Pressure from the crowd: Crowdsourced earnings forecasts and earnings management*

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Abstract

Social-media-based information intermediaries are playing an increasingly important role in the capital markets. We explore the impact of Estimize, a prominent social-media-based information intermediary that collects and disseminates earnings forecasts, on managerial decision making. We start by documenting that the market imposes a significant penalty on a firm that misses Estimize consensus forecast, after controlling for whether the firm meets I/B/E/S consensus. Further, we find that, compared with I/B/E/S consensus forecasts, Estimize consensus forecasts are less likely to become more beatable over time, suggesting that it is more difficult for management to guide Estimize contributors. Consequently, we expect that the pressure to meet or beat Estimize consensus and the challenge to manage expectations motivate management to engage more in earnings management. Using a difference-in-differences approach based on an entropy-balanced control sample not covered by Estimize, we find that firms experience a significant incremental increase in both accrual-based and real-activities-based earnings management after Estimize coverage initiation. The post-coverage increase in total earnings management is more pronounced when firms are under greater pressure to meet a short-term target. The evidence suggests that pressure from the crowd to deliver short-term performance exacerbates managerial myopia. We add to the rising line of research on social media by documenting an unintended impact of crowdsourced investment research on financial reporting and managerial short-termism.

Keywords: Social media; Crowdsourcing; Information intermediary; Earnings management; Managerial myopia

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1. Introduction

The emergence of social media in recent years has substantially changed the firms' information environment (e.g., Blankespoor, Miller, and White 2014; Miller and Skinner 2015). Social media not only provides firms with a new channel for communicating information to the capital markets, but also enables capital market participants to create and disseminate their own content. Various platforms have been established to capture and disseminate the collective wisdom of crowdsourced information to the capital markets. Early evidence suggests that crowdsourcing platforms such as Seeking Alpha and Estimize serve as important information intermediaries that supply useful information to the capital markets (e.g., Chen, De, Hu, and Hwang 2014; Jame, Johnson, Markov, and Wolfe 2016). This burgeoning field of research also shows that crowdsourced investment research has had significant effects on sell-side analysts and investors (e.g., Jame, Markov, and Wolfe 2017; Banker, Khavis, and Park 2017; Brown and Khavis 2017; Farrell, Green, Jame, and Markov 2018). However, there has been no research examining whether and how these crowdsourced information intermediaries influence managerial behavior. In this study, we examine how the pressure from crowdsourced earnings forecasts influence managers' financial reporting choices.

The information intermediary that we study is Estimize. Estimize is primarily a platform that gathers and disseminates crowdsourced earnings forecasts. In this manner, Estimize differs from other crowdsourced finance platforms such as The Motley Fool, StockTwits, and Seeking Alpha, which offer unstructured commentary and opinions about stocks. Estimize's consensus forecasts are increasing in prominence and are now being featured by many leading TV channels and media outlets. Estimize has become an important source of earnings information, and its earnings forecasts convey incremental information to the stock market beyond that conveyed from other sources, such as traditional sell-side analysts (Jame et al. 2016).[1]

Traditional information intermediaries—that is, financial analysts—influence firms' financial reporting in at least two important ways. First, in a beneficial manner, analysts act as external monitors by analyzing financial statements, questioning managers during conference calls, and even getting directly involved in the discovery of corporate frauds (Dyck, Morse, and Zingales 2010). Analyst monitoring therefore should reduce the incidence of earnings management. In support of this claim, Yu (2008) reports that firms engage less in accrual-based earnings management when they are followed by analysts. Estimize contributors are independent professionals who are less likely to be influenced by managers than sell-side analysts, thus making them potentially better monitors (Brown and Khavis 2017). However, they rarely interact with managers and do not issue research reports or recommendations, which makes them less likely to challenge or pressure managers. Therefore, it is unclear whether Estimize would have stronger or weaker direct monitoring effects on managers. However, Estimize may enhance monitoring indirectly through its impact on sell-side analysts. For example, Banker et al. (2017) show that analysts become more responsive to earnings announcements and issue their forecasts earlier when firms are covered by Estimize. In summary, it is likely, but not conclusive, that the introduction of Estimize would enhance analysts' monitoring and thereby curb earning management.

Second, in a detrimental manner, financial analysts can create excessive pressure on managers to meet short-term earnings targets, and thereby exacerbate managerial myopia (e.g., He and Tian 2013; Guo, Pérez-Castrillo, and Toldrà-Simats 2019). Such pressure could induce managers to manage earnings. Consistent with this view, Irani and Oesch (2016) find a decrease in real-activities-based

[1] Another source that provides earnings estimates with crowdsourcing features is whisper number sites. However, they are less transparent and consistent than Estimize and therefore have limited impact on the market (Jame et al. 2016; Banker et al. 2017).

earnings management after firms experience exogenous reductions in analyst following. Unlike traditional sell-side analysts, Estimize contributors primarily forecast one-quarter ahead earnings (Jame et al., 2017). Besides, Estimize earnings forecasts are less pessimistically biased than sell-side analysts' forecasts, probably because its contributors are less influenced by managers (Jame et al. 2016). The stock market, however, reacts negatively when firms miss Estimize forecasts. In addition, as Jame et al. (2017) find, competition from Estimize pressures sell-side analysts to issue less pessimistic earnings forecasts. For all these reasons, coverage by Estimize can raise quarterly earnings targets for firms to meet or beat, which can then exert pressure on managers to take short-term oriented actions, such as managing earnings. Overall, whether coverage by Estimize will motivate or discourage earnings management, either cosmetic or real, is essentially an empirical question.

We begin our empirical analysis by examining some of the underlying factors that could affect how Estimize coverage could influence managerial financial reporting behavior. Consistent with prior studies (e.g., Jame et al. 2016), we find that firms are more likely to miss Estimize than I/B/E/S consensus forecasts. Controlling for whether a firm meets I/B/E/S consensus forecast, we find that the market imposes a significant penalty on a firm that misses the Estimize consensus forecast. We also examine the extent to which Estimize forecasters "walk down" their forecasts to more beatable levels.[2] Examining changes in the percentage of firms meeting or beating Estimize and I/B/E/S forecasts over time, we find that Estimize forecasts are significantly less likely to be "walked down" than I/B/E/S forecasts. Overall, our preliminary evidence suggests that Estimize forecasts are generally more optimistic, less susceptible to "walk down" through expectation management, and more difficult to meet/beat than I/B/E/S forecasts, but the penalty associated with missing Estimize forecasts is comparable to that with missing I/B/E/S forecasts. Together, this evidence suggests that managers are

[2] Prior research finds that analysts first issue optimistic earnings forecasts and then "walk down" their estimates to a level that firms can beat at the earnings announcement, suggesting that firms engage in expectation management (e.g., Bartov, Givoly, and Hayn 2002; Richardson, Teoh, and Wysocki 2004; Das, Kim, and Patro 2011).

likely to face greater short-term pressures when their firms are covered by Estimize, which could induce them to manage earnings in a bid to meet or beat the higher targets set by Estimize.

Our primary analyses examine changes in the levels of earnings management after Estimize coverage initiation. We adopt a differences-in-differences design where we examine earnings management levels for treatment firms (i.e., for those that Estimize initiates coverage) from the year before the coverage initiation to the year after, relative to a sample of control firms that are not covered by Estimize during the same period. While coverage initiation of different firms is staggered over time, it is not completely random. Accordingly, we construct an entropy-balanced control sample based on factors that may affect the likelihood of Estimize coverage, such as firm size, trading volume, growth, volatility, financial and stock performance, and analyst coverage. We examine changes in both accrual-based and real-activities-based earnings management. Following the prior literature, we measure accrual-based earnings management using discretionary accruals and real-activities-based earnings management using abnormal discretionary expenses (Zang 2012; Roychowdhury 2006). The differences-in-differences coefficients for accrual-based, real-activities-based, and total (sum of accrual-based and real-activities-based) earnings management are all positive and significant, which is consistent with greater income-increasing earnings management after Estimize coverage initiation. The evidence suggests that the pressure from the crowd to deliver better short-term earnings performance induces managers to resort to earnings management.

We also explore cross-sectional variation in the extent of increased earnings management after Estimize coverage initiation. First, we expect the pressure from the crowd to increase with the size of the crowd.[3] Consistent with our expectation, we find that the increase in total earnings management is concentrated in treatment firms that are followed by a larger number of Estimize contributors. Second, managers are likely to have stronger incentives to meet or beat earnings targets if their personal wealth

[3] Jame et al. (2016) find that the market's reaction to Estimize consensus forecast error is increasing with the number of Estimize contributors issuing forecasts for the firm.

is more affected by a decline in stock price due to missing earnings targets. Accordingly, we expect managers who hold more shares in their own firms to engage in more egregious earnings management after Estimize coverage. As hypothesized, we find that the increase in total earnings management is concentrated in treatment firms with higher CEO ownership. Finally, we explore how the investment horizon of the shareholders moderates our results. Prior research suggests that when shareholders have shorter investment horizons, managers are under greater pressure to deliver short-term performance (e.g., Shleifer and Vishny 1990; Bushee 1998; Chen, Cheng, Lo, and Wang 2015). Accordingly, we predict that the pressure from the crowd has a greater impact on management's reporting incentives for firms with higher ownership by transient institutional investors. We find evidence consistent with this conjecture.

Our study contributes to three streams of literature. First, we add to the growing research on the effects of social media on the capital markets. Existing research on social media has largely focused on firms' use of social media as a channel of disclosure (Blankespoor et al. 2014; Lee, Hutton, and Shu 2015; Jung, Naughton, Tahoun, and Wang 2018), the usefulness of social-media information (Jame et al. 2016; Bartov et al. 2018), and investors' use of information from social media (Farrell et al. 2018). We add to this literature by examining the effect of social media on financial reporting choices of managers. While, extant research shows that crowdsourced investment research provides useful new information to the capital markets and reduces bias in analyst forecasts (Jame et al., 2017), we suggest that an unintended consequence crowdsourced earnings forecasts is excessive pressure on managers to deliver short-term performance, with associated undesirable effects such as increased earnings management.

Second, we contribute to the literature on information intermediaries (analysts) by exploring the characteristics of crowd-sourced earnings forecasts and its effect on managerial behavior. Crowd-sourced earnings forecasts are less likely to be "walked down" than those of traditional analysts, suggesting that it is more difficult for firms to manage the expectations of the crowd than that of the financial analysts. In addition, while traditional analysts appear to both monitor managers to reduce accrual-based earnings management and pressure them to meet earnings targets and thereby increase real-activities-based earnings management (Irani and Oesch 2016), we show that crowdsourced earnings forecasts appear to escalate both forms of earnings management, suggesting that the pressuring effect of crowdsourcing dominates the monitoring effect, if any.

Third, we contribute to the literature on managerial myopia. Many studies find evidence of accrual-based and real-activities-based earnings management to achieve short-term performance target (e.g., Bushee 1998; Roychowdhury 2006; Edmans et al. 2016). The reduction of discretionary expenses such as R&D and advertising expenditures to meet short-term earnings goals, in particular, has been considered "myopic" because it directly trades off contemporaneous earnings against future competitiveness (Bushee 1998; Kothari et al. 2016; Roychowdhury, Shroff, Verdi 2019). Managerial myopia can be motivated by their compensation (Edmans et al. 2016), employment contract (Chen et al. 2015), access to capital markets (Kothari et al. 2016), reporting frequency (Ernstberger et al. 2017; Kraft et al. 2018), and pressure from traditional sell-side analysts (Irani and Oesch 2016; He and Tian 2013). We find that social media can be another source of pressure that causes managerial myopia.

2. Related literature and hypothesis development

2.1. Estimize—a prominent social-media-based information intermediary

Estimize is an open platform founded in 2011 that crowdsources earnings forecasts with the objective of providing an alternative to sell-side forecasts, which are often biased because of conflicts of interest. Estimize sources its forecasts from a diverse community of contributors, including independent, buy-side, and sell-side analysts, industry experts, corporate financial professionals, and students. As of May 2019, Estimize has attracted forecasts from over 90,000 contributors, covering more than 2,400 firms. The vast majority of Estimize forecasts are short-term forecasts of one-quarter ahead earnings (Jame et al. 2016). Contributors to the Estimize platform can remain anonymous and receive free access to view Estimize forecasts.

Estimize takes measures to manage the quality of its forecasts. It avoids covering microcap or thinly traded stocks to prevent attempts to manipulate prices by submitting biased estimates (Banker et al. 2017). It reviews contributors' forecasts on a regular basis. New contributors are put through a manual review process which considers the depth of their biographical information and the reliability of their first five estimates. After new contributors establish themselves as members of the Estimize community, all estimates will continue to be algorithmically reviewed for reliability. Estimize further promotes forecast accuracy among its members by running accuracy contests and awarding most accurate forecasters with prizes, motivating contributors to build a reputation for accuracy.[4] Consistent with Estimize forecasts providing a viable alternative to sell-side forecasts, Jame et al. (2016) document that quarterly forecasts provided by Estimize are significantly less pessimistic than sell-side forecasts and incrementally useful in forecasting earnings.

Estimize has gained increasing prominence since its inception. Investors can easily and repeatedly access earnings expectations from Estimize, where inputs to the consensus and the opinions of each contributor are easily viewed and tracked over time. Estimize consensus forecasts are also available on Bloomberg, CNBC, and TD Ameritrade, and are regularly referenced in high profile financial media sources including Forbes, Barron's, The Wall Street Journal, and Business Week. Jame et al. (2016) point out that, compared with other social media finance sites such as Seeking Alpha, which offer unstructured commentary data with crowdsourcing features, Estimize directly provides quantitative forecasts and is likely a more important source of earnings information. While whisper number sites of the past share Estimize's general objective of creating an alternative source of earnings

[4] Jame et al. (2016) and Banker et al. (2017) propose several reasons for Estimize contributors to issue accurate forecasts. For example, some portfolio managers and retail investors may contribute forecasts because they want to ensure that prices quickly reflect their information. Other contributors may issue forecasts to build a reputation for accuracy or to win contests and prizes.

estimates, the information they provide was scattered on blogs, bulletin boards, or social media, and was not as transparent (Jame et al. 2016; Banker et al. 2017).[5]

Several studies find Estimize forecasts to have a significant impact on capital market participants. Jame et al. (2016) show that the market reacts to Estimize consensus forecast error and the reaction is not subsumed by the market's reaction to consensus forecast error of sell-side analysts, suggesting that Estimize consensus forecast is an important earnings benchmark used by the market. Jame et al. (2017) document a decline in short-term sell-side forecast bias for firms added to Estimize, indicating that competition from the crowd constrains the behavior of sell-side analysts. In addition, Banker et al. (2017) find that sell-side analysts become more responsive to earnings announcements and start issuing their quarterly forecasts earlier when faced with competition from Estimize. They also show that the increased responsiveness of analysts facilitates market efficiency as it results in greater immediate market reaction to earnings surprises and mostly eliminates the post-earnings-announcement drift.

More broadly, a growing number of research studies the impact of financial sites, forums and other social media platforms on the capital markets. This line of research finds that firms use social media, such as Twitter, to disseminate information (e.g., Blankespoor et al. 2014; Lee et al. 2015; Jung et al. 2018), and that information from social media platforms, such as Seeking Alpha and Twitter, is useful to predict future earnings and returns (e.g., Chen et al. 2014; Bartov et al. 2018). It remains unexplored whether and how social media affects managerial decision making, which is the focus of this paper.

[5] Prior research finds mixed evidence regarding the value of whisper number sites. While Bagnoli, Beneish, and Watts (1999), an early study based on a small sample, find them to convey new information, Bhattacharya, Sheikh, and Thiagarajan (2006) find that whisper forecasts do not contain any incrementally useful information in the post-Reg-FD period. The existence of other crowdsourced earnings forecasts could dampen the importance of Estimize forecasts and reduce the likelihood of finding a significant Estimize impact.

2.2. Traditional information intermediaries and earnings management

Traditional information intermediaries are an important component of the capital markets. As financial professionals with industry expertise, analysts process information from financial statements and other sources and issue short-term and long-term forecasts, recommendations, and research reports for covered firms. When a firm's reported earnings fall short of earnings forecasts issued by financial analysts, there can be significant negative consequences to the firm and its management, such as stock price declines (Skinner and Sloan 2002), a higher likelihood of litigation (Bartov et al. 2002), lower executive compensation (Matsunaga and Park 2001), and forced management turnover (Mergenthaler, Rajgopal, and Srinivasan 2012). As a result, analysts have a significant impact on management's decision making. Prior research argues that analysts can serve as external monitors alongside traditional mechanisms of corporate governance (e.g., Yu 2008; Ellul and Panayides 2009). Analysts often scrutinize management during earnings conference calls by asking a variety of questions. They can also express their concerns about covered firms through research reports, recommendations and forecasts, and their appearance in public media (Yu 2008). Analysts play an active role in corporate fraud detection. Dyck, Morse, and Zingales (2010) document that analysts' involvement contributes directly to the discovery of corporate fraud in a number of companies. Consistent with analysts acting as monitors of management, Ellul and Panayides (2009) show that termination of analyst coverage leads to deteriorating liquidity and price efficiency, more informed trading, and higher profitability of insider trades. Focusing on financial reporting, Yu (2008) finds that firms followed by financial analysts engage less in accrual-based earnings management.

An alternative view holds analysts responsible for creating excessive pressure on managers and exacerbating managerial myopia (e.g., Fuller and Jensen 2002; He and Tian 2013). Fuller and Jensen (2002) argue that managers often conform to excessively aggressive analysts' earnings forecasts and accept external expectations as targets to achieve. In a survey of 401 financial executives, Graham, Harvey, and Rajgopal (2005) find that the majority of executives are willing to sacrifice long-term firm value to meet short-term earnings targets. Thus, financial analysts, by imposing short-term pressure on managers, can exacerbate managerial myopia. Supporting this view, Huang, Pereira, and Wang (2017) find a positive relation between analyst coverage and the likelihood a firm meets or beats consensus analyst earnings forecasts, suggesting that greater analyst coverage creates larger pressure for management to meet short-term performance targets. Consistent with analyst coverage motivating managerial myopia, He and Tian (2013) find that firms with greater analyst coverage are less likely to undertake long-term innovative projects. Predicting that pressure from analysts induces less visible earnings management, Irani and Oesch (2016) find that real-activities-based earnings management decreases after firms experience reductions in analyst following resulting from brokerage house mergers.

Overall, the literature suggests that the impact of traditional information intermediaries on corporate decision making is double edged: analysts can be monitors of managerial misbehavior while inducing managerial myopia. Research on earnings management supports this view by showing that financial analysts help to constrain accrual-based earnings management but motivate real-activities-based earnings management.

2.3. Hypothesis development

While traditional information intermediaries and Estimize, the newly established crowdsourcing information intermediary, both issue earnings forecasts that convey new information to the market, Estimize contributors and forecasts exhibit several key differences from traditional sell-side analysts and their forecasts. First, Brown and Khavis (2017) show that over 93% of Estimize contributors are buy-side analysts, independent financial professionals, and non-financial professionals. These individuals are unlikely to have the same incentives as sell-side analysts to bias their forecasts for the purpose of attracting investment banking business. Second, Brown and Khavis (2017) also find that financial analysts, including both the buy-side and the sell-side, only account for about 22% of the contributors on Estimize. While analysts can interact directly with management, for example, at earnings conference calls, the majority of Estimize contributors likely have no access to direct communication with management. They are therefore less likely to directly challenge managerial decisions or be effectively guided by management when issuing their forecasts. Third, sell-side analysts offer a series of products, including short-term and long-term forecasts, recommendations, and research reports. In contrast, Estimize contributors focus primarily on short-term forecasts. Jame et al. (2016) find that, over the period from 2013 to 2015, more than 90% of all estimates are forecasts of one-quarter ahead earnings.

To understand whether and how Estimize forecasts affect corporate financial reporting, we first examine whether Estimize imposes incremental pressure on management, that is, whether missing Estimize consensus leads to a significant incremental price decline. Jame et al. (2016) find that the market reacts to Estimize consensus forecast error and the reaction is not subsumed by the market's reaction to consensus forecast error of sell-side analysts. We complement their analyses by directly testing the consequences of missing Estimize consensus forecasts. Our first hypothesis is the following:

H1: Firms missing Estimize consensus forecasts experience an incremental price decline upon earnings announcements.

Facing pressure from the analysts, firms can engage in expectation management to guide the forecasts to a beatable target. Indeed, prior research finds that analysts start with optimistic earnings forecasts but then revise their estimates downward to a level that firms can beat at the earnings announcement (e.g., Bartov et al. 2002; Richardson et al. 2004; Das et al. 2011). However, the differences between crowdsourcing and traditional information intermediaries suggest that it is likely difficult for management to communicate with the crowd and guide their forecasts. We expect that Estimize forecasts, compared with I/B/E/S forecasts, are less likely to walk down to a beatable target. Our second hypothesis is therefore:

H2: The increase in the likelihood of meeting or beating I/B/E/S consensus forecast over time is more pronounced than that in the likelihood of meeting or beating Estimize consensus forecast.

Given the differences between crowdsourcing and traditional information intermediaries, it is unclear whether Estimize coverage has the same impact on firms' financial reporting as analyst coverage. Examining firms' financial reports to forecast future performance, Estimize contributors may act as monitors of management. However, they are primarily interested in the accuracy of short-term earnings forecasts, motivated by Estimize accuracy contests or the incentive to build a reputation for accuracy. Although they are more independent, less biased, and less likely to be influenced by management, their narrow focus on accuracy does not necessarily provide strong incentives to challenge management and uncover misbehavior. In addition, as the majority of Estimize contributors are non-analysts, they are unlikely to question management at conference calls or use their recommendation and research reports to voice their concerns, thereby imposing limited direct constraints on managerial behavior. Estimize may enhance monitoring indirectly through its impact on sell-side analysts. Jame et al. (2017) and Banker et al. (2017) argue that Estimize introduces competition that can help to discipline sell-side analysts. Banker et al. (2017) show that analysts become more responsive to earnings announcements and issue their forecasts earlier when firms are covered by Estimize, suggesting that analysts work harder in the presence of competition from the crowd. More diligent analysts can be better monitors. If the increase in monitoring is significant, we expect Estimize coverage initiation to result in a decrease in accrual-based earnings management.

On the other hand, Estimize focuses on short-term earnings and this focus can create significant additional pressure on management to deliver short-term performance. Jame et al. (2016) document that Estimize contributors, lacking incentives to cozy up to corporate management, issue forecasts that are less pessimistically biased than sell-side forecasts. Estimize has made such forecasts widely available and claim that they are used by numerous asset managers and retail investors. Indeed, Jame et al. (2016) find evidence suggesting that investors consider Estimize consensus forecasts to be an important earnings benchmark and missing this target drives down firms' stock prices. While there lacks evidence on whether managers are penalized personally for missing the Estimize benchmark, they are likely motivated to avoid the stock price decline resulting from the failure to meet Estimize consensus forecast. Further, Jame et al. (2017) find that the pessimistic bias in the short-term forecasts of sell-side analysts decreases after Estimize coverage starts, suggesting that competition from Estimize affects analysts' behavior and can subsequently increase the pressure on management to deliver short-term performance. Thus, the emergence of Estimize can set higher short-term performance targets for management, directly through Estimize forecasts and indirectly through less biased analyst forecasts. Such changes may exacerbate managerial short-termism. If this effect dominates, we expect Estimze coverage to induce more accrual-based and real-activities-based earnings management. Our third hypothesis, stated in the null form, is:

H3: Earnings management does not change after firms are covered by Estimize.

3. Market reaction to missing Estimize consensus forecasts

3.1. Sample selection and research design

We start with all firms that are covered by Estimize between 2011 and 2017. Firms in the financial and utilities industry are excluded. We eliminate forecasts "flagged" by Estimize as less reliable (e.g., Jame et al. 2016).[6] We require firms to have both Estimize and I/B/E/S forecasts. Following Jame et al. (2016), we require that Estimize and I/B/E/S report actual EPS that match to two decimal places. Stock price data are extracted from CSRP.

We use the following model to examine the market's reaction to missing Estimize consensus forecasts:

[6] Forecasts are flagged by Estimize if they are considered unreliable or stale after being reviewed manually or algorithmically. About 2.5% of Estimize estimates are flagged.

$$Adj\_RET_{it} = a_0\, IBES\_UE_{it} + a_1\, ESTIMIZE\_UE_{it} + a_2\, IBES\_MISS_{it} + a_3\, ESTIMIZE\_MISS_{it} + e_{it} \tag{1}$$

The dependent variable, *Adj_RET,* is market-adjusted returns measured over the (-1, 1) window around earnings announcements. Analyst forecast error (*IBES_UE*) is computed as actual EPS minus I/B/E/S consensus forecast scaled by stock price as of the end of the prior period. The consensus is either the last reported consensus in the summary file (reported consensus) or computed as the mean forecast over the (-10, -1) window before earnings announcement (constructed consensus).[7] Estimize forecast error (*ESTIMIZE_UE*) is computed in the same way based on Estimize consensus forecasts. Estimize consensus is either the last reported consensus in the Estimize data file or computed as the mean forecast over the (-10, -1) window before earnings announcement. *IBES_MISS* (*ESTIMIZE_MISS*) is an indicator variable equal to one if actual EPS misses I/B/E/S (Estimize) consensus forecast. H1 predicts a_3 to be significantly negative.

3.3. Empirical results

Table 1 Panel A reports the distribution of the sample by year. Using reported and constructed consensus to compute earnings surprises results in different samples. The final sample for the market reaction test includes 22,188 firm-quarters when using reported consensus and 12,820 firm-quarters when using constructed consensus. We classify firms into four groups based on whether they miss I/B/E/S and Estimize consensus forecasts. Mean abnormal returns around earnings announcements of the four groups are reported in Panels B and C. Whether a firm meets or beats (MBE) the consensus is determined using reported consensus in Panel B and constructed consensus in Panel C. More firms are meeting or beating I/B/E/S than Estimize consensus, consistent with the findings of Jame et al. (2016).

[7] Jame et al. (2016) find that the majority of Estimze forecasts are issued shortly before earnings announcements. To analyze earnings surprises based on Estimize and I/B/E/S consensus on an equal basis, we construct the consensus using forecasts issued in the short (-10, -1) window before earnings announcements. Using alternative windows such as (-30, -1), (-60, -1), or (-90, -1) does not change our inferences.

For firms missing I/B/E/S consensus forecasts, Panel B reports that the average stock return around earnings announcements amounts to -3.87%, 5.27% lower than the average stock return of firms meeting or beating the consensus. The average stock return of firms missing Estimize consensus amounts to -2.83%, 4.94% lower than that of MBE firms. Among firms meeting or beating I/B/E/S consensus, the average stock return of those missing Estimize consensus is 3.41% lower than that of firms meeting or beating Estimize consensus. This incremental penalty for missing Estimize consensus is similar in magnitude to the incremental penalty for missing I/B/E/S consensus (3.38%) when firms meet or beat Estimize consensus forecasts. Panel C reports similar results based on constructed consensus. In both panels, we also report abnormal returns around earnings announcements of sample firms before Estimize coverage, where firms are partitioned into two groups based on whether they miss I/B/E/S consensus. The percentage of MBE firms and the penalty for missing I/B/E/S consensus both increase post-Estimize coverage.

Table 2 reports the estimation results of model (1). Earnings surprises and MBE status are determined based on reported consensus in Panel A and constructed consensus in Panel B. Both panels report similar results. Consistent with prior findings, stock returns around earnings announcements are significantly correlated with both I/B/E/S and Estimize forecast errors. The coefficient on *ESTIMIZE_MISS* is significantly negative and comparable to that on *IBES_MISS*, suggesting that missing Estimize consensus has a significant incremental impact on stock prices, similar to that for missing I/B/E/S consensus.

4. Estimize forecasts: more beatable closer to earnings announcements?

4.1. Research design

We explore whether Estimize forecasts, similar to I/B/E/S forecasts, become more beatable over time using all firm-quarters with data available to conduct the analyses. We estimate the following model to examine the difference between Estimize and I/B/E/S in the change of the percentage of MBE firms over time, after controlling for other factors affecting changes in the likelihood of MBE:

$$Change\_MBE_{it} = a_0 + a_1\, ESTIMIZE + a_2\, LOSS4_{it} + a_3\, ABSFE_{it} + a_4\, NOA_{it} + a_5\, MKTCAP_{it} + a_6\, NUMEST_{it} + a_7\, SENS_{it} + a_8\, PERSIST_{it} + a_9\, Change\_Age_{it} + e_{it} \quad (2)$$

Financial data are extracted from Compustat. The variable *Change_MBE* captures the change in a firm's MBE status with respect to Estimize or I/B/E/S consensus. It is set equal to the indicator for MBE with respect to the last consensus minus the indicator for MBE with respect to the first consensus. The indicator for MBE is equal to one if a firm meets or beats consensus forecast and zero otherwise. The first and last consensus are measured in two ways. First, we use the first and the last reported consensus in the (-90, -1) window before earnings announcements. Second, to better capture revision patterns, we focus on I/B/E/S analysts and Estimize contributors who make at least two forecasts for a given firm-quarter. We take the first and the last forecast issued by each individual and construct the first (last) consensus for each firm-quarter as the mean of the first (last) forecasts. Under either method, *Change_MBE* is computed separately using I/B/E/S and Estimize forecasts for each firm-quarter. It takes the value of one if a firm meets or beats the last consensus but not the first one, zero if a firm's MBE status does not change, and negative one if a firm meets or beats the first consensus but misses the last one. The variable of interest, *ESTIMIZE*, is an indicator equal to one if *Change_MBE* is measured using Estimize forecasts, and zero if *Change_MBE* is based on I/B/E/S forecasts. H2 predicts a_1 to be negative, if Estimize forecasts are less likely to become more beatable over time.

Control variables are selected following prior research on walk-down of analyst forecasts (e.g., Das et al. 2011). The variable *LOSS4* is an indicator variable set to one if a firm has negative EPS for the past four quarters consecutively, and zero otherwise. The variable *ABSFE* is computed as the absolute value of the difference between actual earnings and the first consensus analyst or Estimize forecast. *NOA* is net operating assets as of the beginning of the quarter. *MKTCAP* is the market capitalization at the beginning of the quarter in millions. *NUMEST* is the number of analyst estimates.

SENS is computed as the sensitivity of stock price to the surprise in earnings in the prior quarter. *PERSIST* is the number of firm-quarters out of the last four when reported earnings beat analyst forecasts, divided by the number of quarters with consensus data. Finally, we control for the difference in the average age of forecasts between the first to the last consensus. The regression is estimated with firm, year, and quarter fixed effects.

4.2. Empirical results

We perform univariate tests of the change in the frequency of MBE in Table 3. Panel A reports the sample distribution by year. Under the second method, our requirement of individuals issuing multiple forecasts reduces the sample size. Panel B shows that the increase in the frequency of MBE based on Estimize forecasts is significantly smaller than that based on I/B/E/S forecasts. While there is a 1.51% increase in the percentage of MBE based on Estimize forecasts, the increase amounts to 4.53% for I/B/E/S forecasts. Similarly, when we examine MBE using the first and the last forecasts issued by the same analysts, the increase in the frequency of MBE based on Estimize forecasts is also significantly smaller than that based on I/B/E/S forecasts.

Next, we estimate model (2) and report the results in Table 4. Column (1) reports the results based on reported consensus and column (2) presents the results based on forecasts issued by those providing multiple forecasts for a firm-quarter. Consistent with our expectation, in both columns, the coefficient on *Estimize* is significantly negative, suggesting that, getting closer to earnings announcements, the extent to which Estimize consensus becomes more beatable is smaller than that for I/B/E/S consensus. Collectively, the results provide support for H2, consistent with the argument that Estimize forecasts are less likely to be guided down by management.

5. Estimize coverage and earnings management

5.1. Sample selection

Our sample of coverage initiation starts in 2012. We end the sample in 2016 to allow for analyses of the consequences of Estimize coverage. We consider the issuance of the first consensus forecast by Estimize to be the start of Estimize coverage.[8] To identify the immediate effects of Estimize coverage and strengthen causal inferences, we focus on changes from one year before to one year after the year of Estimize coverage initiation. We therefore require firms to have the necessary financial and return data during the period. Firms in the financial and utilities industry are excluded. Estimize produces a consensus when there are three or more unflagged forecasts.

Studies using Estimize data recognize that Estimize coverage is not random (e.g., Jame et al. 2017; Banker et al. 2017). To ensure changes from before to after Estimize coverage initiation are not driven by firm characteristics or general economic changes during the period, we follow prior research and use entropy balancing to control for covariate imbalance (Hainmueller 2012). Entropy balancing utilizes a reweighting scheme that directly incorporates covariate balance into the weight function applied to the sample units. We thus apply entropy balancing to remove any differences between treatment and control firms in factors affecting the likelihood of Estimize coverage initiation, including size, trading volume, growth, volatility, ROA, change in ROA, cash flows, analyst coverage, and stock return in the year before coverage initiation.[9]

The distribution of Estimize coverage initiation by year for treatment firms is reported in Panel A of Table 5. Not surprisingly, the first year, 2012, sees the largest number of coverage initiations (651 firms, 37% of the sample). The rest of coverage initiations are fairly evenly distributed over 2013 to 2016.[10] Descriptive statistics of variables used for entropy balancing are reported in Panel B of Table

[8] Once Estimize coverage starts, it is rare for the coverage to be terminated. About 1% of our treatment firms have their coverage terminated as of 2017.
[9] We require both treatment and control firms to be traded in at least 240 trading days in the year of matching.
[10] Jame et al. (2017) report a larger number of firms being added to Estimize in 2012 since they consider a firm as being added to Estimize if the firm has at least one unflagged Estimize forecast. We expect the presence of Estimize consensus to have a more powerful impact on management since it is Estimize consensus forecast that is available on Bloomberg and broadly disseminated.

5. While the treatment and the control sample are substantially different along multiple dimensions before entropy balancing, there is no significant difference after reweighting the control sample.

5.2. Research design

Following the literature (e.g., Cohen, Dey, and Lys 2008; Zang 2012), we use discretionary accruals to measure accrual-based earnings management. Discretionary accruals are computed using the following modified Jones (1991) model estimated in the cross-section by industry and year:

$$TA_{it} = a_0 + a_1 (1/AT_{it-1}) + a_2 (\Delta Rev_{it} - \Delta AR_{it}) + a_3 PPE_{it} + \varepsilon_{it} \tag{3}$$

The dependent variable, TA_{it}, is firm i's total accruals in year t computed as earnings before extraordinary items and discontinued operations minus operating cash flows deflated by total assets at the end of year t-1. AT_{it-1} is total assets at the end of year t-1. ΔRev_{it} is firm i's change in revenues between year t and year t-1 and ΔAR_{it} is firm i's change in accounts receivable between year t and year t-1, both of which are scaled by total assets at the end of year t-1. PPE_{it} is firm i's gross book value of property, plant and equipment at the end of year t scaled by total assets at the end of year t-1.[11] The residuals from this regression form the discretionary accruals (*DA*).[12]

We then use the following model to test our hypotheses regarding accrual-based earnings management:

$$\begin{aligned} DA_{it} = {} & a_0 + a_1\, Post_{it} + a_2\, Estimize_{it}{*}Post_{it} + a_3\, MTB_{it} + a_4\, Leverage_{it} + a_5\, LnMVE_{it} + a_6\, ROA_{it} + a_7 \\ & CFO_{it} + a_8\, NOA_{it-1} + a_9\, Accruals_{it-1} + a_{10}\, AssetGrowth_{it} + a_{11}\, EmpGrowth_{it} + a_{12}\, Loss_{it} + a_{13} \\ & MA_{it} + a_{14}\, Issuer_{it} + a_{15}\, OCFVol_{it} + a_{16}\, SalesVol_{it} + a_{17}\, \Delta CashSales_{it} + a_{18}\, FirmAge_{it} + Firm \\ & fixed\ effects + Year\ fixed\ effects + \varepsilon_{it} \end{aligned} \tag{4}$$

[11] Including ROA to control for performance, as in Kothari et al. (2005), does not change our main or cross-sectional inferences.
[12] We require a minimum of 10 observations in each industry-year to estimate models (3) and (5).

The dependent variable, *DA*, is discretionary accruals estimated from model (1) above. Since treated and control firms are matched by year, the indicator variable *Post* is equal to one for both treated and control firms for the year after Estimize starts covering the treated firm and zero for the year before. The indicator variable *Estimize* is set equal to one for treated firms and zero for control firms.[13] Thus, the interaction term, $Estimize_{it}*Post_{it}$, captures the incremental change in discretionary accruals from before to after Estimize coverage initiation for treated firms. A positive (negative) coefficient on the interaction term will indicate an incremental increase (decrease) in accrual-based earnings management for treatment firms after Estimize coverage initiation. Standard errors are clustered by industry-year in all regressions.

Control variables are included based on prior studies (e.g., Ali and Zhang 2015; Ham, Lang, Seybert, and Wang 2017). MTB_{it} is the market value of equity divided by the book value of equity at the end of year *t*. Frankel et al. (2002) argue that firms with high growth prospects are more concerned about missing earnings benchmarks and are therefore more likely to inflate earnings. $Leverage_{it}$ is the total debt divided by common equity at the end of year *t*. $LnMVE_{it}$ is the logarithm of market value of equity at the end of year *t*. ROA_{it} is earnings before extraordinary items in year *t* divided by total assets at the end of the year *t*-1. CFO_{it} is cash flow from operations in year *t* scaled by total assets at the end of year *t*-1. ROA_{it} and CFO_{it} are included to control for spurious relation between discretionary accruals and performance (Ashbaugh et al. 2003; Kothari et al. 2005; Ali and Zhang 2015).

The variable $NOA_{it\text{-}1}$ is net operating asset at the end of year *t*-1, defined as shareholders' equity less cash and marketable securities, plus total debt, deflated by sales. Barton and Simko (2002) argue that *NOA* measures constraints faced by firms for managing earnings. $Accruals_{it-1}$ is total accruals in year *t*-1 scaled by total assets at the beginning of the year. $Loss_{it}$ is an indicator variable that equals one if the firm reports a net loss for year *t*, and zero otherwise. MA_{it} is an indicator variable that equals one

[13] The main effect of *Estimize* is subsumed by firm fixed effects. As a result, it is not included in the regression as an explanatory variable.

if the firm has engaged in a merger and acquisition in year *t*, and zero otherwise. $Issuer_{it}$ is an indicator variable that equals one if MA_{it} is not equal to one and if the number of outstanding shares increased by at least 10 percent, long-term debts increased by at least 20 percent, or the firm first appears on the CRSP monthly returns database in year *t*, and zero otherwise. $AssetGrowth_{it}$ is defined as change of total assets during year *t*, scaled by the total assets at the end of year *t*-1. $EmpGrowth_{it}$ is defined as change of employment during year *t*, scaled by the employment at the end of year *t*-1. Ali and Zhang (2015) include these two variables to control for the combined effect of disinvestment and investment in a firm on discretionary accruals. $OCFVol_{it}$ and $SalesVol_{it}$ are the standard deviation of operating cash flows and sales over the past five years scaled by total assets, respectively. Dechow and Dichev (2002) find that these volatility measures are significantly associated with accruals quality. $\Delta CashSales_{it}$ is the percentage change in sales minus the change in accounts receivable over the previous year. Dechow et al. (2011) suggest that changes in cash sales are related to incentives to materially misreport earnings. $FirmAge_{it}$ is the number of years since a firm's IPO, measured as the number of years it has been on CRSP database. Firm and year fixed effects are included.

Graham et al. (2005) provide survey evidence that executives point to the reduction of discretionary expenses such as R&D and SG&A as the most preferred method for overstating earnings. Thus, as in prior research (e.g., Lo et al. 2017; Kothari et al. 2016; Ali and Zhang 2015), we focus on firms' discretionary expenditures including R&D expenditures, advertising expense, and selling, general, and administrative expenses (SG&A). To estimate the abnormal level of discretionary expenses, we use the following cross-sectional model by industry and year (Roychowdhury 2006):

$$DisExp_{it} = a_1 + a_2\,(1\,/\,AT_{it-1}) + a_3\,Rev_{it-1} + \varepsilon_{it} \tag{5}$$

The dependent variable is discretionary expenses, defined as selling, general, and administrative expenses plus R&D and advertising expenses of year *t*, scaled by total assets at the end of year *t*-1. AT_{it-1} is the total assets of firm *i* at the end of year *t*-1. Rev_{it-1} is the sales revenue of firm *i* in year t-1 scaled by total assets. The residuals from model (5) are used to measure abnormal discretionary expenses.

We then use the following model to test our hypotheses regarding real-activities-based earnings management:

$$RAM_{it} = a_0 + a_1\ Post_{it} + a_2\ Estimize_{it}{*}Post_{it} + a_3\ MTB_{it} + a_4\ Leverage_{it} + a_5\ LnMVE_{it} + a_6\ ROA_{it} + a_7\ AssetGrowth_{it} + a_8\ EmpGrowth_{it} + a_9\ Loss_{it} + a_{10}\ MA_{it} + a_{11}\ Issuer_{it} + a_{12}\ OCFVol_{it} + a_{13}\ SalesVol_{it} + a_{14}\ \Delta CashSales_{it} + a_{15}\ FirmAge_{it} + Firm\ fixed\ effects + Year\ fixed\ effects + \varepsilon_{it} \qquad (6)$$

The dependent variable, RAM_{it}, is equal to the negative of abnormal discretionary expenses estimated from model (3) above. Thus, higher values of *RAM* indicate more earnings management through cutting discretionary expenditures. Indicator variables *Post* and *Estimize* are defined as in model (2). The interaction term, $Estimize_{it}{*}Post_{it}$, captures the incremental change in abnormal discretionary expenses from before to after Estimize coverage initiation for treated firms. A positive (negative) coefficient on the interaction term will indicate an incremental increase (decrease) in real-activities-based earnings management for treatment firms after Estimize coverage initiation. Control variables are included following prior studies (e.g., Ali and Zhang 2015) and have been defined in model (4).

Since firms can manage either or both accruals and discretionary expenses to meet earnings targets, total earnings management that incorporates both components will most clearly reflect the impact of Estimize coverage. We thus estimate the following model:

$$TM_{it} = a_0 + a_1\ Post_{it} + a_2\ Estimize_{it}{*}Post_{it} + a_3\ MTB_{it} + a_4\ Leverage_{it} + a_5\ LnMVE_{it} + a_6\ ROA_{it} + a_7\ CFO_{it} + a_8\ NOA_{it-1} + a_9\ Accruals_{it-1} + a_{10}\ AssetGrowth_{it} + a_{11}\ EmpGrowth_{it} + a_{12}\ Loss_{it} + a_{13}\ MA_{it} + a_{14}\ Issuer_{it} + a_{15}\ OCFVol_{it} + a_{16}\ SalesVol_{it} + a_{17}\ \Delta CashSales_{it} + a_{18}\ FirmAge_{it} + Firm\ fixed\ effects + Year\ fixed\ effects + \varepsilon_{it} \qquad (7)$$

We measure total earnings management, *TM*, as the sum of discretionary accruals, *DA*, and abnormal discretionary expenses, *RAM*. The control variables are the same as in model (4) for discretionary accruals since the control variables in model (6) for abnormal discretionary expenses are a subset of those in model (4). The interaction term, $Estimize_{it}*Post_{it}$, captures the incremental change in total earnings management from before to after Estimize coverage initiation for treated firms.

5.3. Accrual-based and real-activities earnings management

Univariate analyses of discretionary accruals, abnormal discretionary expenses, and total earnings management are reported in Panel A of Table 6. Treatment firms experience a significant increase in discretionary accruals after Estimize coverage initiation, while control firms experience a negative but insignificant change in discretionary accruals during the same period. The difference in the change of discretionary accruals around the year of Estimize coverage initiation between treatment and control firms is significant, suggesting that firms increase accrual-based earnings management after Estimize coverage initiation. Treatment firms also experience a significant increase in real-activities-based earnings management after Estimize coverage initiation. The increase in real-activities-based earnings management of treatment firms is significantly larger than that of control firms. Adding up discretionary accruals and abnormal discretionary expenses to measure total earnings management, we find that treatment firms experience a significantly larger increase in total earnings management than control firms.

We report the regression results in Panel B of Table 6. The estimation results of model (4) with discretionary accruals as the dependent variable are presented in column (1). After controlling for various factors that can affect discretionary accruals, the coefficient on *Estimize*Post* is significantly positive, suggesting a significant incremental increase in accrual-based earnings management for treated firms after Estimize coverage initiation, relative to control firms that are not covered by Estimize in the same period. The coefficients on control variables are largely consistent with findings in prior studies. The coefficient on *ROA* is significantly positive, consistent with the result in Kothari et al. (2005). The coefficient on *Loss* is significantly negative and that on *CFO* is significantly negative, consistent with the findings of Ashbaugh et al. (2003). They argue that discretionary accruals models do not completely extract out nondiscretionary accruals that are negatively correlated with cash flows from operations. As in Ali and Zhang (2015), *AssetGrowth* is positively correlated with discretionary accruals.

The estimation results of model (6) regarding real-activities-based earnings management are reported in column (2) of Panel B, Table 6. Consistent with the univariate results, the coefficient on *Estimize*Post* is significantly positive, suggesting that treatment firms exhibit a significant incremental increase in real-activities-based earnings management post Estimize coverage initiation. The coefficients on control variables are also largely consistent with findings in prior studies. Similar to Ali and Zhang (2015), we find *AssetGrowth* to be negatively associated with reductions in abnormal discretionary expenses.

We report the results on total earnings management in column (3) of Panel B. The coefficient on *Estimize*Post* is significantly positive at better than 1% level, suggesting a significant incremental increase in total earnings management post Estimize coverage initiation.

In summary, the univariate and the regression analyses indicate that there is an increase in both accrual-based and real-activities-based earnings management in treated firms after Estimize coverage initiation. The results suggest that Estimize coverage exerts pressure on management and induces earnings management to achieve short-term targets.

5.4. Cross-sectional analyses

5.4.1 Estimize impact and the size of the crowd

Jame et al. (2016) argue that the value of crowdsourced forecasts likely increases with the size of the crowd. Consistent with this argument, they find that the incremental information content in Estimize forecasts and the market’s reaction to Estimize consensus forecast error increase with the number of Estimize contributors covering the firm. Their findings suggest that Estimize consensus forecasts are likely a more important earnings benchmark when the size of the crowd is large. We thus expect the pressure from the crowd to be stronger when a larger number of Estimize contributors follow a company.

We partition the sample into subsamples based on the sample median of the median number of Estimize forecasts for each treated firm over the coverage initiation year. We then estimate models (4), (6), and (7) for the two subsamples separately. The subsample of treatment firms followed by a large crowd has on average 10 Estimize forecasts, while the subsample followed by a small crowd has about 4. The results are reported in Table 7. The first two columns of Table 7, Panel A present the results on accrual-based earnings management while the first two columns of Panel B present the results of real-activities-based earnings management and the first two columns of Panel C report the results of total earnings management. In all three tests, the coefficient on *Estimize*Post* is larger in the subsample of firms that are covered by more Estimize contributors. The difference in the coefficient between the two subsamples is significant for total earnings management, suggesting that the increase in earnings management is more pronounced in treatment firms followed by a larger crowd.

5.4.2 Managerial ownership

Management is likely to have strong incentives to meet or beat Estimize consensus if their personal wealth is more affected by a decline in stock price due to missing the earnings target. We expect that managers who hold more shares of their own firms engage more in earnings management to avoid missing Estimize consensus forecasts. We partition the sample into subsamples with high and low CEO ownership based on CEO shareholdings at the end of the year before Estimize coverage initiation. Model (4) on accrual-based, model (6) on real-activities-based earnings management, and model (7) on total earnings management are estimated separately for the subsamples. The results are reported in columns (3) and (4) of the three panels of Table 7. Consistent with our expectation, the increase in total earnings management is significantly larger in the subsample of firms with more CEO ownership.

5.4.3 Transient institutional ownership and managerial myopia

Shleifer and Vishny (1990) show analytically that shareholders with short investment horizon can induce managers to focus on short-term performance. Empirically, Bushee (1998) documents that transient institutional investors, who have short investment horizon, are more likely to induce managers' myopic behavior. Chen et al. (2015) find that the impact of CEO contractual protection that mitigates managerial myopia is more pronounced in firms with higher transient institutional ownership. Thus, we predict that the pressure from the crowd to deliver short-term performance has a greater impact on management's reporting incentives for firms with higher ownership by transient institutional investors.

We partition the sample into subsamples based on the percentage of transient institutional ownership of each treated firm prior to the coverage initiation year. The average percentage of shares held by transient institutional investors amounts to 25.4% for the subsample of firms with higher transient ownership and 9.4% for the subsample with lower transient ownership. We then estimate models (4), (6), and (7) for the two subsamples separately. The results are reported in columns (5) and (6) in each panel of Table 7. The subsample with high transient institutional ownership exhibits a significantly larger increase in accrual-based earnings management, real-activities-based earnings management, and total earnings management.

5.5 Additional analyses

We perform several additional analyses to test the robustness of our results. First, we estimate variations of models (4), (6), (7) using the treatment and the control firms without entropy balancing. Specifically, we include all explanatory variables and fixed effects in models (4), (6), and (7) except for the indicator variable *Post*, since control firms are not matched with treatment firms and there is no pre- or post-event period for control firms. As noted by Bertrand and Mullainathan (2003) and others (e.g., Armstrong, Balakrishnan, and Cohen 2012), with firm and year fixed effects, this is a difference-in-differences specification and the coefficient on *Estimize*Post* captures the post-coverage change in earnings management. The results are reported in Panel A of Table 8. Consistent with the results based on the entropy-balanced sample reported in Table 6, the coefficient on *Estimize*Post* is significantly positive in all three columns, indicating an increase in accrual-based, real-activities-based, and total earnings management after Estimize coverage initiation.

Second, we include additional controls for potential nonlinear relations between firm growth and earnings management (Collins, Pungaliya, and Vijh 2017). As in Collins et al. (2017), we construct four quintile dummy variables for sales growth, where SG_Rank_k is set equal to one if a firm's sales growth falls into the *k*th quintile of the sample, and zero otherwise. The results of estimating models (4), (6), and (7) using the entropy-balanced sample are reported in Panel B of Table 8. Again, the coefficient on *Estimize*Post* is significantly positive in all three columns, indicating an increase in accrual-based, real-activities-based, and total earnings management after Estimize coverage initiation. We also use the design to examine cross-sectional variations in total earnings management (untabulated). Our cross-sectional predictions continue to hold, suggesting that the increase in earnings management is more pronounced when firms are under greater pressure to deliver short-term performance.

6. Conclusion

Social-media-based information intermediaries are playing an increasingly important role in the capital markets. In particular, crowdsourced earnings forecasts collected and disseminated by Estimize have become an earnings benchmark alternative to sell-side forecasts. While research documents significant impact of Estimize forecasts on analysts and investors, little is known about how they affect management and financial reporting. We document that there is a significant incremental stock price decline for missing Estimize consensus forecasts, controlling for whether firms meet or beat I/B/E/S consensus. Further, we find that, compared to I/B/E/S forecasts, there is less downward revision in Estimize forecasts over time, suggesting that management is less effective in guiding Estimize contributors.

We then explore the impact of Estimize coverage initiation on firms' earnings management using a difference-in-differences approach over the period from 2012 to 2016. We construct an entropy-balanced control sample based on factors that may affect the likelihood of Estimize coverage. We examine changes in both accrual-based and real-activities-based earnings management of treatment firms from the year before to the year after the coverage initiation year, relative to the sample of control firms that are not covered by Estimize during the period. After controlling for other factors affecting accruals and discretionary expenses, we find a significant increase in both accrual-based and real-activities-based earnings management after Estimize coverage initiation for treatment firms. This finding suggests that pressure from the crowd to deliver short-term performance motivates management to engage more in earnings management.

We also examine whether the impact of Estimize on management reporting incentives varies in the cross-section as expected. Consistent with the expectation that the impact of Estimize consensus forecasts increases with the size of the crowd, we find that the increase in total earnings management is concentrated in treatment firms followed by a larger number of Estimize contributors. We also find the increase in total earnings management to be concentrated in the subsample of firms with greater managerial ownership. Finally, we find that the pressure from the crowd has a greater impact on management's reporting incentives for firms with higher ownership by transient institutional investors who have shorter investment horizons.

This study contributes to the literature in several ways. It adds to the rising line of research on social media by documenting an unintended impact of crowdsourced investment research on financial reporting. Our findings suggest that, directly through Estimize forecasts or indirectly through the impact of Estimize on sell-side analysts, the rise of Estimize may have imposed additional pressure on management and exacerbated managerial short-termism. We provide the first empirical evidence of the impact of social media on managerial decision making. In addition, it also contributes to the literature on information intermediaries by documenting the influence of new, social-media-based information intermediaries, on corporations, which differs from that of traditional information intermediaries. Finally, it adds to the literature on managerial myopia by providing new evidence on social media as a source of pressure that induces managerial short-termism.

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Appendix A: Variable Definitions

Variables	Definitions
Earnings Announcements	
Adj_RET	Market-adjusted returns over the (-1, 1) window around earnings announcement
IBES_UE	Actual EPS minus IBES consensus forecast scaled by stock price as of the end of the prior period. The consensus is either the last reported consensus form I/B/E/S summary file or computed as the mean forecasts over the (-10, -1) window before earnings announcement.
ESTIMIZE_UE	Actual EPS minus ESTIMIZE consensus forecast scaled by stock price as of the end of the prior period. The consensus is either the last reported consensus form Estimize data file or computed as the mean forecasts over the (-10, -1) window before earnings announcement.
IBES_MISS	Indicator variable equal to one if actual EPS misses IBES consensus forecast. The consensus is either the last reported consensus form I/B/E/S summary file or computed as the mean forecasts over the (-10, -1) window before earnings announcement.
ESTIMIZE_MISS	Indicator variable equal to one if actual EPS misses ESTIMIZE consensus forecast. The consensus is either the last reported consensus form Estimize data file or computed as the mean forecasts over the (-10, -1) window before earnings announcement.
Forecast Walkdown	
Change_MBE	*Change_MBE* is equal to the indicator for MBE with respect to the last consensus minus the indicator for MBE with respect to the first consensus in the (-90, -1) window before earnings announcements. The MBE indicator equals one for firms meeting or beating consensus forecast and zero otherwise. Consensus is measured (1) using the first and the last consensus reported by I/B/E/S or Estimize, and (2) as the mean of the first and the last forecasts issued by analysts providing multiple forecasts for a firm-quarter. *Change_MBE* takes the value of one if a firm meets or beats the last consensus but not the first one, zero if a firm's MBE status does not change, and negative one if a firm meets or beats the first consensus but misses the last one.
ESTIMIZE	Indicator set to 1 if *Change_MBE* is based on Estimize forecasts, and zero otherwise.
LOSS4	Indicator set to 1 if a firm has negative EPS for the past four quarters consecutively, and zero otherwise.
ABSFE	Absolute value of the difference between actual earnings and the first consensus analyst (Estimize) forecast issued.
NOA	Net operating assets at the beginning of the quarter.
MKTCAP	Market capitalization at the beginning of the quarter ($ millions).
NUMEST	Number of IBES or Estimize estimates.
SENS	Sensitivity of stock price to the surprise in earnings in the prior quarter.

PERSIST	Number of firm-quarters out of the last four when reported earnings beat analyst forecasts, divided by the number of quarters with consensus data.
AGE_DIFF	Difference between the age of the first consensus and that of the last consensus
Earnings Management	
Dependent variables	
DA	*DA* is computed using the following model estimated in the cross-section by industry and year: $TA_{it} = a_0 + a_1 (1/AT_{it-1}) + a_2 (\Delta Rev_{it} - \Delta AR_{it}) + a_3 PPE_{it} + \varepsilon_{it}$ The dependent variable, TA_{it}, is firm *i*'s total accruals in year *t* computed as earnings before extraordinary items and discontinued operations minus operating cash flows deflated by total assets at the end of year *t*-1. AT_{it-1} is total assets at the end of year *t*-1. ΔRev_{it} is firm *i*'s change in revenues between year *t* and year *t*-1 and ΔAR_{it} is firm *i*'s change in accounts receivable between year *t* and year *t*-1, both of which are scaled by total assets at the end of year *t*-1. PPE_{it} is firm *i*'s gross book value of property, plant and equipment at the end of year *t* scaled by total assets at the end of year *t*-1. The residuals from the model form *DA*.
RAM	*RAM* is abnormal discretionary expenses computed using the following cross-sectional model by industry and year: $DisExp_{it} = a_1 + a_2 (1 / AT_{it-1}) + a_3 Rev_{it-1} + \varepsilon_{it}$ The dependent variable is discretionary expenses, selling, general, and administrative expense (including R&D and advertising) of year *t*, scaled by total assets at the beginning of the year. AT_{it-1} is the total assets of firm *i* at the beginning of year *t*. Rev_{it-1} is the sales revenue of firm *i* in year *t*-1 scaled by total assets. *RAM* is set to the negative of residuals from the model.
TM	*TM* is the sum of *DA* and *RAM*.
Explanatory variables	
$Post_{it}$	Indicator variable equal to one for both treated and control firms for the year after Estimize starts covering the treated firm and zero for the year before.
$Estimize_i$	Indicator variable equal to one for treated firms covered by Estimize and zero for control firms not covered by Estimize in year *t* and year *t*+1.
MTB_{it}	Market value of equity divided by the book value of equity at the end of year *t*.
$Leverage_{it}$	Total debt divided by common equity at the end of year *t*.
$LnMVE_{it}$	The logarithm of market value of equity at the end of year *t*.
ROA_{it}	Earnings before extraordinary items in year *t* divided by total assets at the beginning of the year *t*.
CFO_{it}	Cash flow from operations in year *t* scaled by total assets at the beginning of year *t*.
NOA_{it-1}	Net operating asset at the beginning of year *t*, defined as shareholders' equity less cash and marketable securities, plus total debt, deflated by sales.
$Loss_{it}$	Indicator variable equal to one if the firm reports a net loss for year *t*, and zero otherwise.

MA_{it}	Indicator variable equal to one if the firm has engaged in a merger and acquisition in year *t*, and zero otherwise.
$Issuer_{it}$	Indicator variable equal to one if MA_{it} is not equal to one and if the number of outstanding shares increased by at least 10 percent, long-term debts increased by at least 20 percent, or the firm first appears on the CRSP monthly returns database in year *t*, and zero otherwise.
$AssetGrowth_{it}$	Change of total assets during year *t*, scaled by the total assets at the beginning of year *t*.
$EmpGrowth_{it}$	Change of employment during year t, scaled by the employment at the beginning of year t.
$OCFVol_{it}$	The standard deviation of operating cash flows over the past five years scaled by total assets.
$SalesVol_{it}$	The standard deviation of sales over the past five years scaled by total assets
$\Delta CashSales_{it}$	The percentage change in sales minus the change in accounts receivable over the previous year.
$FirmAge_{it}$	The number of years since a firm's IPO, measured as the number of years it has been on CRSP database.

Table 1: Market Reaction to Earnings Announcements – Descriptive Statistics

Panel A: Sample distribution

This panel reports the distribution of the samples used in the earnings announcement analyses.

Year	Sample using reported consensus Number of Firm-Quarters	Sample using constructed consensus Number of Firm-Quarters
2011	46	100
2012	1100	991
2013	1769	1716
2014	2957	2173
2015	4200	2445
2016	5636	2665
2017	6480	2730
Total	22188	12820

Panel B: Univariate Analysis – reported consensus

This panel reports the average market-adjusted return over the (-1, 1) window around earnings announcements, by whether a firm's actual earnings meet or beat Estimize or I/B/E/S consensus, where consensus is taken as reported by Estimize or in I/B/E/S summary files.

			Pre-coverage	Post-coverage			
					ESTIMIZE		
					MBE	MISS	Diff (MBE-MISS)
		Return			0.0210	-0.0283	-0.0494
		p-value			0.0001	0.0001	0.0001
		N			13174	9014	
					59.37%	40.63%	
IBES	MBE	Return	0.0187	0.0139	0.0217	-0.0123	-0.0341
		p-value	0.0001	0.0001	0.0001	0.0001	0.0001
		N	17,922	16720	12893	3827	
			70.29%	75.36%			
	MISS	Return	-0.0294	-0.0387	-0.0120	-0.0402	-0.0281
		p-value	0.0001	0.0001	0.0128	0.0001	0.0001
		N	7,576	5468	281	5187	
			29.71%	24.64%			
	Diff (MBE-MISS)	Return	-0.048	-0.0527	-0.0338	-0.0278	
		p-value	0.0001	0.0001	0.0001	0.0001	

Panel C: Univariate Analysis – constructed consensus using forecasts issued (-10, -1)

This panel reports the average market-adjusted return over the (-1, 1) window around earnings announcements, by whether a firm's actual earnings meet or beat Estimize or I/B/E/S consensus, where consensus is constructed using forecasts issued in the (-10, -1) window before earnings announcements.

			Pre-coverage	Post-coverage			
					ESTIMIZE		
					MBE	MISS	Diff (MBE-MISS)
		Return			0.0183	-0.0229	-0.0411
		p-value			0.0001	0.0001	0.0001
		N			7,663	5,157	
					59.77%	40.23%	
IBES	MBE	Return	0.0153	0.014	0.0197	-0.0057	-0.0254
		p-value	0.0001	0.0001	0.0001	0.0002	0.0001
		N	7,042	9,279	7,191	2,088	
			70.84%	72.38%			
	MISS	Return	-0.0244	-0.0303	-0.0031	-0.0345	-0.0314
		p-value	0.0001	0.0001	0.3327	0.0001	0.0001
		N	2,899	3,541	472	3,069	
			29.16%	27.62%			
	Diff (MBE-MISS)	Return	-0.0397	-0.0443	-0.0228	-0.0288	
		p-value	0.0001	0.0001	0.0001	0.0001	

Table 2: Market Reaction to Earnings Announcements - Regressions

This table reports the regression results of returns on earnings surprises and indicators for missing I/B/E/S or Estimize consensus. The dependent variable is market-adjusted returns around (-1, 1) window around earnings announcements. Variables are defined in Appendix A. Heteroscedasticity-robust standard errors are estimated and clustered at the industry-year level. Firm, year, and quarter fixed effects are included in all regressions. P-values are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, two-sided tests.

Panel A: Reported consensus

Earnings surprises are computed based on the last reported consensus from Estimize or I/B/E/S summary files.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IBES_UE	4.524***		1.690***				2.812***		1.153***
	(<.0001)		(<.0001)				(<.0001)		(0.0017)
ESTIMIZE_UE		5.000***	3.409***					3.054***	1.520***
		(<.0001)	(<.0001)					(<.0001)	((<.0001)
IBES_MISS				-0.059***		-0.034***	-0.043***		-0.024***
				(<.0001)		(<.0001)	(<.0001)		(<.0001)
ESTIMIZE_MISS					-0.051***	-0.034***		-0.037***	-0.027***
					(<.0001)	(<.0001)		(<.0001)	(<.0001)
Observations	22,019	22,019	22,019	22,019	22,019	22,019	22,019	22,019	22,019
R-squared	0.178	0.182	0.184	0.189	0.197	0.211	0.208	0.216	0.225
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: Constructed consensus

Earnings surprises are computed based on consensus constructed using Estimize or I/B/E/S forecasts issued in the (-10, -1) window before earnings announcements.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
IBES_UE	4.825***		1.822***				2.996***		0.862**
	(<.0001)		(<.0001)				(<.0001)		(0.0312)
ESTIMIZE_UE		5.586***	4.139***					3.639***	2.543***
		(<.0001)	(<.0001)					(<.0001)	(<.0001)
IBES_MISS				-0.046***		-0.028***	-0.034***		-0.022***
				(<.0001)		(<.0001)	(<.0001)		(<.0001)
ESTIMIZE_MISS					-0.042***	-0.028***		-0.029***	-0.019***
					(<.0001)	(<.0001)		(<.0001)	(<.0001)
Observations	12,426	12,426	12,426	12,426	12,426	12,426	12,426	12,426	12,426
R-squared	0.200	0.212	0.216	0.211	0.215	0.233	0.228	0.237	0.250
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 3: Change in the percentage of MBE firms over time – Univariate Analyses

Panel A: Sample distribution

This panel reports the distribution of the samples used in the MBE analyses.

Year	Sample using reported consensus Number of Firm-Quarters	Sample using first and last forecast of same analysts Number of Firm-Quarters
2011	8	0
2012	747	160
2013	1010	374
2014	2216	1061
2015	3211	1789
2016	4524	1900
2017	5183	2132
Total	16899	7416

Panel B: Change in the percentage of MBE over time

This table reports the percentage of firms that meet or beat Estimize or I/B/E/S consensus forecast with respect to the first and the last consensus. The consensus is (1) the first and the last reported consensus from IBES summary file or Estimize in the (-90, -1) window before earnings announcements, or (2) the mean of the first and the last forecasts issued by the same analysts in the (-90, -1) window.

	Reported consensus			First and last forecasts of same analysts		
	First (1)	Last (2)	Diff (2) – (1)	First (1)	Last (2)	Diff (2) – (1)
Estimize	58.43%	59.94%	1.51%	57.87%	62.07%	4.20%
IBES	71.54%	76.07%	4.53%	63.73%	74.93%	11.20%
DIFF (EST – IBES)	-13.11%	-16.13%	3.02%	-5.86%	-12.86%	7.00%
p-value			0.0001			0.0001

Table 4: Change in the percentage of MBE firms over time – Regression analyses

This table examines the difference in the extent to which Estimize and I/B/E/S consensus becomes more beatable getting closer to the earnings announcement. The dependent variable *Change_MBE* takes the value of 1 if a firm meets or beats the last consensus (MBE) but misses the first one, 0 if a firm's MBE status does not change, and -1 if a firm meets or beats the first consensus but misses the last one. MBE status is determined using reported consensus in column (1) and forecasts issued by analysts who provide multiple forecasts in column (2). Variables are defined in Appendix A. Heteroscedasticity-robust standard errors are estimated and clustered at the industry-year level. Firm, year, and quarter fixed effects are included in all regressions. P-values are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, two-sided tests.

	Reported consensus (1)	First and last of same analysts (2)
ESTIMIZE	-0.018***	-0.041***
	(0.005)	(0.000)
LOSS4	0.026	0.100
	(0.547)	(0.398)
ABSFE	-0.746	-2.415**
	(0.159)	(0.020)
NOA	0.062**	0.016
	(0.016)	(0.747)
MKTCAP	-0.007	0.043***
	(0.318)	(0.002)
NUMEST	0.001**	0.009***
	(0.015)	(0.000)
SENS	-0.000	0.001
	(0.108)	(0.211)
PERSIST	-0.058***	-0.053***
	(0.000)	(0.001)
AGE_DIFF	0.001***	0.000***
	(0.000)	(0.010)
Observations	33,798	14,832
R-squared	0.088	0.167
Firm FE	YES	YES
Year FE	YES	YES
Quarter FE	YES	YES

Table 5: Sample of Estimize Initiation

This table reports the distribution of Estimize coverage initiation and descriptive statistics. Panel A reports the distribution of Estimize coverage initiation by year. Panel B reports the descriptive statistics.

Panel A: Distribution of the year of Estimize coverage initiation

Year	Frequency	Percent
2012	640	37.94%
2013	322	19.09%
2014	245	14.52%
2015	221	13.10%
2016	259	15.35%
Total	1687	100.00%

Panel B: Descriptive statistics before and after entropy balancing

This panel reports the mean of variables used in entropy balancing before and after entropy balancing for the treatment and the control sample. *T*-tests are conducted to test the difference in means between the treatment and the control sample. *** denotes statistical significance at the 1% level.

	Before entropy balancing			After entropy balancing		
	N= 6113	N = 1687		N= 6113	N = 1687	
	Control	Treated	Difference	Control	Treated	Difference
$LnMVE_{t-1}$	5.5347	7.5660	2.0313***	7.5655	7.5660	0.0004
$Turnover_{t-1}$	0.0075	0.0111	.0036***	0.0111	0.0111	<.0001
BTM_{t-1}	0.7890	0.4581	-.3309***	0.4583	0.4581	-0.0002
$LnCoverage_{t-1}$	1.0271	2.2080	1.1809***	2.2078	2.2080	0.0002
$RETVOL_{t-1}$	0.0335	0.0257	-.0076***	0.0257	0.0257	<.0001
ROA_{t-1}	-0.0543	0.0315	.0858***	0.0315	0.0315	<.0001
CFO_{t-1}	0.0191	0.0923	.0732***	0.0922	0.0923	<.0001
ΔROA_{t-1}	-0.0137	0.0015	.0152***	0.0015	0.0015	<.0001
$BHAR_{t-1}$	-0.0781	0.0609	.1390***	0.0609	0.0609	<.0001

Table 6: Estimize coverage initiation and earnings management

This table reports the results on earnings management. Panel A reports the mean of discretionary accruals (*DA*), abnormal discretionary expenses (*RAM*), and total earnings management (*TM*) before and after the year of Estimize coverage initiation for treatment and control firms. Panel B reports the regression results. Variables are defined in Appendix A.

Panel A. Changes in discretionary accruals and abnormal discretionary expenses

T-tests are conducted to test the difference in means between the year before the year of Estimize coverage initiation and the year after. *, **, *** indicate the significance of differences at the 10%, 5%, and 1% levels, respectively, two-sided tests.

		Pre-initiation	Post-initiation	Change (Post – Pre)
DA	*Treatment*	0.0109	0.0209	0.0101***
	Control	0.0168	0.0157	-0.0012
	Difference (T-C)			0.0113***
RAM	*Treatment*	0.0534	0.0819	0.0284***
	Control	0.0773	0.0885	0.0111**
	Difference (T-C)			0.0173***
TM	*Treatment*	0.0601	0.0962	0.0361***
	Control	0.0826	0.0932	0.0106**
	Difference (T-C)			0.0255***

Panel B. Accruals-based, real-activities-based, and total earnings management

This table reports the tests of changes in accrual-based and real-activities-based earnings management of treatment firms relative to control firms around the year of Estimize coverage initiation. Column (1) presents the results of estimating model (4) with discretionary accruals (*DA*) as the dependent variable. Column (2) presents the results of estimating model (6) with real-activities-based earnings management (*RAM*) as the dependent variable. Column (3) presents the results of estimating model (7) with total earnings management (*TM*) as the dependent variable. Heteroscedasticity-robust standard errors are estimated and clustered at the industry-year level. Firm and year fixed effects are included in all regressions. P-values are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, two-sided tests.

	(1) *DA*	(2) *RAM*	(3) *TM*
$Post_{it}$	0.004*	-0.005*	0.004
	(0.066)	(0.060)	(0.363)
$Estimize_i*Post_{it}$	**0.006****	**0.014*****	**0.018*****
	(0.046)	(0.005)	(0.002)
MTB_{it}	0.000	-0.001	-0.000
	(0.289)	(0.396)	(0.688)
$Leverage_{it}$	0.001	0.001	0.001
	(0.599)	(0.553)	(0.360)
$LnMVE_{it}$	-0.005	0.011*	0.003
	(0.206)	(0.098)	(0.670)
ROA_{it}	0.738***	0.171***	0.912***
	(0.000)	(0.000)	(0.000)
CFO_{it}	-0.786***		-0.719***
	(0.000)		(0.000)
NOA_{it-1}	-0.002		0.001
	(0.365)		(0.762)
$Accruals_{it-1}$	-0.022		0.001
	(0.104)		(0.979)
$AssetGrowth_{it}$	0.014***	-0.114***	-0.082***
	(0.006)	(0.000)	(0.000)
$EmpGrowth_{it}$	-0.005	0.014	-0.004
	(0.514)	(0.267)	(0.796)
$Loss_{it}$	-0.018***	0.004	-0.007
	(0.001)	(0.568)	(0.373)
MA_{it}	-0.000	0.005	-0.002
	(0.939)	(0.142)	(0.750)
$Issuer_{it}$	-0.001	0.003	-0.003
	(0.696)	(0.582)	(0.635)
$OCFVol_{it}$	0.051	-0.176**	-0.085
	(0.341)	(0.029)	(0.356)
$SaleVol_{it}$	0.004	0.012	0.015
	(0.790)	(0.556)	(0.543)
$\Delta CashSales_{it}$	0.011	-0.049***	-0.019
	(0.115)	(0.001)	(0.132)
$FirmAge_{it}$	0.001	0.000	0.002***
	(0.215)	(0.979)	(0.006)
Firm Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Observations	15,546	14,244	15,600
R-squared	0.760	0.930	0.907

Table 7: Cross-sectional analyses

This table reports the cross-sectional results. Panel A reports the results of accrual-based earnings management. Panel B reports the results of real-activities-based earnings management. Panel C reports the results of total earnings management. Variables are defined in Appendix A. Heteroscedasticity-robust standard errors are estimated and clustered at the industry-year level. Firm and year fixed effects are included in all regressions. P-values are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, two-sided tests.

Panel A: Accrual-based earnings management

This panel reports the results of estimating model (4) using the entropy rebalanced sample. Model (4) is estimated for the subsample with large crowd following in column (1), the subsample with small crowd following in column (2), the subsample with high CEO ownership in column (3), the subsample with low CEO ownership in column (4), the subsample with high transient institutional ownership in column (5), and the subsample with low transient ownership in column (6).

	(1)	(2)	(3)	(4)	(5)	(6)
	Large Crowd	Small Crowd	High Ownership	Low Ownership	High Transient	Low Transient
$Post_{it}$	0.005	0.002	0.007**	0.001	0.004	0.005*
	(0.184)	(0.337)	(0.024)	(0.757)	(0.245)	(0.064)
$Estimize_i*Post_{it}$	0.009**	0.004	0.012**	0.002	0.010**	0.002
	(0.017)	(0.213)	(0.011)	(0.631)	(0.017)	(0.625)
MTB_{it}	0.000	0.000	-0.000	-0.000	0.000	0.000
	(0.340)	(0.333)	(0.942)	(0.669)	(0.690)	(0.346)
$Leverage_{it}$	0.000	0.001	0.002	0.003*	0.001	0.001
	(0.981)	(0.414)	(0.162)	(0.081)	(0.362)	(0.440)
$LnMVE_{it}$	-0.001	-0.009*	-0.000	-0.009*	-0.002	-0.006
	(0.875)	(0.050)	(0.965)	(0.058)	(0.653)	(0.132)
ROA_{it}	0.751***	0.749***	0.684***	0.792***	0.733***	0.748***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CFO_{it}	-0.760***	-0.825***	-0.794***	-0.811***	-0.779***	-0.806***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NOA_{it-1}	-0.003	-0.001	-0.004	-0.005	-0.001	-0.001
	(0.189)	(0.453)	(0.273)	(0.175)	(0.594)	(0.710)
$Accruals_{it-1}$	-0.036*	-0.006	-0.042**	-0.011	-0.035**	-0.018
	(0.054)	(0.750)	(0.024)	(0.708)	(0.022)	(0.512)
$AssetGrowth_{it}$	0.021***	0.014**	0.025**	0.014	0.007	0.027***

	(0.000)	(0.024)	(0.014)	(0.129)	(0.322)	(0.000)
EmpGrowth$_{it}$	-0.017**	-0.001	-0.005	-0.010	0.007	-0.025***
	(0.041)	(0.942)	(0.573)	(0.427)	(0.419)	(0.001)
Loss$_{it}$	-0.014**	-0.020***	-0.030***	-0.003	-0.016**	-0.019***
	(0.026)	(0.001)	(0.000)	(0.652)	(0.031)	(0.002)
MA$_{it}$	-0.002	0.001	0.001	-0.007	0.004	-0.004
	(0.566)	(0.781)	(0.744)	(0.147)	(0.434)	(0.194)
Issuer$_{it}$	-0.006	0.002	-0.001	-0.011**	-0.003	-0.001
	(0.112)	(0.673)	(0.816)	(0.044)	(0.453)	(0.765)
OCFVol$_{it}$	0.016	0.054	0.075	0.138*	0.098**	0.024
	(0.813)	(0.351)	(0.410)	(0.058)	(0.031)	(0.737)
SaleVol$_{it}$	-0.001	0.008	0.041*	-0.008	0.017	-0.006
	(0.961)	(0.599)	(0.054)	(0.634)	(0.322)	(0.692)
Δ*CashSales*$_{it}$	0.011	0.012*	0.015	0.013*	0.008	0.019**
	(0.200)	(0.053)	(0.128)	(0.084)	(0.276)	(0.014)
FirmAge$_{it}$	0.001	0.001	0.001	0.001	0.001	0.001
	(0.179)	(0.241)	(0.420)	(0.288)	(0.232)	(0.347)
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
F-test of difference between subsamples						
p-value		0.14		0.07		0.07
Observations	13,670	14,058	13,268	13,268	13,678	13,678
R-squared	0.781	0.758	0.752	0.724	0.774	0.766

Panel B: Real-activities-based earnings management

This panel reports the results of estimating model (6) using the entropy rebalanced sample. Model (6) is estimated for the subsample with large crowd following in column (1), the subsample with small crowd following in column (2), the subsample with high CEO ownership in column (3), the subsample with low CEO ownership in column (4), the subsample with high transient institutional ownership in column (5), and the subsample with low transient ownership in column (6).

	(1) Large Crowd	(2) Small Crowd	(3) High Ownership	(4) Low Ownership	(5) High Transient	(6) Low Transient
$Post_{it}$	-0.011**	0.001	-0.003	-0.002	-0.007	-0.000
	(0.028)	(0.634)	(0.479)	(0.653)	(0.123)	(0.902)
$Estimize_i$*$Post_{it}$	0.017**	0.010**	0.017***	0.010**	0.023***	0.007
	(0.033)	(0.034)	(0.005)	(0.047)	(0.001)	(0.118)
MTB_{it}	-0.001	-0.001	-0.001	0.001	-0.002	0.000
	(0.341)	(0.576)	(0.534)	(0.256)	(0.424)	(0.775)
$Leverage_{it}$	0.002	0.001	0.001	-0.002	0.001	0.001
	(0.498)	(0.483)	(0.677)	(0.121)	(0.801)	(0.547)
$LnMVE_{it}$	0.014	0.009	0.016**	0.004	0.013	0.005
	(0.110)	(0.149)	(0.037)	(0.536)	(0.188)	(0.376)
ROA_{it}	0.193***	0.145***	0.051	0.088	0.220***	0.100***
	(0.000)	(0.000)	(0.459)	(0.166)	(0.000)	(0.001)
$AssetGrowth_{it}$	-0.135***	-0.089***	-0.084***	-0.027***	-0.133***	-0.080***
	(0.000)	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)
$EmpGrowth_{it}$	0.011	0.015	-0.008	-0.016	0.034*	-0.015
	(0.528)	(0.215)	(0.680)	(0.203)	(0.099)	(0.285)
$Loss_{it}$	0.013	-0.002	-0.018*	-0.009	0.010	-0.001
	(0.156)	(0.720)	(0.068)	(0.212)	(0.318)	(0.858)
MA_{it}	0.008	0.001	0.006	0.003	0.006	0.001
	(0.174)	(0.839)	(0.241)	(0.645)	(0.263)	(0.885)
$Issuer_{it}$	0.006	-0.002	-0.001	0.000	0.000	-0.002
	(0.435)	(0.683)	(0.825)	(0.958)	(0.994)	(0.707)
$OCFVol_{it}$	-0.192*	-0.128	-0.151	-0.026	-0.247*	-0.105
	(0.068)	(0.162)	(0.324)	(0.813)	(0.074)	(0.278)
$SaleVol_{it}$	0.016	0.015	0.044**	0.025	0.016	0.013
	(0.541)	(0.401)	(0.048)	(0.252)	(0.558)	(0.507)

$\Delta CashSales_{it}$	-0.039***	-0.061***	-0.042	-0.062***	-0.056***	-0.043**
	(0.007)	(0.000)	(0.109)	(0.000)	(0.003)	(0.010)
$FirmAge_{it}$	-0.001	0.001	-0.002	0.001**	0.000	-0.000
	(0.539)	(0.450)	(0.506)	(0.034)	(0.694)	(0.960)
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
F-test of difference between subsamples						
p-value		0.37		0.26		0.01
Observations	12,512	12,836	12,150	12,144	12,496	12,498
R-squared	0.934	0.931	0.929	0.944	0.924	0.942

Panel C: Total earnings management

This panel reports the results of estimating model (7) using the entropy rebalanced sample. Model (6) is estimated for the subsample with large crowd following in column (1), the subsample with small crowd following in column (2), the subsample with high CEO ownership in column (3), the subsample with low CEO ownership in column (4), the subsample with high transient institutional ownership in column (5), and the subsample with low transient ownership in column (6).

	(1) Large Crowd	(2) Small Crowd	(3) High Ownership	(4) Low Ownership	(5) High Transient	(6) Low Transient
$Post_{it}$	0.003	0.006	0.006	-0.002	-0.001	0.011**
	(0.590)	(0.121)	(0.210)	(0.661)	(0.900)	(0.029)
$Estimize_i*Post_{it}$	0.026***	0.010*	0.023***	0.008	0.029***	0.006
	(0.002)	(0.076)	(0.003)	(0.263)	(0.000)	(0.272)
MTB_{it}	-0.000	0.000	-0.001	-0.002	-0.000	-0.000
	(0.705)	(0.796)	(0.522)	(0.288)	(0.719)	(0.789)
$Leverage_{it}$	0.001	0.001	0.002	0.005*	0.001	0.003
	(0.705)	(0.379)	(0.177)	(0.051)	(0.609)	(0.122)
$LnMVE_{it}$	0.009	-0.004	0.013	-0.000	0.007	-0.003
	(0.324)	(0.580)	(0.119)	(0.952)	(0.439)	(0.678)
ROA_{it}	0.969***	0.893***	0.715***	0.892***	0.834***	0.955***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

$AssetGrowth_{it}$	-0.728***	-0.719***	-0.663***	-0.688***	-0.596***	-0.832***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$EmpGrowth_{it}$	0.007	-0.002	0.001	0.002	0.004	-0.002
	(0.240)	(0.507)	(0.768)	(0.775)	(0.350)	(0.378)
$Loss_{it}$	-0.009	0.008	0.017	0.031	-0.014	-0.011
	(0.860)	(0.798)	(0.756)	(0.548)	(0.779)	(0.796)
MA_{it}	-0.084***	-0.072***	-0.047***	-0.030**	-0.095***	-0.058***
	(0.001)	(0.000)	(0.004)	(0.049)	(0.000)	(0.000)
$Issuer_{it}$	-0.032	0.008	-0.000	-0.018	0.007	-0.032**
	(0.138)	(0.518)	(0.997)	(0.359)	(0.746)	(0.013)
$OCFVol_{it}$	0.009	-0.017**	-0.047***	-0.005	-0.012	-0.004
	(0.405)	(0.039)	(0.000)	(0.645)	(0.305)	(0.642)
$SaleVol_{it}$	-0.002	-0.001	0.001	-0.010	0.005	-0.011*
	(0.796)	(0.844)	(0.819)	(0.203)	(0.554)	(0.082)
$\Delta CashSales_{it}$	-0.003	-0.003	-0.002	-0.004	-0.007	-0.007
	(0.703)	(0.700)	(0.803)	(0.643)	(0.375)	(0.346)
$FirmAge_{it}$	-0.163	-0.024	0.081	0.246**	-0.013	-0.087
	(0.230)	(0.777)	(0.507)	(0.014)	(0.881)	(0.509)
Firm Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
F-test of difference between subsamples						
p-value		0.04		0.06		0.00
Observations	13,716	14,110	13,314	13,314	13,726	13,726
R-squared	0.912	0.907	0.911	0.917	0.902	0.917

Table 8: Robustness tests

This table report examines the impact of Estimize coverage initiation on earnings management using alternative specifications. Panel A reports the results of a difference-in-differences design without entropy-balancing. Panel B reports the results based on the entropy-balanced sample with additional controls for sales growth. Variables are defined in Appendix A. Heteroscedasticity-robust standard errors are estimated and clustered at the industry-year level. Firm and year fixed effects are included in all regressions. P-values are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, two-sided tests.

Panel A: Difference-in-differences without entropy balancing

	(1) *DA*	(2) *RAM*	(3) *TM*
$Estimize_i*Post_{it}$	0.006**	0.013**	0.021***
	(0.046)	(0.022)	(0.002)
MTB_{it}	-0.000	-0.001	-0.001
	(0.831)	(0.196)	(0.351)
$Leverage_{it}$	0.000	0.003***	0.004**
	(0.738)	(0.009)	(0.025)
$LnMVE_{it}$	-0.001	0.004	0.004
	(0.777)	(0.414)	(0.524)
ROA_{it}	0.702***	0.358***	1.000***
	(0.000)	(0.000)	(0.000)
CFO_{it}	-0.732***		-0.682***
	(0.000)		(0.000)
NOA_{it-1}	-0.001*		0.000
	(0.067)		(0.944)
$Accruals_{it-1}$	-0.019		-0.003
	(0.197)		(0.911)
$AssetGrowth_{it}$	0.001	-0.189***	-0.149***
	(0.918)	(0.000)	(0.000)
$EmpGrowth_{it}$	0.007	0.015	0.017
	(0.290)	(0.228)	(0.116)
$Loss_{it}$	-0.024***	0.024***	0.001
	(0.000)	(0.001)	(0.904)
MA_{it}	-0.001	0.012***	0.003
	(0.812)	(0.006)	(0.608)
$Issuer_{it}$	0.001	0.001	0.005
	(0.773)	(0.789)	(0.381)
$OCFVol_{it}$	0.092***	-0.080	-0.040
	(0.003)	(0.189)	(0.471)
$SaleVol_{it}$	-0.017	-0.016	-0.007
	(0.125)	(0.328)	(0.722)
$\Delta CashSales_{it}$	0.010**	-0.042***	-0.020***
	(0.015)	(0.000)	(0.001)
$FirmAge_{it}$	0.001*	-0.000	0.000
	(0.064)	(0.757)	(0.531)
Firm Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Observations	12,296	11,226	12,343
R-squared	0.749	0.892	0.869

Panel B: Entropy balanced sample with additional control for sales growth

	(1) *DA*	(2) *RAM*	(3) *TM*
$Post_{it}$	0.004*	-0.005*	0.003
	(0.061)	(0.067)	(0.381)
$Estimize_i*Post_{it}$	0.007**	0.014***	0.018***
	(0.039)	(0.006)	(0.002)
MTB_{it}	0.000	-0.001	-0.000
	(0.325)	(0.442)	(0.733)
$Leverage_{it}$	0.001	0.001	0.001
	(0.555)	(0.592)	(0.402)
$LnMVE_{it}$	-0.006	0.013*	0.005
	(0.122)	(0.055)	(0.458)
ROA_{it}	0.736***	0.174***	0.917***
	(0.000)	(0.000)	(0.000)
CFO_{it}	-0.785***		-0.719***
	(0.000)		(0.000)
NOA_{it-1}	-0.002		0.001
	(0.317)		(0.671)
$Accruals_{it-1}$	-0.021		-0.001
	(0.127)		(0.972)
$AssetGrowth_{it}$	0.013**	-0.110***	-0.078***
	(0.015)	(0.000)	(0.000)
$EmpGrowth_{it}$	-0.007	0.019	0.003
	(0.312)	(0.133)	(0.832)
$Loss_{it}$	-0.017***	0.003	-0.009
	(0.001)	(0.650)	(0.240)
MA_{it}	-0.001	0.007**	-0.000
	(0.704)	(0.049)	(0.953)
$Issuer_{it}$	-0.001	0.003	-0.003
	(0.703)	(0.585)	(0.643)
$OCFVol_{it}$	0.041	-0.152**	-0.065
	(0.444)	(0.050)	(0.477)
$SaleVol_{it}$	0.008	0.006	0.008
	(0.573)	(0.757)	(0.744)
$\Delta CashSales_{it}$	0.005	-0.025	-0.004
	(0.457)	(0.202)	(0.782)
$FirmAge_{it}$	0.001	0.000	0.002***
	(0.223)	(0.885)	(0.006)
SG_Rank1	-0.003	0.014**	0.017**
	(0.606)	(0.041)	(0.037)
SG_Rank2	-0.005	0.012***	0.008
	(0.130)	(0.005)	(0.124)
SG_Rank4	0.004	-0.007	-0.002
	(0.183)	(0.165)	(0.705)
SG_Rank5	0.010*	-0.020**	-0.021**
	(0.066)	(0.028)	(0.020)
Firm Fixed Effects	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Observations	15,546	14,244	15,600
R-squared	0.761	0.930	0.907