector of firm characteristics, *IND* is a vector of 12 Fama and French (1997) industry dummies, and *QTR* is a vector of 24 quarter dummies. Panel B of Table 3 reports the results when the regression residual, *Abnormal Bias/Prc*, is the outcome variable. We find that treated firms experience a statistically significant decline in *Abnormal Bias/Prc* of 3.08 percentage points, control firms experience a significant increase of 6.31 percentage points, and the difference-in-difference of -9.39 percentage points is highly significant.

5.2 Changes in Bias – Alternative Specifications

In Table 4, we examine whether our results are sensitive to how we select control firms, measure sell-side bias, and define treatment firms. For reference, the first row reports the difference-in-difference estimates from Table 3.

First we replace the portfolio-matched control firms with propensity-score matched control firms. Reported in Row 2, the difference-in-difference estimates of the change in *Bias/Prc* and *Abnormal Bias/Prc* are -9.45% and -8.40%; these estimates are remarkably close to the baseline findings of -8.89% and -9.39%, respectively. To ensure that our results are not driven by poor matching (violations of the common support assumption), in Row 3 we limit the sample of treated firms to those with a propensity score within 0.25% of the propensity score of the matched control firm. Despite a sample attrition of 169 firms, we still document comparable difference-in-difference estimates of -10.66% and -9.99%.

We conduct the same analysis after replacing *Bias/Prc* with our two alternative measures of bias: *Bias/AbsConsensus* and *MBE*. The results, reported in Rows 4 and 5, respectively, are very similar to our baseline estimates.

Finally, we define treated firms as firms added to Estimize in 2013.[22] Reported in Row 6, the difference-in-difference estimates of *Bias/Prc* and *Abnormal Bias/Prc* are -4.29% and -3.69%; these estimates are the lowest in Table 4 and statistically insignificant. We attribute the weaker results to Estimize coverage: on average, firms added to Estimize in 2013 are covered by only 2.53 contributors, whereas firms added in 2012 are covered by 11.7 contributors (see Table 1).

5.3 Changes in Bias – Non-Parametric Tests

The results so far speak to an average decline in sell-side forecast bias following the creation of Estimize. In this section, we assess the pervasiveness of this effect by examining the entire distribution of forecast bias in the pre-event and post-event periods. Specifically, we plot the difference between the quarterly average *Abnormal Bias/Prc* of a treated firm and that of its match in 2010-2011 and in 2013-2014, with control firms matched on size, book-to-market, and *Abnormal Bias/Prc* estimated over the four quarters in 2009.[23]

Figure 1 plots the distributions. We observe a significant leftward shift in the entire distribution of forecast pessimism in the post-event window.[24] For example, the median value falls by 7.4 percentage points and the 25th (75th) percentile falls by 11.6 (4.1) percentage points. Similarly, the percentage of forecasts where the difference in *Abnormal Bias/Prc* is greater than zero (i.e., when forecasts are more pessimistic for treated firms relative to control firms) falls from

[22] We measure pre-event bias over the period 2009-2011 and post-event bias over 2014 and 2015.
[23] Matching on *Abnormal Bias/Prc* in the pre-event period, 2009-2011, mechanically compresses the distribution of the difference between the *Abnormal Bias/Prc* of a treated firm and that of a control firm in the same period; in fact, with perfect matching, the aforementioned distribution collapses to one with mean and standard deviation of zero. To avoid this problem, we match in 2009 and define the pre-event period as 2010-2011; for symmetry, we also shorten the post-event period to 2013-2014.
[24] A Kolmogorov-Smirnov tests is able to reject the hypothesis of equality of distributions at a 1% significance level.

54% in the pre-event window to 36% in the post-event window. Collectively, the evidence suggests that treated firms experience a pervasive and economically large reduction in bias.

5.4 Changes in Other Forecast Properties - Representativeness and Accuracy

Increased competition may also improve other properties of analysts' forecasts. For example, a new competitor, Estimize, may place pressure on sell-side analysts to gather and incorporate more information in their earnings forecasts, resulting in a sell-side consensus that is both more accurate and more representative of the market expectation. We explore this hypothesis using Section 5.1's approach, except that the outcome variable is now *AbsFE* or *Representativeness*. We tabulate our results in Table 5, Panel A and Panel B, respectively.

We find that treated firms experience a statistically significant average reduction in *AbsFE* of 11.89 percentage points, while control firms experience an insignificant decline of 4.78 percentage points. The difference-in-difference estimate of -7.10 percentage points is highly significant. In untabulated analysis, we find similar results when we define the outcome variable as *Abnormal AbsFE* or identify control firms using the propensity score-based matching method.[25]

Similarly, we find that *Representativeness* increases significantly for treated firms but not for control firms. In particular, for treated firms, a one-standard deviation increase in unexpected earnings is associated with a 2.75% three-day earnings announcement return in the pre-event period and 4.78% in the post-event period; for control firms, the corresponding figures are 2.29% and 2.12%. The difference-in-difference estimate of 2.21% is economically and statistically significant.

6. Strengthening Causal Inference

[25] We compute *Abnormal AbsFE* as the residual from equation 3 after replacing *Bias/Prc* with *AbsFE.*

In this section, we seek to increase confidence in the causal interpretation of our findings by demonstrating that 1) the parallel trends assumption underlying the difference-in-difference approach is valid, 2) the decline in pessimism varies as predicted by economic theory and intuition, and 3) sell-side biases that should not be affected by the arrival of Estimize are indeed unaffected.

6.1 Time-Series Patterns in the Decline of Pessimism

The assumption of parallel trends asserts that the change in bias in the treatment and control samples would have been the same had Estimize not been created in 2012. To investigate the parallel trends assumption, we examine changes in bias of treatment and control firms during the pre-event window. Demonstrating equality helps alleviate the concern that the documented difference around the event reflects the continuation or the reversal of an earlier difference in trends.

Figure 2 plots the difference-in-difference in *Abnormal Bias/Prc* over the period 2010-2015, with 2009 as the baseline year.[26] In 2010 and 2011, the change in bias in the treatment sample is indistinguishable from that in the control sample: the difference-in-difference is less than 1.3 percentage points in absolute value and statistically insignificant. The statistically insignificant difference-in-difference estimates in the pre-event period are consistent with the parallel trends assumption and suggest that pre-trends are unlikely to explain our results. Turning to the post-event window (i.e., 2013-2015), we find that the difference-in-difference estimates are significantly negative in each year, with point estimates ranging from -5.3 to -11.2. The consistently negative estimates in the post-event window suggest an immediate and permanent decline in pessimism following the introduction of Estimize.

6.2 Cross-Sectional Patterns in the Decline of Pessimism

[26] As in Section 5.3, for each treated firm we select a control firm matched on size, book-to-market, and *Abnormal Bias/Prc* estimated over the four quarters in 2009.

We next examine whether the decline in pessimism is stronger in circumstances where the disciplining effects of Estimize are likely to be greater. First, we expect that the disciplining effect of Estimize is greater when the level of existing sell-side competition is lower. Extending Gentzkow and Shapiro's (2008) argument to our setting, higher sell-side competition implies greater diversity of incentives among analysts, which in turn implies a greater likelihood of drawing an unbiased analyst/forecasts.[27] One or several analysts issuing unbiased forecasts would exert a disciplining effect on the rest, thus diminishing the value of Estimize as a disciplining device. As in Hong and Kacperczyk (2010), our measure of competition is the number of analysts covering a firm, calculated at the end of 2011.

Also, we suggest that the disciplining effect of Estimize is greater when earnings uncertainty is higher. The reason is that high uncertainty makes it difficult for investors to unravel sell-side bias on their own, increasing their demand for an external benchmark. We consider two proxies for earnings uncertainty: analyst forecast dispersion (Baginski et al., 1993; Diether et al., 2002; Clement et al., 2003) and market-to-book ratio (Pastor and Veronesi, 2003).

Finally, we conjecture that a less biased and more accurate Estimize consensus is more effective as a disciplining device. Investors should more easily unravel sell-side pessimism when they have access to a benchmark that is relatively less pessimistic and more accurate, which should put greater pressure on sell-side analysts to reduce their bias. More broadly, we suggest that Estimize is a greater threat to the sell-side and more likely to illicit a sell-side response when it is perceived by investors as a valuable information source – accuracy and unbiasedness are

[27] Hong and Kacperczyk (2010) make the same argument in an analyst setting.

universally accepted determinants of information value. Estimize consensus bias (*Estimize Bias/Prc*) and Estimize consensus accuracy (*Estimize AbsFE)* are measured as in Table 2.[28]

Table 6 sorts treated firms into quartiles based on each of the five variables and reports the difference-in-difference estimate, computed as in Panel B of Table 3, for each quartile and the *High-Low* quartile spread. The results are consistent with our predictions. In particular, when existing sell-side coverage is low (high), the difference-in-difference estimate is -14.97 (-4.36) percentage points. In the top quartiles of forecast dispersion and market-to-book ratio, the difference-in-difference estimates are -13.40 and -18.72 percentage points, respectively; the corresponding figures for the bottom quartiles are -5.84 and -3.38 percentage points, neither statistically different from zero. The spread in difference-in-difference estimates for the measures of benchmark effectiveness are also consistent with our expectations. In particular, when the Estimize consensus is most (least) biased, the difference-in-difference estimate is 2.23 (-10.84) percentage points, and when the Estimize consensus is most (least) accurate, the difference-in-difference estimate is -9.68 (0.37) percentage points. For all but one variable, sell-side forecast dispersion, we reject the null hypothesis of equality of difference-in-difference estimates in the top and bottom quartiles.[29]

In sum, we find that the decline in sell-side analysts' pessimism is greater when existing competition is lower, earnings uncertainty is greater, and Estimize is a more effective benchmark. These findings raise the hurdle for alternative explanations. In particular, any alternative

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[28] We drop post-event observations where the Estimize consensus includes less than three forecasts. The Estimize consensus is available on the Estimize platform next to the sell-side consensus and on external sites only if it includes three or more forecasts. While investors can calculate a consensus that comprises one or two individual Estimize forecasts, the location and limited availability of these forecasts hinder their usefulness as a disciplining device. Including these observations yields similar results for *Estimize Bias/Prc* but weaker results for *Estimize AbsFE*.

[29] In a univariate regression setting, even forecast dispersion significantly explains the decline in sell-side bias; in a multiple regression setting, all five variables contribute to explaining the decline in sell-side bias. Results are untabulated for brevity.

explanation would have to explain not only why the decline in sell-side pessimism is coincident with the arrival of Estimize and limited to stocks covered by Estimize, but also why it varies in relation to sell-side competition, earnings uncertainty, and Estimize accuracy and unbiasedness.

6.3 The Impact of Estimize on Longer-Horizon Earnings Bias and Recommendation Bias

An alternative hypothesis is that reputational concerns or other broad forces mitigating analyst conflicts of interest strengthen for stocks in the treatment sample but not in the control sample. This hypothesis predicts a reduction in bias not only for short-term earnings forecasts, but also for longer-term earnings forecasts and investment recommendations. In contrast, if the reduction in short-term pessimism is driven by competition from Estimize, we would not expect a reduction in bias for longer-term forecasts (which account for less than 4% of all Estimize forecasts) or stock recommendations (which are not available on the Estimize platform).

To preclude the alternative hypothesis, we first examine the effect of Estimize on the bias of sell-side analysts' forecasts of *t*-quarter ahead earnings, $Bias_t/Prc$, where *t* ranges from two to five. In computing $Bias_2/Prc$ ($Bias_3/Prc$), we require that the forecast period indicator, as reported in IBES, is equal to '7' ('8'), and we limit the sample to forecasts issued 90-210 (180-300) days prior to the earnings announcement.[30] The selection of the matched control firm is similar to Table 3, except we now match on $Bias_t/Prc$ rather than *Bias/Prc.*

Panels A through D of Table 7 report the results for $Bias_2/Prc$, $Bias_3/Prc$, $Bias_4/Prc$, and $Bias_5/Prc$, respectively. Consistent with prior literature, we find that earnings forecasts are more optimistic over longer horizons. For example, in the pre-event window, the average $Bias_2/Prc$ ($Bias_5/Prc$) is 0.95% (-19.40%). There is no evidence that treatment firms experience a reduction

[30] For reference, in computing *Bias/Prc* (or equivalently $Bias_1/Prc$), we require the forecast period indicator to equal '6' and limit the sample to forecasts issued 1-120 days prior to the earnings announcement. Thus, for each additional quarter we shift the beginning and ending dates by 90 days.

in longer-horizon bias. In all four cases, the difference-in-difference estimate is statistically insignificant. Furthermore, the sign is generally in the wrong direction (i.e. long-horizon optimism becomes more severe) and the point estimates are economically small.[31]

We also examine whether Estimize reduces recommendation bias, measured as the average recommendation level at the end of each quarter (*Rec Level*). In computing *Rec Level*, we convert recommendations to a numeric value using the following five rankings: 1 for strong buy, 2 for buy, 3 for hold, 4 for sell/underperform, and 5 for strong sell. The results from Panel E of Table 7 indicate that *Rec Level* increases (i.e., recommendations become less optimistic) following the introduction of Estimize for both treated and the matched control firms. The difference-in-difference estimate is statistically significant, but the point estimate is in the wrong direction. In particular, optimism among investment recommendations declines less for treated firms relative to control firms. Further, in untabulated analysis, we find this specific conclusion is sensitive to methodological choices. For example, using *Abnormal Rec Level* (i.e., the residual from equation 3 after replacing *Bias/Prc* with *Rec Level)* instead of *Rec Level* yields a difference-in-difference estimate of 0.01 (t=0.36). Overall, there is very little evidence that Estimize constrains sell-side analysts' tendency to issue optimistic longer-horizon earnings forecasts or investment recommendations. Thus, our findings suggest that direct competition from Estimize, rather than more pervasive economic forces, reduces short-term sell-side bias.

7. Conclusion

[31] In comparing the economic magnitudes to Table 3, it is important to account for the fact that the standard deviation of *Bias/Prc* increases substantially with forecast horizon. For example, the cross-sectional standard deviation of $Bias_1/Prc$ ($Bias_5/Prc$) is about 38% (110%). Thus, the main effects documented in Table 3 reflect roughly 35% of a one-standard deviation change, while the effects documented in Panel D reflect 4% of a one standard deviation change.

The last two decades have witnessed a sharp decline in information and communication costs and the creation of new sources of information; some of them directly competing with and potentially disrupting traditional sources of investment research. We examine whether increased competition stemming from recent technological and institutional innovations has a disciplining effect on sell-side analysts. We focus on Estimize, an open platform that crowdsources short-term quarterly earnings forecasts. Less pessimistic than sell-side forecasts but similarly accurate and readily available, Estimize forecasts present a unique opportunity for addressing this question.

We find that sell-side analysts' tendency to issue pessimistic short-term forecasts significantly weakens for firms added to Estimize relative to a sample of matched control firms. The decline in sell-side forecast pessimism is accompanied by an increase in forecast accuracy and representativeness of the market expectation.

Several additional results point towards a causal relation between the arrival of a new competitor, Estimize, and the decline in sell-side bias. In the time-series, we find no evidence of a decline in pessimism in the three years prior to the creation of Estimize suggesting that pre-trends are unlikely to explain our findings. In the cross-section, we find that the decline in sell-side pessimism is larger when theory suggests a greater disciplining role for Estimize. In particular, the decline in pessimism is greater when 1) existing competition is lower, 2) earnings uncertainty is greater, and 3) Estimize is a more effective benchmark (i.e., more accurate and less biased). Finally, placebo tests show that biases in longer-term earnings forecasts and investment recommendations – unlikely to be affected by the arrival of a short-term forecast provider – remain unchanged, indicating that broad economic forces are unlikely to be driving our results.

Our study has important policy implications. In particular, concerned with the adverse consequences of biased sell-side research such as inefficient prices and wealth transfers from less sophisticated to more sophisticated investors, in the last two decades regulators have comprehensively reformed sell-side analyst activities and communications with investment bankers and required extensive conflict of interest disclosures. These regulations have reduced analyst bias but at the cost of lower analyst coverage and lower research informativeness (Kadan et al., 2009). Our findings suggest that encouraging new forms of competition may be effective in both reducing investor reliance on the sell-side and in constraining sell-side bias, without the unintended adverse consequences of traditional regulatory approaches.

Appendix: Description of Variables

The variables discussed in this appendix are partitioned into two groups: forecast characteristics and firm characteristics.

A.1 Forecast Characteristics

- $Bias\ /\ Prc_{j,t} = \dfrac{Actual_{j,t} - Consensus_{j,t}}{Price_{j,t-1}} * 100.$
    - *Actual* = reported earnings.
    - *Consensus* = the average forecasted earnings across all forecasters. We drop forecasts issued more than 120 days prior to the earnings announcement and use the most recent forecast for each forecaster.
    - *Price* – the stock price at the end of the prior year.
    - We winsorize *Bias/Prc* at 2.5% and 97.5%.

- *Abnormal Bias/Prc*$_{j,t}$ = The residual from a panel regression of *Bias/Prc* on the following characteristics: Log(*Size*), *Book-to-Market*, Log(*Coverage*), Log(*Turnover*), Log(*Volatility*), *Returns*, *Forecast Age*, *Guidance*, and industry and quarter fixed effects.
    - *Forecast Age* and *Guidance* are measured in period t, while all other characteristics are measured in period *t-1*.

- $Bias\ /\ AbsConsensus_{j,t} = \dfrac{Actual_{j,t} - Consensus_{j,t}}{\left|Consensus_{j,t}\right|}.$
    - We winsorize |*Consensus*| at 0.02 and *Bias/Consensus* at 2.5% and 97.5%.

- *MBE (Meet or Beat Earnings)* = a dummy variable equal to one for firms who reported earnings greater than or equal to the consensus, and zero otherwise.
- *AbsFE* (*Absolute Forecast Error*) = the absolute value of *Bias/Prc.*
- *Representativeness* (*Earnings Response Coefficient - ERC*) = the slope coefficient from the following time-series regression: $CAR_{j,t} = \alpha + \beta UE_{j,t} + \varepsilon_t$.
    - *CAR* = the cumulative market-adjusted return in the three trading days around the earnings announcement date.
    - *UE* = unexpected earnings, defined as actual earnings less forecasted earnings, scaled by price.
        - We standardize *Bias* to have mean 0 and standard deviation 1, and winsorize β at the 1^{st} and 99^{th} percentile.
    - We exclude firms with fewer than six quarters of Estimize forecasts.
- *Forecast Age* = the number of calendar days between the forecast issue date and the earnings announcement date. This measure is averaged across all forecasts in the consensus.

- *Rec Level* = the consensus recommendation level at the end of each quarter. Recommendations are converted to numeric values using the following scale: 1 for strong buy, 2 for buy, 3 for hold, 4 for sell/underperform, and 5 for strong sell.
- *Estimize Bias/Prc* = *Bias/Prc* computed using only forecasts provided by Estimize Contributors.
    - This value is set to zero for all firm-quarters in the pre-event period and is set to missing for post-event quarters with fewer than 3 Estimize contributors.
    - We winsorize Estimize *Bias/Prc* at 2.5% and 97.5%.
- *Estimize AbsFE* = the absolute value of *Estimize Bias/Prc.*
    - This value is set to zero for all firm-quarters in the pre-event period and is set to missing for post-event quarters with fewer than 3 Estimize contributors.

A.2 Firm Characteristics

- *Size* = market capitalization computed as share price times total shares outstanding as of the end of the year prior to the earnings announcement date.
- *Coverage* = the total number of sell-side analysts (in IBES) covering a firm in a year.
- *BM (Book-to-Market)* = the book value of equity for the most recent fiscal year prior to the earnings announcement year, scaled by market capitalization on December 31st of the same fiscal year.
- *Turnover* = average daily turnover defined as share volume scaled by shares outstanding in the calendar year prior to the earnings announcement date.
- *Volatility* = the standard deviation of daily returns over the calendar year prior to the earnings announcement date.
- *Return* = the average daily market-adjusted return over the calendar year prior to the earnings announcement date.
- *Guidance* = a dummy variable equal to one if the firm issues earnings guidance during the quarter.
- *Dispersion* = the standard deviation of earnings forecasts scaled by the stock price at the end of the previous year.

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Table 1: Estimize Summary Statistics

This table reports summary statistics for forecasts submitted on Estimize from January 2012 to December 2015. Panel A reports the breadth and depth of Estimize coverage across the four years in the sample. Panel B partitions Estimize firms into five groups based on the year in which the company was first added to Estimize, and reports summary statistics for each group. The sample includes 1,842 firms with 1) continuous sells-side coverage from 2009-2015, 2) a stock price of at least $5 at the end of 2011, and 3) non-missing book-value of equity at the end of 2011.

Panel A: Breadth and Depth of Estimize Coverage

Year	Firms Covered	Firm-Quarters	Contributors	Forecasts	Contributors per Firm-Quarter: Mean	Contributors per Firm-Quarter: Median	Average Firms Followed
All (2012-2015)	1,391	15,120	11,167	172,566	9.05	4	8.06
2012	772	1,694	1,370	13,007	6.61	3	6.42
2013	1,271	3,781	1,612	24,750	5.88	3	9.67
2014	1,326	4,634	2,167	44,457	7.88	3	10.61
2015	1,362	5,011	7,555	90,352	13.82	6	7.05

Panel B: Characteristics of Firms Covered by Estimize

	Observations	Contributors Per Firm Quarter: Average	Contributors Per Firm Quarter: Median	% Quarters with Coverage	IBES Coverage	Average Firm Characteristics: Market Cap ($Bil)	Average Firm Characteristics: Book-to-Market
2012 Additions	772	11.70	6.25	90.02%	20.17	18.62	0.41
2013 Additions	509	2.53	2.09	75.87%	12.35	3.71	0.53
2014 Additions	74	1.66	1.46	48.09%	9.14	2.24	0.43
2015 Additions	36	1.02	0.42	12.50%	8.11	1.20	0.47
Not on Estimize	451	0	0	0%	7.96	2.54	0.58

Table 2: A Comparison of Estimize and IBES Quarterly Forecasts

This table examines key attributes of Estimize and IBES consensus forecasts. In computing a consensus, we limit the sample to earnings forecasts issued within 120 calendar days of the earnings announcement and use the most recent forecast by a contributor or an analyst. We also exclude forecasts flagged as unreliable by Estimize. We report mean and median attribute values, as well as the percentage of the times that the Estimize value exceeds the IBES value. Forecast attributes are defined in the Appendix. The sample is limited to the 772 firms that were added to Estimize in 2012. For all attributes except *Representativeness*, the sample includes 8,265 firm-quarters over the 2013-2015 period. For *Representativeness*, the sample includes one observation for each firm.

	Estimize Mean	Estimize Median	IBES Mean	IBES Median	% Estimize > IBES
Forecasters Per Stock	12.64	6	14.83	14	23.91%
Forecast Age	9.71	6.33	63.82	66.76	1.37%
BIAS/Prc	0.26%	0.92%	5.81%	3.75%	19.18%
Bias/Consensus	-1.36%	0.80%	5.51%	3.19%	17.57%
MBE	55.81%	100%	70.02%	100%	-
AbsFE	17.19%	7.86%	15.87%	8.06%	45.15%
Representativeness (ERC)	4.65%	2.90%	5.39%	3.06%	38.98%

Table 3: The Effect of Estimize Coverage on Bias

This table examines sell-side bias before (from 2009 to 2011) and after the arrival of Estimize (from 2013 to 2015) for treated and matched control firms. Treated firms are those added to the Estimize platform in 2012. Candidate control firms are those not added to Estimize as of 2015. A matched control firm satisfies two conditions: it has the same size quintile and book-to-market quintile as the treated firm, based on breakpoints estimated at the end of 2011, and the smallest difference in pre-event period bias from the treated firm. The sample includes 772 treated firms and 17,877 treated-firm quarters. Panels A and B report mean *BIAS/Prc* and *Abnormal BIAS/Prc*, respectively. *BIAS/Prc* is the difference between actual earnings and the consensus IBES forecast, scaled by stock price at the end of the previous year (reported in percent). *Abnormal Bias/Prc* is the residual from a panel regression of *BIAS/Prc* on control variables (*Size, Book-to-Market, Coverage, Turnover, Volatility, Return, Forecast Age, Guidance*, and industry and time fixed effects). All variables are defined in the Appendix. Reported t-statistics are based on standard errors that are double-clustered by firm and quarter.

Panel A: *BIAS/Prc*

	Before	*After*	*Difference*	*t(Dif.)*
Estimize	13.81	5.08	-8.73	(-4.13)
Matched Control	11.14	11.31	0.17	(0.05)
Estimize - Control	2.66	-6.23	-8.89	(-3.72)

Panel B: *Abnormal BIAS/Prc*

	Before	*After*	*Difference*	*t(Dif.)*
Estimize	1.94	-1.14	-3.08	(-3.16)
Matched Control	1.25	7.57	6.31	(2.86)
Estimize - Control	0.69	-8.70	-9.39	(-3.91)

Table 4: The Effects of Estimize Coverage on Bias – Alternative Specifications

This table examines sell-side bias before (from 2009 to 2011) and after the arrival of Estimize (from 2013 to 2015) for treated and matched control firms using alternative matching approaches, alternative measures of bias, and an alternative treatment sample. Row 1 reports the baseline results for *Bias/Prc* and *Abnormal Bias/Prc* as reported in Panels A and B of Table 3, respectively. Rows 2 and 3 repeat the baseline analysis but now select the matched control firm using propensity score matching. We estimate the propensity score with a logistic regression where the dependent variable equals 1 for treated firms (i.e., stocks added to Estimize in 2012) and 0 for candidate control firms (stocks not added to Estimize as of 2015). The independent variables include four firm characteristics: *Size*, *Book-to-Market*, *Turnover*, and *Coverage*, estimated at the end of 2011, and two forecast characteristics: *Bias/Prc* and *AbsFE*, estimated over the 12 quarters in the pre-event window. For each treated firm, we select a control firm with the closest propensity score. Rows 2 report the results for the full sample of treated firms (772 treated firms and 17,626 firm-quarter observations), and Row 3 limits the sample to 503 treated firms (11,590 firm-quarters), each with a propensity score within 0.25% of the matched control firm (i.e., common support). Rows 4 and 5 repeat the analysis in Row 2 after replacing *Bias/Prc* with two alternative measures of bias: *Bias/AbsConsensus* and *MBE*. Row 6 repeats the analysis in Row 2 after redefining treated firms as firms added to Estimize in 2013 and re-defining the post-event window as 2014-2015. The sample in Row 6 includes 489 treated firms and 9,457 firm-quarter observations. The reported t-statistics are computed based on standard errors double-clustered by firm and quarter.

	Bias	*Abnormal Bias*
1. Table 3 Baseline Results	-8.89	-9.39
	(-3.72)	(-3.91)
Alternative Matching Approaches:		
2. Propensity Score Matching	-9.45	-8.40
	(-3.45)	(-3.04)
3. Propensity Score Matching - Require Common Support	-10.66	-9.99
	(-3.92)	(-3.66)
Alternative Measures of Bias:		
4. *Bias/AbsConsensus*	-12.03	-11.36
	(-4.36)	(-4.05)
5. *MBE*	-10.70	-8.56
	(-2.64)	(-2.07)
Alternative Treatment Sample:		
6. 2013 Additions	-4.29	-3.69
	(-1.23)	(-1.06)

Table 5: The Effect of Estimize Coverage on Accuracy and Representativeness

This table examines sell-side forecast accuracy and representativeness before (from 2009 to 2011) and after the arrival of Estimize (from 2013 to 2015) for treated and matched control firms. Treated firms are those added to the Estimize platform in 2012. Candidate control firms are those not added to Estimize as of 2015. A matched control firm satisfies two conditions: it has the same size quintile and book-to-market quintile as the treated firm, based on breakpoints estimated at the end of 2011, and the smallest difference in pre-event period accuracy (or representativeness) from the treated firm. Accuracy is inversely related to the absolute value of the consensus forecast error (*AbsFE*), whereas *Representativeness* is defined as the earnings response coefficient from a firm-specific earnings-returns regression. See the Appendix for details. The sample in Panel A includes 772 treated firms and 17,877 firm-quarter observations. The sample in Panel B includes 767 treated firms and 1,534 firm observations. The table reports the sample means. Reported t-statistics are based on standard errors that are double-clustered by firm and quarter in Panel A and clustered by firm in Panel B.

Panel A: *Absolute Forecast Error (AbsFE)*

	Before	*After*	*Difference*	*t(Dif)*
Estimize	31.76	19.87	-11.89	(-3.58)
Matched Control	30.59	25.81	-4.78	(-1.46)
Estimize - Control	1.16	-5.94	-7.10	(-5.05)

Panel B: *Representativeness* (*ERCs*)

	Before	*After*	*Difference*	*t(Dif)*
Estimize	2.75	4.78	2.04	(6.88)
Matched Control	2.29	2.12	-0.17	(-1.24)
Estimize - Control	0.46	2.67	2.21	(6.84)

Table 6: Systematic Variation in The Effect of Estimize Coverage on Sell-Side Bias

This table reports the mean difference-in-difference estimates of *Abnormal Bias/Prc* conditional on the level of existing sell-side competition, measured as the number of sell-side analysts covering the firm in 2011 (*Coverage*); earnings uncertainty, measured as the standard deviation of earnings forecasts scaled by price (*Dispersion)* or the market-to-book ratio, both estimated in 2011; and Estimize effectiveness as a benchmark, defined as bias (*Estimize Bias/Prc)* or accuracy (*Estimize AbsFE)* of the Estimize consensus, both estimated in the prior quarter. The table reports the mean difference-in-difference estimates of *Abnormal Bias/Prc*, as computed in Panel B of Table 3, after partitioning firms into quartiles based on the variable of interest. The reported t-statistics (in parentheses) are computed based on standard errors double-clustered by firm and quarter.

	Competition	***Earnings Uncertainty***		***Benchmark Effectiveness***	
	Coverage	*Dispersion*	*Market-to-Book*	*Estimize Bias/Prc*	*Estimize AbsFE*
	[1]	[2]	[3]	[4]	[5]
4 (High)	-4.36	-13.40	-18.72	2.23	0.37
	(-1.68)	(-4.16)	(-3.50)	(0.84)	(0.20)
3	-9.84	-6.56	-9.69	-11.14	-10.13
	(-2.96)	(-1.93)	(-2.60)	(-5.17)	(-3.83)
2	-8.21	-10.95	-3.36	-9.84	-10.33
	(-2.39)	(-3.23)	(-1.07)	(-4.15)	(-4.07)
1 (low)	-14.97	-5.84	-3.38	-10.84	-9.68
	(-3.44)	(-1.22)	(-0.91)	(-4.20)	(-4.24)
High - Low	10.61	-7.56	-15.34	13.08	10.05
	(2.23)	(-1.13)	(-2.38)	(3.47)	(3.74)

Table 7: The Effect of Estimize Coverage on Bias in Longer-Horizon Forecasts and Recommendation Levels
This table examines bias in sell-side analysts' longer-horizon earnings forecasts and investment recommendations before and after the arrival of Estimize in 2012. We use the difference-in-difference approach of Panel A of Table 3, except we now define the outcome variable as the bias in two- to five-quarter ahead consensus earnings forecasts (Panels A through D) or the consensus recommendation (Panels E and F). In matching a treated firm to a control firm, we use the values of the respective outcome variable in the pre-event period. Recommendations are converted to numeric values using the following scale: 1 for strong buy, 2 for buy, 3 for hold, 4 for sell/underperform, and 5 for strong sell. The reported t-statistics are based on standard errors double-clustered by firm and quarter.

Panel A: Two-Quarter Ahead Earnings

	Before	*After*	*Difference*	*t(Dif)*
Estimize	0.95	-6.48	-7.43	(-1.15)
Matched Control	2.31	0.91	-1.40	(-0.28)
Estimize - Control	-1.35	-7.39	-6.04	(-1.68)

Panel B: Three-Quarter Ahead Earnings

	Before	*After*	*Difference*	*t(Dif)*
Estimize	-8.54	-14.58	-6.04	(-0.62)
Matched Control	-5.05	-4.79	0.26	(0.03)
Estimize - Control	-3.48	-9.79	-6.31	(-1.26)

Panel C: Four-Quarter Ahead Earnings

	Before	*After*	*Difference*	*t(Dif)*
Estimize	-18.35	-20.14	-1.79	(-0.14)
Matched Control	-11.83	-13.08	-1.25	(-0.13)
Estimize - Control	-6.52	-7.06	-0.54	(-0.08)

Panel D: Five-Quarter Ahead Earnings

	Before	*After*	*Difference*	*t(Dif)*
Estimize	-19.40	-23.80	-4.40	(-0.30)
Matched Control	-16.04	-15.96	0.08	(0.01)
Estimize - Control	-3.36	-7.84	-4.48	(-0.59)

Panel E: Rec Level

	Before	*After*	*Difference*	*t(Dif)*
Estimize	2.27	2.35	0.08	(3.50)
Matched Control	2.35	2.50	0.15	(8.22)
Estimize - Control	-0.09	-0.15	-0.07	(-2.69)

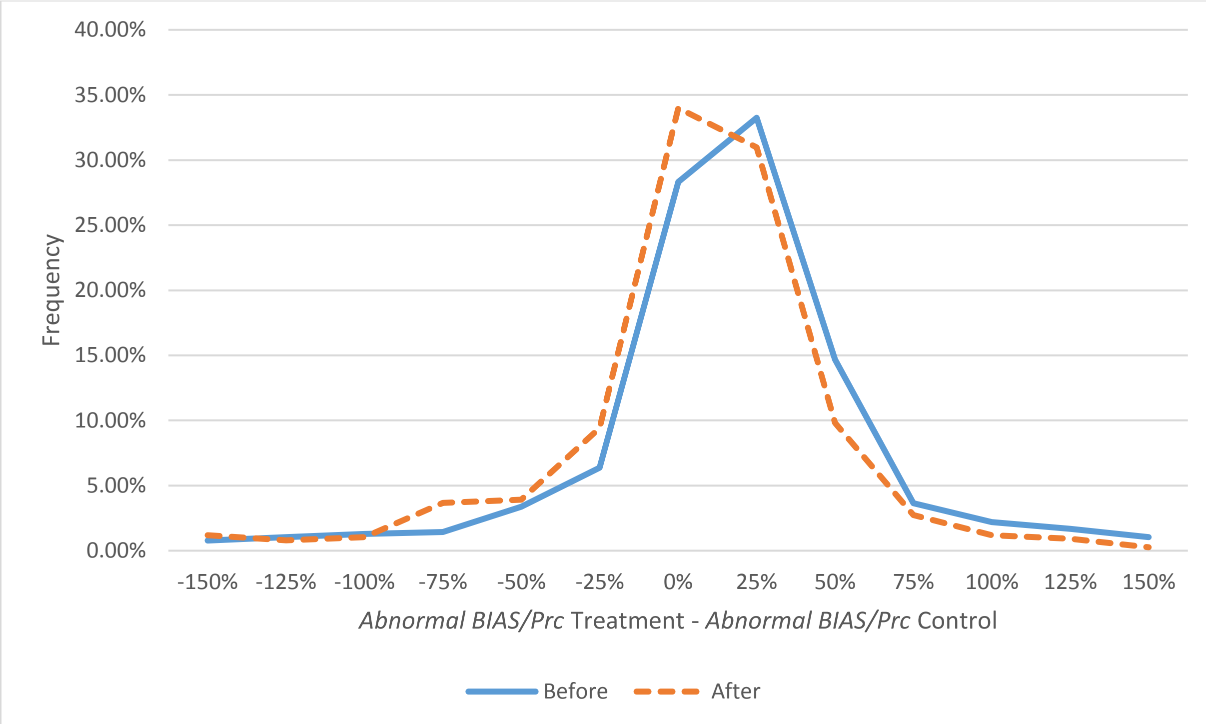

Figure 1: Distribution of the Difference in *Bias* of Treatment and Control Groups Before and After Estimize
This figure plots the distribution of *Abnormal BIAS/Prc* of treatment and control firms before and after the introduction of Estimize. Treated firms are those added to the Estimize platform in 2012 (772 firms). Control firms are those not added to Estimize as of 2015. For each treated firm, we require that candidate control firms be in the same size quintile and book-to-market quintile. We then select the candidate control firm that has the smallest difference in *Abnormal BIAS/Prc* (averaged across all 4 quarters in 2009). We compute the difference in *Abnormal Bias/Prc* for treated and control firms over 2010-2011 ("before") and 2013-2014 ("after"). *BIAS/Prc* is defined as the difference between actual earnings and the consensus IBES forecast, scaled by stock price at the end of the previous year, and *Abnormal Bias/Prc* is the residual from a panel regression of *BIAS/Prc* on control variables (*Size*, *Book-to-Market*, *Coverage*, *Turnover*, *Volatility*, *Returns*, *Forecast Age*, *Guidance*, and industry and time fixed effects). Additional details on variable definitions are in the Appendix.

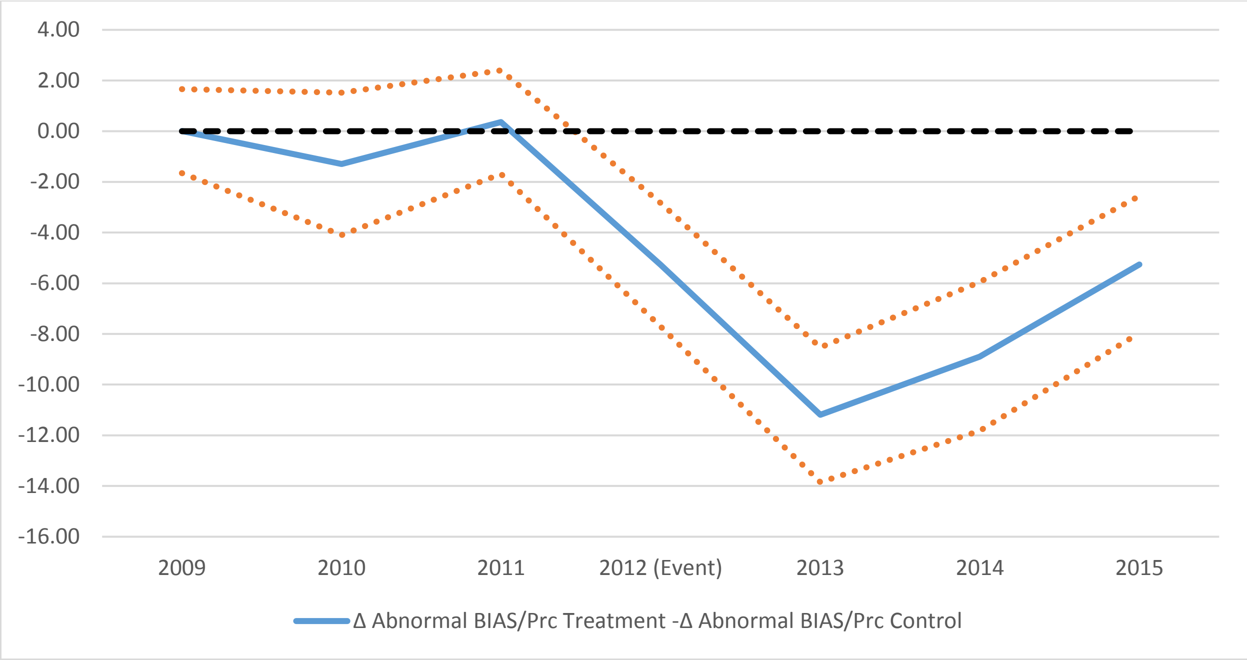

Figure 2: Difference-in-Difference in Bias in Event Time

This figure reports the difference-in-difference in *Abnormal Bias/Prc* from 2009 to 2015, using 2009 as the benchmark year. The event year is 2012 which corresponds to the introduction of Estimize. Treated firms are those added to the Estimize platform in 2012 (772 firms). Control firms are those not added to Estimize as of 2015. For each treated firm, we require that candidate control firms be in the same size quintile and book-to-market quintile. We then select the candidate control firm that has the small difference in *Abnormal BIAS/Prc* (averaged across all 4 quarters in 2009). We report the average difference in *Abnormal Bias/Prc* for treated and control firms each year, less the average difference in *Abnormal Bias/Prc* for treated and control firms in 2009. *BIAS/Prc* is defined as the difference between actual earnings and the consensus IBES forecast, scaled by stock price at the end of the previous year, and *Abnormal Bias/Prc* is the residual from a panel regression of *BIAS/Prc* on control variables (*Size*, *Book-to-Market*, *Coverage*, *Turnover*, *Volatility*, *Returns*, *Forecast Age*, *Guidance*, and industry and time fixed effects). Additional details on variable definitions are in the Appendix. The dotted orange lines plot the 90% confidence interval based on standard errors clustered by firm.