Institutional Investor Attention and Firm Disclosure

Inna Abramova
lobanova@mit.edu
(617) 253-7974

John E. Core
jcore@mit.edu
(617) 715-4819

Andrew Sutherland
(617) 324-3894
ags1@mit.edu

First Draft: July 2017
This Draft: November 2019

Abstract

We study how short-term changes in institutional owner attention affect managers' disclosure choices. Holding institutional ownership constant and controlling for industry-quarter effects, we find that managers respond to attention by increasing the number of forecasts and 8-K filings. Rather than alter the decision of whether to forecast or to provide more informative disclosures, attention causes minor disclosure adjustments. This variation in disclosure is primarily driven by passive investors. Although attention explains significant variation in the quantity of disclosure, we find little change in abnormal volume and volatility, the bid-ask spread, or depth. Overall, our evidence suggests that management responds to temporary institutional investor attention by making disclosures that have little effect on information quality or liquidity.

Keywords: disclosure, management forecasts, 8-K filings, information quality, liquidity, institutional ownership, passive investors, monitoring
JEL Classification: G23, G32, G34, G12, G14

* This paper was previously circulated under the title "Institutional Investor Attention and Demand for Inconsequential Disclosures". All authors are from the MIT Sloan School of Management. We gratefully acknowledge comments from Steve Balsam, Sudipta Basu, Ed deHaan, Eric Floyd, Jacquelyn Gillette, Todd Gormley, Michelle Hanlon, Nick Guest, Zachary Kaplan, Stephen Karolyi, Alina Lerman, Maria Loumioti, Jeremy Michels (discussant), S. Katie Moon (discussant), Paul Reeder, Delphine Samuels, David Thesmar, Aadhaar Verma, Rodrigo Verdi, and seminar participants at Carnegie Mellon, the 2018 CFEA conference, the 2019 FARS conference, MIT Sloan, the University of California- Berkeley, the University of California- San Diego, Temple University, the University of Michigan, University of Texas at Dallas, and Washington University in St. Louis. We thank Oliver Spalt for sharing his data on institutional investor distractions. We gratefully acknowledge the financial support of MIT Sloan.

1. Introduction

Much research on voluntary disclosure focuses on decisions stemming from persistent factors. For example, the economic forces that give rise to a firm's level of proprietary costs are largely persistent, and how the voluntary disclosure decision is affected by proprietary costs is persistent. Institutional investor ownership (IO) is another relatively stable determinant of disclosure. Prior research indicates that increases in disclosure associated with increases in IO can decrease information asymmetry and improve liquidity. In this paper, we hold IO constant, and examine how short-term changes in IO attention affect the firm's short-term disclosure choices, and the resulting information quality and liquidity consequences.

To motivate our analysis, we begin by documenting significant short-term changes in disclosure. Between 2001 and 2016, the typical firm switched the number of forecasts, 8-Ks, and total disclosures provided 8.9, 10.9, and 12.1 times, respectively. This pattern of small increases and decreases in disclosure is quite different from the large one-time changes associated with index reconstitutions studied in related work.

To investigate whether fleeting investor attention helps explain transient disclosure behavior, we use the proxy for distraction created and validated by Kempf et al. (2017). The intuition behind the Kempf et al. approach is that a firm's IOs have other investments as well, and when return shocks affect those other investments, the IOs will pay less attention to the firm. This distraction measure assumes that investor attention paid to a firm declines when an investor in that firm has other portfolio firms that experience large positive or negative industry returns. The measure classifies an industry as attention-grabbing when it experiences the highest or lowest returns of all industries that quarter. The appeal of this measure is that distraction events arising in other industries are, by construction, exogenous to the firm, and that firms within the same industry are differentially exposed due to differences in their investor bases. The Kempf et al. measure is continuous: Low values indicate low distraction (high attention), and high values indicate high distraction (low attention). We therefore refer to attention and distraction interchangeably throughout the paper.

We find that disclosure has a negative relation with IO distraction. Because variation in distraction comes from developments in other industries, and because we control for industry-quarter and firm-calendar quarter effects, it is unlikely that our results reflect shocks in the firm's own industry (e.g., economic conditions or an M&A wave), or firm-specific disclosure habits (always forecasting in the first quarter). The effects of IO attention on disclosure are economically significant. The coefficient estimate implies that a one standard deviation increase in IO distraction decreases the number of total disclosures by 6.4%. We find that distraction explains similar declines in the number of forecasts and 8-Ks, but not the propensity to forecast, consistent with managers responding to IO attention with relatively minor changes in disclosure.

We perform a variety of robustness checks to ensure that the variation in disclosure we find is not simply a manifestation of shocks to firm fundamentals, of changes in the IO base, or of management attempting to conceal bad behavior or bad news.

Next, we study the consequences of attention-driven changes in disclosure, including forecast features, market responses to disclosures, and liquidity. We find that IO attention has little effect on average forecast horizon, but decreases average forecast precision. We also find that managers respond to IO attention with minor disclosure changes. Specifically, managers increase forecasts of secondary instead of core items, and do not add new forecasts outside the earnings announcement period.

And, despite our earlier evidence of significant decreases in disclosure quantity, abnormal volume and volatility are no different during periods of IO distraction. Consistent with this, we find little relation between IO attention and the bid-ask spread or depth. This evidence is consistent with management responding to temporary IO attention by making disclosures that are not substantial on their own and do not represent a commitment to increased disclosure, and therefore do not improve information quality or liquidity (Leuz and Verrecchia 2000). Our large panel of firm-quarters and plausibly exogenous variation in IO attention reduce the possibility that our non-results stem from power or endogeneity problems.

The combined results raise the question of why IOs ask for more disclosure, when management responds with minor disclosure adjustments. We find that quarterly disclosure is most sensitive to the attention of passive IOs, the least informed IOs. If every quarter, passive IOs did not express their preference for more disclosure, then the preferences of both management and non-passive IOs would be more highly weighted. Management and non-passive IOs generally prefer less disclosure (e.g., Bushee and Noe 2000). Therefore, one plausible interpretation is that, while passive IOs asking for more disclosure does not yield more quality disclosure this quarter, it yields more quality disclosure overall than if passive IOs did not voice their preferences. In other words, in the counterfactual world where passive IOs did not ask for disclosure, firms would provide fewer and lower quality disclosures because they would cater more to non-passive IOs who prefer less disclosure. Related, as we discuss below, passive IOs rely on disclosures for reasons in addition to trading (e.g., monitoring, due diligence, and voting). In both cases, firms have incentives to respond to attention and demand for disclosure by passive IOs, because passive IOs are active participants in all shareholder votes.

Our paper contributes to research concerned with understanding firm disclosure choices (Verrecchia 1990; Healy and Palepu 2001; Beyer et al. 2010), and forecasts and 8-Ks in particular (Lerman and Livnat 2010; Noh et al. 2019). A common theme in this literature is that firms develop a long-term disclosure policy that incorporates their competitive environment, proprietary and agency costs, and investor base. Consistent with this literature, we find that managers rarely adjust their decision to forecast. However, we also find that the number of forecasts and 8-Ks provided change regularly in the short-term, and that this variation is predictably related to IO attention.[1] One novel aspect of this finding is that managers reduce disclosure without worsening information quality or liquidity.

We contribute to an emerging literature that seeks to provide causal evidence of a relation between IO and firm disclosure. Boone and White (2015) and Bird and Karolyi (2016) advance this literature by studying index reconstitutions. However, index reconstitutions are rare, affect a small subset of (similarly-sized) firms, and represent a different form of change in institutional ownership/attention than what we study. Identifying whether IO attention could alter disclosure policy has been challenging, because attention-grabbing events for the firm (e.g., capital raising, losses) can cause disclosure changes for their own reasons. Our analysis builds on the insight that IOs have limited attention (Hirshleifer, Lim, and Teoh 2009; Blankespoor, deHaan, and Marinovic 2019), and that attention-grabbing events occurring in other industries can exogenously shift oversight away from the firm.

Our paper is also relevant to the literature studying IO monitoring. The shift of public firm ownership from active IOs to passive IOs has generated interest in how IOs influence management

[1] In this way, our paper also relates to work studying strategic disclosure timing in the context of overall market attention (e.g., Damodaran 1989; deHaan et al. 2015; Niessner 2015).

behavior, including disclosure. Debate has followed about whether IO ownership improves or worsens monitoring of the firm. One line of work (e.g., Boone and White 2015; Bird and Karolyi 2016) finds that passive IOs are associated with more voluntary disclosure and higher disclosure quality, which leads to reductions in information asymmetry and improvements in liquidity. Others (e.g., Schmidt and Fahlenbrach 2017) caution that passive investors often employ uniform rules-based monitoring techniques that are not effective for more complicated situations, and in some cases impose unnecessary costs on management. Consistent with disclosure being costly and passive IOs asking management for incremental disclosures, we find that managers increase disclosure when more passive IO attention is paid to them, but that these adjustments have little effect on information quality.

2. Related literature and motivation

Our prediction that IO attention affects firms' disclosure is based on the observations that: (1) IOs care about disclosure and monitor firms' disclosure practices; (2) IOs communicate these preferences to management; and (3) IOs can get distracted, and this can affect their monitoring. In terms of IOs' interest in disclosure, BlackRock's corporate governance guidelines state that "where company reporting and disclosure is inadequate… we will engage with the company and/or use our vote to encourage a change in practice" (BlackRock 2017).[2] In addition to voting, IOs communicate their disclosure preferences through interactions with management and through analysts (e.g., Jung, Wong, and Zhang 2015). Brown et al. (2019) find that phone calls with management are one of the most important means for IOs to communicate with firms. For example,

[2] Fidelity (2018), State Street Global Advisors (2018), and Vanguard (2018) have similar guidelines. See also Park et al. (2019).

one investor relations officer reports that "I'll initiate calls or calls will come into me, and that happens on a daily basis" (p. 64).

IO distractions can affect monitoring because IOs are constrained in their attention. Kempf et al. (2017) find that when a firm's IOs are distracted, there is less participation in conference calls, fewer shareholder proposals, and less trading. In addition, Schmidt and Fahlenbrach (2017) discuss how passive IOs must oversee a large number of portfolio firms at a low cost, which limits the effectiveness of their monitoring. Vanguard and other institutions typically have a centralized team focused on engaging firms on governance and disclosure matters (Vanguard 2018), and when this team is focused on events in one industry, it is less able to pay attention to other industries.

How disclosure responds to IO attention may depend on whether the attention is permanent or temporary. Theoretical and empirical research suggests that a commitment to greater disclosure improves firm liquidity (Leuz and Verrecchia 2000). Recent research finds that large increases in passive IO caused by index reconstitutions are associated with a sustained increase in voluntary disclosure (Boone and White 2015; Bird and Karolyi 2016; Schoenfeld 2017). These increases in passive IO are also associated with increases in information quality, as measured by abnormal return volatility and the length and content of 8-Ks, and increases in liquidity as measured by volume and bid-ask spreads. However, index reconstitutions occur rarely, affect only a small percentage of firms whose market value is around the cut-off, and cause large changes to institutional ownership.[3] In addition, the market capitalization that Russell uses to assign index membership is not observable to researchers. Various approaches have been developed to address

[3] For example, Table 2 and Figure 4 of Boone and White report that firms affected by reconstitutions tend to have market capitalization ranging from $1.1 billion to $1.6 billion.

this non-observability, but none of these approaches is perfect, and different approaches can lead to different inferences (Chen et al. 2019).

Whether more routine IO (or attention) changes have the same consequences for disclosure and information quality as in the above studies is unclear for a number of reasons. First, managers may not reduce disclosure when IOs are distracted, given that attention will return in the long run. For example, to the extent that the firm commits to a certain level of disclosure, deviating from this commitment can result in repercussions for management (Graham et al. 2005). Maintaining disclosure levels can also help the firm sustain visibility among investors, analysts, and the media (Lang and Lundholm 1996; Anantharaman and Zhang 2011). Second, firms incur costs when increasing disclosures and wish to limit these costs. For example, firms invest in fixed accounting resources based on their needs, and demands for additional resources can cause errors (Gillette et al. 2017). Chapman and Green (2018) argue that adjustment costs include information processing and collection costs, opportunity costs of adding disclosures within space limitations, and potential reputation and litigation costs arising from incorrect predictions of uncertain future outcomes. Third, additional disclosures can increase proprietary and agency costs.

On the other hand, managers may instead find ways of adjusting disclosure to respond to temporary attention without meaningfully improving either information quality or liquidity. That is, while large permanent changes in ownership may require significant increases in disclosure and information quality that improve liquidity, managers could respond to temporary demand by IOs with minor disclosure changes. For example, managers may provide more forecasts than usual, but the forecasts contain little new information and are provided at times when the firm is already making other disclosures.

3. Data and research design

3.1 Sample and Data

We construct our sample from the intersection of several datasets. We begin by matching a firm-calendar quarter panel of the Kempf et al. (2017) distraction measure to the Thomson Reuters institutional holdings database. We then merge in management forecasts from I/B/E/S, 8-K filings from EDGAR, firm stock price, return and volume data from CRSP, bid-ask spread and depth data from DTAQ, and fundamental data from Compustat. The Compustat data is for the firm's fiscal quarter, while the Kempf et al. (2017) measure is for each calendar quarter. We therefore match data from Compustat to the calendar quarter that ends on or after the fiscal quarter (for example, for a firm with a January fiscal year-end, we match the April fiscal quarter to the June calendar quarter, the July fiscal quarter to the September calendar quarter, etc.).

We analyze the post-Reg FD period starting in 2001 and ending in the first quarter of 2016.[4] We require non-missing data on our dependent variables and the control variables described below. These requirements result in a final dataset of 100,378 quarterly observations from 2001 to the first quarter of 2016. To mitigate the effect of outliers, we winsorize all continuous variables by quarter at the 1st and 99th percentiles.

3.2 Distraction

$Distraction_{i,t}$, is based on the Kempf et al. (2017) measure of IO distraction, and is measured every calendar quarter using the holdings of each IO of each firm.[5] To ensure that IO is

[4] We start our main sample in 2001 to avoid issues with respect to missing forecasts in the early years of the Thomson First Call guidance dataset (Chuk et al. 2013), and because Regulation Fair Disclosure was enacted in 2000, which changed forecast behavior. Nevertheless, if we repeat our tests on samples beginning in 1994 or 1998, we find the same results.

[5] In February 2018, Wharton Research Data Services (WRDS) issued a statement about quality problems with the Thomson Reuters data (https://wrds-web.wharton.upenn.edu/wrds/news/index.cfm?display=read&news_id=616). They suggest using data gathered by WRDS directly from EDGAR to compute institutional ownership measures starting in June 2013, and computing ownership measures as described in Ben-David et al. (2019). We use this data and the Ben-David et al. method to compute our institutional ownership and attention measures starting in June 2013. As an

meaningful and that data is available on sample firms, $Distraction_{i,t}$ is calculated excluding micro-cap firms, defined as stocks with market value below the 20th NYSE percentile breakpoint following Fama and French (2008). $Distraction_{i,t}$ is the weighted average of the firm's IOs' distractions that quarter, where distractions are assigned to IOs in industries with the largest or smallest returns that quarter, using the Fama-French 12 industry classifications. The degree to which a given IO is distracted is determined by the IO's weight in the industries with extreme returns: If the IO has no weight (a high weight) in those industries, it is not distracted (is highly distracted). The firm-level distraction measure is calculated by aggregating the distraction levels of all of its IOs. In this way, a discrete event (an extreme industry return) is transformed into a continuous measure (a sum across all the firms' IOs weighted by their positions in that industry).[6] Taking the weighted average allows us to capture the attention of the "representative" shareholder.[7]

Figure 1 provides an intuitive illustration of how the distraction measure is constructed. In our illustration, we assume that a retail firm has only one IO, and that the IO equally weights that retail firm and an energy firm in its portfolio. Thus, the distraction measure for the retail firm would equal 0.50 if the energy industry has the highest or lowest return that quarter, and zero otherwise. We provide the details of the calculation of $Distraction_{i,t}$ in our Appendix A.

We measure contemporaneous distraction because we expect disclosure changes to occur relatively quickly, unlike the merger activity studied in Kempf et al. However, in robustness

---

additional step in Table A1 of the online appendix, we repeat our tests on our pre-2013 observations, and find that our inferences are unchanged.

[6] This approach is akin to recent work exploiting shocks in one part of a bank's portfolio to study how monitoring changes for the bank's other clients (e.g., Gopalan et al. 2011, Murfin 2012).

[7] As Kempf et al. discuss, "We do not assume that *all* shareholders are distracted when *D* is high. We do assume that higher *D* proxies for times when the *representative* shareholder is distracted: that is, we assume that lack of attention by one investor cannot be costlessly and instantaneously compensated for by increased attention by other investors." (p. 1677).

analyses below, we find similar results if examine distraction over a three-quarter window. To facilitate interpretation of our results, we standardize *Distraction* to mean zero and standard deviation of one.

It is important to note that the Kempf et al. measure is measured at the institution level, not at the fund level. For example, when the Vanguard Group reports holdings in a company, it reports the aggregate holdings of many Vanguard funds that own the company. Because Vanguard and other institutions typically have a centralized team focused on engaging firms on governance and disclosure matters (Vanguard 2018), the relevant distractions occur at the institution level, and this is where we measure them.

If the firm's industry has the highest or lowest return of all industries that quarter, the distraction variable is recorded as missing and the observation is omitted from the analysis. We omit these observations to avoid the endogeneity concern that firms in industries experiencing extreme returns may be altering their disclosures for performance reasons, rather than because attention is paid to them.

Kempf et al. validate their distraction measure by showing that when IOs are distracted, there is: 1) less trading in the firm's stock; 2) less conference call participation; and 3) fewer shareholder proposals. In a contemporaneous study, Basu et al. (2019) report that management forecasts, non-GAAP disclosures, and conference calls are also negatively associated with the Kempf et al. distraction measure. While the Kempf et al. approach exploits exogenous shocks to unrelated parts of institutional shareholders' portfolios and the aggregation of these shocks plausibly proxy for IO attention, we do not have a direct measure of IO attention. For parsimony, we refer to IO attention where we mean "a proxy for IO attention."

3.3 Research design

Our tests employ the following specification:

$$y_{i,t} = \beta_1 \times Distraction_{i,t} + \alpha_{i,q} + \alpha_{j,t} + \gamma \times Controls_{i,t} + \varepsilon_{i,t}, \quad (1)$$

where the dependent variable, $y_{i,t}$ is a measure of quarterly disclosure activity by firm i in quarter t, $Distraction_{i,t}$ is measured as described above, $\alpha_{i,q}$ and $\alpha_{j,t}$ are firm-calendar quarter and industry-quarter fixed effects, respectively, and $Controls$ are firm controls for voluntary disclosure choices.

The dependent variable, $y_{i,t}$, is an indicator for providing a management forecast, or the number of forecasts, 8-K filings, and total disclosures at the firm-quarter level. *Forecast Firm* (the indicator) and *Forecasts* (count) measure all types of forecasts (earnings, revenues, dividends, cash flow, etc.) that quarter, while *8-Ks* measures the number of 8-Ks. We measure all 8-Ks because the degree of management discretion differs across item types (Lerman and Livnat 2010; Gleason, Ling, and Zhao 2018), and we assume that any variation in total 8-Ks related to attention comes from voluntary instead of mandatory disclosures (similar to Bird and Karolyi 2016).[8] When firms have multiple forecasts or 8-Ks on the same day, we count them separately (i.e., an earnings and cash flow forecast issued on the same day are counted as two forecasts). We also measure total disclosure using *Disclosures*, equal to the sum of the number of forecasts and 8-Ks. For this variable, if the firm has a forecast and an 8-K on the same day, we do not count the 8-K under the assumption that it relates to the forecast. We take the log of one plus our disclosure count measures, given skewness in these measures.

[8] If we repeat our estimation of equation 1 for only Item 8.01 (Other Events) filings, we find the same results as when we count all 8-K filings.

This distraction measure offers two important advantages for our research question. First, distractions to the firm's institutional shareholder base are exogenous to the firm itself, by construction, because they arise from extreme returns in other industries. Second, in our setting distraction events occur in different industries over time, and firms' investors have different holdings across industries. This allows us to not only link transitory disclosure changes to variation in short term distractions, but also to control for firm-calendar quarter and industry-quarter fixed effects, $\alpha_{i,q}$ and $\alpha_{j,t}$. We measure these industry and firm effects by calendar quarter because the Kempf et al. (2017) measure is for each calendar quarter. To create the firm-calendar quarter effect, we take the cross product of the four calendar quarters with the firm indicator. This firm-calendar quarter fixed effect controls for firm-specific seasonal disclosure habits (e.g., the firm always forecasts in the first quarter of the year). Consistent with Kempf et al., we use the Fama-French 12 industry classification scheme, and create an industry-quarter fixed effect for each industry and calendar quarter.

Controlling for industry-quarter fixed effects reduces the threat that managers adjust their disclosure to changes in industry-wide competition or profitability, merger waves, macroeconomic conditions, or changes in IO holdings across industries. For example, in the event that one industry's performance (or disclosure strategy) is somehow connected to another industry's extreme returns, the industry-quarter indicators control for any connection effect common to all firms in the industry. Including industry-quarter fixed effects also removes variation in disclosure regulation affecting all firms (e.g., the expansion of mandatory 8-K items in 2004) from our tests. In sum, our specification effectively compares disclosure for firms in the same industry at the same time, across IOs with high and low portfolio exposure to distraction events. This also aligns our specification with that of Kempf et al., who compare firm actions within industry-quarters.

Performing the estimation within-firm calendar quarter allows us to focus on transitory changes in disclosure, while accounting for relatively time-invariant determinants such as the firm's size and growth opportunities. Because of differences in investor base, industry rivals can face different levels of investor attention. To illustrate, consider the consumer nondurables industry in the second quarter of 2011. Molson Coors Brewing Co. had a raw (i.e., unstandardized) distraction measure of 0.263, while InBev (parent of Anheuser Busch) had a raw distraction measure of 0.178. This difference arises because Molson Coors' IOs had large portfolio concentrations in energy and healthcare, and these industries experienced extreme returns that quarter.

Although we expect that our fixed effects structure mitigates many omitted variable-related concerns, we also include other control variables that prior literature has associated with either institutional ownership or short-term changes in disclosure (e.g., Goodman et al. 2013; Ali et al. 2014; Kempf et al. 2017). Specifically, we control for the average percentage of ownership by institutions and the percentage of IO by the five largest institutions, both measured at the start of the quarter.[9] To account for performance, our regressions include firm stock returns last quarter, indicators for losses and earnings increases last quarter, and the absolute value of the earnings change from five quarters ago to last quarter. We control for the number of analysts making earnings estimates in the quarter, to account for analyst attention in the firm.[10] We also control for lagged stock return volatility, and firm fundamentals measured at the beginning of the quarter including leverage, size, and the book to market value of assets. If we instead use

[9] Including these controls and firm fixed effects reduces the concern that our results could be driven by large changes in IO, such as those studied by Boone and White (2015) or Bird and Karolyi (2016). Nevertheless, we repeat our tests after controlling for changes in IO and find our results are unaffected.

[10] We control for contemporaneous coverage to measure current analyst attention in the firm, but our results are the same if we control for lagged coverage. Our results are also the same if we instead control for the number of analyst reports that quarter as a proxy for attention.

contemporaneous versions of these variables, our results are unaffected. We cluster our standard errors by firm and industry-quarter. Appendix A provides definitions for our control variables.

3.4 Summary statistics

Table 1 presents summary statistics for our disclosure and control variables for the 4,408 firms in our sample. Panel A shows summary statistics for *Distraction.* The first percentile value is 0.041 (attentive), and the 99th percentile value is 0.354 (distracted). The mean is 0.146 and the median value is 0.124. These mean and median values indicate the typical value of *Distraction* is relatively not attentive nor distracted.

Panel B shows that for the typical firm-quarter in our sample, the probability of making at least one forecast is 64.2%. The average number of forecasts is 2.5; conditional on making a forecast, the average is 3.9. The average number of 8-K filings per firm-quarter is 2.8. When we combine the number of 8-Ks and forecasts, and drop 8-Ks accompanying forecasts, the resulting average number of total disclosures is 4.6.

Panel C shows that in the typical firm-quarter, IOs own 69.5% of the equity, and the five largest investors account for 40.3% of IO. The average quarterly return is 3.5%. Seventeen percent (60%) of firms experience a loss (EPS increase), and the average lagged unsigned EPS change from four quarters ago is 10.4%. At the beginning of the quarter, leverage, market value of equity, and book-to-market average 25.1%, $6.7 billion, and 0.70, respectively. The average lagged return volatility (annualized) is 38.1%. Analyst coverage for the average firm-quarter is 11.0.

Table 2 shows the cumulative number of within-firm changes in *Disclosures*, *Forecasts*, *8-Ks,* and *Forecast Firm* for the average firm. We study the first calendar quarter for each firm-year, but note that our results are similar if we examine other quarters. Each column compares the first quarter of a given year to the first quarter in the prior year, such that a switch measures a change in disclosure from Q1 of one year to Q1 of the next year. To exclude the effects of composition changes, we present figures for a constant sample of firms with observations in each year from 2001 to 2016. Requiring a constant sample limits our analysis here to 725 firms.

In 2002, the average number of switches in disclosures is 0.712 times. The second and third columns reveal that slightly more of the changes in total disclosure come from transient 8-K filings than transient forecasts. Changes in forecasts are happening mostly along the intensive margin (that is, managers are primarily altering the degree to which they forecast conditional on forecasting, rather than altering the decision of whether or not to forecast). While the average number of switches in forecasts is 0.501 times between 2001 and 2002 (second column), the fourth column shows that the average number of times firms just started or stopped forecasting altogether is 0.306.

Disclosure changes also occur in subsequent years such that over time, the typical firm adjusts its disclosure multiple times. By 2016, the average number of switches in *Disclosures*, *Forecasts*, and *8-Ks* since 2001 is 12.1, 8.9, and 10.9, respectively. By comparison, the typical firm only changes its decision of whether or not to provide a forecast 2.4 times over the same period. Moreover, the changes in disclosure we document do not simply reflect a systematic expansion in disclosure over the past 16 years. In untabulated analysis, we find that although the average level of disclosure has increased during this period, firms are roughly equally likely to decrease as increase disclosure in most individual years after 2007. This pattern of small increases and decreases in disclosure is quite different from the large one-time changes associated with index reconstitutions studied in related work.

In sum, although disclosure policy has a permanent component, there is also a significant transitory component. Moreover, the transient component primarily reflects management altering the number of forecasts or 8-Ks they provide, rather than changing their decision to provide forecasts. Our next tests study whether changes in investor attention contribute to this transitory disclosure behavior.

4. Results

4.1 IO distraction and disclosure

Table 3, Panel A presents the results of estimating equation (1). The first column shows that *Distraction* is insignificantly negatively related to whether the firm provides forecasts. On the other hand, in Column 2, we find distraction has a significantly negative effect on the number of forecasts. Economically, a one standard deviation increase in *Distraction* reduces the number of forecasts by 5.2%.

Columns 3 and 4 study 8-Ks and total disclosure. The number of 8-Ks declines with *Distraction*. A one standard deviation increase in *Distraction* reduces the number of 8-Ks by 2.7%. Column 4 presents results for *Disclosures*, which is the sum of our forecast and 8-K filing variables after we eliminate 8-Ks on forecast days. We find the number of disclosures is negatively and significantly related to *Distraction*. A one standard deviation increase in *Distraction* reduces the number of disclosures by 6.4%.

In terms of the control variables, forecasts are positively related to leverage, size, and analyst coverage, and are negatively related to returns, losses, the absolute change in earnings, and stock return volatility. With the exception of EPS increase, the signs of the control variables in our quarterly specification are consistent with Ali et al. (2014), who use an annual specification with many of the same controls. In contrast, in our 8-K specification, losses and stock return volatility have signs opposite to those in the forecast specification. This difference is consistent with 8-Ks and forecasts substituting for one another (Noh et al. 2019). Finally, *Disclosures* are positively related to size, leverage, stock return volatility, and analyst coverage, and are negatively related to returns and to the absolute change in earnings.

Next, in Panel B we subject our initial results to a series of robustness tests. For brevity, we tabulate results for only *Disclosures*, but note that our findings are similar for other measures examined in Table 3, Panel A. All columns include the same control variables as Panel A, but we do not report coefficients for them.

First, we support our use of *Distraction* as a continuous measure capturing both attention and distraction periods. Specifically, we calculate *Distraction+* and *Distraction-*, equal to *Distraction* when (standardized) *Distraction* is greater than and less than or equal to zero, respectively, and zero otherwise. If our initial results were primarily driven by high distraction periods, we would expect a significantly negative coefficient on *Distraction+* and a null result for *Distraction-*. However, column 1 shows a significantly negative coefficient for both measures; moreover, the magnitude of the two coefficient is not significantly different.

Second, we assess the sensitivity of our results to an alternative distraction window. Our main specification focuses on contemporaneous distraction, because we expect changes in disclosure to occur relatively quickly. However, one could also envision distraction having an effect over multiple quarters, especially considering that return shocks could happen late in a quarter. In column 2, we follow Table 2, Panel B of Kempf et al. (2017) and measure distraction over three quarters (*Distraction[-2,0]*).[11] The coefficient on *Distraction[-2,0]* is negatively significant, and roughly half the size of our original coefficient from Panel A, column 4. Thus, while we find results over a longer window, they are economically and statistically less significant.

Third, to test our maintained assumption that our results are coming from changes in IO distraction rather than changes in IO composition, we eliminate observations with a 5% or more increase or decrease in institutional ownership from the previous quarter. Despite a 37% reduction in our sample, Column 3 shows that we continue to find IO distractions reduce disclosure.

Fourth, we investigate whether changes in firm fundamentals rather than attention are causing our results. Although we control for industry-quarter effects, and lagged returns and accounting performance, as an additional step we eliminate firms experiencing significant changes in their performance. Each firm-quarter, we measure the absolute change in EPS, and eliminate observations in the highest quartile. Column 4 shows that our results are the same for the remaining firm-quarters, indicating that performance shocks do not explain our results.

Fifth, in Column 5 we omit financial firms. For these firms, regulatory oversight and reliance on leverage can cause disclosure practices and the investor base to differ from firms in other industries. We find our results are the same when we omit financial firms.

4.2 Why does IO distraction affect disclosure?

In this section, we attempt to shed light on why managers' disclosure choices are sensitive to attention. One possibility is that when given the option, managers decrease disclosure to conceal value-destroying actions. Kempf et al. (2017) find that managers take advantage of distraction periods to decrease dividends and undertake diversifying, value-destroying mergers. Decreasing

[11] Specifically, we sum *Distraction* over quarters t-2, t-1, and t, and standardize this sum.

disclosure around such events can make it more difficult for investors to become aware of the actions management is carrying out. Managers may also manipulate disclosure to engage in insider trading or to delay the revelation of bad news (Kothari et al. 2009; Zhou and Zhou 2017). Related work finds that managers release more bad news when they think investors are distracted (Damodaran 1989; deHaan et al. 2015; Niessner 2015).

Our next set of tests assesses whether our main finding of a negative relation between *Disclosures* and *Distraction* is robust to eliminating observations where value-destroying behavior or an attempt to hide bad news is most likely. Our goal with these tests is not to rule out the possibility that managers could exploit IO distractions to behave opportunistically. Rather, our goal is to assess whether changes in disclosure we document earlier are primarily coming from management attempting to conceal opportunistic behavior by reducing forecasts or 8-Ks.[12]

Table 4 repeats our test in column 4 of Table 3, Panel A after eliminating firm-quarters where management may have incentives to reduce disclosure to hide value-destroying behavior. Column 1 restricts our sample to observations where firms do not undertake a diversifying M&A transaction, where we follow Kempf et al. and define a diversifying M&A transaction as a deal for more than $1M for a target outside of the acquirer's two-digit SIC industry. Column 2 omits firm-quarters for dividend-paying firms that decreased their dividend from the same quarter last year. In Column 3, we measure the profit on insider trades, and omit observations in which insiders earn 1% or more abnormal profits on their trades.[13] Next, we consider scenarios where IO distractions could lead to diminished participation in director elections and annual meetings (e.g., Liu et al.

[12] For example, managers are required to file 8-Ks for certain events (e.g., dividend decreases), but have discretion for others (Gleason et al. 2018). Managers can also reduce forecasting activity.
[13] Following Jagolinzer et al. (2011), we measure trade profitability as the intercept from the four factor Fama and French (1993) and Carhart (1997) model estimated over the 180 days following each transaction.

2017). Column 4 eliminates observations from the first two fiscal quarters of the year (when director elections and annual meetings are concentrated), a restriction costing half of our sample. Across all four columns, we continue to find a significantly negative coefficient on *Distraction* of a comparable magnitude to our original result (Table 3, Panel A, Column 4 shows a coefficient of -0.064).

While our tests exclude cases of self-dealing behavior that related literature has linked to IO distraction, there are other self-dealing actions that management can take, and management could reduce disclosure to conceal these actions. Similarly, management may reduce disclosure if it anticipates bad news and does not want to draw attention to this news. Rather than attempt to rule out each alternative form of self-dealing behavior, we make the assumption that the behavior most likely to contaminate our results will reveal itself in the form of poor future stock returns.[14] As a final step in Column 5, we omit firm-quarters with the lowest quintile of industry-adjusted returns over the next twelve months. We continue to find a negative relation between disclosure and *Distraction*.[15]

In sum, the foregoing analysis suggests that the disclosure changes that we find are not simply manifestations of the M&A activity and dividend cuts documented in Kempf et al. (2017), more general self-dealing behavior resulting in subsequent losses or negative returns, or the desire to hide negative future news. This raises the possibility, investigated in our next tests, that managers make non-substantive adjustments to disclosure in response to attention.

4.3 How does disclosure respond to IO distraction?

[14] As Kempf et al. argue, "many value-destroying actions self-interested managers can take are unobservable to the econometrician. Stock returns can act as a summary measure of the economic impact of these actions" (p. 1689).
[15] Our results are also similar if we model forecasts or 8-Ks separately rather than total disclosures.

In this section, we explore how forecasting activity responds to distraction. We decompose our quarterly *Forecasts* variable into *EAD Forecasts* (equal to the number of forecasts made within one day of an earnings announcement day ("EAD")) and *Non-EAD Forecasts* (number of forecasts made not within one day of an EAD). We only examine forecasts for the 64,062 observations for which a non-pre-earnings announcement forecast is made.[16] Then, we study which types of forecasts are most sensitive to changes in attention. To do this, we create indicators for two types of core forecasts (net earnings and revenues) and two types of secondary forecasts (other income forecasts including pre-tax income, EBITDA, and gross margin; and other forecasts including cash flow, capex, and dividends). We view our tests as providing descriptive evidence of *how* disclosure responds to IO attention, which helps motivate our later analyses of the consequences of disclosure responses.

Table 5 summarizes these forecast variables, conditional on a forecast being made during the quarter. The typical firm makes 2.9 (0.9) *EAD Forecasts* (*Non-EAD Forecasts*) during the quarter. Net earnings and revenue forecasts are provided in 73% and 48% of the quarters, respectively, while other income forecasts and other forecasts are provided in 23% and 46% of the quarters, respectively.

Columns 1 and 2 of Table 6, Panel A model *EAD Forecasts* and *Non-EAD Forecasts* using equation (1). We find that only *EAD Forecasts* is responsive to IO attention. Therefore, the sensitivity of forecasts to IO attention documented in our main results is primarily operating through the intensive margin (managers adding new forecasts conditional on forecasting around

[16] One potential drawback of conditioning on the provision of a forecast is that forecasting is a choice. Although identifying a suitable instrument for this selection issue is challenging, we note that Table 2 shows the choice to forecast is relatively stable within-firm, and that our tests include firm fixed effects.

the EAD) instead of the extensive margin (managers, for example, adding mid-quarter forecasts). Columns 3 and 4 find that the provision of net earnings and revenue forecasts is not significantly related to IO attention. Columns 5 and 6 study the secondary forecasts, and find that both other income and other forecasts vary significantly with attention.[17]

We also examine forecast properties, which we compute as follows: *Horizon* is the fraction of a year from the forecast to the forecasted fiscal period end. We measure forecast *Precision* following Rogers and Van Buskirk (2009) as equal to 4 for point estimates, 3 for range estimates, 2 for open-ended estimates, and 1 for qualitative estimates. All else equal, longer horizon forecasts and more precise forecasts provide more information about future performance to investors. For both of these measures, we follow Boone and White (2015) and delete pre-earnings announcement forecasts made after the fiscal quarter end but prior to the earnings announcement.[18] We compute the average value of *Horizon* and *Precision* over the quarter. Table 5 shows that the sample mean horizon per forecast and mean precision per forecast are 0.47 years and 2.8, respectively. The mean forecast horizon of 0.47 years suggests that the typical firm uses a combination of quarterly and longer-horizon forecasts, and the mean precision is a range estimate.

Table 6, Panel B presents the results of estimating equation (1) for our forecast property variables. Column 1 shows no change in average *Horizon* when IO attention decreases. The fact that there is no change in average horizon suggests that the *Horizon* of the incremental forecast(s) is economically and statistically similar to the previous average. By contrast, there is a significant 2.5% increase in average precision with a one standard deviation increase in *Distraction* (Column

[17] We obtain similar results on a smaller sample if we drop observations prior to 2007. Coverage of capital expenditure forecasts in I/B/E/S Guidance is incomplete prior to 2007 (Huang 2018).
[18] Pre-earnings announcement forecasts made after the fiscal quarter have negative horizon.

2), consistent with the incremental forecasts associated with attention being less precise than existing forecasts.

Together, these tests offer evidence consistent with managers' forecast choices being responsive to IO attention. Forecast changes occur through shifts in the number of forecasts on or around earnings announcements, rather than additions of new forecasts during other times in the quarter. In response to attention, managers are more likely to adjust forecasts for secondary than core items. The added forecasts have the same horizon, but are less precise. Our next tests study the consequences of these and other disclosure adjustments.

4.4 Attention-driven disclosure, information quality, and liquidity

We study two sets of variables: market-based information quality measures (*Abnormal Volatility* and *Abnormal Volume*) and liquidity measures (*Abnormal Bid-Ask Spread* and *Abnormal Depth*).

Prior literature finds that abnormal volatility and abnormal volume increase in the amount of information in disclosure (e.g., Lerman and Livnat 2010). We study abnormal information quality and liquidity over the entire quarter.[19] *Abnormal Volatility* is the natural logarithm of [total daily squared abnormal returns in the quarter divided by total daily squared abnormal returns in the prior quarter]. Abnormal returns are calculated as the daily return on a stock minus the return on the value-weighted market portfolio. *Abnormal Volume* is the natural logarithm of [total daily volume divided by total daily volume in the prior quarter]. We calculate daily volume as the

[19] In results reported in Table A2 of the Online Appendix, we compute abnormal information quality and liquidity during the three days surrounding the disclosure date, and find that our inferences are unaffected.

number of shares traded divided by shares outstanding to ensure that the volume measure is unaffected by stock splits.

Last, we study liquidity as proxied by bid-ask spread and depth. We predict that informative disclosures will improve liquidity by reducing spreads and increasing depths. *Abnormal Bid-Ask Spread* is the natural logarithm of [total daily bid-ask spread over the quarter, divided by the total daily bid-ask spread over the prior quarter]. *Abnormal Depth* is the natural logarithm of [total daily depth over the quarter, divided by the total daily depth over the prior quarter]. We use the DTAQ database to compute average daily percent quoted bid-ask spreads and depths. Daily percent spread is the daily average of each quote's spread, calculated as the difference between an offer price and a bid price divided by the midpoint of the offer and bid price. The daily depth is the daily average of each quote's depth, calculated as the sum of the dollar offer size and the dollar bid size. Both the depth and the spread are time-weighted during trading hours for each day according to the procedure described in Holden and Jacobsen (2014).

Table 7 shows that *Abnormal Volatility*, *Abnormal Volume*, *Abnormal Bid-Ask Spread*, and *Abnormal Depth*, have median values that are approximately equal to one, suggesting that the typical information quality and liquidity do not differ across quarters. Data on these variables is missing for about 1,100 observations in our sample, generally because data is not available in the previous quarter.

In Table 8, we study the market-based measures of information quality and liquidity using equation (1). Columns 1 and 2 show that abnormal volatility and abnormal volume are not significantly related to *Distraction.* Columns 3 and 4 model our liquidity variables. In the bid-ask spread regressions, we include the prior quarter average depth as a control, and in the depth regressions, we include the prior quarter average bid-ask spread as a control. We do this following Bushee et al. (2010) and Blankespoor et al. (2014) to control for the fact that market makers can protect themselves against information asymmetry by increasing spreads or reducing depths, and they can offset a change in spreads with a change in depth in the opposite direction (Bushee et al. 2010; Yohn 1998). We find a significant 1.9% reduction in the bid-ask spread in response to one standard deviation increase in attention. This reduction represents under 30% of the 6.4% decrease in disclosure reported in column 4 of Table 3, Panel A, and the two coefficients are significantly different (p-value < 0.05). In addition, we find a 1.2% reduction in depth when attention increases by one standard deviation, which is marginally significant (p-value < 0.15). And, as before, the difference in *Distraction* coefficients across the disclosure and depth regressions is significant (p-value <0.05). While the spread and depth measure different aspects of liquidity, the combination of an increase in spread (decrease in liquidity) and an increase in depth (increase in liquidity) suggests mixed effects on overall liquidity when *Distraction* increases.

In Table A3 of the online appendix, we conduct additional tests to establish the robustness of our Table 8 results. Specifically, we examine the robustness of our findings to studying wider distraction windows, conditioning our sample on changes in disclosure, eliminating firm-quarters where future returns are poor, or employing an instrumental variables specification using *Distraction* as our instrument for *Disclosures*. We continue to find no relation between information quality and IO attention, except when we study abnormal volume for the sample of firms with changes in disclosure. The results for abnormal spread are weaker, with one insignificant coefficient and a significantly negative coefficient in the instrumental variables specification. We find no significant relation between depth and IO attention.

We interpret our results as showing that IO attention-driven changes in disclosure have little effect on information quality or liquidity. We caveat that our market-based tests are potentially affected not only by the informativeness of incremental disclosure but also by investors' attention to the disclosure. In other words, if investors are more attentive and pay more attention to incremental disclosure, this attentiveness could increase market reactions and liquidity. As one way of addressing this, we estimate path models for information quality and liquidity that allow distraction to affect these directly and indirectly through disclosure. In untabulated results, we find that the indirect path is insignificant, consistent with IO attention-driven changes in disclosure having little effect on information quality or liquidity.

However, we acknowledge that null results cannot be proven, and that weaknesses in any study's design can generate null findings. For example, a lack of power or endogeneity can cause non-results. We study plausibly exogenous changes in disclosure in a panel of roughly 100,000 firm-quarters, reducing concerns that problems with our research design prevent us from detecting a link between IO-attention-driven disclosure, information quality, and liquidity.

4.5 Attention by passive vs. non-passive IOs

Thus far, we have focused on aggregate attention from all IOs. However, the increased share of investment by passive IOs has raised interest in the differences between passive and non-passive IO monitoring (e.g., Appel et al. 2016; Malenko and Shen 2016; Schmidt and Fahlenbrach 2017; Heath et al. 2019). Passive IOs have to oversee more firms at a lower cost than their actively managed counterparts, have little incentive or ability to collect private information, and are less likely to specialize by industry. Monitoring is still important to passive investors, however, because passive investors have limited ability to sell shares in underperforming firms (Romano 1993). Public disclosure is therefore an important, low cost way for passive IOs to monitor.

We explore differences in attention between active and passive IOs. Doing so helps us understand differences in monitoring across passive and non-passive IOs, and explore whether these differences explain why attention seems to carry little information quality or liquidity consequence. One limitation of this analysis is that by separately analyzing passive and non-passive investors, we ignore potential interactions between them. The Kempf et al. measure for all IOs has fewer of these problems because aggregation cancels across-IO effects. Our results using the separate measures should therefore be interpreted with caution.

We define passive IOs as quasi-index investors using the classification scheme of Bushee (2001) and Bushee and Noe (2000).[20] We calculate *Passive IO Distraction*$_{i,t}$ and *Non-Passive IO Distraction*$_{i,t}$, which are separate distraction measures for each IO type based on the Kempf et al. (2017) IO distraction measure described above. The typical firm in our sample has 150 passive IOs and 67 non-passive IOs. Again, to facilitate interpretation of our results, we standardize *Passive IO Distraction* and *Non-Passive IO Distraction* to mean zero and standard deviation of one. We use the same specification as in equation (1), except that we use the separate distraction measures, and that we control separately for the average percentage of ownership by passive and non-passive institutions, the percentage of IO held by the five largest passive and non-passive IOs, and the percentage of IO held by passive institutional investors in the firm at the beginning of the quarter.

Table 9, Panel A extends the results from Table 3 to study the relation between both passive and non-passive distractions and disclosure. As in Table 3, Panel A neither *Passive IO Distraction* nor *Non-Passive IO Distraction* are significantly negatively related to whether the firm provides

[20] According to Bushee (2001) and Bushee and Noe (2000), quasi-indexers consist of purely passive index funds and active funds that are effectively passive in that they trade infrequently and closely benchmark against indexes.

forecasts. In Column 2, we find both types of distraction have a significantly negative effect on the number of forecasts. Column 3 shows that the number of 8-Ks declines with only *Passive IO Distraction*. Column 4 presents results for *Disclosures*. We find the number of disclosures is over three times more sensitive to *Passive IO Distraction* than it is to *Non-Passive IO Distraction*. As shown near the bottom of the table, the difference in the *Passive IO Distraction* and *Non-Passive IO Distraction* coefficients is significant at the 1% level for *Forecasts*, *8-Ks*, and *Disclosures*. Our Panel A findings are consistent with passive IOs' distractions having a larger effect on disclosure than non-passive IOs' distractions.

We next revisit the forecast properties, information quality, and liquidity consequences of these changes. Table 9, Panel B extends the results from Tables 6 and 8 to study both passive and non-passive distractions. Column 1 shows a small, but significant decrease in average *Horizon* when *Passive IO Distraction* increases. This 0.8% change in average horizon suggests that the *Horizon* of the incremental forecast(s) is economically similar to the previous average. Column 2 shows significant increase in average precision for both passive and non-passive IO distraction. As in Table 6, this increase in precision with distraction is consistent with the incremental forecasts associated with attention being less precise than existing forecasts. Columns 3 and 4 show insignificant relations between passive or non-passive IO attention, volatility and volume. These results are in line with our Table 8 findings.

Finally, columns 5 and 6 show a significant 1.3% increase in the bid-ask spread and a significant 1.7% increase in depth when *Passive IO Distraction* increases. Similar to Table 8, the combination of an increase in spread (decrease in liquidity) and an increase in depth (increase in liquidity) suggests mixed effects on overall liquidity when *Passive IO Distraction* increases. What is new here is that the change in liquidity (and disclosure) is only significant for passive IOs.

Our finding that passive IOs are causing significant changes in disclosure that carry little information quality or liquidity effect is consistent with recent work on IO monitoring. Specifically, Schmidt and Fahlenbrach (2017) caution that passive investors often employ uniform rules-based monitoring techniques that are not effective for more complicated situations, and in some cases impose unnecessary costs on management. Consistent with disclosure being costly and IOs asking management for incremental disclosures, we find that managers increase disclosure when more attention is paid to them, but that these adjustments have no overall effect on information quality or liquidity. Because passive IOs comprise a large share of total ownership and participate in shareholder votes, managers have incentives to respond to passive IO requests for disclosure.

5. Conclusion

We hold IO constant, and examine how exogenous short-term changes in IO attention affect managements' short-term disclosure choices, and the resulting information asymmetry and liquidity consequences. For our sample of firms from 2001-2016, we find that managers regularly undertake minor adjustments to their disclosure policy, frequently changing the number of disclosures provided but rarely changing the overall decision to forecast. We find that IO attention helps explain these short-term changes: a one standard deviation increase in IO attention increases disclosure by 6.4%. These results are not driven by firm or industry-level shocks to fundamentals, and are not consistent with management simply taking advantage of distraction windows to conceal opportunistic behavior or bad news. Attention from passive investors drives most of the variation in disclosure. Adjustments to disclosure in response to attention appear relatively minor in that managers rarely change the overall decision to disclose on a given day, and any alterations occur through less informative types of disclosures. Although we find attention increases the quantity of disclosure, we find little overall change in abnormal returns, abnormal volume, or liquidity. In sum, our evidence suggests that management responds to temporary IO attention by making disclosures that have little effect on information quality or liquidity.

Our results offer a novel contribution to the literature studying management disclosure choices. Whereas prior work typically models disclosure as a persistent decision with significant consequences for information quality and liquidity, we show that managers make frequent but inconsequential disclosure changes in response to fleeting IO attention. In this way, our results also add to recent work studying the effectiveness of passive IO monitoring (e.g., Kempf et al. 2017; Appel et al. 2016; Schmidt and Fahlenbrach 2017).

References

Ali, A., Klasa, S., & Yeung, E. (2014). Industry concentration and corporate disclosure policy. *Journal of Accounting and Economics*, *58*(2), pp.240-264.

Anantharaman, D., & Zhang, Y. (2011). Cover me: Managers' responses to changes in analyst coverage in the post-Regulation FD period. *The Accounting Review*, *86*(6), 1851-1885.

Appel, I. R., Gormley, T. A., & Keim, D. B. (2016). Passive investors, not passive owners. *Journal of Financial Economics*, *121*(1), 111-141.

Basu, R., Pierce, S., & Stephan, A. (2019). The effect of investor inattention on voluntary disclosure. Working paper, SSRN.

Ben-David, I., Franzoni, F., Moussawi, R., & Sedunov, J. (2019). The granular nature of large institutional investors. CEPR Discussion Papers No 13427.

Beyer, A., Cohen, D.A., Lys, T.Z., & Walther, B.R. (2010). The financial reporting environment: Review of the recent literature. *Journal of Accounting and Economics*, 50(2), pp.296-343.

Bird, A., & Karolyi, S. A. (2016). Do Institutional Investors Demand Public Disclosure? *The Review of Financial Studies*, *29*(12), 3245-3277.

BlackRock. (2017). BlackRock investment stewardship: Global corporate governance and engagement principles. October 2017.

Blankespoor, E., deHaan, E. & Marinovic, I. (2019). Disclosure Processing Costs, Investors' Information Choice, and Equity Market Outcomes: A Review. Available at SSRN: https://ssrn.com/abstract=3449751.

Blankespoor, E., Miller, B. P., & White, H. D. (2014). Initial evidence on the market impact of the XBRL mandate. *Review of Accounting Studies*, *19*(4), 1468-1503.

Boone, A. L., & White, J. T. (2015). The effect of institutional ownership on firm transparency and information production. *Journal of Financial Economics*, *117*(3), 508-533.

Brown, L. D., Call, A. C., Clement, M. B., & Sharp, N. Y. (2019). Managing the narrative: Investor relations officers and corporate disclosure. *Journal of Accounting and Economics*, *67*(1) 58-79.

Bushee, B. J. (2001). Do institutional investors prefer near-term earnings over long-run value? *Contemporary Accounting Research*, *18*(2), 207-246.

Bushee, B. J., & Noe, C. F. (2000). Corporate disclosure practices, institutional investors, and stock return volatility. *Journal of Accounting Research*, *38*, 171-202.

Bushee, B. J., Core, J. E., Guay, W., & Hamm, S. J. (2010). The role of the business press as an information intermediary. *Journal of Accounting Research*, *48*(1), 1-19.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance, 52*(1), 57-82.

Chapman, K., & Green, J. (2018). Analysts' Influence on Managers' Guidance. *The Accounting Review, 93*(1), 45-69-.

Chen, S., Huang, Y., Li, N., & Shevlin, T. (2019). How Does Quasi-Indexer Ownership Affect Corporate Tax-Planning? *Journal of Accounting and Economics, 67*(2), 278-296.

Chuk, E., Matsumoto, D., & Miller, G. S. (2013). Assessing methods of identifying management forecasts: CIG vs. researcher collected. *Journal of Accounting and Economics*, *55*(1), 23-42.

Damodaran, A., 1989. The weekend effect in information releases: A study of earnings and dividend announcements. *The Review of Financial Studies*, *2*(4), pp.607-623.

deHaan, E., Shevlin, T., & Thornock, J. (2015). Market (in) attention and the strategic scheduling and timing of earnings announcements. *Journal of Accounting and Economics, 60*(1), 36-55.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*(1), 3-56.

Fama, E. F., & French, K. R. (2008). Average returns, B/M, and share issues. *The Journal of Finance*, *63*(6), 2971-2995.

Fidelity. (2018). Proxy voting. Accessed April 4, 2018. Available at https://www.fidelity.com/about-fidelity/fidelity-by-numbers/fmr/proxy-voting-overview.

Gillette, J. R., Jayaraman, S., & Zimmerman, J. L. (2017). Measuring Firms' Investment in Accounting Resources: Implications for Malfeasance Versus Optimal Incompetence. Working paper, MIT.

Gleason, C. A., Ling, Z., & Zhao, R. (2018). Selective Disclosure and the Role of Form 8-K in the Post-Reg FD Era. *Journal of Business Finance and Accounting,* In-Press.

Goodman, T.H., Neamtiu, M., Shroff, N., & White, H.D. (2013). Management forecast quality and capital investment decisions. *The Accounting Review, 89*(1), pp.331-365.

Gopalan, R., Nanda, V., & Yerramilli, V. (2011). Does poor performance damage the reputation of financial intermediaries? Evidence from the loan syndication market. *The Journal of Finance*, *66*(6), 2083-2120.

Graham, J. R., Harvey, C. R., & Rajgopal, S. (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics*, *40*(1), 3-73.

Healy, P. M., & Palepu, K. G. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics*, *31*(1), 405-440.

Heath, D., Macciocchi, D., Michaely, R., & Ringgenberg, M. (2018). Do Index Funds Monitor? Working paper, Swiss Finance Institute.

Hirshleifer, D., Lim, S. S., & Teoh, S. H. (2009). Driven to distraction: Extraneous events and underreaction to earnings news. *The Journal of Finance*, *64*(5), 2289-2325.

Holden, C. W., & Jacobsen, S. (2014). Liquidity measurement problems in fast, competitive markets: Expensive and cheap solutions. *The Journal of Finance*, *69*(4), 1747-1785.

Huang, Y. (2018). Does the visible hand make firms more visible? The effect of government subsidies on corporate disclosure. Working paper. University of Texas at Dallas.

Jagolinzer, A. D., Larcker, D. F., & Taylor, D. J. (2011). Corporate governance and the information content of insider trades. *Journal of Accounting Research*, *49*(5), 1249-1274.

Jung, M. J., Wong, M. F., & Zhang, X. F. (2015). Analyst interest as an early indicator of firm fundamental changes and stock returns. *The Accounting Review*, *90*(3), 1049-1078.

Kempf, E., Manconi, A., & Spalt, O., 2017. Distracted shareholders and corporate actions. *Review of Financial Studies*, 30 (5): 1660-1695.

Kothari, S. P., Shu, S., & Wysocki, P. D. (2009). Do managers withhold bad news? *Journal of Accounting Research*, *47*(1), 241-276.

Lang, M. H., & Lundholm, R. J. (1996). Corporate disclosure policy and analyst behavior. *Accounting review*, 467-492.

Lerman, A., & Livnat, J. (2010). The new Form 8-K disclosures. *Review of Accounting Studies*, *15*(4), 752-778.

Liu, C. Y., Low, A., Masulis, R. W., & Zhang, L. (2017). Monitoring the monitor: Distracted institutional investors and board governance. Working paper, European Corporate Governance Institute.

Leuz, C., & Verrecchia, R. E. (2000). The economic consequences of increased disclosure. *Journal of Accounting Research*, *38*, 91-124.

Malenko, N., & Shen, Y. (2016). The role of proxy advisory firms: Evidence from a regression-discontinuity design. *The Review of Financial Studies*, *29*(12), 3394-3427.

Murfin, J. (2012). The supply-side determinants of loan contract strictness. *The Journal of Finance*, *67*(5), 1565-1601.

Niessner, M. (2015). Strategic disclosure timing and insider trading. Yale University working paper.

Noh, S., So, E. C., & Weber, J. (2019). Switching from Voluntary to Mandatory Disclosure: Do Managers View Them as Substitutes? *Journal of Accounting and Economics*, *68*(1).

Park, J., Sani, J., Shroff, N., & White, H. (2019). Disclosure incentives when competing firms have common ownership. *Journal of Accounting and Economics*.

Rogers, J. L., & Van Buskirk, A. (2009). Shareholder litigation and changes in disclosure behavior. *Journal of Accounting and Economics*, *47*(1), 136-156.

Romano, R. (1993). Public pension fund activism in corporate governance reconsidered. *Columbia Law Review*, *93*(4), 795-853.

Schmidt, C., & Fahlenbrach, R. (2017). Do exogenous changes in passive institutional ownership affect corporate governance and firm value? *Journal of Financial Economics*, *124*(2), 285-306.

Schoenfeld, J. (2017).The effect of voluntary disclosure on stock liquidity: New evidence from index funds. *Journal of Accounting and Economics*, 63 (1): 51-74.

State Street Global Advisors. (2018). Proxy voting and engagement guidelines. North America. March 2018.

Vanguard Index Funds (2018). Statement of additional information. *https://www.vanguard.com/pub/Pdf/sai040.pdf* *(*Accessed August 16, 2018).

Verrecchia, R. E. (1990). Information quality and discretionary disclosure. *Journal of Accounting and Economics*, *12*(4), 365-380.

Yohn, T. L. (1998). Information asymmetry around earnings announcements. *Review of Quantitative Finance and Accounting*, *11*(2), 165-182.

Zhou, F., & Zhou, Y. (2017). The Tale of Silent Dogs: Do Stock Prices Fully Reflect the Implication of News Withholding? Working paper

Appendix A: Variable Definitions

This appendix provides definitions for variables used throughout the paper.

Distraction Variables	Description
Distraction	Based on the Kempf et al. 2017 investor distraction measure. Distraction is calculated using the following equation: $$D_{i,t} = \sum_{f \in F_{t-1}} \sum_{IND \neq IND_i} w_{ift-1} \times w_{ft-1}^{IND} \times IS_t^{IND}$$ F_{t-1} refers to the set of firm i's institutional investors at the end of quarter t-1, IND refers to Fama-French 12 industries, and IND_i refers to firm i's industry. The weight w_{ift-1} considers how large investor f's stake is in firm i, and how much of f's portfolio is comprised of the investment in i. The calculation for this weight is provided in equation 2 of Kempf et al. 2017. w_{ft-1}^{IND} is the weight of industry IND in investor f's portfolio at the end of last quarter. IS_t^{IND} is an indicator for whether that industry had the highest or lowest returns of all Fama-French 12 industries that quarter. The variable is set to missing if the firm's industry has the highest or lowest return. To facilitate interpretation of our results, we standardize the variable to mean zero and standard deviation of one (by subtracting the mean and dividing by the standard deviation).
Distraction+	Equal to Distraction when Distraction is greater than zero, and zero otherwise.
Distraction-	Equal to Distraction when Distraction is less than or equal to zero, and zero otherwise.
Distraction[-2,0]	Distraction measured over three quarters. Specifically, we sum Distraction for the firm over quarters t -2, t -1, and t and then standardize this sum.
Disclosure Quantity Variables	
Forecast Firm	An indicator equal to one if the firm makes a forecast that quarter, and zero otherwise.
Forecasts	The natural logarithm of one plus the number of forecasts by the firm that quarter.
8-Ks	The natural logarithm of one plus the number of 8-K filings by the firm that quarter.
Disclosures	The natural logarithm of one plus the sum of forecasts and 8-Ks by the firm that quarter. If the firm has a forecast and an 8-K on

	the same day, we do not count the 8-K under the assumption that it relates to the forecast.
EAD Forecasts	The natural logarithm of one plus the number of forecasts by the firm that quarter within one day of an earnings announcement.
Non-EAD Forecasts	The natural logarithm of one plus the number of forecasts by the firm that quarter not within one day of an earnings announcement.
Earnings Forecast	An indicator equal to one if the firm made an earnings forecast during the quarter, and zero otherwise. We count all forecasts of net earnings, including earnings per share, net income, ROE, and ROA.
Revenue Forecast	An indicator equal to one if the firm made a revenue forecast during the quarter, and zero otherwise.
Other Income Forecast	An indicator equal to one if the firm made another earnings forecast during the quarter, and zero otherwise. We count all forecasts of non-bottom line earnings, including pre-tax income, EBITDA, and gross margin.
Other Forecast	An indicator equal to one if the firm made another forecast during the quarter, and zero otherwise. We count all forecasts of cash flow, CAPEX, and dividends.
Disclosure Quality Variables	
Horizon	The fraction of a year from the date of the forecast until the end of the forecast period. We average the variable over all forecasts in the quarter, add one, and take natural logarithm.
Precision	The natural logarithm of one plus forecast precision. Following Rogers and Van Buskirk (2009), forecast precision equals 4 for point estimates, 3 for range estimates, 2 for open-ended estimates and 1 for qualitative estimates. We average the variable over all forecasts in the quarter, add one, and take natural logarithm.
Abnormal Volatility	The natural logarithm of [total daily squared abnormal returns in the quarter divided by total daily squared abnormal returns in the prior quarter]. Abnormal returns are calculated as the daily return on a stock minus the return on the value-weighted market portfolio.
Abnormal Volume	The natural logarithm of [total daily shares traded/shares outstanding in quarter divided by total daily shares traded/shares outstanding in the prior quarter].
Abnormal Bid-Ask Spread	The natural logarithm of [total daily bid-ask spread over the quarter, divided by the total daily bid-ask spread over the prior quarter]. The daily bid-ask spread is the daily average of each quote's spread, calculated using DTAQ as the difference between an offer price and a bid price divided by the midpoint of the offer and bid price, where the spread is time-weighted during trading

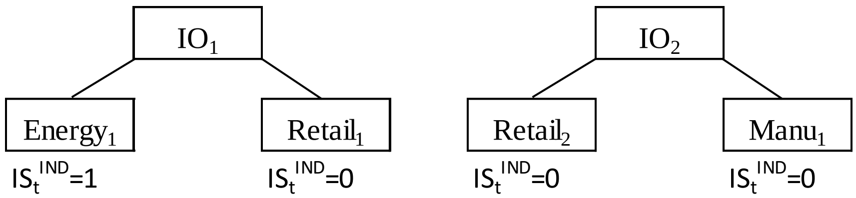
	hours for each day according to the procedure described in Holden and Jacobsen (2014).
Abnormal Depth	The natural logarithm of [total daily depth over the quarter, divided by the total daily depth over the prior quarter]. The daily depth is the daily average of each quote's depth, calculated using DTAQ as the sum of the dollar offer size and the dollar bid size where the depth is time-weighted during trading hours for each day according to the procedure described in Holden and Jacobsen (2014).
Control Variables	
Institutional Ownership$_{t-1}$	The percentage ownership by institutional investors at the beginning of the quarter.
Institutional Ownership Top 5$_{t-1}$	The percentage of institutional ownership held by the five largest institutional investors in the firm at the beginning of the quarter.
Returns$_{t-1}$	Stock returns for the firm last quarter.
Loss$_{t-1}$	An indicator equal to one if the firm reports a loss last quarter.
EPS Increase$_{t-1}$	An indicator equal to one if the firm reports an increase in earnings per share last quarter compared to five quarters ago.
Absolute EPS Change$_{t-1}$	The absolute value of the firm's change in earnings from five quarters ago to last quarter deflated by the stock price four quarters ago.
Leverage$_{t-1}$	The leverage ratio for the firm, measured at the beginning of the quarter.
Size$_{t-1}$	The natural logarithm of the market value of equity for the firm, measured at the beginning of the quarter.
Book-to-Market$_{t-1}$	The book-to-market ratio of assets for the firm, measured at the beginning of the quarter.
Return Volatility$_{t-1}$	The natural logarithm of the standard deviation of daily returns for the firm last quarter.
Analyst Coverage$_t$	The natural logarithm of one plus the number of analysts providing an earnings estimate for the firm that quarter.
Table 9 Variables	
Passive IO Distraction	A measure of Distraction calculated for passive investors only. We standardize the variable to mean zero and standard deviation of one (by subtracting the mean and dividing by the standard deviation) to facilitate comparison between passive and non-passive IO distraction. Passive investors are defined as quasi-index investors using the classification scheme of Bushee (2001) and Bushee and Noe (2000).
Non-Passive IO Distraction	A measure of Distraction calculated for non-passive investors only. We standardize the variable to mean zero and standard deviation of one (by subtracting the mean and dividing by the standard deviation) to facilitate comparison between passive and non-passive IO distraction. Non-Passive investors are defined

	using the classification scheme of Bushee (2001) and Bushee and Noe (2000).
Passive IO as a % of IO_{t-1}	The percentage of institutional ownership held by passive institutional investors in the firm at the beginning of the quarter.
Passive Institutional $Ownership_{t-1}$	The percentage ownership by passive institutional investors at the beginning of the quarter.
Non-Passive Institutional $Ownership_{t-1}$	The percentage ownership by non-passive institutional investors at the beginning of the quarter.
Passive Institutional Ownership Top 5_{t-1}	The percentage of institutional ownership held by the five largest passive institutional investors in the firm at the beginning of the quarter.
Non-Passive Institutional Ownership Top 5_{t-1}	The percentage of institutional ownership held by the five largest non-passive institutional investors in the firm at the beginning of the quarter.

Figure 1: Measurement of Distraction and Research Design

This figure provides a stylized illustration of the Kempf et al. distraction measure.

Consider two institutional investors, IO_1 and IO_2. IO_1 owns all of the shares of an energy firm and all of the shares of a retail firm, $Energy_1$ and $Retail_1$. IO_2 owns all of the shares of a different retail firm and all of the shares of a manufacturing firm, $Retail_2$ and $Manu_1$. All four firms are the same size. Therefore, IO_1 (IO_2) has a 50% exposure to both the energy and retail industries (retail and manufacturing industries). This quarter, the energy and healthcare industries experienced extreme returns.



In this illustration, *Distraction* is calculated as the product of:

a. The share of the firm owned by the IO at the start of the quarter (w_{ift-1});[21]
b. The weight of *other industries* in the IO's portfolio at the start of the quarter (w_{ft-1}^{IND}); and
c. An indicator for whether the other industries have extreme returns that quarter (IS_t^{IND}).

$$D_{i,t} = \sum_{f \in F_{t-1}} \sum_{IND \neq IND_i} w_{ift-1} \times w_{ft-1}^{IND} \times IS_t^{IND}$$

Therefore, *Distraction* for the two retail firms, $Retail_1$ and $Retail_2$, is calculated as follows:

	w_{ift-1}	x	w_{ft-1}^{IND}	x	IS_t^{IND}
Distraction $Retail_1$ =	1.0	x	0.5	x	1 = 0.50 (IO_1 exposed to energy)
Distraction $Retail_2$ =	1.0	x	0.5	x	0 = 0.00 (IO_2 not exposed to energy)

Because our research design includes industry x quarter fixed effects, we effectively compare disclosure behavior for $Retail_1$ and $Retail_2$, who face different levels of *Distraction* through their IO base.

While the above example uses an IO that has a 50% exposure to an industry with an extreme return, it can easily be modified to allow industry weights to change. This would have the effect of changing distraction continuously from 0% (no distraction) to 100% (full distraction). Thus, the measure transforms a discrete event (an extreme industry return) into a continuous measure of distraction.

[21] In practice, the weight w_{ift-1} incorporates both how large investor f's stake is in firm i, and how much of f's portfolio is comprised of the investment in i. The exact calculation for this weight is provided in equation 2 of Kempf et al. 2017.

Table 1: Summary Statistics

This table provides summary statistics for the variables used in our main tests. The sample consists of 100,378 quarterly observations from 2001-2016. Panel A describes the Distraction variable, Panel B describes the disclosure variables, and Panel C describes the control variables. To facilitate interpretation, we report statistics for the raw version of our disclosure, size, and return volatility variables, while our regressions use logarithmic transformations. See Appendix A for variable definitions.

Panel A: Distraction

	Mean	*SD*	*P1*	*P10*	*P25*	*Median*	*P75*	*P90*	*P99*	*N*
$Distraction_t$ (unstandardized)	0.146	0.081	0.041	0.051	0.080	0.124	0.210	0.260	0.354	100,378
$Distraction_t$ (standardized)	0.000	1.000	-1.306	-1.179	-0.821	-0.280	0.781	1.405	2.574	100,378

	Mean	*SD*	*P1*	*P10*	*P25*	*Median*	*P75*	*P90*	*P99*	*N*
$Distraction_t$ (unstandardized)	0.146	0.081	0.041	0.051	0.080	0.124	0.210	0.260	0.354	100,378
$Distraction_t$ (standardized)	0.000	1.000	-1.306	-1.179	-0.821	-0.280	0.781	1.405	2.574	100,378

Panel B: Disclosure Variables

	Mean	*Std Dev*	*25%*	*50%*	*75%*	*N*
Forecast Firm	0.642	0.479	0.000	1.000	1.000	100,378
Forecasts	2.505	3.215	0.000	1.000	4.000	100,378
8-Ks	2.769	2.300	1.000	2.000	4.000	100,378
Disclosures	4.576	3.718	2.000	4.000	6.000	100,378

Panel C: Control Variables

	Mean	*Std Dev*	*25%*	*50%*	*75%*	*N*
Institutional Ownership$_{t-1}$	0.695	0.263	0.541	0.757	0.900	100,378
Institutional Ownership Top 5$_{t-1}$	0.403	0.151	0.304	0.374	0.467	100,378
Returns$_{t-1}$	0.035	0.222	-0.074	0.031	0.135	100,378
Loss$_{t-1}$	0.166	0.372	0.000	0.000	0.000	100,378
EPS Increase$_{t-1}$	0.596	0.491	0.000	1.000	1.000	100,378
Absolute EPS Change$_{t-1}$	0.104	16.698	0.002	0.005	0.013	100,378
Leverage$_{t-1}$	0.251	0.205	0.074	0.225	0.378	100,378
Size$_{t-1}$ (millions)	6,678	15,000	513	886	1,884	100,378
Book-to-Market$_{t-1}$	0.698	0.317	0.469	0.691	0.905	100,378
Return Volatility$_{t-1}$	0.381	0.228	0.230	0.321	0.459	100,378
Analyst Coverage$_{t}$	10.992	7.776	3.000	5.000	9.000	100,378

Table 2: Cumulative Number of Switches in Disclosure Variables for Average Firm

This table studies the cumulative number of switches for each of our disclosure variables for a constant sample of 725 firms with observations in each year from 2001 to 2016. We define a switch as an increase or decrease in the disclosure variable from the first quarter of the prior year to the first quarter of the current year. We then cumulate the total switches for each firm up to that year. For example, the 1.423 figure for Disclosures in 2003 means that the typical firm has changed Disclosures 1.423 times between 2001 and 2003. See Appendix A for variable definitions.

	Cumulative Switches for Average Firm			
Year	Disclosures	Forecasts	8-Ks	Forecast Firm
2001				
2002	0.712	0.501	0.537	0.306
2003	1.423	0.969	1.164	0.534
2004	2.247	1.558	1.947	0.802
2005	3.123	2.242	2.745	0.967
2006	3.926	2.813	3.467	1.099
2007	4.923	3.905	4.279	1.281
2008	5.678	4.066	5.099	1.471
2009	6.549	5.191	5.789	1.604
2010	7.356	5.535	6.578	1.710
2011	8.150	6.147	7.282	1.773
2012	8.947	6.672	8.014	1.908
2013	9.632	6.813	8.724	2.135
2014	10.553	7.912	9.433	2.104
2015	11.331	8.390	10.161	2.183
2016	12.129	8.903	10.885	2.354

Table 3: Disclosures and IO Distraction

This table presents OLS regressions estimating equation (1). The sample consists of 100,378 quarterly observations from 2001-2016. Panel A models the incidence and frequency of various disclosures. Panel B provides robustness analyses for these results. Panel B, Columns 1 and 2 use the full sample. Column 3 eliminates firms whose IO increased or decreased by 5% or more from the previous quarter. Column 4 eliminates firm-quarters in the highest quartile of absolute earnings changes. Column 5 eliminates financial firms, defined by membership in Fama-French industry 11. For brevity, we do not report coefficients for the control variables included in Table 3, Panel B, although our tests include them. See Appendix A for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered by firm and industry-quarter. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

Panel A: Disclosures

	(1) Forecast Firm	(2) Forecasts	(3) 8-Ks	(4) Disclosures
$Distraction_t$	-0.012	-0.052***	-0.027**	-0.064***
	[-1.12]	[-2.60]	[-2.17]	[-3.95]
Institutional $Ownership_{t-1}$	0.033*	0.057**	-0.051**	-0.014
	[1.95]	[2.14]	[-2.56]	[-0.64]
Institutional Ownership Top 5_{t-1}	0.007	0.061*	0.090***	0.061**
	[0.34]	[1.91]	[4.64]	[2.50]
$Returns_{t-1}$	-0.026***	-0.053***	-0.009	-0.026***
	[-3.26]	[-4.66]	[-0.98]	[-2.65]
$Loss_{t-1}$	-0.025***	-0.042***	0.039***	0.012
	[-4.13]	[-4.46]	[6.00]	[1.61]
EPS $Increase_{t-1}$	0.002	0.002	-0.014***	-0.005
	[0.56]	[0.39]	[-4.30]	[-1.33]
Absolute EPS $Change_{t-1}$	0.000	-0.002**	0.000	-0.001**
	[-0.55]	[-2.29]	[0.72]	[-2.53]
$Leverage_{t-1}$	0.059**	0.110**	0.043	0.085**
	[2.39]	[2.54]	[1.58]	[2.58]
$Size_{t-1}$	0.045***	0.082***	0.010	0.051***
	[5.72]	[6.16]	[1.18]	[5.05]
Book-to-$Market_{t-1}$	0.009	0.001	0.007	-0.015
	[0.45]	[0.03]	[0.28]	[-0.58]
Return $Volatility_{t-1}$	-0.007	-0.035***	0.050***	0.033***
	[-0.83]	[-2.71]	[5.73]	[3.29]
Analyst $Coverage_t$	0.096***	0.149***	0.016*	0.088***
	[11.89]	[11.71]	[1.96]	[9.27]
Adj R-Sq.	0.525	0.637	0.638	0.653
N	100,378	100,378	100,378	100,378
Firm x Calendar Quarter FEs	Yes	Yes	Yes	Yes
Industry x Quarter FEs	Yes	Yes	Yes	Yes

Panel B: Robustness

	(1) Disclosures	(2) Disclosures	(3) Disclosures	(4) Disclosures	(5) Disclosures
$Distraction_t+$	-0.063***				
	[-3.25]				
$Distraction_t-$	-0.065**				
	[-2.22]				
$Distraction_t[-2,0]$		-0.031***			
		[-2.60]			
$Distraction_t$			-0.053***	-0.067***	-0.065***
			[-2.90]	[-3.69]	[-3.73]
Adj R-Sq.	0.653	0.652	0.675	0.655	0.661
N	100,378	97,112	63,119	74,937	80,728
Sample	Full	Full	IO change <.05	No Extreme EPS Change	No Financials
Controls	Yes	Yes	Yes	Yes	Yes
Firm x Calendar Quarter FEs	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FEs	Yes	Yes	Yes	Yes	Yes

Table 4: Opportunism and Disclosure Sensitivity to IO Distraction

This table presents OLS regressions estimating equation (1) after eliminating certain observations. The sample consists of quarterly observations from 2001-2016. Column 1 eliminates firms that experience a diversifying M&A transaction that quarter. Column 2 eliminates firms decreasing their dividend that quarter compared to the same quarter last year. Column 3 (4) eliminates firms with an average abnormal profit from insider trades exceeding 1% (observations from the first and second fiscal quarter of the year). Column 5 eliminates firm-quarters in the bottom quintile of industry-adjusted returns over the next twelve months. For brevity, we do not report coefficients for the control variables included in equation (1), although our tests include them. See Appendix A for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered by firm and industry-quarter. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

	(1) Disclosures	(2) Disclosures	(3) Disclosures	(4) Disclosures	(5) Disclosures
$Distraction_t$	-0.060***	-0.066***	-0.066***	-0.054***	-0.051***
	[-3.76]	[-4.06]	[-3.79]	[-2.60]	[-3.00]
Sample	No Div. M&A	No Dividend Decrease	No IT Profit	No Fiscal Q1 or Q2	No Low Future Ind-Adj Returns
Adj R-Sq.	0.654	0.653	0.667	0.638	0.657
N	98,169	98,547	73,501	48,615	81,109
Controls	Yes	Yes	Yes	Yes	Yes
Firm x Calendar Quarter FEs	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FEs	Yes	Yes	Yes	Yes	Yes

Table 5: Summary Statistics for Forecast Type and Forecast Properties Variables

This table provides summary statistics for the variables used in our forecast type and forecast properties tests. The sample consists of quarterly observations from 2001-2016 where a forecast was made. To facilitate interpretation, we report statistics for the raw version of our variables, while our regressions use logarithmic transformations. See Appendix A for variable definitions.

	Mean	*Std Dev*	*25%*	*50%*	*75%*	*N*
EAD Forecasts	2.971	1.000	1.000	2.000	6.000	64,062
Non-EAD Forecasts	0.944	0.000	0.000	0.000	3.000	64,062
Earnings Forecast	0.725	0.000	0.000	1.000	1.000	64,062
Revenue Forecast	0.480	0.000	0.000	0.000	1.000	64,062
Other Income Forecast	0.226	0.000	0.000	0.000	1.000	64,062
Other Forecast	0.460	0.000	0.000	0.000	1.000	64,062
Horizon	0.471	0.315	0.197	0.425	0.667	64,062
Precision	2.841	0.854	2.667	3.000	3.273	64,062

Table 6: Forecast Types, Forecast Properties, and IO Distraction

This table presents OLS regressions studying forecast types and forecast properties using equation (1). The sample consists of 64,062 quarterly observations from 2001-2016. For brevity, we do not report coefficients for the control variables included in equation (1), although our tests include them. See Appendix A for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered by firm and industry-quarter. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

Panel A: Forecast Types

	(1) EAD Forecasts	(2) Non-EAD Forecasts	(3) Earnings Forecast	(4) Revenue Forecast	(5) Other Income Forecast	(6) Other Forecast
$Distraction_t$	-0.058***	0.018	-0.001	-0.014	-0.043***	-0.040**
	[-2.83]	[0.80]	[-0.04]	[-1.07]	[-3.25]	[-2.40]
Adj R-Sq.	0.566	0.242	0.664	0.677	0.516	0.565
N	64,062	64,062	64,062	64,062	64,062	64,062
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm x Calendar Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Forecast Properties

	(1) Horizon	(2) Precision
$Distraction_t$	-0.007	0.025**
	[-1.38]	[2.38]
Adj R-Sq.	0.578	0.478
N	64,062	64,062
Controls	Yes	Yes
Firm x Calendar Quarter FEs	Yes	Yes
Industry x Quarter FEs	Yes	Yes

Table 7: Summary Statistics for Information Quality and Liquidity Variables

This table provides summary statistics for the variables used in our information quality and liquidity tests. The sample consists of quarterly observations from 2001-2016. To facilitate interpretation, we report statistics for the raw version of our variables, while our regressions use logarithmic transformations. See Appendix A for variable definitions.

	Mean	*Std Dev*	*25%*	*50%*	*75%*	*N*
Abnormal Volatility	1.823	2.874	0.473	0.969	1.983	100,365
Abnormal Volume	1.090	0.469	0.826	0.999	1.224	100,376
Abnormal Bid-Ask Spread	1.033	0.414	0.806	0.965	1.161	99,162
Abnormal Depth	1.009	0.240	0.863	0.991	1.128	99,162

Table 8: Information Quality, Liquidity, and IO Distraction

This table presents OLS regressions studying information quality and liquidity using equation (1). The sample consists of quarterly observations from 2001-2016. For brevity, we do not report coefficients for the control variables included in equation (1), although our tests include them. See Appendix A for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered by firm and industry-quarter. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

	(1) Abnormal Volatility	(2) Abnormal Volume	(3) Abnormal Bid-Ask Spread	(4) Abnormal Depth
$Distraction_t$	-0.003	-0.013	0.019**	0.012
	[-0.08]	[-1.06]	[2.09]	[1.48]
Adj R-Sq.	0.101	0.184	0.610	0.413
N	100,365	100,376	99,162	99,162
Controls	Yes	Yes	Yes	Yes
Firm x Calendar Quarter FEs	Yes	Yes	Yes	Yes
Industry x Quarter FEs	Yes	Yes	Yes	Yes

Table 9: Passive vs. Non-Passive IO Distraction

This table presents OLS regressions estimating equation (1) using *Passive IO Distraction* and *Non-Passive IO Distraction*. The sample consists of quarterly observations from 2001-2016. Panel A models the incidence and frequency of various disclosures (analogous to Table 3). Panel B models information quality and liquidity (analogous to Table 8). For brevity, we do not report coefficients for the control variables included in equation (1), although our tests include them. See Appendix A for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered by firm and industry-quarter. The row "Difference in Coefficients" reports the difference between the coefficients on *Passive IO Distraction* and *Non-Passive IO Distraction*, and indicates if this difference is significant. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

Panel A: Disclosures

	(1) Forecast Firm	(2) Forecasts	(3) 8-Ks	(4) Disclosures
Passive IO Distraction	-0.010	-0.037**	-0.025**	-0.057***
	[-1.22]	[-2.40]	[-2.57]	[-4.59]
Non-Passive IO Distraction	-0.004	-0.020**	-0.005	-0.018**
	[-0.70]	[-2.22]	[-0.78]	[-2.38]
Difference in Coefficients:				
Passive-Non Passive IO Distraction	-0.006	-0.017***	-0.020***	-0.039***
Adj R-Sq.	0.525	0.638	0.638	0.654
N	100,378	100,378	100,378	100,378
Controls	Yes	Yes	Yes	Yes
Firm x Calendar Quarter FEs	Yes	Yes	Yes	Yes
Industry x Quarter FEs	Yes	Yes	Yes	Yes

Panel B: Forecast Properties, Information Quality, and Liquidity

	(1) Horizon	(2) Precision	(3) Abnormal Volatility	(4) Abnormal Volume	(5) Abnormal Bid-Ask Spread	(6) Abnormal Depth
Passive IO Distraction	-0.008*	0.018**	-0.001	-0.004	0.013*	0.017***
	[-1.91]	[2.04]	[-0.04]	[-0.42]	[1.85]	[2.73]
Non-Passive IO Distraction	0.002	0.012**	-0.005	-0.004	0.006	0.001
	[0.73]	[2.58]	[-0.30]	[-0.72]	[1.45]	[0.16]
Difference in Coefficients:						
Passive-Non Passive IO Distraction	-0.010***	-0.006	0.004	0.000	0.007	0.016***
Adj R-Sq.	0.578	0.478	0.101	0.184	0.611	0.414
N	64,062	64,062	100,365	100,376	99,162	99,162
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm x Calendar Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes

Online Appendix to:

Institutional Investor Attention and Firm Disclosure

November 2019

This online appendix tabulates additional analyses.

Table A1: Eliminate Observations after 2012

This table presents OLS regressions estimating equation (1), except we eliminate observations after 2012. For brevity, we do not report coefficients for the control variables included in Table 3, Panel A, although our tests include them. See Appendix A for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered by firm and industry-quarter. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

	(1) Disclosures	(2) Abnormal Volatility	(3) Abnormal Bid-Ask Spread
$Distraction_t$	-0.067***	0.032	0.029***
	[-3.65]	[0.88]	[3.08]
Adj R-Sq.	0.651	0.113	0.656
N	78,314	78,303	77,732
Controls	Yes	Yes	Yes
Firm x Calendar Quarter FEs	Yes	Yes	Yes
Industry x Quarter FEs	Yes	Yes	Yes

Table A2: Announcement Abnormal Information Quality and Liquidity

This table repeats our Table 8 tests using announcement abnormal measures of information quality and liquidity instead of full quarter measures. Our announcement abnormal measures are similar to the quarter measures, except they are calculated using the average in the three days around the disclosure date scaled by the average in days -63 through -8 prior to the disclosure date. For example, the Announcement Abnormal Volume is calculated as the average shares traded/shares outstanding in the three days around the disclosure date, scaled by average shares traded/shares outstanding in days -63 through -8 prior to the disclosure date excluding the three trading days around any disclosures during the non-event period. We then total the variables over all disclosure dates in the quarter and take the natural logarithm. A disclosure date is a date when an 8-K or a forecast is provided.

The sample consists of quarterly observations from 2001-2016. For brevity, we do not report coefficients for the control variables included in Table 3, Panel A, although our tests include them. See Appendix A for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered by firm and industry-quarter. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

	(1) Announcement Abnormal Volatility	(2) Announcement Abnormal Volume	(3) Announcement Abnormal Bid-Ask Spread	(4) Announcement Abnormal Depth
$Distraction_t$	-0.003	0.002	0.005	0.005
	[-0.08]	[0.10]	[0.25]	[0.24]
Adj R-Sq.	0.244	0.334	0.384	0.377
N	90,038	90,038	88,876	88,876
Controls	Yes	Yes	Yes	Yes
Firm x Calendar Quarter FEs	Yes	Yes	Yes	Yes
Industry x Quarter FEs	Yes	Yes	Yes	Yes

Table A3: Information Quality and Liquidity Robustness

This table presents robustness analyses for our Table 8 results. The sample consists of quarterly observations from 2001-2016. Panel A (B) studies information quality (liquidity). For brevity, we do not report coefficients for the control variables included in equation (1), although our tests include them. Columns 1 and 2 examine distraction over three quarters (*Distraction[-2,0]*). Columns 3 and 4 study firm-quarters where *Disclosures* changed from four quarters ago. Columns 5 and 6 eliminate firm-quarters in the bottom quintile of industry-adjusted returns over the next twelve months. In Columns 7 and 8, we use an instrumental variables strategy, using *Distraction* as our instrument for *Disclosures*. See Appendix A for variable definitions. Reported below the coefficients are t-statistics based on standard errors that are clustered at the firm and quarter level. *, **, and *** indicate significance at the two-tailed 10%, 5%, and 1% levels, respectively.

Panel A: Information Quality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Abnormal Volatility	Abnormal Volume	Abnormal Volatility	Abnormal Volume	Abnormal Volatility	Abnormal Volume	Abnormal Volatility	Abnormal Volume
$Distraction_t[-2,0]$	-0.020	0.001						
	[-0.92]	[0.15]						
$Distraction_t$			-0.067	-0.034**	-0.013	-0.017		
			[-1.33]	[-2.38]	[-0.32]	[-1.22]		
$Disclosure_{t(IV)}$							0.042	0.205
							[0.08]	[1.00]
Adj R-Sq.	0.102	0.181	0.102	0.187	0.103	0.197	0.101	0.131
N	97,110	97,112	66,966	66,968	81,102	81,108	100,365	100,376
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm x Calendar Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Liquidity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Abnormal Bid-Ask Spread	Abnormal Depth	Abnormal Bid-Ask Spread	Abnormal Depth	Abnormal Bid-Ask Spread	Abnormal Depth	Abnormal Bid-Ask Spread	Abnormal Depth
$Distraction_t$[-2,0]	0.012**	0.004						
	[2.24]	[0.81]						
$Distraction_t$			-0.008	0.006	0.020**	0.013		
			[-0.70]	[0.60]	[2.21]	[1.61]		
$Disclosure_{t(IV)}$							-0.288*	-0.180
							[-1.84]	[-1.34]
Adj R-Sq.	0.612	0.414	0.618	0.410	0.614	0.409	0.494	0.290
N	96,074	96,074	66,407	66,407	80,141	80,141	99,162	99,162
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm x Calendar Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes