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Real-time revenue and firm disclosure

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Abstract
We examine firm disclosure choice when information is received on a real-time, continuous basis. We use transaction-level credit and debit card sales for a sample of retail firms to construct a weekly measure of abnormal revenue for each firm. We validate the informativeness of this abnormal real-time revenue information, confirming its positive correlation with abnormal returns, unexpected revenue realizations, and management revenue forecast news. Using revenue forecasts, we find that firms are less likely to disclose abnormally negative news early in the quarter. As the quarter progresses, firms reduce their withholding of negative news. These results are consistent with impending earnings announcements disciplining managers to provide negative news. This pattern of initial withholding and then disclosure exists primarily in firms with high analyst coverage, high institutional ownership, or high litigation risk. Finally, we find increased insider stock sales in weeks with abnormally negative news and no firm disclosure. Overall, our study provides evidence of the informativeness of real-time information and manager discretion in its release.

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1 Introduction

Managers' disclosure decisions have been studied for years. In the simplest disclosure model, an event occurs and managers decide whether to disclose or not. In observable capital markets, though, both information arrival and the disclosure decision are often more complex. Rather than receive a discrete piece of information about a specific event (e.g., a warehouse fire), managers often receive a continuous flow of information (e.g., sales for the week) and must decide whether and when an information event has occurred that is relevant for shareholders. Managers then choose whether to disclose now, disclose at a later point after more information is received, or simply allow the information to be revealed at a future mandatory disclosure event (e.g., earnings announcement). We use a proxy for real-time revenues to examine managers' disclosure choice in the presence of continuous information flow.

The relation between continuous information flow and managers' disclosure decision is becoming more important as managers' and investors' access to continuous real-time data increases. Managers' ability to capture and analyze granular firm information continues to improve with investments in information systems and artificial intelligence.[1] Empirical evidence is mounting that sophisticated investors have both the resources and ability to obtain and process satellite imagery, web traffic, and other alternative data sources in recent years to create profitable trading strategies at the expense of less sophisticated investors (e.g., Froot et al. 2017; Deloitte 2018; Huang 2018; Katona et al. 2021; Zhu 2019; Agarwal et al. 2021; Kang et al. 2021). These findings indicate that real-time information about firm performance is not immediately incorporated into stock price, raising questions as to whether, when, and how a firm's real-time performance influences managers' disclosure decisions. Unfortunately, this relation between continuous information flow and managers' disclosure decision is difficult to empirically study due to the unobservable nature of a firm's real-time performance when using public information alone.

To overcome this challenge, we use a proprietary database of 1.6 billion transaction-level credit and debit card sales representing $69.9 billion of sales from 2012 through early 2016 for a sample of retail firms. We select retail firms because consumer sales are more likely to drive the firm's total revenue relative to other industries. With the granularity of this data, we can create proxies for a firm's real-time revenues at any date, allowing us to examine how disclosure decisions are influenced by the firm's continuous flow of real-time information.

We validate the accuracy of this data in our setting in multiple ways. First, we document a 0.78 correlation between quarterly real-time revenue and quarterly reported revenue from Compustat. Second, we use the transaction-level data to create a weekly,

[1] See, e.g., https://www.wsj.com/articles/ikeas-meatball-supply-chain-goes-digital-11580501597 or https://www.wsj.com/articles/ab-inbev-uses-ai-to-assess-beer-quality-creditworthiness-of-distributors-11574677800.

firm-specific measure of cumulative abnormal revenue and validate the informativeness of this revenue news measure. Specifically, we first estimate the quarterly revenue implied by the transaction-level data as of the end of each week in the firm's fiscal quarter. We then adjust this amount for the market expectation of quarterly revenue by subtracting the analyst consensus revenue forecast as of the end of the prior week (beginning of the current week). After scaling by the consensus and ranking in quartiles, we validate the informativeness of this abnormal revenue measure by finding a positive relation between weekly abnormal revenue and future stock returns, unexpected quarterly revenue, and managers' forecast news if they choose to disclose. Overall, the evidence suggests that real-time revenue information can predict future outcomes yet is not immediately incorporated into market price.

We next examine managers' disclosure decision, turning to analytical models to inform our predictions. In classic one-period disclosure models, the primary factor influencing disclosure choice is the economic implications of the news. Positive news is more likely to be disclosed than negative news, assuming a friction such as disclosure costs or uncertainty about managers' private information prevents full unraveling, i.e., prevents the market from disciplining nondisclosure to the point of full disclosure (Verrecchia 1983; Dye 1985; Jung and Kwon 1988). When a disciplining mechanism such as litigation risk is incorporated, disclosure of negative news generally increases (e.g., Skinner 1994).

If the real-time, evolving nature of information and disclosure is considered, though, two possible adjustments arise: (1) the market's perception of lack of disclosure at a given point in time might be different, and (2) disclosure could be affected by variations in the intensity of disciplining mechanisms over time. Marinovic and Varas's (2016) model of disclosure choice conditional on managers receiving continuous information helps us consider these adjustments. First, investors in Marinovic and Varas's (2016) model recognize that disclosure is costly and thus do not expect firms to disclose continuously. Instead, investors rely on regulation and litigation to ensure that sufficiently negative news is disclosed in a timely manner, and they interpret firm silence as the lack of bad news rather than the existence of bad news. This results in a prediction of less than full disclosure of any news event, good or bad.

Second, Marinovic and Varas (2016) further show that when the cost of withholding negative information is higher, managers tend to disclose bad news (i.e., their ability to withhold disclosure of negative news declines). They model withholding cost using litigation cost and the probability of a public news event that would reveal the information even absent firm disclosure, under the assumption that litigation cost is higher if the manager does not preemptively disclose negative news. Thus, the model predicts less disclosure of negative news when the news is less likely to be independently discovered or when litigation costs are lower, and more disclosure of negative news when the probability of a public news revelation or litigation costs is higher. In our intra-quarter setting with mandatory information release at the end, these insights could manifest as increased disclosure of negative news as the end of the quarter (and the earnings announcement) draws near, for two reasons. One, following Marinovic and Varas's (2016) assumption, litigation cost may be higher if managers do not preemptively disclose the negative news. There is empirical evidence of reduced litigation cost for firms that warn of bad news (e.g., Field, Lowry, and Shu 2005; Donelson et al. 2012; Billings and Cedergren 2015), and this prediction is consistent with managers' ability to withhold negative news diminishing as investors' expectation that managers have accurate information to disclose increases (Verrecchia 1990). Two, greater investor and intermediary attention near the end of the quarter may increase the likelihood of independent discovery and release of the negative news, again increasing litigation cost for managers that withhold.

We use management revenue guidance to measure disclosure because of its direct connection to real-time revenue information and its use by a broad set of firms. Consistent with the prediction that managers often choose not to disclose their continuous information, we find that managers issue revenue forecasts in only 2% of weeks with abnormal revenues in the top or bottom quartile (more than 21% above or 14% below analyst revenue expectations). When we examine the likelihood of positive versus negative news, we find that firms with more negative abnormal revenue (i.e., bottom quartile) are less likely to provide a forecast that week. We then compare disclosure withholding patterns within the quarter. Consistent with our prediction of more frequent negative disclosure as time passes, we find that firms are more likely to disclose abnormal negative revenue news later in the quarter than earlier. The results are robust to different model specifications, control variables, and firm and time fixed effects.

We explore further by examining whether analyst coverage, institutional ownership, and litigation risk appear to act as disciplining agents within this framework, encouraging firm disclosure. We find that the main results of withholding bad news early in the quarter and disclosing it later in the quarter exist primarily in the sample of firms with above-median analyst coverage, institutional ownership, or litigation risk, consistent with analysts, institutional investors, and litigation risk aiding in market discipline.

We also explore the role of information accuracy in our setting. Specifically, we motivate our prediction of increased negative disclosure as the quarter progresses as due in part to managers' decreasing ability to claim poor information accuracy when dealing with investors. However, if managers' information accuracy is in fact improving over the quarter, managers' resolution of uncertainty could also increase disclosure independent of investor expectations. While either path is interesting, establishing that the effect exists even controlling for information accuracy provides further insight into disclosure incentives. We calculate the accuracy of weekly implied quarterly revenue relative to total quarterly real-time revenue. Accuracy improves later in the quarter, but our primary results continue to hold when we control for weekly accuracy, suggesting the disclosure patterns we observe are due to more than simply managers' uncertainty resolution. In addition, these findings provide further evidence that our real-time revenue measures are informative. However, we acknowledge that our real-time transaction dataset is only a small fraction of our firms' actual revenues (1.31% of the firm's Compustat revenue on average), increasing the importance of our validation of its informativeness via multiple methods.

Finally, we ask whether managers choose to use real-time revenue information to trade for personal gain rather than disclose the information. We find that managers are more likely to sell shares in weeks with abnormal negative revenue news. However, there is no increase in insider sales during weeks when managers disclose the abnormal negative news, suggesting that managers choose to disclose or to trade on negative real-time information rather than to disclose or abstain from trading as a fiduciary duty would require.

Our study makes several contributions. First, we contribute to the disclosure literature by using a detailed measure of managers' private positive and negative information at repeated points in time to examine the classic question of disclosure choice. A number of accounting studies have examined the question of whether firms withhold disclosure of bad news relative to good news. However, an enduring challenge is that the amount and timing of managers' private information is unobservable. Early studies infer managers' private information during the quarter based on quarter-end realizations, patterns of stock returns upon eventual disclosure, strategic timing of disclosure around other events, or other assumptions about the amount and timing of information (e.g., Skinner 1994; Kasznik and Lev 1995; Aboody and Kasznik 2000; Kothari, Shu, and Wysocki 2009; Roychowdhury and Sletten 2012). Several recent papers propose two more-precise proxies for managers' private negative information: the dates when firms were first informed of an SEC investigation, and residual short interest (Bao et al. 2019; Blackburne and Quinn 2020; Blackburne et al. 2021). Our approach builds on these studies by capturing positive as well as negative private information about revenues, a topic central to firm performance and common across many firms.

Further, we contribute by providing conclusions that differ from those of Froot et al. (2017), who use online consumer activity that suggests intent to visit a specific retail store (e.g., search for directions, search for store location, and coupon download) as a measure of managers' private information. Specifically, Froot et al. capture growth in this online activity in the portion of the current quarter before the announcement of the prior quarter's earnings, and they document that *conditional on providing guidance at the announcement*, managers with online activity growth are more likely to forecast earnings that are less positive than the eventual realized earnings. Based on this evidence, they conclude that managers withhold good news but not bad news, contrasting with much of the existing accounting literature and highlighting the importance of continued work in this area. Our tests use unique data based on weekly consumer purchases to examine the fundamental decision of *whether or not to disclose private information throughout the quarter*. Our results confirm and deepen the accounting literature's findings about intra-quarter disclosure dynamics, with the most negative private information being initially withheld and then released as a disciplining event approaches, while the most positive private information does not spur additional disclosure.

Second, because our information arrives in a repeated fashion, we can delve into the implications of continuous information flow for disclosure decisions. When information is repeatedly updated, managers must first use the information flow to-date to determine whether an event worth disclosing has occurred, and then how investor response might differ based on disclosure timing. Investors' awareness of continuous information flow could easily affect their expectation for disclosure and their interpretation of lack of disclosure. Recent analytical studies have begun modeling multiple period disclosure decisions with dynamic information flow (e.g., Guttman et al. 2014; Marinovic and Varas 2016; Aghamolla and An 2021). With our measure of manager information, we can empirically explore this interesting new research area using a model with assumptions aligned with our setting.

Third, our study contributes to the growing literature exploring alternative or "big data" sources. Recent studies examine data such as online browsing behavior, satellite images of cars in parking lots, credit card transactions, and even firms' electricity consumption, with much of the focus on the informativeness and pricing of the data (e.g., Froot et al. 2017; Zhu 2019; Agarwal et al. 2021; Allee et al. 2021; Dichev and Qian 2021; Jin et al. 2021. Our study confirms the value of alternative data sources such as credit and debit card transactions, highlights managers' delayed conveyance of the data and the markets' delayed understanding of the data, and provides information of how continuous information flow interacts with disciplining mechanisms and events to affect disclosure decisions.

2 Background and data

2.1 Background and motivation

The classic disclosure models predict that firms disclose all information in equilibrium (i.e., full unraveling) because investors discipline nondisclosing firms (e.g., Grossman and Hart 1980; Grossman 1981; Milgrom 1981). However, when frictions such as disclosure costs or uncertainty about the existence or quality of the information appear, disclosure choice becomes a function of the economic nature of the information: firms have incentives to disclose positive news and withhold negative news (e.g., Verrecchia 1983; Dye 1985; Verrecchia 1990; Beyer et al. 2010). Focusing on the friction of uncertainty about managers' information set, Jung and Kwon (1988) show that negative disclosure increases with the probability that managers received information. As they explain, their findings have implications for how disclosure patterns might change over time. Specifically, if managers are more likely to have received information as time passes in a quarter, then negative news is more likely to be disclosed later in the quarter.

These overarching theories typically focus on a firm's decision to disclose one piece of information. In reality, firms receive a continuous flow of real-time information about their performance.[2] Timely disclosure of relevant real-time information could provide investors with a highly accurate perspective of the firm's performance. However, the costs of continually disclosing are significant. Continual disclosure requires resources to prepare the disclosure and discuss the information with analysts and stakeholders. If performance is more volatile in the short run, frequent disclosure can shift market and manager focus away from long-term goals and toward less relevant short-term fluctuations. There could be a greater risk of competitors obtaining proprietary information from the granular information. In addition, continual disclosure could shift, to investors, the burden of identifying important information within the numerous disclosures, creating information processing costs that outweigh the information benefit.

Marinovic and Varas (2016) highlight the potential proprietary cost of continual disclosure, building a model in which investors do not expect continual disclosure in equilibrium because of its cost, under the assumption that the firm's value is somewhat

[2] For example, dashboards with real-time information on revenues, costs, and company forecasts were available to executives as early as the mid-2000s (e.g., Hymowitz 2005). Recent enhancements focus on integrating data, personalizing displays, enabling mobile access, and using artificial intelligence to highlight key information. For a discussion of potential features, see https://sloanreview.mit.edu/article/tomorrows-kpi-dashboards-will-be-your-boss/ or https://www.domo.com/roles/operations.

persistent. Marinovic and Varas (2016) also assume a capital market regime where there is enough regulatory oversight and litigation risk that investors believe significant negative information will be disclosed. The assumption that oversight ensures disclosure of negative news is consistent with US capital markets providing several avenues for firm disclosure to be disciplined, such as class action and regulatory lawsuits as well as informal reputation damage from analysts, media, and other intermediaries. In Marinovic and Varas's (2016) model, investors recognize the high cost of continual disclosure but also understand that withholding information for too long is risky for firms. So, they rely on their belief that significant negative information will eventually be disclosed, and interpret a lack of disclosure as the lack of bad news. Firms, in turn, initially withhold information.

When the cost of withholding information increases, though, firms stop withholding. Marinovic and Varas (2016) model the cost of withholding by increasing the likelihood of a public news event that would release the information regardless of the firm's disclosure choice. The model shows more disclosure of bad news as the likelihood of the news event increases, with litigation risk described as a disciplining mechanism that reduces withholding before the news event. This same idea can extend to litigation risk before the mandatory earnings announcement. Prior empirical literature provides evidence of litigation risk increasing managers' incentives to warn investors of negative performance (e.g., Skinner 1994, 1997). Field et al. (2005) find that firms with higher litigation risk are more likely to disclose early to preempt potential lawsuits (even after controlling for the endogeneity between disclosure and litigation), and that early disclosure reduces litigation risk. Donelson et al. (2012) find fewer lawsuits when firms' bad news is incorporated into analyst forecasts sooner; Billings and Cedergren (2015) find that firms that warn of negative earnings experience less litigation; and Billings et al. (2021) find that firms increase bad news forecasts following litigation. Houston et al. (2019) find evidence as well that managers perceive a litigation benefit to voluntary disclosure, using a difference-in-differences design around three distinct legal events to show that when firms expect litigation risk to be lower (higher), they tend to make fewer (more) negative news warnings. Securities regulations and court decisions combine to create ambiguity about firms' legal requirements to disclose intra-quarter performance information (Mendelsohn and Brush 2015), leaving disclosure as a potentially safer alternative to nondisclosure and a way to reduce the amount of time during which market price deviates from fundamental value. More broadly, the confirmation theory literature provides evidence consistent with mandatory earnings announcements disciplining and incentivizing managers to voluntarily release earnings information early due to credibility and litigation reasons (e.g., Ball and Shivakumar 2008; Ball et al. 2012; Roychowdhury and Sletten 2012).

Analysts or institutional investors could also act as a disciplining mechanism to motivate firm disclosure before the news event. Prior empirical evidence suggests that analyst coverage and institutional ownership are associated with better disclosure and perhaps even motivate improved disclosure. A survey of managers conducted by the National Investor Relations Institute (NIRI) indicates that 98% of managers believe that analysts want guidance (NIRI 2003). Consistent with analysts valuing firm disclosure, Lang and Lundholm (1996) find that firms with more informative disclosure policies have larger analyst following, more accurate analyst earnings forecasts, less dispersion among individual analyst forecasts, and less volatility in forecast revisions.

Matsumoto's (2002) findings suggest that firms' forecasts can help them avoid negative earnings surprises at earnings announcements by guiding analyst forecasts downward. Further, because nondisclosure can deter analysts, Arya and Mittendorf (2007) argue that analyst following motivates competing firms to disclose despite potential proprietary costs. Similarly, firms with more institutional ownership are more likely to issue forecasts, and these forecasts are more specific and accurate and less biased (Ajinkya et al. 2005). More recently, Abramova et al. (2020) find that firms increase the number of forecasts provided when their institutional investors are less distracted. In addition, greater intermediary attention before the earnings announcement could increase the risk of bad news being independently discovered, spurring firms to preemptively disclose this negative information.

For all three disciplining mechanisms, investors' expectation of managers' information quality would lead to an increase in withholding cost as the public news event draws near. Specifically, for real-time information that accumulates over time (as, for example, revenue in a fiscal quarter), managers early in the quarter can rely on arguments of little or low-quality information to explain lack of disclosure to capital market participants (e.g., Jung and Kwon 1988; Verrecchia 1990). However, once a greater portion of the quarter has been realized, investors and intermediaries are more likely to expect managers to have better quality information and to penalize firms for lack of disclosure, whether with litigation or reputational costs. Note that the cost of withholding could increase (and thus disclosure could also increase), whether or not the investors' expectation is correct. In the case where managers' information quality does improve during the quarter, resolution of managers' information uncertainty as the quarter progresses would prompt managers to withhold the lower quality information at the beginning of the quarter and disclose the better quality data closer to the news event simply out of caution. Somewhat consistent with this, survey evidence finds that managers say they delay disclosure if they believe bad interim news will resolve to a good overall outcome (Graham et al. 2005). But as public release of the information draws near, there is less time for the bad news to reverse.[3] However, even if managers know their information quality is high throughout the quarter, their ability to pool with firms that have low-quality information early in the quarter would result in the same pattern of increasing withholding costs and disclosure as the quarter progresses.

Applying the above arguments to our setting of real-time revenue information, we expect firms to withhold negative information at the beginning of the quarter. If the mandatory release of quarterly performance information at the end of the quarter acts as an impending public news event disciplining disclosure, we would then expect an increase in the probability of negative news disclosure as the quarter progresses.

2.2 Real-time revenue data

To estimate real-time revenue, we obtain credit card and bank transactions from a firm that provides financial software to large banks, including five of the top ten U.S. banks, and collects all transactions from individual bank accounts and credit cards. We received a random sample of transactions. Our data spans January 1, 2012, through May 31, 2016, and each transaction includes information on the merchant, transaction

[3] In Section 5.2, we further explore the role of information accuracy in our disclosure setting.

amount, and transaction category. We exclude transaction categories and merchants that are unlikely to represent transactions contributing to firm revenues.[4]

2.3 Sample selection and descriptive statistics

We begin with firm-quarters from the linked Compustat-CRSP database during 2012 to 2016. Because the real-time dataset includes credit or debit card business-to-consumer transactions (whether online or physical), we choose a sample of firms for which credit and debit card sales are more likely to represent a meaningful proportion of overall firm revenues: consumer-oriented firms.[5] Specifically, we limit ourselves to the following consumer-focused industries: consumer durables and apparel (GICS group 2520), consumer services (2530), media (2540), retailing (2550), and food and staples retailing (3010).

We use the transaction's merchant name to match our real-time transaction data to either the firm name in Compustat-CRSP or the firm's subsidiary names in Exhibit 21 of its annual filing. To facilitate better matching, we remove capitalization, punctuation, symbols, and common naming conventions (e.g., "inc," "llc") from the merchant, firm, and subsidiary names. If a transaction merchant name matches to more than one firm in Compustat, we keep the firm with the greater fuzzy match score. Because many Compustat firms have subsidiaries and because the real-time transaction data includes slight variations of firm names, the matching process generally associates each Compustat firm with multiple transaction merchant names.[6] To mitigate the risk of noise in identification of the merchant or revenue-related transaction categories, we also exclude firms when more than 20% of their total transacted amount is in transaction categories dissimilar to the firm's GICS industry classification, based on manual review by research assistants. Lastly, to assess the reasonableness of our underlying real-time sales transaction data, we examine the average transaction amount for our sample firms, finding descriptive statistics that are consistent with expected transaction amounts at these firms. For example, our data reveal that the average transaction value at McDonald's Corp is $8.73, which closely resembles consumer reports that indicate the average McDonald's customer purchases three items and spends $8.35 per visit

[4] For example, we exclude ATM and cash withdrawals, paychecks and salary, deposits and transfers, and similar transaction categories. We also exclude merchant names such as 401 K, taxes, Medicare, and checks that do not reference a firm.

[5] Findings from the Federal Reserve's 2019 Diary of Consumer Payment Choice indicate that cash payments represent an increasingly small proportion of consumer transactions. As of 2016 (the end of our sample period), consumers use cash for only 31% of transactions and are most likely to use cash when transactions are less than $10.00, suggesting that our focus on non-cash payment types is likely to reflect most (and the most substantial) consumer transactions (CPO 2019). We also examine accounts receivable turnover ratios during our sample period and find that the average ratio for firms in our selected consumer-focused industries is 5.4 times larger than other industries, i.e., 32.58 vs. 6.04. This difference is consistent with our firms having predominantly credit card sales (which often stay in a receivable for only 2–3 days) and few business-to-business sales, which typically have longer collection periods, mitigating concerns that by excluding transactions on trade credit, our real-time revenue measure excludes substantial portions of revenue.

[6] For example, for Starbucks Corp. (which has a subsidiary named Seattle's Best Coffee LLC), we include the following merchant names: Starbucks, STARBUCKS, Seattle's Best Coffee, Seattles Best Coffee, and Starbucks Coffee. Importantly, the parameters chosen for our fuzzy match process also exclude non-firm-related merchants such as Seattle's Best Locksmith.

(Meisenzahl 2021). Similarly, we find the average transaction value at Time Warner Cable is $116.70, which is similar to reports that the average monthly bill for Time Warner Cable customers is $106.98 (Seward 2014).

We require at least four quarters of prior real-time transaction data to construct our measure of real-time sales, as well as the additional controls in our primary analyses. As shown in Table 1 Panel A, our final sample is 2602 firm-quarters, representing 243 firms and 33,826 firm-weeks when observations are at the fiscal-week level.[7] Panel B provides details about the distribution of our sample across years and industries. Our sample observations are evenly spread across 2013, 2014, 2015, and the first few months of 2016, with a greater proportion of companies in retailing and consumer services.

Panel A of Table 2 provides descriptive statistics for our sample of firms at the firm-quarter observation level. We winsorize all continuous variables at 1% and 99% to reduce the influence of outlier observations. Panel A reveals that the mean quarterly revenues using our real-time revenue data source, *RT_rev*, are $24.24 million. For the average firm, this real-time revenue amount is 1.31% of their reported revenues over the same quarter per Compustat (*Comp_rev*), and this percentage ranges from 0.23% to 1.76% for the first to third quartile. While this is a small fraction of reported revenues, our proportional coverage is larger than in other studies that use credit and debit card transactions as measures of firm sales, which range from 0.002% (Aghamolla and An 2021) to 0.6% (Baker et al. 2021) of reported revenues. The first and third quartiles for *Size* (defined as the natural log of a firm's market value of equity) are 6.49 and 8.96, or $660 million and $7.8 billion, respectively. This indicates substantial variation in the size of firms included in our sample. The mean number of analysts for our sample firms, *Analyst_coverage*, is 11.6, which is higher than the 6.14 mean number of analysts covering all firms at the intersection of CRSP, Compustat, and I/B/E/S databases per Lehavy et al. (2011).

Panel B of Table 2 provides Pearson correlation coefficients between variables presented in Panel A. As shown, and of primary interest, we find that the correlation between *RT_rev* and *Comp_rev* is 78%. This bivariate correlation provides initial evidence that our real-time revenue data source provides accurate information about firms' quarterly revenues. Panel B provides additional information for our sample of firms, revealing relations consistent with prior literature. For example, we see a positive relation between a firm's size and analyst coverage, and a negative correlation between size and earnings volatility (Alexander 1949; Frankel and Litov 2009).

Figure 1 displays the distribution of how firms earn real-time revenue throughout the fiscal quarter, focusing on the percentage of quarterly revenue earned from the beginning of the quarter through the week noted on the x axis. The horizontal line at 0% represents an even flow of revenue across the weeks in the fiscal quarter. For lines above 0%, the difference represents the additional percentage of quarterly revenue

[7] We use seven-day increments to create fiscal-week-level observations. For example, Target's first fiscal quarter in 2015 began on February 1, 2015. We thus define the first fiscal week for this quarter as the first seven days of the quarter (February 1–7, 2015), the second fiscal week as the subsequent seven days (February 8–14, 2015), and so forth. This method results in each quarter having 13 weekly intervals. Because the number of days in a fiscal quarter can slightly vary based on the calendar months included, the number of days in the final week can vary between five and eight days.

Table 1 Final sample

Panel A. Sample selection process

Details	**Firm-quarter observations**	**Firm observations**
Firm-quarters with Compustat, 10-K subsidiary, and real-time revenue data in relevant industries	3,612	247
Less: Firm-quarters without prior year, same quarter real-time revenue data to calculate *AbnRev*	(1,010)	(4)
Final sample	**2,602**	**243**

Panel B: Sample distribution

GICS Group Industry	**2013**	**2014**	**2015**	**2016**	**Total**
2520 – Consumer durables & apparel	102	99	98	24	323
2530 – Consumer services	196	222	242	63	723
2540 – Media	48	51	47	10	156
2550 – Retailing	311	368	366	146	1,191
3010 – Food & staples retailing	66	62	60	21	209
Total	**723**	**802**	**813**	**264**	**2,602**

Notes: Table 1 Panel A details our sample selection process. Panel B details the distribution of our final sample by both year and GICS group industry classification

recognized to date by that firm relative to even recognition over time, and vice versa for a line below 0%. The median firm is close to the 0% benchmark and thus earns revenue approximately evenly over the quarter. There is substantial variation across firms in our sample, with firms in the ninetieth percentile collecting 14% more of their quarterly revenue by the end of the sixth week than firms in the tenth percentile.

3 Measuring and understanding real-time abnormal revenues

3.1 Measuring real-time abnormal revenues

To proxy for managers' private information about revenues *during* the quarter, we need to create an abnormal revenue measure, based on how the real-time revenue data compares to the market's expectation of firm revenues. We begin by cumulating each firm's real-time revenues on a fiscal weekly basis to capture the to-date quarterly revenues as of the end of each week of the fiscal quarter. Then, we adjust the cumulative to-date real-time revenues to a quarterly basis and compare them to a benchmark market expectation of quarterly revenue as of that fiscal week. Specifically, we calculate our real-time revenues as:

$$AbnRev_{i,j,t} = \frac{Quarterly\ Rev\ Implied\ by\ RT\ Rev_{i,j,t} - Mkt\ Expected\ Quarterly\ Rev_{i,j,t-1}}{Mkt\ Expected\ Quarterly\ Rev_{i,j,t-1}}$$

Table 2 Descriptive statistics

Panel A Descriptive statistics

Variable Name	**Obs**	**Mean**	**Std Dev**	**Q1**	**Mdn**	**Q3**
RT_rev	2,602	24.24	67.79	0.69	2.91	15.08
Comp_rev	2,602	2,184	4,719	180	571	1,762
Size	2,602	7.74	1.77	6.49	7.71	8.96
BTM	2,602	0.35	0.33	0.16	0.28	0.48
Momentum	2,602	0.07	0.26	−0.09	0.06	0.22
Earn_vol	2,602	0.02	0.04	0.00	0.01	0.02
Lit_risk	2,554	0.22	0.19	0.09	0.15	0.27
Analyst_coverage	2,602	11.6	8.35	5.00	10.00	18.00

Panel B Pearson Correlation coefficients

Variable Name		*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
RT_rev	*1*	**1**							
Comp_rev	*2*	**0.78**	**1**						
Size	*3*	**0.49**	**0.61**	**1**					
BTM	*4*	**−0.11**	**−0.13**	**−0.42**	**1**				
Momentum	*5*	**0.02**	**0.06**	**0.14**	**−0.19**	**1**			
Earn_vol	*6*	**−0.10**	**−0.12**	**−0.38**	**0.18**	**−0.03**	**1**		
Lit_risk	*7*	**0.20**	**0.24**	**0.11**	**−0.06**	**0.11**	**0.33**	**1**	
Analyst_coverage	*8*	**0.40**	**0.37**	**0.69**	**−0.32**	0.00	**−0.28**	**0.08**	**1**

Notes: Table 2 Panel A provides descriptive statistics for our sample of firms at the firm-quarter observation level. All variables are defined in Appendix 1 of this paper. Panel B provides Pearson correlation coefficients for our sample of firms at the firm-quarter observation level. Bold correlation coefficients indicate statistical significance at 10% or better. All variables are defined in Appendix of this paper

where $AbnRev_{i,j,t}$ is the abnormal real-time revenues for firm i, quarter j, and week t. $Quarterly\ Rev\ Implied\ by\ RT\ Rev_{i,j,t}$ is calculated in three steps. First, we sum the daily transaction-level revenues from the beginning of quarter j for firm i through the end of week t. Second, we transform this real-time cumulative to-date measure to a quarterly basis using historical revenue movements through the quarter. Specifically, we divide the cumulative revenue to-date by the average percentage of firm i's quarterly revenues received as of the end of week t for all same-fiscal-period firm-quarters prior to quarter j, to account for any firm-specific seasonality in intra-quarter revenue movements.[8] Third, we adjust the magnitude from real-time revenue levels to Compustat levels so that we can compare the final implied quarterly revenue to a market expectation of

[8] This method incorporates all prior information available about each firm's revenue movements. However, it also means the latter portion of our sample incorporates more prior information, which could increase the accuracy of the implied quarterly revenue estimates. Untabulated findings reveal that if we only use the same quarter information from one year prior rather than all prior information, we continue to find decreased withholding of negative news over time.

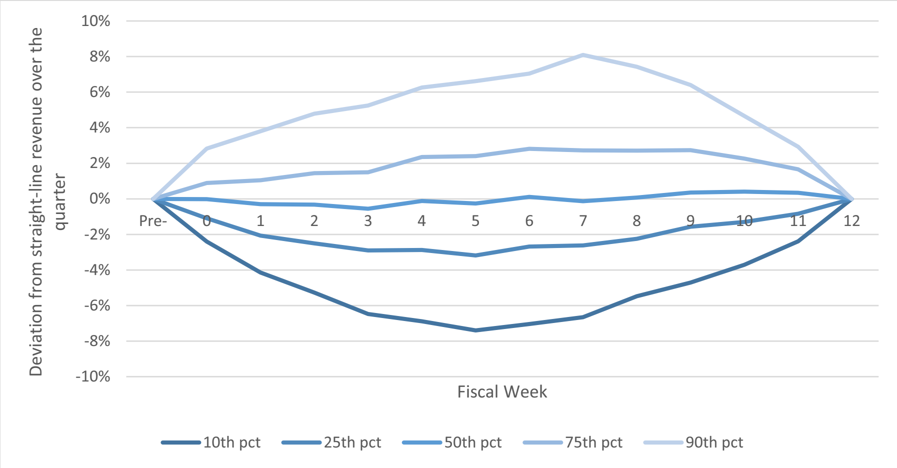

Fig. 1 Distribution of real-time revenue progress over the fiscal quarter. This figure shows the distribution of firms' real-time revenue throughout the quarter. Real-time revenue as of the end of each fiscal week is divided by the firm's total quarterly real-time revenue for that quarter to estimate the percentage of quarterly revenue earned as of each week. The horizontal line at 0% represents straight-line receipt of revenue during the quarter. The remaining lines provide the distribution of firms' real-time revenue progress relative to straight-line receipt of revenue

quarterly revenue. Specifically, we divide the implied quarterly revenue on a real-time revenue basis by the average percentage of firm *i*'s quarterly Compustat revenue reflected by our real-time revenue data, for all firm-quarters prior to quarter *j*. For example, suppose (1) a firm had \$5 million in real-time revenue over the first three weeks of the quarter, (2) the firm typically recognizes 20% of its quarterly revenue during the first three weeks of this fiscal quarter, and (3) the real-time revenue we capture is typically 1% of the firm's reported revenue per Compustat. Implied quarterly revenue as of the end of week 3 would be (\$5 million / 20%) / 1% = \$2500 million.

From this implied measure, we then subtract the market's expectation of real-time revenues for quarter *j* as of the end of week *t-1* to create an unscaled measure of abnormal real-time revenues for firm *i*, quarter *j*, and week *t*. We measure the market's expectation of real-time revenues using the analyst median consensus revenue forecast for firm *i*, quarter *j*, as of the end of week *t-1*. Finally, we scale this unexpected revenue by the same market expectation of revenues to aid in comparisons across firms. In summary, we use customer purchasing behavior to estimate revenue information received by management, prior firm-fiscal-quarter revenue patterns to estimate managers' assumptions about what the weekly revenue information implies for the likely quarterly revenue, and current market expectations to estimate whether managers' timely estimate of quarterly revenue is positive or negative private information. We believe our measurement adjustments for firm and seasonal differences in intra-quarter purchase patterns and our use of current market expectations enable more precise measurement of private information at a specific point in time (e.g., as compared to the approach in Froot et al. (2017), which assumes similar online activity over the quarter when estimating implied quarterly news and uses average online activity over the prior four quarters as the market expectation for activity).[9]

3.2 Abnormal real-time revenues: Descriptive statistics

As outlined above, *AbnRev* captures abnormal revenues in comparison to the prior week's analyst consensus estimate on a real-time weekly basis throughout the fiscal quarter. We rank *AbnRev* into quartiles to create *AbnRevRank*, assigning the value of 3 (0) when a firm's abnormal revenue for the week is in the highest (lowest) quartile. By using quartiles, we are able to focus on the subset of weeks when managers are more likely to have substantial positive or negative private information they could share with the market, and we avoid concerns that results using a continuous version of the granular variable might be driven by extreme outliers or measurement error. Panel A of Table 3 provides descriptive statistics for these measures of abnormal revenues, as well as for other variables used in our study, at the firm-week observation level. We winsorize all continuous variables at 1% and 99%. As shown, *AbnRev* has a mean of 0.06, suggesting that firms' intra-quarter revenues are, on average, 6% above market expectations. The standard deviation for this measure is 0.43, indicating substantial variation among our sample of firms. The threshold value for the lowest (highest) quartile of *AbnRev* is −0.14 (0.21), or 14% below (21% above) analyst expectation. As shown in Panel B, *AbnRevRank* is highly consistent from one week to the next, with its rank remaining the same 85% to 92% of the time. A firm's *AbnRevRank* midway through the quarter, i.e., $t = 6$, is consistent with its end-of-quarter, i.e., $t = 12$, rank 68% to 80% of the time, as evidenced by Panel C, and Panel D indicates that *AbnRevRank* as of the first week of the quarter, i.e., $t = 0$, is consistent with the end-of-quarter rank 47% to 56% of the time. Across all three panels, when future weeks have a different rank, that future rank is most often one rank different, reducing concerns about uninformative volatility over time. As shown in Fig. 2, the highest and lowest values for *AbnRevRank* are more likely to occur early in the quarter, but all rank levels occur throughout the quarter.

To capture disclosure, we focus on revenue forecasts for two reasons. First, forecasts are a commonly used and effective way of updating investors about the performance of the firm during the quarter. Second, our measure of abnormal revenue has a more direct, easily interpretable relation with revenue forecasts than with forecasts of other

[9] Our primary approach assumes that the magnitude of revenue earned to-date in the quarter will continue for the rest of the quarter, following the historical seasonal pattern of revenue. For robustness, we also replicate our main analyses using two alternative measures that adjust these assumptions. First, to simplify, we use a non-seasonally-adjusted method and assume the average daily sales in the most recent fiscal week continue for the rest of the fiscal quarter. Second, to relax the assumption about the permanence of the observed real-time revenues, we create a measure where revenue expectations gradually revert to the firm's long-run revenue growth. Specifically, we assume that all unobserved weeks in the fiscal quarter will instead have sales equal to the real-time revenue in the same fiscal quarter last year multiplied by the average year-over-year Compustat revenue growth reported for that firm-fiscal quarter for the past five years. We average the abnormal revenue based on this alternative assumption with our primary measure to approximate a gradual reversion from the most recently observed real-time revenue to the long-run revenue growth rate. In both cases, our main findings remain the same, with coefficients of interest remaining the same sign and significant at the 10% level or better.

Table 3 Real-time abnormal revenues

Panel A Descriptive statistics

Variable	Obs	Mean	Std Dev	Q1	Mdn	Q3
AbnRev	33,826	0.06	0.43	−0.14	0.04	0.21
AbnRevRank	33,826	1.50	1.12	1.00	2.00	3.00
AFE_rev	33,826	−0.52	2.88	−0.72	−0.09	0.29
Forecast_news	539	−0.02	0.04	−0.03	−0.01	0.00
Ret	33,722	−0.01	0.16	−0.10	−0.01	0.08
AFE_EPS	33,826	−0.22	1.68	−0.17	0.00	0.11
Disclose	33,826	0.02	0.14	0.00	0.00	0.00
Week	33,826	6.00	3.74	3.00	6.00	9.00
After_EA	33,826	0.60	0.49	0.00	1.00	1.00
EA_week	33,826	0.08	0.27	0.00	0.00	0.00
Prior_disclose	33,826	0.15	0.36	0.00	0.00	0.00

Panel B Transition Matrix: *AbnRevRank i,j,t* to *AbnRevRank i,j,t+1*

	AbnRevRank i,j,t+ 1			
AbnRevRank i,j,t	0	1	2	3
0	92.0%	7.3%	0.4%	0.3%
1	5.0%	85.1%	9.1%	0.7%
2	0.1%	9.0%	84.9%	6.0%
3	0.1%	0.4%	8.4%	91.2%

Panel C Transition Matrix: *AbnRevRank i,j,t=6* to *AbnRevRank i,j,t=12*

	AbnRevRank i,j,t= 12			
AbnRevRank i,j,t= 6	0	1	2	3
0	80.2%	16.6%	1.6%	1.6%
1	9.4%	69.6%	18.6%	2.5%
2	1.0%	19.5%	67.8%	11.7%
3	0.3%	2.5%	23.2%	74.0%

Panel D Transition Matrix: *AbnRevRank i,j,t=0* to *AbnRevRank i,j,t=12*

	AbnRevRank i,j,t= 12			
AbnRevRank i,j,t= 6	0	1	2	3
0	56.2%	26.7%	9.3%	7.9%
1	13.5%	47.2%	30.0%	9.4%
2	5.3%	28.6%	51.9%	14.2%
3	3.3%	11.2%	31.6%	54.0%

Panel E Pearson Correlation coefficients

Variable Name		***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***	***11***
AbnRev	***1***	**1**										
AbnRevRank	***2***	**0.78**	**1**									
AFE_rev	***3***	**0.09**	**0.10**	**1**								
Forecast_news	***4***	0.07	**0.15**	**0.51**	**1**							
Ret	***5***	**0.05**	**0.09**	**0.21**	**0.08**	**1**						

Table 3 (continued)

AFE_EPS	*6*	**0.02**	**0.02**	**0.30**	**0.22**	**0.18**	**1**					
Disclose	*7*	0.00	0.00	0.00	.	0.00	0.00	**1**				
Week	*8*	0.00	**0.01**	**0.06**	−0.03	0.00	**0.04**	**−0.06**	**1**			
After_EA	*9*	0.00	**0.02**	**0.09**	**0.09**	**0.01**	**0.06**	**−0.15**	**0.79**	**1**		
EA_week	*10*	0.00	0.00	**−0.02**	**−0.10**	0.01	**−0.01**	**0.45**	**−0.13**	**−0.35**	**1**	
Prior_disclose	*11*	**0.01**	**0.02**	**0.08**	**0.12**	0.01	**0.06**	**−0.03**	**0.27**	**0.34**	**−0.12**	**1**

Notes: Table 3 Panel A provides descriptive statistics for our sample of firms at the firm fiscal-week observation level. All variables are defined in Appendix 1 of this paper. Panel B provides a transition matrix between a firm's *AbnRevRank* value in week *t* and its *AbnRevRank* value in week *t+ 1*. As detailed in Sections 3.1 and 3.2 of this paper, *AbnRevRank* is a quartile-ranking of *AbnRev*, which captures abnormal revenues in comparison to the prior week's analyst consensus estimate on a real-time weekly basis. *AbnRevRank* takes the value of 3 (0) when a firm's abnormal revenue for the week is in the highest (lowest) quartile. Panel C provides a transition matrix between a firm's *AbnRevRank* value in week *t*=6 and its *AbnRevRank* value in week *t*=12. As detailed in Sections 3.1 and 3.2 of this paper, *AbnRevRank* is a quartile-ranking of *AbnRev*, which captures abnormal revenues in comparison to the prior week's analyst consensus estimate on a real-time weekly basis. *AbnRevRank* takes the value of 3 (0) when a firm's abnormal revenue for the week is in the highest (lowest) quartile. Panel D provides a transition matrix between a firm's *AbnRevRank* value in week *t*= 0 and its *AbnRevRank* value in week *t*=12. As detailed in Sections 3.1 and 3.2 of this paper, *AbnRevRank* is a quartile-ranking of *AbnRev*, which captures abnormal revenues in comparison to the prior week's analyst consensus estimate on a real-time weekly basis. *AbnRevRank* takes the value of 3 (0) when a firm's abnormal revenue for the week is in the highest (lowest) quartile. Panel E provides Pearson Correlation coefficients for our sample of firms at the firm fiscal week observation level. Bold correlation coefficients indicate statistical significance at 10% or better. All variables are defined in Appendix 1 of this paper

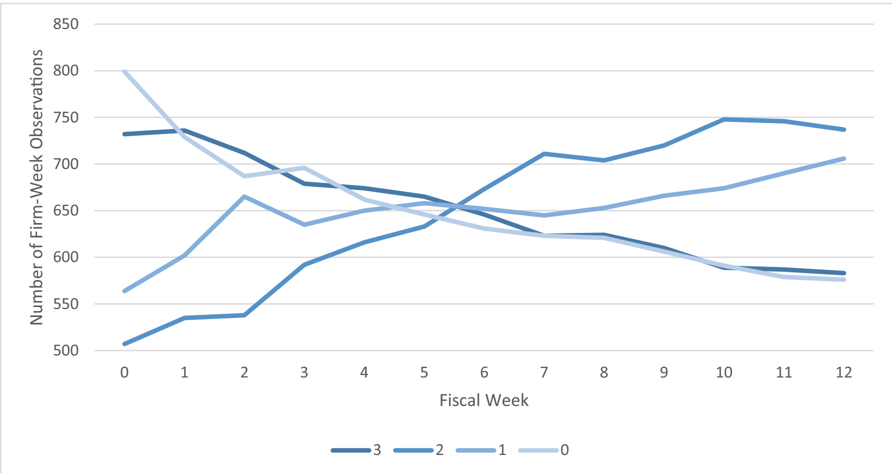

Fig. 2 Abnormal real-time revenue rank throughout the fiscal quarter. This figure shows the number of firm-week observations with each of the abnormal real-time revenue rank values (*AbnRevRank* = 0, 1, 2, 3), by fiscal week in the quarter. *AbnRevRank_high* is when *AbnRevRank* = 3, and *AbnRevRank_low* is when *AbnRevRank* = 0

performance measures that incorporate information relating to both revenues and expenses (e.g., earnings forecasts). We gather quarterly and annual management revenue forecasts from IBES, which collects quantitative guidance put forth by management. *Disclose* has a mean value of 0.02, indicating that firms issue a revenue forecast in approximately 2% of weeks. *Prior_disclose* has a mean value of 0.15, indicating that in 15% of fiscal weeks, the firm previously provided a revenue forecast for that quarter during the quarter. *After_EA* has a mean of 0.60, indicating that 60% of fiscal weeks for quarter *j* are after the week including the firm's earnings announcement for quarter *j-1*. More generally, 51.0% of firms provide a revenue forecast at some point during our sample period, and 14.4% of firms provide a revenue forecast at least once per quarter during the period. Firm-weeks in the highest or lowest *AbnRevRank* quartile issue revenue forecasts only 2% of the time, consistent with MV's (2016) prediction that many firms will choose not to disclose real-time information.

3.3 Validating abnormal real-time revenues

3.3.1 Validating abnormal real-time revenues: Unexpected future revenue and management forecast news

Our primary assumption is that our measures of intra-quarter real-time revenues provide valuable information about actual firm revenues. Panel B of Table 2 supports this assumption at the firm-quarter level, revealing a strong positive correlation between quarterly real-time revenues and Compustat revenues. We next consider the relevance of intra-quarter information by examining the correlations between our real-time measures of abnormal revenues and two information events: unexpected future revenue and management guidance.

First, if real-time abnormal revenue is informative, it should positively correlate with the unexpected realized revenue for the quarter – essentially the analyst revenue forecast error, i.e., *AFE_rev*. We calculate *AFE_rev* as the realized revenue for current quarter *j* minus the median analyst consensus forecast at the end of week *t-1*, all scaled by the firm's market value of equity as of the beginning of the quarter. As shown in Panel E of Table 3, *AbnRevRank* and *AFE_rev* are positively correlated, suggesting that abnormal real-time revenue provides information about future quarterly revenue to market participants.

Second, we examine the relation of real-time abnormal revenue with management guidance news. Disclosure choice can be complex, and we examine the decision to provide disclosure more fully in Section 4. However, if managers believe real-time abnormal revenue is informative, it should positively correlate on average with the news of management forecasts. We estimate management revenue forecast news, *Forecast_news*, as management's revenue forecast in week *t* minus the analyst consensus forecast as of the end of week *t-1*, all scaled by the analyst consensus forecast as of the end of week *t-1*. As shown in Panel E of Table 3, *AbnRevRank* and *Forecast_news* are positively correlated. Although this evidence is limited to the subset of information disclosed, it provides further evidence of the informativeness of abnormal real-time revenue.

3.3.2 Validating abnormal real-time revenues: Abnormal stock returns

An important way to validate the overall informativeness of abnormal real-time revenue is by examining its relation to abnormal future stock returns, *Ret*, defined as the cumulative market-adjusted returns from the end of week *t* through two days after the earnings announcement for quarter *j*. This assessment is especially important because our prediction assumes that real-time revenue is private information of management. If market price already reflects real-time revenue, then managers' disclosure incentives are more complicated.

The correlations in Panel E of Table 3 provide the first piece of evidence: a positive correlation between *AbnRevRank* and *Ret* (= 0.09). We next turn to the regression analysis, estimating the following pooled OLS model at the firm-week level:

$$Ret_{i,j,t} = AbnRevRank_{i,j,t} + Size_{i,j} + BTM_{i,j} + Momentum_{i,j} + Days\_FQE\_EA_{i,j,t} + \varepsilon_{i,j,t} \tag{1}$$

where *Ret*, *AbnRevRank*, and *Size* are as described previously and in Appendix. *BTM* is the book value of equity divided by the market value of equity. *Momentum* is the cumulative returns from six months prior to the beginning of the fiscal quarter through the beginning of the fiscal quarter. *Days_FQE_EA* is the number of days between the end of fiscal quarter *j* and the earnings announcement related to quarter *j*, which occurs in quarter $j + 1$. We cluster standard errors by firm.

Table 4 presents the results of estimating Eq. (1). Column 1 reveals a significantly positive coefficient for *AbnRevRank*, suggesting that the information conveyed by *AbnRevRank* is not fully incorporated on a real-time basis into firms' equity prices.[10] Column 2 estimates Eq. (1), using a model that incorporates the actual analyst forecast error for firm *i* in week *t* of quarter *j* for firm revenues (*AFE_rev*) and earnings per share (*AFE_EPS*). *AFE_rev* is as described in Section 3.3.1. *AFE_EPS* is the realized earnings per share (EPS) for current quarter *j* minus the median analyst EPS consensus forecast at the end of week *t-1*, all scaled by the firm's stock price as of the beginning of the quarter. Prior research finds a positive association between analyst earnings and revenue forecast errors and abnormal stock returns (e.g., Skinner and Sloan 2002; Bartov et al. 2002; Jegadeesh and Livnat 2006). Consistent with this prior research, Column 2 reveals that the coefficients for *AFE_rev* and *AFE_EPS* are 0.009 and 0.012. In addition, the coefficient for *AbnRevRank* remains positive and statistically significant in this model, providing further evidence that our measure reflects valuable private information about future stock returns.

As a final validation, we consider a perfect foresight model, where we examine how the value associated with knowing a firm's final *AbnRevRank* varies throughout a firm's quarter. We expect that the value of this information, in terms of its ability to predict abnormal stock returns, will decline over time as the market gradually learns of the firm's abnormal revenues. To examine this, we regress $Ret_{i,j,t}$ on $AbnRevRank_{i,j,t=12}$ for all weeks *t* in firms' fiscal quarters. Figure 3 plots the *AbnRevRank* coefficients from

[10] Like all our continuous variables, we winsorize *Ret* to reduce the effect of outliers. However, when we repeat the analysis using unwinsorized *Ret*, we continue to find positive relations for our variables of interest that are significant at the 1% level, with very similar coefficient magnitudes.

Table 4 *AbnRevRank* and future returns

	Ret	
	(1)	(2)
AbnRevRank	0.013***	0.011***
	(0.000)	(0.000)
Size	0.010***	0.006***
	(0.000)	(0.006)
BTM	0.024*	0.031**
	(0.076)	(0.026)
Momentum	0.027*	0.013
	(0.053)	(0.301)
Days_FQE_EA	0.000	0.001*
	(0.173)	(0.057)
AFE_Rev		0.009***
		(0.000)
AFE_EPS		0.012***
		(0.000)
N	33,722	33,722
R2	0.019	0.068

Notes: Table 4 presents the results from an OLS regression of firm *i*'s cumulative market-adjusted returns from the end of week *t* through two days after the earnings announcement for quarter *j* on *AbnRevRank* and control variables. *AbnRevRank* is a quartile-ranking of *AbnRev*, which captures abnormal revenues in comparison to the prior week's analyst consensus estimate on a real-time weekly basis. *AbnRevRank* takes the value of 3 (0) when a firm's abnormal revenue for the week is in the highest (lowest) quartile. Standard errors are clustered at the firm level. See Appendix 1 for variable definitions. *** designates statistical significance at 1%, ** at 5%, and * at 10%

these estimations, revealing that the relation between a firm's final real-time revenue and abnormal stock returns is positive throughout the quarter, with the greatest value at the quarter's beginning and the lowest value at its end. The gradual downward trajectory suggests that a gradual leakage of performance-related information occurs over the quarter.

Overall, the validation tests provide evidence that our real-time abnormal revenue measure helps predict future outcomes yet is not fully and immediately incorporated into price. Thus, we assume our measure reflects managers' real-time private information about firm revenues.

4 Empirical results – Disclosure choice and timing

4.1 Real-time revenue and disclosure

We begin our main empirical analysis by examining the relation between a firm's real-time abnormal revenues and its issuance of a revenue forecast. We estimate the following two models at the firm-week level:

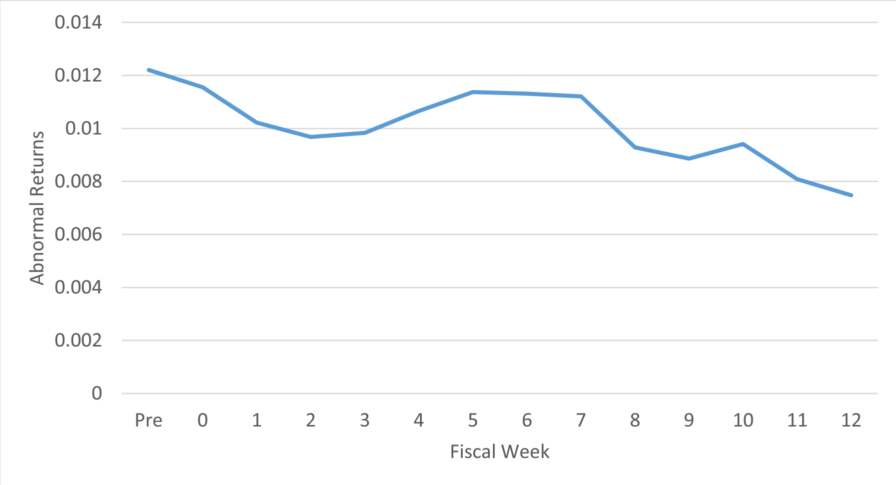

Fig. 3 Relation between abnormal returns and abnormal real-time revenue rank throughout the fiscal quarter. This figure shows the coefficient on *AbnRevRank* from regressions of abnormal returns from the end of the fiscal week shown through two days after the earnings announcement for the quarter on *AbnRevRank* as of the last fiscal week of the quarter (Week 12)

$$\begin{aligned} Disclose_{i,j,t} = {} & AbnRevRank_{i,j,t} + Size_{i,j} + BTM_{i,j} + Momentumi_{i,j} + Prior\_disclose_{i,j,t} \\ & + EA\_week_{i,j-1,t} + Earn\_vol_{i,j} + \text{Fiscal } Week{-}Year\ Fixed\ Effects \\ & + Firm\ Fixed\ Effects + \varepsilon_{i,j,t} \end{aligned} \tag{2}$$

$$\begin{aligned} Disclose_{i,j,t} = {} & AbnRevRank\_high_{i,j,t} + AbnRevRank\_low_{i,j,t} + Size_{i,j} + BTM_{i,j} + Momentumi_{i,j} \\ & + Prior\_disclose_{i,j,t} + EA\_week_{i,j-1,t} + Earn\_vol_{i,j} \\ & + Fiscal\ Week{-}Year\ Fixed\ Effects + Firm\ Fixed\ Effects + \varepsilon_{i,j,t} \end{aligned} \tag{3}$$

where $Disclose_{i,j,t}$ is an indicator variable equal to one if firm *i* releases a quarterly or annual management forecast for quarter *j*'s revenues in week *t*. Our measure of abnormal revenues is *AbnRevRank* (as previously defined) in Eq. (2) and *AbnRevRank_high* and *AbnRevRank_low* in Eq. (3). These latter two variables are indicator variables equal to one if *AbnRevRank* is equal to 3 (i.e., top quartile of abnormal revenues) and 0 (i.e., bottom quartile of abnormal revenues), respectively. By substituting these variables for *AbnRevRank*, Eq. (3) allows us to examine the relation for positive and negative news separately.

We also include several control variables when estimating Eqs. (2) and (3). *Size*, *BTM*, *Momentum*, and *Prior_disclose* are as previously defined. $EA\_week_{i,j\text{-}1,t}$ is an indicator variable equal to one if firm *i* reports earnings for quarter *j-1* in week *t*. *Earn_vol* reflects the historical volatility of quarterly earnings for firm *i*, as measured by the standard deviation of firm *i*'s net income over the eight quarters prior to quarter *j*, scaled by its beginning of quarter market value of equity. We also include firm and fiscal week-year fixed effects to mitigate concerns about unobservable correlated omitted variables that are related to firm type or to consumer industry-wide events affecting firms at the same time (i.e., invariant within firms or within specific time windows), and we cluster standard errors by firm and fiscal week-year (Cameron et al. 2011).[11,12]

Table 5 presents the results of estimating Eqs. (2) and (3) using OLS. In Column 1, we find that a firm's probability of providing a revenue forecast is positively related to its real-time abnormal revenues (i.e., *AbnRevRank* = 0.002). Considering the unconditional mean of *Disclose* is 0.02 (see Panel A of Table 3), this suggests that a one-unit change in a firm's quartile ranking of abnormal real-time revenues is positively associated with a 10% change in disclosure probability for that week. Consistent with prior empirical findings that firm guidance is often bundled with the earnings announcements for the prior quarter (e.g., Rogers and Van Buskirk 2013), *EA_week* has a positive coefficient. We also find a negative coefficient for *Prior_disclose*, suggesting that firms that have already issued a revenue forecast during the quarter are less likely to issue additional disclosure during that same quarter, consistent with the negative disclosure autocorrelation predicted by Aghamolla and An's (2021) model.

Column 2 of Table 5 presents the results of estimating Eq. (3). We find evidence consistent with abnormal real-time revenues having an asymmetric relation with firm disclosure. In particular, the coefficient for *AbnRevRank_low* is significantly negative, while the coefficient for *AbnRevRank_high* is not statistically different from zero. These findings indicate that the results from Column 1 are driven by firms with "bad news" (i.e., those in the lowest quartile of *AbnRevRank*) being less likely to provide revenue forecasts, consistent with classic discretionary disclosure models that highlight the importance of the economic implications of the news for the disclosure decision (e.g., Verrecchia 1983; Dye 1985). We do not, however, find evidence of greater disclosure of the most positive news relative to moderate or no news weeks. This suggests that the economic implication of the news has a nonlinear effect on the probability of disclosure.

[11] Note that by "fiscal week-year fixed effects," we mean indicators for 2014 fiscal week 1, 2014 fiscal week 2, etc., where we define "fiscal week" in footnote 6. We perform diagnostics to determine how much variation in our primary variables of interest remains after including our firm and fiscal week-year fixed effects (deHaan 2021), and find that 78%, 84%, and 78% of the variation in *AbnRevRank*, *AbnRevRank_high*, and *AbnRevRank_low* remains within the fixed effects structure. Although substantial variation remains, we also repeat our primary tests using a less granular time fixed effect, i.e., fiscal year-quarter, and we continue to find decreased withholding of negative news over time.

[12] We use a linear probability model (OLS) in our primary tests because the inclusion of fixed effects in nonlinear limited dependent variable models (such as the binary response model) can severely bias coefficients and standard errors due to the incidental parameter problem (Neyman and Scott 1948; Lancaster 2000; Greene 2004). Angrist and Pischke (2009) support the use of a linear probability model. As robustness, we also estimate Eqs. (2) and (3) using corrected probit and corrected logit models that use the analytical bias correction derived in Fernández-Val and Weidner (2016) to compute the probit fixed effects estimator (Cruz-Gonzalez et al. 2017, probitfe and logitfe). This reduces concerns about bias but does not allow for clustering of standard errors. We find qualitatively similar results, with the average marginal effects of all variables of interest remaining the same sign and significant at the 10% level or better, except for *Rank* (which remains positive but not significant at 10% level in both models) and *Rank**Week* in the logit model (which remains positive but not significant at the 10% level). We also note that these nonlinear specifications with time fixed effects are effectively an implementation of a hazard model that is discrete-time to more easily accommodate the time-varying explanatory variables of this setting (Kennedy 2008).

Table 5 Real-time abnormal revenues and firm disclosure

	Disclose	
	(1)	(2)
AbnRevRank	0.002* (0.076)	
AbnRevRank_high		−0.002 (0.269)
AbnRevRank_low		−0.006** (0.038)
Size	0.002 (0.593)	0.002 (0.626)
BTM	−0.007 (0.182)	−0.007 (0.187)
Momentum	−0.008** (0.021)	−0.008** (0.025)
Prior_disclose	−0.079*** (0.000)	−0.079*** (0.000)
EA_week	0.226*** (0.000)	0.226*** (0.000)
Earn_vol	−0.009 (0.896)	−0.009 (0.902)
Firm Fixed Effects	Included	Included
Fiscal Week-Year Fixed Effects	Included	Included
N	33,826	33,826
R2	0.279	0.279

Notes: Table 5 presents the results from OLS regressions of the probability of disclosing management forecasts related to current quarter revenues on *AbnRevRank*, *AbnRevRank_high*, and *AbnRevRank_low* as well as controls. Coefficients are shown above, with p-values below them. Standard errors are clustered by firm and fiscal week-year. See Appendix 1 for variable definitions. *** designates statistical significance at 1%, ** at 5%, and * at 10%

4.2 Real-time revenue, disclosure, and intra-quarter timing

We next exploit the granularity of our real-time revenue measure and explore whether time progression during the quarter influences the relation between a firm's real-time abnormal revenues and issuance of a revenue forecast. We alter Eqs. (2) and (3) to include an interaction between our measures of abnormal revenues and *Time_Var*, where *Time_Var* reflects the progression of time during the fiscal quarter and equals either *Week* or *After_EA*. *Week* is a continuous variable representing the week of the fiscal quarter, ranging from zero to 12. *After_EA* is an indicator equal to one if week t is after the earnings announcement week and zero otherwise.

Table 6 presents the results of estimating these modified versions of Eqs. (2) and (3). Columns 1 and 2 present the results using *Week* as our measure of intra-quarter time progression.[13] We continue to see a significantly positive coefficient for *AbnRevRank*

[13] The main effect for *Week* is subsumed by the fiscal week-year fixed effects.

in Column 1. Consistent with managers' voluntary disclosure choice being affected by impending mandatory disclosure, we find a significantly negative coefficient on the interaction between *AbnRevRank* and *Week*.

To examine separately the effect on disclosure of good and bad news, Column 2 presents the results from estimating the modified version of Eq. (3). We find a significant negative coefficient for *AbnRevRank_low* (= − 0.0093) and a positive coefficient for the interaction of this variable with *Week* (= 0.0006). These coefficients suggest a weekly moderating effect of 6.45% (= 0.0006/−0.0093 = −6.45%) and, considering the highest value for *Week* = 12, a near-complete moderation (77.4% = 12 weeks * 6.45%) of a firm's propensity to withhold bad news by the end of the quarter. This finding is consistent with MV's (2016) prediction that firms increase their disclosure (or equivalently reduce their withholding) of negative news as a public news event draws nearer. In contrast, we find no evidence of a statistically significant coefficient for the interaction between *AbnRevRank_high* and *Week*.

Columns 3 and 4 of Table 6 present the results of estimating these modified versions of Eqs. (2) and (3) using *After_EA* as our measure of intra-quarter time progression. As

Table 6 Real-time abnormal revenues and intra-quarter timing of firm disclosure

	Disclose			
	(1)	(2)	(3)	(4)
AbnRevRank	0.0032** (0.028)		0.0028* (0.092)	
*AbnRevRank * Time_Var*	−0.0003* (0.063)		−0.0017 (0.342)	
AbnRevRank_high		−0.0007 (0.795)		−0.0051 (0.159)
AbnRevRank_low		0.0093*** (0.008)		−0.0126*** (0.003)
*AbnRevRank_high * Time_Var*		−0.0003 (0.403)		0.0047 (0.246)
*AbnRevRank_low * Time_Var*		0.0006** (0.032)		0.0121*** (0.005)
Time_Var			0.0230*** (0.006)	0.0159** (0.044)
Measure used for *Time_Var*	*Week*	*Week*	*After_EA*	*After_EA*
Remaining Controls	Included	Included	Included	Included
Firm Fixed Effects	Included	Included	Included	Included
Fiscal Week-Year Fixed Effects	Included	Included	Included	Included
N	33,826	33,826	33,826	33,826
R2	0.279	0.279	0.280	0.280

Notes: Table 6 presents the results from OLS regressions of the probability of disclosing management forecasts related to current quarter revenues on *AbnRevRank*, *AbnRevRank_high*, and *AbnRevRank_low*, and the interaction of these real-time revenue measures with *Time_Var*, which takes the value of *Week* or *After_EA*, and control variables. Coefficients are shown above, with p-values below them. Standard errors are clustered by firm and fiscal week-year. See Appendix 1 for variable definitions. *** designates statistical significance at 1%, ** at 5%, and * at 10%

a binary indicator, *After_EA* is a more crude proxy for time than *Week*, but it allows for the possibility that managers view the earnings announcement as a fundamental demarcation point in the quarter. Results are generally consistent. In Column 3, we continue to find a positive relation between abnormal revenue and disclosure that is attenuated later in the quarter. Although the interaction coefficient is not significantly different from zero (= −0.0017), its magnitude suggests a moderating effect greater than 50% (= −0.0017/0.0028 = −60.7%). When we examine disclosure likelihood for positive and negative news separately in Column 4, our findings of a negative coefficient for *AbnRevRank_low* * *After_EA* continue to indicate that managers withhold negative news less in the latter part of the quarter. Together, these findings provide further evidence that intra-quarter time progression increases a firm's propensity to disclose negative news, but not positive news.[14]

5 Additional tests

5.1 Real-time revenue, disclosure, and disciplining mechanisms

We perform tests to further explore potential disciplining mechanisms that facilitate real-time revenue disclosure prior to a public event. If analysts, institutional owners, and litigation risk are disciplining mechanisms, then firms with greater analyst coverage, institutional ownership, or litigation risk would be more likely to stop withholding bad news as the quarter-end approaches.[15] We re-estimate the models from Section 4.2 for subsamples partitioned on these potential disciplining mechanisms. We first split the sample based on median analyst coverage, presenting the results in Panel A of Table 7. Columns 1 and 2 report the results using *Week* as our measure of intra-quarter time progression. Similar to Table 6 findings that reveal bad news withholding early in the quarter and disclosure later in the quarter, Column 1 finds a significant negative coefficient for *AbnRevRank_low* and a positive coefficient for the interaction of this variable with *Week* for the sample of firms with high analyst following. In contrast, Column 2 reveals that the coefficient for *AbnRevRank_low* * *Week* is not statistically significant among our sample of firms with low analyst following. These findings indicate that our main findings are concentrated among the subsample of firms with

[14] We examine real-time revenue and disclosure in the same week, assuming that managers obtain and review sales information in a timely fashion to make operational and disclosure decisions. However, we repeat tests using lagged abnormal revenue to allow firms more time to collect and disclose information. We find similar but slightly weaker results, with coefficients of interest of the same sign and significant at 10% or better, except that *AbnRevRank_low* remains negative but becomes marginally insignificant (p value = 0.106) in the overall quarter specification and *AbnRevRank*Week* remains negative but becomes marginally insignificant (p value = 0.115).

[15] Firms with stronger monitors might also be less likely to withhold bad news throughout the entire quarter. This disclosure outcome would require strong enough monitors that firms expect timely, independent discovery of news that motivates immediate disclosure. Prior research suggests that this might be the less likely outcome, e.g., with even sophisticated investors facing information processing constraints that prevent continual monitoring (Blankespoor et al. 2020). Our empirical findings support the prediction that monitoring becomes stronger at the end of the quarter. However, either scenario would still provide evidence that monitoring mechanisms influence managers' disclosure patterns.

high analyst coverage, consistent with analysts aiding in market discipline that motivates firms to stop withholding negative news as the quarter progresses. In Columns 3 and 4, we repeat these analyses using *After_EA* as our measure of intra-quarter time progression and find the same inferences.

In Panels B and C of Table 7, we perform the same estimations as in Panel A using subsamples partitioned on median institutional ownership (Panel B) and litigation risk (Panel C). We measure institutional ownership percentage using Thomson Reuters 13f holdings, and litigation risk using quarterly Compustat data, monthly CRSP data, and the coefficients from model (3) of Table 7 of Kim and Skinner (2012). In each Panel, Columns 1 and 2 (3 and 4) report the results of these estimations using *Week* (*After_EA*) as our measure of intra-quarter time progression. We find that the main results of bad news withholding early in the quarter and disclosure later in the quarter exist only in the sample of firms with above-median institutional ownership (i.e., Columns 1 and 3 in Panel B) and the sample of firms with above-median litigation risk (i.e., Columns 1 and 3 in Panel C). Thus our main findings are concentrated among firms with high institutional ownership and firms with high litigation risk, consistent with institutional owners and litigation risk aiding in market discipline as well.

We find less disclosure of bad news on average in the below-median institutional ownership sample (Panel B), consistent with firms taking advantage of low monitoring to hide bad news throughout the quarter. We do not find asymmetric withholding of bad news in the below-median analyst or litigation risk samples (Panels A and C) though. A possible reason for the lack of asymmetric bad news withholding is that firms with low analyst coverage or litigation risk disclose less on average, making the low rates of bad news disclosure indistinguishable from the overall low rates of disclosure. In other words, rather than asymmetric low disclosure of bad news, there is consistently low disclosure in all settings because of a lack of market demand or penalties for withholding. Consistent with the possibility that disclosure rates in general are lower for these low-monitored subsamples, firms with low analyst coverage disclose in 1.7% of weeks versus 2.4% for firms with high analyst coverage, and firms with low litigation risk disclose in 2.0% of weeks versus 2.2% for firms with high litigation risk.

5.2 Real-time revenue: Information accuracy

As discussed in Section 2.1, our prediction that firms increase their disclosure of negative news as a public news event draws nearer is partly motivated by uncertainty resolution: managers may wait to disclose bad news until later in the quarter because they think their information is less accurate during earlier periods than during later periods. To better understand intra-quarter accuracy and its effect on firm disclosure in our setting, we create a measure ($RT\_rev\_acc_{i,j,t}$) that reflects the accuracy of implied quarterly real-time revenue throughout the quarter. We first take the firm's actual real-time revenue for firm i in quarter j and subtract week t's implied real-time quarterly revenue (i.e., the sum of daily transaction-level revenues from the beginning of quarter j through the end of week t transformed to a quarterly amount using historical real-time revenue movements through the quarter, i.e., the first two steps of the process to create *Quarterly Rev Implied by RT* $Rev_{i,j,t}$, as described in Section 3.1). We then scale this difference by the firm's actual real-time quarterly revenue and take the absolute value.

Table 7 Disclosure disciplining mechanisms

Panel A The disciplining role of analyst coverage

	Disclose			
	High Analyst Coverage	Low Analyst Coverage	High Analyst Coverage	Low Analyst Coverage
	(1)	(2)	(3)	(4)
AbnRevRank_high	0.001 (0.883)	−0.001 (0.708)	−0.003 (0.606)	−0.006 (0.196)
AbnRevRank_low	−0.016*** (0.009)	−0.005 (0.175)	−0.020*** (0.004)	−0.007 (0.130)
*AbnRevRank_high * Week*	−0.001 (0.302)	−0.000 (0.710)		
*AbnRevRank_low * Week*	0.001** (0.044)	0.000 (0.440)		
*AbnRevRank_high * After_EA*			0.001 (0.877)	0.007 (0.177)
*AbnRevRank_low * After_EA*			0.017** (0.014)	0.006 (0.193)
After_EA			−0.000 (0.973)	0.029*** (0.001)
Remaining Controls	Included	Included	Included	Included
Firm Fixed Effects	Included	Included	Included	Included
Fiscal Week-Year Fixed Effects	Included	Included	Included	Included
N	17,212	16,614	17,212	16,614
R2	0.319	0.257	0.319	0.260

Panel B The disciplining role of institutional ownership

	Disclose			
	High Institutional Ownership	Low Institutional Ownership	High Institutional Ownership	Low Institutional Ownership
	(1)	(2)	(3)	(4)
AbnRevRank_high	−0.001 (0.763)	−0.001 (0.832)	−0.003 (0.619)	−0.007 (0.110)
AbnRevRank_low	−0.009* (0.096)	−0.009** (0.045)	−0.013** (0.045)	−0.012** (0.034)
*AbnRevRank_high * Week*	−0.000 (0.858)	−0.000 (0.368)		
*AbnRevRank_low * Week*	0.001** (0.047)	0.000 (0.314)		
*AbnRevRank_high * After_EA*			0.001 (0.859)	0.007 (0.118)
*AbnRevRank_low * After_EA*			0.015** (0.014)	0.008 (0.164)

Table 7 (continued)

After_EA			0.022* (0.052)	0.011 (0.242)
Remaining Controls	Included	Included	Included	Included
Firm Fixed Effects	Included	Included	Included	Included
Fiscal Week-Year Fixed Effects	Included	Included	Included	Included
N	16,913	16,913	16,913	16,913
R2	0.308	0.278	0.309	0.279

Panel C The disciplining role of litigation risk

	Disclose			
	High Litigation Risk	Low Litigation Risk	High Litigation Risk	Low Litigation Risk
	(1)	(2)	(3)	(4)
AbnRevRank_high	0.000 0.977	0.001 0.865	−0.004 0.408	−0.004 0.409
AbnRevRank_low	−0.016*** 0.001	−0.003 0.471	−0.019*** 0.001	−0.007 0.195
*AbnRevRank_high * Week*	−0.000 0.939	−0.001 0.143		
*AbnRevRank_low * Week*	0.001*** 0.010	0.000 0.961		
*AbnRevRank_high * After_EA*			0.007 0.207	0.002 0.656
*AbnRevRank_low * After_EA*			0.017*** 0.005	0.006 0.220
After_EA			0.011 0.293	0.024** 0.012
Remaining Controls	Included	Included	Included	Included
Firm Fixed Effects	Included	Included	Included	Included
Fiscal Week-Year Fixed Effects	Included	Included	Included	Included
N	16,601	16,601	16,601	16,601
R2	0.298	0.295	0.299	0.296

Notes: Table 7 Panel A presents the results of regressing the probability of disclosing management forecasts related to current quarter revenues on *AbnRevRank_high* and *AbnRevRank_low*, and the interaction of these real-time revenue measures with two measures of intra-quarter time progression (i.e., *Week* and *After_EA*), and control variables. We split the sample based on median analyst coverage, with Columns 1 and 3 (2 and 4) presenting results from estimations on the sample of firms with high (low) analyst coverage. Coefficients are shown above, with p-values below them. Standard errors are clustered by firm and fiscal week-year. See Appendix for variable definitions. *** designates statistical significance at 1%, ** at 5%, and * at 10%. Panel B presents the results of regressing the probability of disclosing management forecasts related to current quarter revenues on *AbnRevRank_high* and *AbnRevRank_low*, and the interaction of these real-time revenue measures with two measures of intra-quarter time progression (i.e., *Week* and *After_EA*), and control variables. We split the sample based on median institutional ownership, with Columns 1 and 3 (2 and 4) presenting results from estimations on the sample of firms with high (low) institutional ownership. Coefficients are shown above, with p-values below the coefficients. Standard errors are clustered by firm and fiscal week-year. See Appendix for variable definitions. *** designates statistical significance at 1%, ** at 5%, and * at 10%. Panel C presents the results of regressing the probability of disclosing management forecasts related to current quarter revenues on *AbnRevRank_high* and *AbnRevRank_low*, and the interaction of these real-time revenue measures with two measures of intra-quarter time progression (i.e., *Week* and *After_EA*), and control variables. We split the sample based on median litigation risk, as measured using coefficient estimates from Model 3 of Kim and Skinner (2012), with Columns 1 and 3 (2 and 4) presenting results from estimations on the sample of firms with high (low) litigation risk. Coefficients are shown above, with p-values below them. Standard errors are clustered by firm and fiscal week-year. See Appendix for variable definitions. *** designates statistical significance at 1%, ** at 5%, and * at 10%

Finally, for ease of interpretation, we multiply the absolute value by −1 so that higher values correspond to greater accuracy.

Fig. 4 charts the mean, median, and upper and lower quartile values for *RT_rev_acc*. Consistent with the manager's information about quarterly revenues improving over time, Fig. 4 reveals that the accuracy of implied quarterly real-time revenue increases monotonically throughout the quarter. We then re-estimate models from Section 4.2 while including *RT_rev_acc* as a control variable. Table 8 provides the results from these estimations. As shown, we find a significantly positive coefficient for *RT_rev_acc*, consistent with information accuracy relating positively to firm disclosure. More importantly, Table 8 also reveals that our primary findings from Section 4.2 are robust to the inclusion of this control variable, mitigating concerns that they are solely driven by intra-quarter information accuracy.

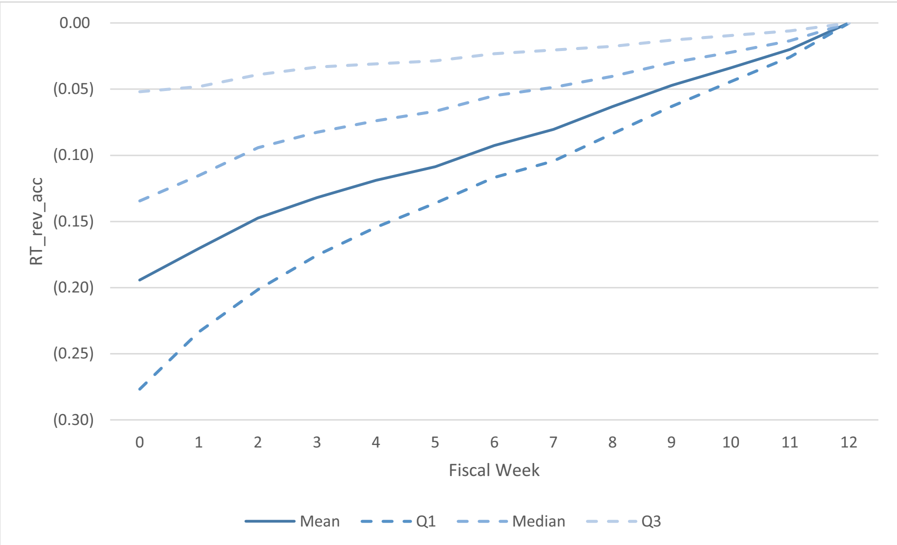

Fig. 4 Accuracy of implied quarterly real-time revenue throughout the fiscal quarter. This figure provides descriptive statistics for our measure of the accuracy of implied quarterly real-time revenue, *RT_rev_acc*, throughout the fiscal quarter. As described in Section 5.2, we compute this measure by taking the firm's actual real-time revenue for firm *i* in quarter *j* and subtracting week *t*'s implied real-time quarterly revenue (i.e., the sum of daily transaction-level revenues from the beginning of quarter *j* through the end of week *t* transformed to a quarterly amount using historical real-time revenue movements through the quarter). We then scale this difference by the firm's actual real-time quarterly revenue and take the absolute value. Finally, for ease of interpretation, we multiply the absolute value by −1 so that the higher values correspond to greater accuracy

Table 8 Real-time abnormal revenues, disclosure, and accuracy

	Disclose			
	(1)	(2)	(3)	(4)
AbnRevRank	0.0033**		0.0029*	
	(0.023)		(0.081)	
*AbnRevRank * Time_Var*	−0.0003*		−0.0017	
	(0.059)		(0.335)	
AbnRevRank_high		0.0007		−0.0042
		(0.811)		(0.249)
AbnRevRank_low		−0.0082**		−0.0120***
		(0.017)		(0.004)
*AbnRevRank_high * Time_Var*		−0.0004		0.0040
		(0.193)		(0.338)
*AbnRevRank_low * Time_Var*		0.0005*		0.0114***
		(0.085)		(0.008)
Time_Var			0.0230***	0.0162**
			(0.006)	(0.041)
RT_rev_acc	0.0183***	0.0161**	0.0178***	0.0128**
	(0.006)	(0.014)	(0.007)	(0.045)
Measure used for *Time_Var*	*Week*	*Week*	*After_EA*	*After_EA*
Remaining Controls	Included	Included	Included	Included
Firm Fixed Effects	Included	Included	Included	Included
Fiscal Week-Year Fixed Effects	Included	Included	Included	Included
N	33,826	33,826	33,826	33,826
R2	0.279	0.279	0.280	0.280

Notes: Table 8 presents the results from OLS regressions of the probability of disclosing management forecasts related to current quarter revenues on *AbnRevRank*, *AbnRevRank_high*, *AbnRevRank_low*, the interaction of these real-time revenue measures with *Time_Var*, which takes the value of *Week* or *After_EA*, *RT_rev_acc*, and other control variables. Coefficients are shown above, with p-values below them. Standard errors are clustered by firm and fiscal week-year. See Appendix 1 for variable definitions. *** designates statistical significance at 1%, ** at 5%, and * at 10%

With *RT_rev_acc*, we can focus on the intra-quarter predictive value of our implied real-time revenue data without the complexity of magnitude adjustments to Compustat levels for comparison to a market expectation of quarterly revenue. To expand our analysis to incorporate the transformation to Compustat levels, we create a second accuracy measure that includes this adjustment. In untabulated findings, we again find that accuracy improves monotonically throughout the quarter and that our Section 4.2 findings are robust to the inclusion of this measure as a control variable.

5.3 Real-time revenue and insider trading

In this study, we focus on managers' choice to disclose real-time revenue. However, the continuous and private nature of real-time revenue creates an information advantage for managers, which they could exploit by trading for personal gain. Studies find evidence of managers trading based on private information in a variety of settings despite the risk of violating their fiduciary duty to "disclose or abstain (from trading)" (e.g., Ke et al. 2003; Piotroski and Roulstone 2005; Blackburne et al. 2021). Given our evidence of delayed bad news disclosure within the quarter, a natural question is whether managers with real-time revenue information abstain from disclosure but not from trading. In addition, examining insider trading can provide additional evidence on the quality of the real-time revenue signal. Specifically, if we find that insider trading is correlated with real-time revenue, it will provide evidence that managers perceive real-time revenue to be informative, reducing any concerns that delayed disclosure was due to poor information quality.

We examine the potential for insider trading in two ways. First, we test whether insider sales and purchases are associated with abnormal real-time revenue. We regress several measures of insider trading – insider sales volume (*ISV*), insider purchases volume (*IPV*), an indicator equal to one if there is a net insider sale (*I(IS)*) during the week, and net insider sales volume (*ISPV*), all based on senior manager and director trading data from Thomson Reuters Insider Filings – on our abnormal revenue measures. We also include firm and fiscal week-year fixed effects, and control variables following Blackburne et al. (2021). In particular, we control for firm size (*Size*), book-to-market ratio (*BTM*), and a blackout period indicator (*BlackoutPd*) based on prior research that finds less trading in blackout periods (Bettis et al. 2000). Bettis et al. (2000) also include historical stock volatility as a proxy for the information asymmetry between insiders and investors in their examination of insider trading activity, finding evidence of a significantly positive relation. Thus, we include controls for return volatility and abnormal returns over weekly and annual periods (*WeeklyVolatility*, *Volatility*, *WeeklyAbnRet*, and *AbnRet*). See Appendix 1 for variable definitions.

As shown in Table 9 Panel A Column 1, we find a positive coefficient on *AbnRevRank_low*, consistent with greater insider selling in the weeks that managers observe the most negative abnormal real-time revenue. As expected, Column 1 also indicates a negative relation for *BlackoutPd*, consistent with less insider trading during blackout periods, and we find significantly positive coefficients for *WeeklyAbnRet*, *AbnRet*, and *WeeklyVolatility*.[16]

Per Column 2, we do not find a statistically significant relation between insider purchases and either low or high abnormal real-time revenue. This is perhaps due to fewer insider purchases, with only 195 weeks with insider purchases versus 1895 weeks with insider sales. Columns 3 and 4 combine purchases and sales into a "net sales minus purchases" indicator and continuous measures (respectively), and continue to find evidence of the most negative abnormal real-time revenue information being associated with greater net insider selling activity. Overall, bad news is associated with more insider selling, while good news is not associated with a change in trading behavior.

[16] We note that the sign and statistical significance of our control variables are largely consistent with those presented in Table 5 of Blackburne et al. (2021), with the exception that they report a significantly negative coefficient for volatility. Although the difference in sample period and industry composition prevents us from reconciling the difference, our finding of a positive coefficient is consistent with higher volatility offering more opportunity for insiders to profit from insider trading. This finding is also consistent with prior research that finds a positive relation between stock volatility and both the size and profitability of insider trades (Bettis et al. 2000; Roulstone 2003).

Table 9 Real-time abnormal revenues and insider trading

	ISV	*IPV*	*I(IS)*	*ISLPV*
	(1)	(2)	(3)	(4)
Panel A Insider Trading				
AbnRevRank_high	−0.005	−0.021	0.001	−0.005
	(0.797)	(0.317)	(0.874)	(0.795)
AbnRevRank_low	0.047**	0.019	0.014***	0.046**
	(0.026)	(0.452)	(0.001)	(0.027)
Size	0.038	−0.082	0.014*	0.040
	(0.228)	(0.244)	(0.098)	(0.215)
BTM	−0.087	−0.042	−0.018	−0.086
	(0.153)	(0.827)	(0.240)	(0.159)
BlackoutPd	−0.057**	−0.001	−0.019**	−0.056**
	(0.037)	(0.952)	(0.013)	(0.038)
WeeklyAbnRet	0.717***	−0.440**	0.162***	0.721***
	(0.000)	(0.027)	(0.000)	(0.000)
WeeklyVolatility	2.031***	3.868***	0.304***	2.039***
	(0.000)	(0.000)	(0.007)	(0.000)
AbnRet	0.068*	0.019	0.017**	0.069*
	(0.050)	(0.614)	(0.011)	(0.050)
Volatility	−0.256	0.278	−0.009	−0.257
	(0.335)	(0.491)	(0.863)	(0.333)
Firm Fixed Effects	Included	Included	Included	Included
Fiscal Week-Year Fixed Effects	Included	Included	Included	Included
N	33,826	33,826	33,826	33,826
R2	0.084	0.056	0.146	0.084
Panel B - Insider Trading and Disclosure				
*AbnRevRank_high*Disclose*	−0.085	0.238*	−0.019	−0.085
	(0.610)	(0.061)	(0.557)	(0.608)
*AbnRevRank_low*Disclose*	−0.351***	0.007	−0.046*	−0.350***
	(0.002)	(0.956)	(0.063)	(0.002)
AbnRevRank_high	−0.002	−0.025	0.001	−0.002
	(0.902)	(0.211)	(0.779)	(0.900)
AbnRevRank_low	0.055***	0.019	0.015***	0.055***
	(0.009)	(0.469)	(0.000)	(0.009)
Disclose	0.152	−0.047	0.025	0.153
	(0.118)	(0.390)	(0.171)	(0.117)
Controls	Included	Included	Included	Included
Firm Fixed Effects	Included	Included	Included	Included
Fiscal Week-Year Fixed Effects	Included	Included	Included	Included
N	33,826	33,826	33,826	33,826
R2	0.085	0.056	0.146	0.085

Notes: Table 9 Panel A presents the results from OLS regressions of insider trading sales volume (*ISV*), insider trading purchase volume (*IPV*), an indicator equal to one if there is a net insider sale (*I(IS)*), and net insider trading sales less purchase volume (*ISPV*) on *AbnRevRank_high* and *AbnRevRank_low* as well as controls. Coefficients are shown above, with p-values below them. Standard errors are clustered by firm and fiscal week-year. See Appendix 1 for variable definitions. *** designates statistical significance at 1%, ** at 5%, and * at 10%. Panel B presents the results from OLS regressions of insider trading sales volume (*ISV*), insider trading purchase volume (*IPV*), an indicator equal to one if there is a net insider sale (*I(IS)*), and net insider trading sales less purchase volume (*ISPV*) on *AbnRevRank_high*, *AbnRevRank_low*, *Disclose*, and interactions between the real-time revenue measures and *Disclose*, as well as controls. Coefficients are shown above, with p-values below them. Standard errors are clustered by firm and fiscal week-year. See Appendix 1 for variable definitions. *** designates statistical significance at 1%, ** at 5%, and * at 10%

Second, we test whether insider trading around real-time revenue news is associated with managers' disclosure choice. If managers follow their fiduciary duty to abstain from trading when they do not disclose the news, we will observe a positive relation between disclosing and trading on the abnormal revenue information, i.e., managers waiting to trade until they disclose. However, if managers choose to trade *rather than* disclose, we will find less trading when disclosure occurs.

As shown in Table 9 Panel B Column 1, we continue to find more insider selling in the weeks with the most negative abnormal revenue, but this increased insider selling disappears in weeks when firms choose to disclose. Specifically, the coefficient on *AbnRevRank_low*Disclose* completely offsets the sum of the coefficients on *AbnRevRank_low* and *Disclose*; the sum of the three coefficients is negative and statistically different from zero (p value = 0.03), suggesting that managers are less likely to sell shares during weeks they disclose bad news. As shown in Column 2, we do not find substantial changes in insider purchasing related to real-time revenue. The coefficient on *AbnRevRank_high*Disclose* is positive, which suggests that there is greater insider purchasing when managers receive and disclose a more positive abnormal revenue signal and is consistent with managers abstaining from trading on good news until they have disclosed the information, per their fiduciary duty. However, the sum of *AbnRevRank_high*, *Disclose*, and *AbnRevRank_high*Disclose* is not statistically different from zero, confirming the earlier finding that there is little evidence of managers buying shares in response to good news. Columns 3 and 4 combine insider sales and purchases and find evidence (similar to Column 1) of managers choosing to trade on negative news only during weeks when they do not disclose. The sum of the *AbnRevRank_low*, *Disclose*, and *AbnRevRank_low*Disclose* coefficients in Column 3 (4) is not (is) statistically different from zero (p-values = 0.75 and 0.03, respectively), finding evidence of the same or less insider selling during weeks when bad news is disclosed.[17]

Overall, managers seem to recognize the value in the real-time revenue information and trade on the more negative abnormal real-time revenue signals only when they do not disclose them, and they are less likely to sell shares when they receive and disclose negative news than when they do not have abnormal revenue signals. These findings build on Billings and Cedergren's (2015) evidence that disclosure and insider trading are substitutes, i.e., that the likelihood of a warning decreases with insider sales.

[17] When we repeat Column 3 analyses using an indicator for insider sales (rather than sales less purchases), we find similar results. Adjusting Column 4 analyses to only include insider sales results in the model portrayed in Column 1.

6 Conclusion

This study uses a proxy for real-time revenues to examine managers' disclosure choice in the presence of continuous information flow. We use a proprietary database of transaction-level credit and debit card sales from 2012 through early 2016 for a sample of retail firms to overcome the challenge of not being able to observe managers' real-time revenue. We validate the accuracy of this data in our setting, finding a 0.78 correlation between quarterly real-time revenue and quarterly reported revenue from Compustat. We use this transaction-level data to create a weekly, firm-specific measure of cumulative abnormal revenue. We also validate the informativeness of this abnormal revenue measure, finding a positive relation between weekly abnormal revenue and future stock returns, the unexpected portion of realized quarterly revenue, and managers' forecast news if they choose to disclose. Overall, the evidence suggests that our real-time revenue information can predict future outcomes yet is not immediately incorporated into market price.

When we examine managers' disclosure decision, we find low disclosure despite real-time revenue suggesting private information; firms disclose in only 2% of the weeks with the most positive or most negative abnormal revenue (top or bottom quartiles). Firms with more negative abnormal revenue are less likely to provide a forecast than those with moderate or highly positive abnormal revenue. For disclosure withholding patterns within the quarter, we find that firms are more likely to disclose abnormal negative revenue news later in the quarter than earlier. We also find empirical associations between greater firm disclosure and analysts, institutional ownership, and litigation risk, suggesting they act as disciplining agents within this framework. Finally, we find evidence that managers are more likely to sell shares in weeks with abnormal negative revenue news, unless they choose to disclose the negative news.

We contribute in several ways. First, we use a detailed measure of managers' private positive and negative information at repeated points in time to examine the classic question of disclosure choice conditional on economic news. Our results confirm and deepen earlier findings, providing evidence of initial withholding of bad news followed by the release of bad news when a disciplining event draws near, but no evidence of disclosure adjustments for good news. Second, recent analytical studies have begun modeling multiple period disclosure decisions with dynamic information flow (e.g., Marinovic and Varas 2016; Aghamolla and An 2021), revealing that investors' awareness of continuous information flow could affect their expectation for disclosure and their interpretation of lack of disclosure. With our granular measure of manager information, we empirically explore this interesting new research area, benchmarking our findings with these analytical predictions. Third, our study contributes to the growing literature exploring alternative or "big data" sources. Our study confirms the value of alternative data sources and provides initial evidence on how continuous information flow might affect disclosure decisions.

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Appendix 1 – Variable Descriptions

AbnRet	Market-adjusted returns over the year ending at the start of fiscal quarter *j*
AbnRev	*Quarterly Rev Implied by RT Rev* as of week *t*, less *Mkt Expected Quarterly Rev* as of the end of week *t-1*, all scaled by *Mkt Expected Quarterly Rev* as of the end of week *t-1*
AbnRevRank	Quartile rank of *AbnRev*, ranging from 0 to 3
AbnRevRank_high	Indicator equal to one if *AbnRevRank* is in the top quartile and zero otherwise
AbnRevRank_low	Indicator equal to one if *AbnRevRank* is in the bottom quartile and zero otherwise
AFE_EPS	Analyst forecast error calculated as actual EPS less the median analyst consensus forecast updated at the end of week *t-1*, scaled by the beginning of quarter stock price, times 100
AFE_rev	Analyst forecast error calculated as actual revenues less the median analyst consensus forecast updated at the end of week *t-1*, scaled by the beginning of quarter market value of equity, times 100
After_EA	Indicator equal to one if the week is after the week of the earnings announcement and zero otherwise
Analyst_coverage	Number of analysts providing a revenue forecast in I/B/E/S in the quarter
BlackoutPd	Indicator equal to one if the beginning of week *t* falls within [−46,+1] days of the quarterly earnings announcement
BTM	Book value of equity divided by market value of equity at the beginning of the quarter
Comp_rev	Quarterly Compustat revenues
Days_FQE_EA	Number of days between the fiscal quarter end and earnings announcement
Disclose	Indicator equal to one if firm *i* provides a management revenue forecast for fiscal quarter *j* (or for the fiscal year ending in fiscal quarter *j*) during week *t* of fiscal quarter *j* and zero otherwise
EA_week	Indicator equal to one if week is the week of the earnings announcement and zero otherwise
Earn_vol	Standard deviation of net income over the prior eight quarters scaled by the beginning of quarter market value of equity
Forecast_news	(Value of management quarterly revenue guidance less median analyst consensus forecast as of the end of the week before the guidance is released) scaled by analyst consensus forecast as of the end of the week before the guidance is released, where each analyst's most recent forecast is used to construct the consensus forecast
I(IS)	Indicator equal to one if insiders at the firm are net sellers during week *t* and zero otherwise
IPV	Insider purchasing volume during week *t* scaled by shares outstanding and normalized using the sample average and standard deviation
ISPV	Insider selling volume – purchasing volume during week *t* scaled by shares outstanding and normalized using the sample average and standard deviation

ISV	Insider selling volume during week *t* scaled by shares outstanding and normalized using the sample average and standard deviation
Lit_risk	Litigation risk, as measured using coefficient estimates from litigation risk model 3 in Kim and Skinner (2012)
Mkt Expected Quarterly Rev	Median analyst consensus quarterly revenue forecast as of the end of week *t-1*
Momentum	Cumulative returns from six months prior to the beginning of the fiscal quarter through the beginning of the fiscal quarter
Prior_disclose	Indicator equal to one if, prior to the current week in fiscal quarter *j*, the firm provides a management forecast for fiscal quarter *j* or for the fiscal year ending in fiscal quarter *j*
Quarterly Rev Implied by RT Rev	Calculated in three steps: (1) Sum of the daily transaction-level revenues from the beginning of quarter *j* for firm *i* through the end of week *t*. (2) Step 1 figure divided by the average percentage of firm *i*'s quarterly revenues received as of the end of week *t* for all same-fiscal firm-quarters prior to quarter *j*. (3) Estimate the average firm *i*'s quarterly real-time revenue divided by firm *i*'s quarterly Compustat revenue, for all firm-quarters prior to quarter *j*. Divide step (2) figure by the figure calculated in step (3).
Ret	Cumulative market-adjusted returns from the end of week *i* through two days after the earnings announcement
RT_rev	Quarterly real-time revenues
RT_rev_acc	Calculated in four steps: (1) Sum of the daily transaction-level revenues from the beginning of quarter *j* for firm *i* through the end of week *t*. (2) Step 1 figure divided by the average percentage of firm *i*'s quarterly revenues received as of the end of week *t* for all same-fiscal firm-quarters prior to quarter *j*. (3) Subtract Step 2 figure from firm *i*'s actual real-time revenue in quarter *j* and scale by firm *i*'s actual real-time revenue in quarter *j*. (4) Take absolute value of Step 3 figure and multiply by −1 (for ease of interpretation).
Size	Natural logarithm of market value of equity at the beginning of the quarter
Volatility	Standard deviation of monthly stock returns over the year ending at the start of fiscal quarter *j*
Week	Week of the fiscal quarter, ranging from 0 to 12
WeeklyAbnRet	Market adjusted buy and hold return during week *t,* beginning three trading days before the start of the week
WeeklyVolatility	Standard deviation of daily stock returns during week *t,* beginning three trading days before the start of the week

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