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The Information Content of Operational Effectiveness

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ABSTRACT

We address whether and why a firm's operational effectiveness, *OpEff*, has information content for investors and what role that information plays in the price discovery process at quarterly earnings announcements. We measure *OpEff* using the cash conversion cycle (CCC) multiplied by –1, such that higher *OpEff* reflects better operational effectiveness. Higher *OpEff* is associated with higher abnormal stock returns and trading volume at earnings announcements and with higher future earnings and cash flows, which helps explain the positive return and volume relations. Higher *OpEff* also is associated with larger post-earnings-announcement drift and less timely incorporation of information in earnings announcements into stock prices. However, this relation largely is attributable to firms that announce bad earnings news. Together, we infer that operational effectiveness is informative to investors because it comprises forward-looking information about earnings and cash flows and that announcements of improvements in *OpEff* along with bad earnings news impede the price discovery process.

JEL Classification: G11, G12, G14, M41

1 | Introduction

We address whether and why a firm's operational effectiveness has information content for investors and what role that information plays in the price discovery process at quarterly earnings announcements. We measure operational effectiveness using the firm's cash conversion cycle, CCC. CCC reflects the average number of days it takes the firm to convert \$1 invested in inventory into \$1 collected from sales.[1] Thus, the shorter is CCC, the more effective the firm's operations are. This effectiveness enables firms with shorter CCC to generate earnings and cash flows faster.[2] We define operational effectiveness, *OpEff*, as CCC multiplied by –1 such that larger values of *OpEff* reflect higher operational effectiveness, and observe that it varies not only across industries, but also across firms within an industry. We predict that intra-industry differences in *OpEff* are informative to investors because we expect that larger *OpEff* is predictive of higher future earnings and operating cash flows. We also investigate the implications of the information content of operational effectiveness for price discovery at quarterly earnings announcements.

The motivation for our study stems from the observation that *OpEff* comprises information on three key dimensions of a firm's operations, expressed in days—obtaining credit from suppliers, producing and selling inventory, and providing credit to customers—that affect a firm's future earnings and operating cash flows. However, little is known about whether and why the market reacts to information in *OpEff* and what role that information plays in stock price discovery at earnings announcements.

Wang (2019) is perhaps the study most closely related to ours. Wang (2019) investigates the asset pricing implications of CCC and, thus, operational effectiveness and finds that monthly hedge portfolios that buy (sell) stocks of firms in the shortest (longest)

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CCC decile deliver abnormal returns that cannot be explained by known factors or equity return predictors. The study concludes that the hedge portfolio returns are associated with mispricing. Wang (2019) also finds that the highest (lowest) deciles of CCC are negatively (positively) associated with future earnings. However, Wang (2019) does not address whether the market reacts to information in CCC. The study also does not identify the channel through which operational effectiveness contributes to the prediction of stock returns and, thus, is silent about the role the information in operational effectiveness plays in stock price discovery. Our study addresses these questions.

Prior research relating to quarterly earnings announcements predominantly focuses on the information content of earnings news and largely overlooks other potentially important measures that can be inferred from financial statement amounts. *OpEff* is one such measure. To construct *OpEff*, investors need to extract particular accounting amounts from financial statements such as accounts receivable, accounts payable, and inventory. Prior research finds that it takes time for investors to comprehend fully accounting information that is not readily available and, thus, for stock prices to reflect fully that information. Hence, investigating the information content of *OpEff* also can shed light on the availability and price discovery consequences of an important forward-looking measure calculated from financial statement amounts.

Consistent with the possibility that lack of transparent disclosure of *OpEff* impedes price discovery at earnings announcements, the Financial Accounting Standards Board (FASB) recently issued a requirement for firms to disclose information regarding the structure of their payments to suppliers (FASB 2022). One reason the FASB offers for issuing this requirement is that firms increasingly are financing payments to suppliers through third parties, and information about a firm's CCC would allow investors to predict better the firm's future operating cash flows. In contrast, firms assert that the disclosure would not be informative to investors. Our investigation informs this debate by providing evidence on the informativeness of *OpEff*. In particular, we assess how information about operational effectiveness relates to stock price discovery at earnings announcements. This assessment enables our study to provide insights into the potential that improvements in financial statement transparency have to facilitate price discovery at earnings announcements.

We address our research questions using a sample of 119,143 quarterly earnings announcements by 4,752 firms from the fourth calendar quarter of 1987 to the first calendar quarter of 2022. Regarding our first research question—whether a firm's operational effectiveness, *OpEff*, has information content for investors—we find that a firm's operational effectiveness does have information content for investors. We find that, on average, a one standard deviation increase in the level of *OpEff* is associated with a 0.24% (1.27%) higher abnormal return (trading volume) at quarterly earnings announcements. We also find that, on average, a one standard deviation increase in the quarterly change in *OpEff* is associated with a 0.51% (2.57%) higher abnormal return (trading volume) reaction.

Regarding our second research question—why a firm's operational effectiveness as reflected in *OpEff* is informative to investors—we first show that a higher level of, and larger quarterly change in, *OpEff* predicts higher future earnings and future operating cash flows. Next, we show that the future earnings and future operating cash flows reflected in *OpEff* are positively associated with the stock price and trading volume reactions at quarterly earnings announcements. Relatedly, we show that measures of *OpEff* amplify the relation between firms' current quarter returns and next quarter's earnings. Together, these findings indicate that *OpEff* provides investors with forward-looking information that is helpful in predicting future earnings and future cash flows.

With respect to our third research question—what role does the information content of *OpEff* play in the price discovery process at quarterly earnings announcements—we find that measures of *OpEff* are positively associated with the magnitude of post-earnings-announcement drift and negatively associated with the speed of price discovery at quarterly earnings announcements. These findings are consistent with prior research that documents a positive association between longer *OpEff* and higher future stock returns. However, we find that the less timely incorporation into stock prices of information about operational effectiveness is concentrated in firms that announce bad earnings news. This finding suggests that when reacting to information in earnings announcements, investors focus on the stock price implications of bad earnings news and are slower to react to any concurrent favorable stock price implications of information reflected in operational effectiveness.

In additional analyses, we show that our inferences about the informativeness and price discovery implications of *OpEff* are not driven by any of the three components that form it—that is, inventory management, collection of receivables, and payment to suppliers—alone. Specifically, the associations of *OpEff* with abnormal returns and volume, future earnings and cash flows, and measures of price discovery are not subsumed by any individual *OpEff* component. Hence, *OpEff* acts as a sufficient statistic for a firm's operational effectiveness that contains forward-looking information. Furthermore, we show that our findings are not an artifact of research design choices such as industry classification or sample period such as periods of financial distress.

Our study contributes to related research in several ways. Regarding our first research question, we find that a firm's operational effectiveness as reflected in *OpEff* is informative to investors because a higher *OpEff* predicts higher future operating cash flows as well as future earnings. Moreover, we find that investors react to information reflected in both the current level of and most recent quarterly change in *OpEff* and incorporate this information into stock prices. These findings shed light on how operational effectiveness contributes to the prediction of stock returns documented in Wang (2019).

Regarding our second research question, we find that *OpEff* is positively associated with post-earnings-announcement drift and negatively associated with the speed of price discovery at quarterly earnings announcements. Thus, our findings reveal that stock prices do not reflect in a timely manner forward-looking positive information reflected in *OpEff*. However, these findings largely are attributable to firms that announce bad earnings news, which indicates that investors fail to react fully on a timely basis to the information in operational effectiveness when that information is positive and the firm has negative earnings news. Specifically, we find that the price discovery process is slower when an improvement in *OpEff* coincides with negative earnings news. This finding is new to the literature and suggests that investors tend to focus on negative earnings news and take longer to process positive information regarding operational effectiveness when the earnings announcement contains these conflicting signals about a firm's future prospects.

The article proceeds as follows. Section 2 discusses related research, and Section 3 outlines the research design. Section 4 describes the sample and data and provides descriptive statistics. Sections 5 and 6 present the findings and results of additional analyses. Section 7 summarizes and concludes the study.

2 | Related Research

Our study relates to two strands of literature. The first strand examines whether and to what extent investors react to accounting information and, thus, the extent to which stock prices reflect this information. The second investigates whether fundamental performance measures based on accounting information, such as earnings and cash flows, have predictive power for stock returns.[3]

In relation to the first strand, a vast literature beginning with Ball and Brown (1968) and Beaver (1968) studies the market reaction to accounting information. This literature primarily focuses on unexpected earnings and, to some extent, on other readily available financial statement amounts such as revenues and expenses. This literature consistently finds that investors perceive accounting amounts as reflecting information relevant to their investment decisions as evidenced by abnormal equity price changes and trading volume at the time the information is released (Lev 1989; Kothari 2001; Ertimur et al. 2003). This literature also finds that stock prices do not reflect fully accounting information in a timely manner. Sloan (1996) shows that the stock price reaction to accounting information is incomplete in that investors fail to incorporate fully into prices the information about future earnings that is reflected in current accruals and cash flows. Relatedly, Israeli (2015) finds that investors fail to incorporate fully into stock prices accounting information about fair value-based net income relating to investment properties that are measured for accounting purposes using the cost model. As with *OpEff*, the information necessary to estimate this fair value-based net income is available in financial statements but is not disclosed per se.

Our study contributes to this literature by showing that operational effectiveness is informative to investors. Specifically, we find that both the current level of and most recent quarterly change in the firm's CCC—which we measure using disclosed accounting amounts—are positively associated with abnormal stock price and trading volume at earnings announcements. However, we find that investors do not incorporate fully the information in operational effectiveness in a timely manner, particularly for firms with bad earnings news. These findings suggest that readily available information about operational effectiveness could be helpful to investors and facilitate more informative stock prices.

There also is a vast literature documenting that accounting amounts have predictive ability for fundamental performance measures and for stock returns. Most relevant to our study is research that examines the predictive ability of accounting amounts used to construct *OpEff*, namely, inventory, accounts receivable, accounts payable, sales, and cost of goods sold. For example, Ou and Penman (1989), Ou (1990), and Piotroski (2000) find that many accounting-based ratios and other accounting amounts have predictive ability for future earnings and stock returns. Two of these accounting amounts are used to construct *OpEff*—change in inventory and change in sales. In addition, Ali (1994) shows that working capital from operations has incremental explanatory power for stock returns, and Alan et al. (2014) shows that inventory turnover predicts stock returns. Relatedly, Nissim and Penman (2001, 2003) show that financial statement analysis can help in the prediction of fundamental performance and equity valuation, and Raddatz (2006) shows that effective working capital management reduces the need for external liquidity and enhances the firm's performance and shareholder value creation. Other studies show that the level of a firm's operational effectiveness is positively associated with the firm's contemporaneous and future profitability (Jose et al. 1996; Shin and Soenen 1998; Deloof 2003).[4]

Our study contributes to this literature by showing that forward-looking earnings and cash flow information reflected in measures of operational effectiveness helps explain the price and volume reactions to *OpEff*. Our study also contributes to this literature by assessing whether the predictive ability of accounting amounts used to construct *OpEff* identified in prior research is attributable to particular accounting amounts—such as inventory and sales—or to a construct that includes them as inputs—such as operational effectiveness. We find that it is the latter by showing that *OpEff* has predictive ability incremental to its components. This is important because *OpEff* captures the effectiveness of a firm's operations along its three key dimensions: obtaining credit from suppliers, producing and selling inventory, and providing credit to customers. This finding extends Dechow et al. (1998), which develops a model in which current earnings have greater ability than current cash flows to predict future cash flows. In the model, the superior predictive ability of earnings is increasing in operational effectiveness, measured by CCC.

Moreover, Wang (2019) finds that operational effectiveness can be used to predict future returns on a portfolio that buys (sells) stocks of firms in the shortest (longest) CCC decile that cannot be explained by known factors or equity return predictors. Thus, Wang (2019) concludes that the hedge portfolio returns are associated with mispricing. Our study extends Wang (2019) by identifying a source of return predictability embedded in operational effectiveness.[5] We find that the market does not reflect the information in *OpEff* fully on a timely basis when a positive change in *OpEff* is accompanied by negative earnings news. This finding reveals a channel for the return predictability documented in Wang (2019), namely, a prolonged price discovery process at earnings announcements for firms with bad earnings news and positive news relating to operational effectiveness.

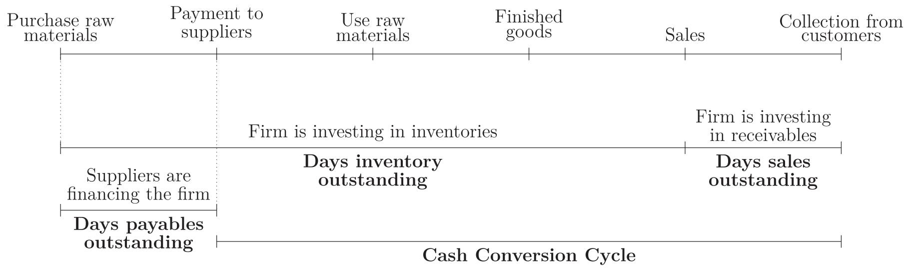

FIGURE 1 | Graphic representation of a firm's cash conversion cycle. This figure presents the cash conversion cycle (CCC) of a firm with a positive cycle. A firm's CCC begins with the purchase of raw materials or inventory, then the firm either produces final inventory or prepares it for sale and sells it. The cycle finishes with collection of cash from sales. CCC is the sum of days inventory outstanding and days receivable outstanding minus days payable outstanding. All variables and components of the cash conversion cycle are defined in the Appendix.

3 | Research Design

3.1 | Measuring Operational Effectiveness

We measure a firm's operational effectiveness, *OpEff*, using the CCC. Because shorter CCCs reflect better operational effectiveness, in measuring *OpEff*, we multiply CCC by −1 so that higher values of *OpEff* reflect better operational effectiveness. Textbooks often identify CCC as a proxy for how effectively the firm manages its operations (Hanlon et al. 2020; Libby et al. 2021) and present it, or its components, as an input for some equity valuation models (Nissim 2024). CCC is the number of days it takes a firm to convert \$1 invested in inventory into \$1 collected from sales. Hence, a shorter CCC indicates faster generation of cash from the firm's operating activities. Figure 1 presents the timeline of events in the definition of CCC. The figure reveals that the cycle starts when the firm invests in inventory, continues with payments to suppliers and sales of finished goods, and ends when sales on credit are collected.[6]

CCC typically is calculated as the sum of days inventory outstanding and days sales outstanding minus days payable outstanding (Richards and Laughlin 1980):

$$CCC_{i,t} = DIO_{i,t} + DSO_{i,t} - DPO_{i,t},$$

where DIO is days inventory outstanding, $DIO_t = 90 \times \frac{(INV_{t-1} + INV_t)/2}{COGS_t}$, DSO is days sales outstanding, $DSO_t = 90 \times \frac{(AR_{t-1} + AR_t)/2}{SALES_t}$, and DPO is days payable outstanding, $DPO_t = 90 \times \frac{(AP_{t-1} + AP_t)/2}{COGS_t}$.[7] INV, $COGS$, AR, $SALES$, and AP denote inventory, cost of goods sold, accounts receivable, sales, and accounts payable.[8] i and t denote firms and quarters. We multiply CCC by 90 to reflect the number of days during the quarter.

Firms in different industries are likely to have different levels of CCC. For example, firms in the communication industry are likely to have a much shorter CCC than firms in the construction industry. To mitigate the possibility of industry heterogeneity affecting our inferences, we follow Wang (2019) and focus on a firm's industry-adjusted CCC. Specifically, we assign firms to Fama and French (1997) 48-industries and subtract from a firm's CCC the median CCC of the firm's industry, where the median CCC is based on CCC values from the previous quarter.[9]

Thus, we calculate a firm's CCC as follows:[10]

$$OpEff_{i,t} = -1 \times \left(CCC_{i,t} - CCC^{IndMed}_{j,t-1} \right) / 100$$

where $CCC_{i,t}$ is the cash conversion cycle of firm i during quarter t and $CCC^{j,t-1}_{IndMed}$ is the median cash conversion cycle in quarter $t-1$ of industry j to which firm i belongs. For ease of exposition, we scale the negative difference between $CCC_{i,t}$ and $CCC^{j,t-1}_{IndMed}$ by 100.

In addition to the level of *OpEff*, we also consider the change in *OpEff* from the prior quarter to the current quarter, $\Delta OpEff_{i,t}$, as our proxy for the quarterly change in a firm's operational effectiveness (Lee 2012):

$$\Delta OpEff_{i,t} = -1 \times \left(\Delta CCC_{i,t} - \Delta CCC^{IndMed}_{j,t-1} \right) / 100$$

where $\Delta CCC_{i,t}$ ($\Delta CCC^{j,t-1}_{IndMed}$) is the change from quarter $t-1$ to quarter t in CCC of firm i (in the median CCC of industry j to which firm i belongs).

Investors can calculate *OpEff* from information disclosed in the firm's quarterly earnings announcement—namely, sales and cost of goods sold for the quarter and inventory, accounts receivable, and accounts payable at the end of the quarter, together with these three amounts at the end of the previous quarter. For example, Bassett's (NASDAQ: BSET) January 21, 2021 earnings announcement—for its quarter ended November 28, 2020—reveals that its CCC is 79 days.[11] This number indicates that Bassett takes, on average, 79 days to convert \$1 of investment in inventory into \$1 of cash collected from customers. Bassett belongs to the consumer goods industry, which had a median CCC of 98 days in the previous quarter, that is, the quarter ended August 29, 2020. Hence, Bassett's *OpEff* is $0.19 = -1 \times (79 - 90)/100$, which means that Bassett's operations are more effective than those of the median firm in its industry.

For most firms, the raw—that is, not industry-adjusted—CCC is positive. However, for some firms, it is negative. Negative CCC occurs when the firm collects cash from sales before it pays suppliers. For example, Apple Inc's (NASDAQ: AAPL) January 27, 2021 earnings announcement for its quarter ended December 26, 2020 reveals that its CCC is −26 days, which means that Apple collects cash from sales on average 26 days before it pays its suppliers.[12] Apple is in the electronic equipment industry, and the median CCC in this industry in the previous quarter—that is, the quarter ended September 26, 2020—was 94 days. Thus, Apple's *OpEff* is $1.20 = -1 \times (-26 - 94)/100$, which indicates that Apple's operations are substantially more effective than other firms in its industry.

These two examples emphasize the differences in *OpEff* between firms and industries. For Bassett, the main driver of *OpEff* is days inventory outstanding, which is typical for firms with such large physical inventories. This may imply that Bassett has higher inventory costs. For Apple, the main driver of *OpEff* is days payable outstanding, which is not surprising for an industry leader with strong bargaining power over its suppliers. These longer days payable outstanding can imply that Apple carries higher supplier financing costs and risks. To address these differences between firms and industries, and to ensure our inferences are not affected by them, we disaggregate *OpEff* into its components and examine each component separately. The findings are presented in Section 6.1.

3.2 | Informativeness of Operational Effectiveness

To address whether and why firms' operational effectiveness is informative to investors, we proceed in two steps. First, we determine whether investors react to information reflected in *OpEff*. We do so by testing whether the current level of, or most recent quarterly change in, *OpEff* is associated with abnormal stock returns and trading volume at quarterly earnings announcements. Next, we test whether the channel through which *OpEff* is informative to investors is its association with future earnings and operating cash flows, and whether the future earnings and operating cash flows associated with *OpEff* help explain the abnormal returns and trading volume at earnings announcements.

3.2.1 | Price and Volume Reactions at Earnings Announcements

To test whether the information reflected in *OpEff* is associated with abnormal price or trading volume reactions to earnings announcements, we estimate several versions of the following equation:

$$REACT_{i,t} = \beta_1 OpEff_{i,t} + \sum\nolimits_k \beta_k Controls_{i,t} + \gamma_j + \delta_t + U_{i,t} \quad \text{(1a)}$$

where *REACT* is *CAR*[−1, 1] or *ATVol*. *CAR*[−1, 1] is the firm's cumulative abnormal equity return during days [−1, 1] relative to the quarter's earnings announcement. It is the firm's raw return minus the value-weighted return for a portfolio of firms matched on 5 × 5 sorts of equity market value and market-to-book ratio (Daniel et al. 1997). *ATVol*, abnormal trading volume, is the natural logarithm of one plus the share turnover ratio during days [−1, 1], scaled by the average daily turnover ratio during days [−54, −52] relative to the quarter's earnings announcement (Israeli, Kaniel, and Sridharan 2022). If operational effectiveness provides incremental information to investors, we expect β_1 in Equation (1a) is positive.

Controls includes several variables that prior research suggests are associated with the market reaction to earnings announcements (Israeli, Kasznik, and Sridharan 2022; Berkovitch et al. 2024; Berkovitch et al. 2025). These are standardized unexpected earnings, *SUE* (Bernard and Thomas 1989);[13] return on equity, *ROE* (Fama and French 2006); an indicator variable for whether a firm reports a loss, *Loss* (Hayn 1995); operating accruals, *OAcc* (Sloan 1996); institutional ownership, *InstOwn* (Bartov et al. 2000); analyst following, *Analyst* (Lang and Lundholm 1996); the natural logarithm of equity market value, *Size* (Fama and French, 1993); the natural logarithm of equity book-to-market ratio, *BTM*; and return momentum, *Mom* (Jegadeesh and Titman 1993). γ and δ denote industry and year-quarter fixed effects. We include these fixed effects as controls for time-invariant industry characteristics and time-varying economic conditions that could be associated with operational effectiveness and result in variation in investor reactions to information in earnings announcements.[14] We base our inferences from Equation (1a) and all other equations that follow on standard errors clustered by firm and year-quarter.

To determine whether the association between operational effectiveness and the market reaction to information in quarterly earnings announcements relates to the most recent quarterly change in *OpEff* rather than its level, we disaggregate *OpEff* into the change in *OpEff* during the quarter, $\Delta OpEff_{i,t}$, and the level of *OpEff* in quarter $t-1$, $OpEff_{i,t-1}$. This yields the following equation:

$$REACT_{i,t} = \beta_1 \Delta OpEff_{i,t} + \beta_2 OpEff_{i,t-1} + \sum\nolimits_k \beta_k Controls_{i,t} + \gamma_j + \delta_t + U_{i,t} \quad \text{(1b)}$$

If the most recent quarterly change in *OpEff* provides incremental information that engenders a positive market reaction, we expect β_1 in Equation (1b) is positive.

3.2.2 | Is OpEff Associated With Future Earnings and Operating Cash Flows?

To provide insights into why operational effectiveness has information content for investors, we proceed in two steps. First, we determine whether operational effectiveness is positively associated with future earnings and future operating cash flows. We expect these associations are positive because we expect that greater operational effectiveness is associated with higher future earnings and operating cash flows. Second, we test the prediction that the forward-looking information reflected in operational effectiveness is positively related to the stock price and trading volume reactions to quarterly earnings announcements.

Specifically, we implement a two-stage least squares (2SLS) approach. In the first stage, we estimate the relation between next quarter's earnings or operating cash flows and the current quarter's level of *OpEff*—in Equation (2a)—or most recent quarterly change in *OpEff*—in Equation (2b):

$$FuturePerf_{i,t+1} = \beta_1 OpEff_{i,t} + \gamma_i + \delta_t + U_{i,t} \quad \text{(2a)}$$

$$FuturePerf_{i,t+1} = \beta_1 \Delta OpEff_{i,t} + \beta_2 OpEff_{i,t-1} + \gamma_j + \delta_t + U_{i,t} \quad \text{(2b)}$$

FuturePerf is earnings before extraordinary items, *EARN*, or cash flows from operating activities, *CFO*, scaled by market value of equity at the end of the quarter.

In the second stage, we use the fitted values from Equations (2a) and (2b) as replacements for *OpEff* in Equation (1a) and for $\Delta OpEff_{i,t}$ and $OpEff_{i,t-1}$ in Equation (1b). These fitted values capture the information about future earnings and future operating cash flows that is reflected in *OpEff* and Δ*OpEff*. Significantly positive coefficients on the fitted values in the second stage indicate that the information reflected in *OpEff* about future earnings and operating cash flows is reflected in returns and trading volume at quarterly earnings announcements. This indicates that operational effectiveness is a channel through which investors obtain this forward-looking information. Following Chen et al. (2023), we use bootstrapping to adjust the second-stage standard errors for the first-stage estimation.

To provide additional evidence on the predictive ability of *OpEff* for future earnings—that is, to address further the question of why *OpEff* is informative to investors—we follow prior research that uses future earnings response coefficients (FERC) as a measure of the extent to which current stock returns reflect future firm earnings (Lundholm and Myers 2002; Ettredge et al. 2005; Choi et al. 2011; Israeli et al. 2017). Specifically, we estimate the following equations:

$$\begin{aligned} RET_{i,t} = {} & \beta_1 EARN_{i,t+1} + \beta_2 \Delta EARN_{i,t} + \beta_3 OpEff_{i,t} \\ & + \beta_4 OpEff_{i,t} \times EARN_{i,t+1} + \beta_5 OpEff_{i,t} \times \Delta EARN_{i,t} \\ & + \sum\nolimits_k \beta_k Controls_{i,t} + \gamma_j + \delta_t + U_{i,t} \end{aligned} \tag{3a}$$

$$\begin{aligned} RET_{i,t} = {} & \beta_1 EARN_{i,t+1} + \beta_2 \Delta EARN_{i,t} + \beta_3 \Delta OpEff_{i,t} \\ & + \beta_4 OpEff_{i,t-1}\ \beta_5 \Delta OpEff_{i,t} \times EARN_{i,t+1} + \beta_6 \Delta OpEff_{i,t} \\ & \times \Delta EARN_{i,t} + \beta_7 OpEff_{i,t-1} \times EARN_{i,t+1} + \beta_8 OpEff_{i,t-1} \\ & \times \Delta EARN_{i,t} + \sum\nolimits_k \beta_k Controls_{i,t} + \gamma_j + \delta_t + U_{i,t} \end{aligned} \tag{3b}$$

RET is stock return for quarter t, beginning the last month of quarter t and ending 2 months after quarter t ends.[15] We include as explanatory variables *OpEff* and the lagged level and current quarterly change in *OpEff* as well as the interaction between them and past, current, and future earnings. *Controls* includes variables that prior research finds are determinants of returns associated with earnings and operational effectiveness (Ettredge et al. 2005; Israeli et al. 2017), namely, RET_{t+1}, *InstOwn*, *ATGROWTH*, *Loss*, and *Size*.[16]

If operational effectiveness contains information about future earnings, we expect that the coefficients on the interactions of *OpEff* or Δ*OpEff* with current and future earnings are positive. Such a finding would indicate that FERCs are higher for firms with higher *OpEff*. Thus, if *OpEff* reflects information about future earnings, we expect β_4 and β_5 in Equation (3a) and β_7 and β_8 in Equation (3b) are positive.

3.3 | What Is the Role of Information About Operational Effectiveness in Price Discovery?

To investigate the role of operational effectiveness, as reflected in the CCC, in the price discovery process at earnings announcements, we test how *OpEff* relates to post-earnings-announcement drift and to measures of timeliness and effectiveness with which information in quarterly earnings announcements is incorporated into stock prices.

3.3.1 | Is OpEff Associated With Post-Earnings-Announcement Drift?

To test whether operational effectiveness helps explain post-earnings-announcement drift, we estimate several versions of the following equations:

$$\begin{aligned} CAR[2,61]_{i,t} = {} & \beta_1 CAR[-1,1]_{i,t} + \beta_2 OpEff_{i,t} + \beta_3 OpEff_{i,t} \\ & \times CAR[-1,1]_{i,t} + \sum\nolimits_k \beta_k Controls_{i,t} + \gamma_j + \delta_t + U_{i,t} \end{aligned} \tag{4a}$$

$$\begin{aligned} CAR[2,61]_{i,t} = {} & \beta_1 CAR[-1,1]_{i,t} + \beta_2 \Delta OpEff_{i,t} + \beta_3 OpEff_{i,t-1} \\ & + \beta_4 \Delta OpEff_{i,t} \times CAR[-1,1]_{i,t} + \beta_5 OpEff_{i,t-1} \\ & \times CAR[-1,1]_{i,t} + \sum\nolimits_k \beta_k Controls_{i,t} + \gamma_j + \delta_t + U_{i,t} \end{aligned} \tag{4b}$$

$CAR[2,61]$ is the abnormal stock return during trading days [2, 61] relative to the quarter's earnings announcement day 0, calculated following Daniel et al. (1997). *Controls* comprises *CAR*[−1, 1] as well as the control variables included in Equations (1a) and (1b)—*AbsSUE*, *ROE*, *Loss*, *OAcc*, *InstOwn*, *Analyst*, *Size*, *BTM*, and *Mom*—as controls for the return reaction to information at quarterly earnings announcements.

Equations (4a) and (4b) include as additional explanatory variables *CAR*[−1, 1] and *CAR*[−1, 1] interacted with measures of operational effectiveness. If the information reflected in *OpEff* is associated with higher post-earnings-announcement drift, we expect β_3 in Equation (4a) and β_4 in Equation (4b) are positive.

3.3.2 | Do Stock Prices Timely Reflect Information About Operational Effectiveness?

To test whether stock prices reflect information in *OpEff* in a timely manner, we examine the association between *OpEff* and measures of the speed of price discovery at quarterly earnings announcements by estimating several versions of the following equations:

$$IPX_{i,t} = \beta_1 OpEff_{i,t} + \sum\nolimits_k \beta_k Controls_{i,t} + \gamma_j + \delta_t + U_{i,t} \tag{5a}$$

$$IPX_{i,t} = \beta_1 \Delta OpEff_{i,t} + \beta_2 OpEff_{i,t-1} + \sum\nolimits_k \beta_k Controls_{i,t} + \gamma_j + \delta_t + U_{i,t} \tag{5b}$$

IPX denotes either intraperiod timeliness, *IPT*, or intraperiod efficiency, *IPE*. $Controls_{i,t}$ in Equations (5a) and (5b) comprise the same variables as in Equations (4a) and (4b).

Following prior research (Blankespoor et al. 2018; Israeli, Kasznik, and Sridharan 2022; Berkovitch et al. 2023), we measure IPT as

$$IPT_{i,t} = \sum\nolimits_{d=0}^{5} \frac{CAR_{i,t}[0,d]}{CAR_{i,t}[0,5]} + 0.5,$$

where $CAR[0, j]$ is the cumulative abnormal return for firm i from day 0 through day d, relative to quarter t's earnings announcement. Each $[0, d]$ return is scaled by the total cumulative return for the $[0, 5]$ day period. This "area under the curve" approach reveals the speed with which information is impounded into equity prices. We measure *IPE* as

$$IPE_{i,t} = 1 - \sum_{d=0}^{5} \frac{\left|CAR_{i,t}[0,5] - CAR_{i,t}[0,d]\right|}{\left|CAR_{i,t}[0,5]\right|}.$$

We use both *IPT* and *IPE* because prior research suggests that *IPT* does not account for possible overreactions and reversals during the measurement window (Thomas and Zhang 2008). Unlike *IPT*, *IPE* penalizes overreactions and reversals, such that only a price response that reaches its cumulative day 5 value on day 1 has *IPE* = 1. As before, our tests use the current level of *OpEff* in Equation (5a) and most recent quarterly change in *OpEff* in Equation (5b).

If a firm's level of operational effectiveness, as measured by *OpEff*, is informative to investors but investors fail to incorporate fully the information in *OpEff* into stock prices at the earnings announcement, we expect β_1 in Equation (5a) is negative. If the recent quarterly change in *OpEff* provides incremental information to the market and investors fail to incorporate it fully into stock prices at earnings announcements, we expect β_1 in Equation (5b) is negative.

4 | Sample, Data, and Descriptive Statistics

4.1 | Sample and Data

Our sample comprises quarterly observations of firms with common equity shares listed on NYSE, AMEX, and NASDAQ from October 1987 to March 2022.[17] We begin our sample in the fourth calendar quarter of 1987 because this is the first quarter in which cash flow data are available for a large sample of firms (Barth et al. 2016). We obtain financial statement data from Compustat, stock market data from CRSP, analyst coverage information from *I/B/E/S*, and institutional ownership data from Thomson Reuters.

We exclude from our sample financial firms, that is, SIC code = 6, because days inventory outstanding, *DIO*, days sales outstanding, *DSO*, and days payable outstanding, *DPO*, are not meaningful for such firms. We exclude observations with negative equity book value.[18] We also exclude observations with the end-of-quarter share price below $1 to avoid distortions associated with penny stocks and with cost of goods sold or sales less than $10 million because these variables serve as deflators for components of CCC. In addition, to mitigate measurement error concerns when computing IPT and IPE, we exclude observations for which *CAR*[0, 5] is less than 2% (Blankespoor et al. 2018; Israeli, Kasznik, and Sridharan 2022). These criteria yield a sample of 119,143 quarterly observations for 4,752 firms. To reduce the potential effect of outliers on our inferences, we winsorize all continuous variables at the 1st and 99th percentiles of their distributions.[19]

4.2 | Descriptive Statistics

Table 1 presents descriptive statistics for the variables we use in our main analyses. Panel A (Panel B) presents distributional statistics (Pearson and Spearman correlations). Panel A reveals that the mean of *OpEff* is −0.7, which indicates that a firm is, on average, less effective in its operations by 6.5 days relative to the median operational effectiveness of firms in its industry. The standard deviation as well as the 25th, 50th, and 75th percentiles of *OpEff* reveal substantial variation in operational effectiveness among sample firms, with *OpEff* of a firm in the 25th (75th) percentile being 29 (26) days less (more) effective than the median value of operational effectiveness of a firm's industry. On average, ΔOpEff is −0.001, which indicates that, on average, the change in a firm's operational effectiveness from one quarter to the next is similar to the change in the median value of operational effectiveness of the firm's industry.

Panel A also reveals that during the earnings announcement window, that is, days [−1, 1], firms experience an average abnormal stock return of 0.56% (mean *CAR*[−1, 1] = 0.56) and trading volume that is twice the level during days [−54, −5] (mean *ATVol* = 2.00). In addition, on average, firms in our sample are profitable (mean *ROE* = 2%) with only 21% reporting losses (mean *Loss* = 0.21), have 60% institutional ownership (mean *InstOwn* = 0.60), and are followed by more than seven analysts (*Analyst* = 1.71, that is, mean of number of analysts following a firm is 7.13).

Panel B of Table 1 reveals that, consistent with information about operational effectiveness as reflected in *OpEff* being informative to investors, *OpEff* and Δ*OpEff* are positively correlated with both abnormal returns and abnormal trading volume at quarterly earnings announcements. The Pearson (Spearman) correlations of *OpEff* and Δ*OpEff* with *CAR*[−1, 1] are 0.02 and 0.07 (0.02 and 0.09), and of *OpEff* and Δ*OpEff* with *ATVol* are 0.01 and 0.02 (0.03 and 0.02).

Consistent with Wang (2019), untabulated statistics reveal that *OpEff*, Δ*OpEff*, and their three components—*DIO*, *DSO*, and *DPO*—exhibit considerable variation within industries and across quarters. In particular, the statistics reveal that the mean firm-by-firm AR(1) coefficient for *OpEff* is 0.64 and for Δ*OpEff* is − 0.14.[20] These statistics suggest that measures of operational effectiveness—especially quarterly changes in *OpEff*—exhibit moderate, not high, persistence. Thus, both the current level of, and most recent quarterly change in, *OpEff* change over time for a given firm.

5 | Findings

5.1 | Information Content of Operational Effectiveness

5.1.1 | Market Reaction to Information About Operational Effectiveness

Table 2 presents summary statistics from estimating Equations (1a) and (1b). Panel A presents summary statistics from estimating the equations when *CAR*[−1, 1] is the dependent

TABLE 1 | Descriptive statistics.

Panel A: Distributional statistics

	Mean	Standard Deviation	25th percentile	Median	75th percentile
OpEff	−0.07	0.63	−0.29	0.00	0.26
$\Delta OpEff$	−0.001	0.24	−0.06	0.00	0.06
$CAR[-1,1]$	0.56	10.26	−5.02	0.30	5.84
ATVol	2.00	1.50	1.09	1.62	2.41
SUE	0.03	0.07	0.003	0.01	0.02
ROE	0.02	0.07	0.005	0.02	0.04
Loss	0.21	0.41	0	0	0
OAcc	−0.01	0.04	−0.03	−0.01	0.004
InstOwn	0.60	0.27	0.40	0.65	0.83
Analyst	1.71	0.94	1.10	1.79	2.40
Size	6.62	1.91	5.25	6.53	7.90
BTM	−0.70	0.77	−1.17	−0.66	−0.19
Mom	0.08	0.35	−0.13	0.05	0.24

Panel B: Correlations

	OpEff	$\Delta OpEff$	$CAR[-1,1]$	*ATVol*	*SUE*	*ROE*	*Loss*	*OAcc*	*InstOwn*	*Analysts*	*Size*	*BTM*	*Mom*
OpEff		0.20	0.02	0.01	0.03	0.05	−0.04	−0.06	0.02	0.10	0.07	−0.12	0.05
$\Delta OpEff$	0.12		0.07	0.02	0.02	0.07	−0.06	−0.06	0.00	0.00	0.00	0.00	0.02
$CAR[-1,1]$	0.02	0.09		0.03	0.09	0.11	−0.12	−0.02	0.00	−0.02	−0.02	0.03	0.00
ATVol	0.03	0.02	0.03		0.05	0.06	−0.05	0.01	0.02	0.00	−0.03	−0.02	0.03
SUE	0.05	0.05	0.20	0.09		0.38	−0.23	0.22	0.00	−0.02	0.01	−0.09	0.15
ROE	0.10	0.09	0.15	0.12	0.38		−0.65	0.33	0.09	0.10	0.15	−0.22	0.17
Loss	−0.03	−0.05	−0.12	−0.07	−0.32	−0.70		−0.24	−0.07	−0.08	−0.10	0.22	−0.15
OAcc	−0.08	−0.12	−0.03	0.00	0.15	0.20	−0.22		−0.01	−0.04	0.00	−0.05	0.08
InstOwn	0.03	0.00	0.01	0.16	−0.01	0.08	−0.07	−0.02		0.54	0.13	−0.26	0.01
Analysts	0.12	0.00	0.00	0.15	−0.04	0.16	−0.08	−0.05	0.51		0.41	−0.37	−0.02
Size	0.12	0.00	−0.01	0.12	0.00	0.28	−0.19	0.00	0.54	0.79		−0.20	0.02
BTM	−0.14	0.00	0.01	−0.13	−0.07	−0.43	0.18	−0.03	−0.25	−0.40	−0.52		−0.26
Mom	0.05	0.01	0.01	0.05	0.24	0.23	−0.18	0.08	0.05	0.01	0.13	−0.29	

Note: This table presents descriptive statistics for the variables underlying our analyses. Panel A presents distributional statistics and Panel B presents Pearson (Spearman) correlations above (below) the diagonal. The sample comprises 119,143 quarterly earnings announcements by 4,752 firms from the fourth calendar quarter of 1987 to the first calendar quarter of 2022. See the Appendix for definitions of all variables.

TABLE 2 | Informativeness of operational effectiveness.

Panel A: Operational effectiveness and earnings announcement returns

	$CAR[-1,1]$			
	(1)	**(2)**	**(3)**	**(4)**
$OpEff_t$	0.38***	0.38***		
	(6.65)	(6.25)		
$\Delta OpEff_t$			2.49***	1.98***
			(14.32)	(11.50)
$OpEff_{t-1}$			0.19***	0.24***
			(3.29)	(3.92)
SUE	12.45***	9.06***	12.37***	9.10***
	(18.08)	(13.63)	(18.06)	(13.68)
ROE		11.70***		11.20***
		(13.29)		(12.65)
Loss		−2.27***		−2.23***
		(−17.53)		(−17.48)
OAcc		−18.38***		−17.60***
		(−12.07)		(−11.64)
InstOwn		0.14		0.12
		(0.82)		(0.75)
Analyst		0.21**		0.22**
		(2.55)		(2.56)
Size		−0.35***		−0.34***
		(−7.69)		(−7.57)
BTM		2.17***		2.10***
		(9.33)		(9.03)
Mom		−0.45***		−0.45***
		(−2.97)		(−2.99)
Industry FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	119,143	119,143	119,143	119,143
Adjusted R^2	0.01	0.03	0.02	0.04

Panel B: Operational effectiveness and abnormal trading volume at earnings announcements

	ATVol			
	(1)	**(2)**	**(3)**	**(4)**
$OpEff_t$	0.03***	0.02*		
	(2.73)	(1.96)		
$\Delta OpEff_t$			0.14***	0.10***
			(7.04)	(4.93)
$OpEff_{t-1}$			0.02*	0.01
			(1.66)	(1.22)
AbsSUE	0.23**	0.62***	0.23**	0.61***
	(2.36)	(6.74)	(2.34)	(6.72)
ROE		1.50***		1.47***
		(10.85)		(10.75)

(Continues)

Panel B: Operational effectiveness and abnormal trading volume at earnings announcements

	ATVol			
	(1)	**(2)**	**(3)**	**(4)**
Loss		−0.13***		−0.12***
		(−6.96)		(−6.84)
OAcc		−0.43**		−0.39**
		(−2.59)		(−2.39)
InstOwn		−0.06*		−0.06*
		(−1.69)		(−1.71)
Analyst		0.17***		0.17***
		(10.57)		(10.59)
Size		−0.13***		−0.13***
		(−17.99)		(−17.95)
BTM		−0.13***		−0.13***
		(−3.79)		(−3.90)
Mom		0.10***		0.10***
		(5.62)		(5.61)
Industry FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	119,143	119,143	119,143	119,143
Adjusted R^2	0.05	0.06	0.05	0.06

Note: This table presents regression summary statistics from estimating Equations (1a) and (1b). Panel A presents results showing the association between current *OpEff* and its lagged level and recent quarterly change in *OpEff* and returns at earnings announcements, *CAR* [−1, 1]. Panel B presents results using abnormal trading volume, *ATVol*. Industry fixed effects are based on the Fama and French (1997) 48-industry classification. *t*-statistics based on standard errors clustered by firm and year-quarter appear in parentheses. *, **, *** indicate significance at 10%, 5%, and 1%. The sample comprises 119,143 quarterly earnings announcements by 4,752 firms from the fourth calendar quarter of 1987 to the first calendar quarter of 2022. See the Appendix for definitions of all variables.

variable. Columns (1) and (3) present results from estimating a baseline version of each equation, in which we include *SUE* as the only control variable. These columns reveal that the current level of, and most recent quarterly change in, *OpEff* are positively associated with abnormal returns at earnings announcements (coefs. = 0.38 and 2.49; *t*-stats. = 6.65 and 14.32) even when we include a reduced set of control variables. Columns (2) and (4) present summary statistics from estimating the fully specified versions of the equations. Consistent with Columns (1) and (3), we find significantly positive associations between abnormal returns and the current level of, and most recent quarterly change in, *OpEff* (coefs. = 0.38 and 1.98; *t*-stats. = 6.25 and 11.50). These coefficients imply that a one standard deviation higher current level of (most recent quarterly change in) *OpEff* is associated with a 0.24% (0.51%) higher 3-day earnings announcement return.[21]

Table 2, Panel B, presents summary statistics from estimating Equations (1a) and (1b) when *ATVol* is the dependent variable. As with Panel A, Columns (1) and (3) (Columns (2) and (4)) present summary statistics of estimating baseline (full) versions of the equations using only *SUE* as a control variable (full set of control variables). Columns (2) and (4) reveal inferences similar to those relating to *CAR*[−1, 1]. In particular, the current level of, and most recent quarterly change in, *OpEff* are significantly positively associated with abnormal trading volume (coefs. = 0.02 and 0.10; *t*-stats. = 1.96 and 4.93). These coefficients imply that a one standard deviation higher current level of (most recent quarterly change in) *OpEff* is associated with a 1.27% (2.57%) higher 3-day earnings announcement abnormal trading volume.[22]

Together, the findings in Table 2 support the inference that operational effectiveness is informative to investors.[23,24]

5.1.2 | Measures of Operational Effectiveness and Forward-Looking Information About Earnings and Operating Cash Flows

Table 3, Panels A and B, presents summary statistics from our two-stage tests of whether operational effectiveness reflects information about future earnings, $EARN_{t+1}$, and future operating cash flows, CFO_{t+1}. In each panel, Columns (1) and (4) present summary statistics from estimating the first-stage Equations (2a) and (2b). Columns (2) and (5) (Columns (3) and (6)) present the corresponding statistics from the second-stage versions of Equations (1a) and (1b) when *CAR*[−1, 1] (*ATVol*) is the dependent variable.

Panel A, Columns (1) and (4), reveals, as expected, that the current level of, and most recent quarterly change in, *OpEff*

TABLE 3 | Informativeness channel.

Panel A: Future earnings

	$EARN_{t+1}$ (1)	$CAR[-1,1]$ (2)	$ATVol$ (3)	$EARN_{t+1}$ (4)	$CAR[-1,1]$ (5)	$ATVol$ (6)
$OpEff_t$	0.001***					
	(8.34)					
$\Delta OpEff_t$				0.004***		
				(12.27)		
$OpEff_{t-1}$				0.001***		
				(5.99)		
$\widehat{EARN}_{t+1\text{Levels}}$		3.19***	0.20*			
		(5.97)	(1.96)			
$\widehat{EARN}_{t+1\text{Changes}}$					4.58***	0.23***
					(12.75)	(4.67)
Controls	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes
Year-Quarter FE	No	Yes	Yes	No	Yes	Yes
Observations	119,143	119,143	119,143	119,143	119,143	119,143
Adjusted R^2	0.001	0.03	0.06	0.001	0.04	0.06

Panel B: Future cash flows from operations

	CFO_{t+1} (1)	$CAR[-1,1]$ (2)	$ATVol$ (3)	CFO_{t+1} (4)	$CAR[-1,1]$ (5)	$ATVol$ (6)
$OpEff_t$	0.004***					
	(21.88)					
$\Delta OpEff_t$				0.01***		
				(13.57)		
$OpEff_{t-1}$				0.004***		
				(20.18)		
$\widehat{CFO}_{t+1\text{Levels}}$		0.90***	0.06*			
		(5.97)	(1.96)			
$\widehat{CFO}_{t+1\text{Changes}}$					1.30***	0.07***
					(8.65)	(2.75)
Controls	No	Yes	Yes	No	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes
Year-Quarter FE	No	Yes	Yes	No	Yes	Yes
Observations	119,143	119,143	119,143	119,143	119,143	119,143
Adjusted R^2	0.004	0.03	0.06	0.004	0.03	0.06

Note: This table presents summary statistics from estimating a two-stage least squares approach. The first stage estimates versions of Equations (2a) and (2b) that specify the relation between operating effectiveness and future performance. Operating effectiveness is $OpEff_t$ ($\Delta OpEff_t$ and $OpEff_{t-1}$) in Equation (2a) (Equation (2b)). Future firm performance is next quarter's earnings, $EARN_{t+1}$, or cash flow from operations, CFO_{t+1}. These versions differ from Equations (2a) and (2b) in that they do not include industry or year-quarter fixed effects or any of the other control variables in Equations (2a) and (2b). The second stage estimates Equations (2a) and (2b) with the fitted values from the corresponding first-stage equation in place of $OpEff_t$ ($\Delta OpEff_t$ and $OpEff_{t-1}$) in Equation (2a) (Equation (2b)). Panel A (Panel B) presents the first- and second-stage estimates when $EARN_{t+1}$ (CFO_{t+1}) is the measure of future firm performance. Industry fixed effects are based on the Fama and French (1997) 48-industry classification. t-statistics based on standard errors clustered by firm and year-quarter appear in parentheses. *, **, *** indicate significance at 10%, 5%, and 1%. The sample comprises 119,143 quarterly earnings announcements by 4,752 firms from the fourth calendar quarter of 1987 to the first calendar quarter of 2022. See the Appendix for definitions of all variables.

are significantly positively associated with future earnings (t-stats. = 8.34 and 12.27). Columns (2) and (3) (Columns (5) and (6)) reveal, as expected, that *OpEff* is a channel through which investors obtain information about future earnings that is evident in price changes and abnormal trading volume at earnings announcements. In particular, the fitted values from the first-stage estimations are significantly positively associated with $CAR[-1, 1]$ and *ATVol* (t-stats. range from 1.96 to 12.75).

Panel B presents analogous statistics when future cash flow from operations, CFO_{t+1}, is the dependent variable. Columns (1) and (4) reveal, as expected, that the current level of, and most recent quarterly change in, *OpEff* are significantly positively associated with future operating cash flows (t-stats. = 21.88 and 13.57). Columns (2) and (3) (Columns (5) and (6)) reveal, as expected, that *OpEff* also is a channel through which investors obtain information about future operating cash flows that is evident in price changes and abnormal trading volume at earnings announcements. In particular, the fitted values from the first-stage estimations are significantly positively associated with $CAR[-1, 1]$ and *ATVol* (t-stats. range from 1.96 to 8.65).

Table 4 presents summary statistics from estimating Equations (3a) and (3b). The table reveals that the coefficients on $OpEff \times EARN_{t+1}$ and $\Delta OpEff \times EARN_{t+1}$ are significantly positive (t-stats. = 2.28 and 2.24). These findings reveal that the association between next quarter's earnings and current quarter returns is stronger for firms with better operational effectiveness. This evidence reinforces the Table 2 findings that operational effectiveness is positively associated with price and trading volume reactions at quarterly earnings announcements, and the Table 3 findings that these reactions are associated with information reflected in *OpEff* about future earnings and future cash flow from operations.

Together, the findings in Tables 3 and 4 support the inference that operational effectiveness contains forward-looking information that, at least partially, is impounded into stock prices.[25]

TABLE 4 | Operational effectiveness and the relation between current returns and future earnings.

	RET_t	
	(1)	**(2)**
$OpEff_t \times EARN_{t+1}$	0.18**	
	(2.28)	
$OpEff_t \times \Delta EARN_t$	4.35	
	(0.91)	
$\Delta OpEff_t \times EARN_{t+1}$		0.33**
		(2.24)
$\Delta OpEff_t \times \Delta EARN_t$		−5.14
		(−0.76)
$OpEff_{t-1} \times EARN_{t+1}$		0.18**
		(2.29)
$OpEff_{t-1} \times \Delta EARN_t$		8.42
		(1.61)
$OpEff_t$	0.01***	
	(5.83)	
$\Delta OpEff_t$		0.04***
		(9.31)
$OpEff_{t-1}$		0.01***
		(3.77)
$\Delta EARN_t$	20.78***	19.90***
	(6.62)	(6.32)
$EARN_{t+1}$	1.51***	1.51***
	(16.65)	(16.66)
Controls	Yes	Yes
Industry FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Observations	108,753	108,753
Adjusted R^2	0.18	0.18

Note: This table presents summary statistics from estimating Equations (3a) and (3b). Panel A presents statistics using lagged, current, and future levels of earnings. Panel B presents statistics using the recent change in earnings and the future level of earnings. Industry fixed effects are based on the Fama and French (1997) 48-industry classification. t-statistics based on standard errors clustered by firm and year-quarter appear in parentheses. *, **, *** indicate significance at 10%, 5%, and 1%. The sample comprises 119,143 quarterly earnings announcements by 4,752 firms from the fourth calendar quarter of 1987 to the first calendar quarter of 2022. See the Appendix for definitions of all variables.

5.2 | Operational Effectiveness and Price Discovery

5.2.1 | The Role of Operational Effectiveness in Price Discovery

Table 5 presents summary statistics from estimating Equations (4a) and (4b). Consistent with the observation that investors fail to incorporate fully into stock prices information about operational effectiveness, Table 5 reveals that the current level of, and most recent quarterly change in, *OpEff* are significantly positively related to post-earnings-announcement drift. In particular, the coefficients on $OpEff \times CAR[-1, 1]$ and between $\Delta OpEff$ and $CAR[-1, 1]$ are significantly positive (coefs. = 0.05 and 0.11; t-stats. = 4.13 and 3.03). These findings indicate that an improvement in the level of, and most recent quarterly change in, operational effectiveness is associated with more post-earnings-announcement drift.

Table 6 presents summary statistics from estimating Equations (5a) and (5b). Columns (1) and (2) present results when intraperiod timeliness, *IPT*, is the dependent variable. The columns reveal that the current level of, and most recent quarterly change in, *OpEff* are significantly negatively associated with the speed with which quarterly earnings announcement information is incorporated into stock prices (coefs. = −0.03 and −0.07; t-stats. = −2.69 and −2.48). Consistent with Table 5 findings, these findings indicate that an improvement in *OpEff* reduces the speed with which stock prices reflect information in quarterly earnings announcements. Thus, investors do not incorporate fully into

TABLE 5 | Operational effectiveness and post-earnings-announcement drift.

	CAR [2, 61]			
	(1)	(2)	(3)	(4)
$OpEff_t \times CAR\,[-1, 1]$		0.05***		
		(4.13)		
$\Delta\, OpEff_t \times CAR\,[-1, 1]$				0.11***
				(3.03)
$OpEff_{t-1} \times CAR\,[-1, 1]$				0.05***
				(3.80)
$OpEff_t$	0.55***	0.54***		
	(5.11)	(5.10)		
$\Delta OpEff_t$			0.58*	0.62**
			(1.89)	(2.06)
$OpEff_{t-1}$			0.53***	0.53***
			(4.97)	(5.07)
$CAR\,[-1, 1]$	0.12***	0.12***	0.12***	0.12***
	(7.73)	(7.95)	(7.69)	(7.90)
SUE	4.44*	4.47*	4.44*	4.50*
	(1.71)	(1.73)	(1.71)	(1.74)
ROE	2.54	2.44	2.54	2.38
	(0.79)	(0.76)	(0.78)	(0.73)
Loss	−0.23	−0.25	−0.23	−0.25
	(−0.55)	(−0.59)	(−0.54)	(−0.59)
OAcc	−34.61***	−34.63***	−34.60***	−34.58***
	(−12.70)	(−12.71)	(−12.71)	(−12.70)
InstOwn	−1.08**	−1.08**	−1.08**	−1.08**
	(−2.21)	(−2.20)	(−2.21)	(−2.21)
Analyst	0.61**	0.61**	0.61**	0.61**
	(2.31)	(2.31)	(2.31)	(2.31)
Size	−0.55***	−0.55***	−0.55***	−0.54***
	(−4.38)	(−4.36)	(−4.38)	(−4.34)
BTM	3.41***	3.42***	3.41***	3.40***
	(3.95)	(3.95)	(3.95)	(3.96)
Mom	1.22*	1.22*	1.22*	1.22*
	(1.78)	(1.79)	(1.78)	(1.79)
Industry FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	119,143	119,143	119,143	119,143
Adjusted R^2	0.02	0.02	0.02	0.02

Note: This table presents regression summary statistics from estimating Equations (4a) and (4b) that specify the relation between current quarter *OpEff*, its lagged level, and the most recent quarterly change in *OpEff* and post earnings announcement returns, *CAR* [2, 61]. Industry fixed effects are defined based on the Fama and French (1997) 48-industry classification. *t*-statistics based on standard errors clustered by firm and year-quarter appear in parentheses. *, **, *** indicate significance at 10%, 5%, and 1%. The sample comprises 119,143 quarterly earnings announcements by 4,752 firms from the fourth calendar quarter of 1987 to the first calendar quarter of 2022. See the Appendix for definitions of all variables.

TABLE 6 | Operational effectiveness and the timeliness and efficiency of price discovery at earnings announcements.

	IPT		*IPE*	
	(1)	**(2)**	**(3)**	**(4)**
$OpEff_t$	−0.03***		−0.004***	
	(−2.69)		(−2.71)	
$\Delta OpEff_t$		−0.07**		−0.01**
		(−2.48)		(−2.41)
$OpEff_{t-1}$		−0.03**		−0.004**
		(−2.44)		(−2.33)
AbsSUE	0.15	0.15	−0.04**	−0.04**
	(1.03)	(1.04)	(−2.16)	(−2.15)
ROE	0.57***	0.58***	0.08***	0.08***
	(3.32)	(3.39)	(3.60)	(3.67)
Loss	−0.08***	−0.08***	−0.02***	−0.02***
	(−3.47)	(−3.50)	(−7.64)	(−7.66)
OAcc	−0.05	−0.07	−0.005	−0.01
	(−0.26)	(−0.35)	(−0.18)	(−0.23)
InstOwn	0.22***	0.22***	0.05***	0.05***
	(5.70)	(5.71)	(10.00)	(10.00)
Analyst	0.06***	0.06***	0.001	0.001
	(4.11)	(4.11)	(0.35)	(0.34)
Size	0.004	0.004	0.01***	0.01***
	(0.56)	(0.54)	(13.41)	(13.41)
BTM	−0.05	−0.05	−0.01**	−0.01**
	(−1.28)	(−1.26)	(−2.12)	(−2.09)
Mom	0.02	0.02	−0.01	−0.01
	(0.68)	(0.69)	(−1.45)	(−1.45)
CAR [−1, 1]	0.01***	0.01***	−0.001***	−0.001***
	(6.71)	(6.74)	(−4.65)	(−4.63)
Industry FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	119,143	119,143	119,143	119,143
Adjusted R^2	0.02	0.02	0.05	0.05

Note: This table presents regression summary statistics from Equations (4a) and (4b) that specify the relation between current quarter *OpEff*, its lagged level, and the most recent quarterly change in *OpEff* and stock price informativeness denoted as *IPT* in Columns (1) and (2) or as *IPE* in Columns (3) and (4). Industry fixed effects are based on the Fama and French (1997) 48-industry classification. *t*-statistics based on standard errors clustered by firm and year-quarter appear in parentheses. *, **, *** indicate significance at 10%, 5%, and 1%. The sample comprises 119,143 quarterly earnings announcements by 4,752 firms from the fourth calendar quarter of 1987 to the first calendar quarter of 2022. See the Appendix for definitions of all variables.

stock prices in a timely manner the information reflected in operational effectiveness.

Columns (3) and (4) present summary statistics from estimating Equations (5a) and (5b) when intraperiod efficiency, *IPE*, is the dependent variable. These columns reveal that the current level of, and most recent quarterly change in, *OpEff* are significantly negatively associated with the efficiency with which quarterly earnings announcement information is incorporated into stock prices (coefs. = −0.004 and −0.01; *t*-stats. = −2.71 and −2.41). These findings indicate that an increase in *OpEff* is associated with lower efficiency with which stock prices reflect information in quarterly earnings announcements.

Together, the findings in Tables 3–6 support the inference that *OpEff* reflects forward-looking information about earnings and cash flow from operations that helps to explain future stock returns. However, investors do not incorporate fully this information into stock prices in a timely or efficient manner. Thus, our findings help identify investors' delayed reaction to information about operational effectiveness as a source of the stock return predictability documented in Wang (2019).

5.2.2 | When Does the Information in Operational Effectiveness Prolong Price Discovery?

To identify circumstances in which information about operational effectiveness prolongs price discovery, we focus on instances when the firm reveals operational effectiveness news along with bad or good earnings news. Specifically, we create two indicator variables. The first is SUE_{TOP}, which equals 1 if the firm's *SUE* is in the top tercile of earnings announcements in a year-quarter and zero otherwise. The second is SUE_{BOT}, which equals 1 if the firm's *SUE* is in the bottom tercile and zero otherwise. We refer to firm-quarter observations in the top (bottom) *SUE* tercile as releasing good (bad) earnings news.[26] We then estimate Equations (4b) and (5b), adding interactions between $\Delta OpEff$ and SUE_{TOP} and SUE_{BOT}. For completeness, we also include in the modified versions of Equations (4b) and (5b), the SUE_{TOP} and SUE_{BOT} indicators, the previous quarter level of *OpEff*, and their interactions.

Table 7 presents summary statistics from estimating Equation (4b) using two subsamples based on the terciles of *SUE*. The firms in the subsample underlying the statistics in Column (1) (Column (2)) have good (bad) earnings news. Column (1) reveals that when firms have good earnings news, there is no significant relation between $CAR[2, 61]$ and $\Delta OpEff \times CAR\,[-1, 1]$. That is, when firms have good earnings news, there is no significant relation between the most recent quarterly change in *OpEff* and post-earnings-announcement drift. In contrast, Column (2) reveals that when firms have bad earnings news, the relation between $CAR[2, 61]$ and $\Delta OpEff \times CAR\,[-1, 1]$ is significantly positive (*t*-stat. = 1.93). These findings reveal that the significantly positive relation between and post-earnings-announcement drift in Table 5 is evident only for firms with bad earnings news.

Columns (3) and (4) present summary statistics from a similarly modified Equation (5b). Column (3) reveals that when firms have good earnings news, the association between $\Delta OpEff$ and *IPE* is not significant, which is consistent with the findings relating to post-earnings-announcement drift in Column (1). Specifically, the coefficient on is −0.01 and that on $\Delta OpEff \times SUE_{TOP}$ is 0.02 (*t*-stats. = −3.50 and 2.21). Untabulated statistics reveal that the sum of these coefficients, 0.01, is not significantly different from zero (*p*-value = 0.53). This finding indicates that when firms have good earnings news, information about operational effectiveness is not

TABLE 7 | When does information about operational effectiveness prolong price discovery?

	***CAR* [2, 61]**		***IPE***	
	(1)	**(2)**	**(3)**	**(4)**
	Top *SUE* Tercile	**Bottom *SUE* Tercile**	**Full Sample**	**Full Sample**
$\Delta\ OpEff_t \times CAR\ [-1,1]$	0.09	0.09*		
	(1.36)	(1.93)		
$\Delta\ OpEff_t \times SUE_{TOP}$			0.02**	
			(2.21)	
$\Delta\ OpEff_t \times SUE_{BOT}$				−0.02**
				(−2.27)
SUE_{TOP}			−0.002	
			(−1.01)	
SUE_{BOT}				0.003*
				(1.78)
$\Delta OpEff_t$	0.88	0.88	−0.01***	−0.001
	(1.53)	(1.60)	(−3.50)	(−0.24)
$CAR\ [-1,1]$	0.13***	0.08***	−0.001***	−0.001***
	(6.41)	(4.29)	(−4.52)	(−4.40)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	39,719	39,756	119,143	119,143
Adjusted R^2	0.03	0.04	0.05	0.05

Note: This table presents regression summary statistics from estimating Equations (5a) and (5b). Columns (1) and (2) present results for Equation (5a) after partitioning the sample based on the top (bottom) tercile of earnings surprise, *SUE*. Column (3) (Column (4)) presents statistics for Equation (5b) with the addition of an indicator variable for the top (bottom) tercile of earnings surprise, SUE_{TOP} (SUE_{BOT}) and its interaction with the most recent quarterly change in *OpEff*, $\Delta OpEff \times SUE_{\mathrm{TOP}}$ ($\Delta OpEff \times SUE_{\mathrm{BOT}}$). Industry fixed effects are based on the Fama and French (1997) 48-industry classification. *t*-statistics based on standard errors clustered by firm and year-quarter appear in parentheses. *, **, *** indicate significance at 10%, 5%, and 1%. The sample comprises 119,143 quarterly earnings announcements by 4,752 firms from the fourth calendar quarter of 1987 to the first calendar quarter of 2022. See the Appendix for definitions of all variables.

associated with prolonged price discovery at quarterly earnings announcements.

In contrast, Column (4) reveals that when firms have bad earnings news, the association between $\Delta OpEff$ and *IPE* is significantly negative, which is consistent with the findings relating to post-earnings-announcement drift in Column (2). Specifically, the coefficient on $\Delta OpEff$ is −0.001 and that on $\Delta OpEff \times SUE_{BOT}$ is −0.02 (*t*-stats. = −0.24 and −2.27). Untabulated statistics reveal that the sum of these coefficients, −0.021, is significantly different from zero (*p*-value = 0.00). This finding indicates that when firms have bad earnings news, information about operational effectiveness is significantly negatively related to the efficiency of price discovery.

Together, the Table 7 findings suggest that information reflected in operational effectiveness prolongs price discovery only for firms with positive news about operational effectiveness and bad earnings news. This evidence suggests that investors focus on the bad earnings news and fail to incorporate fully into stock prices the positive news regarding operational effectiveness.

6 | Additional Analyses

6.1 | Information About Operational Effectiveness in Its Components

A potential concern with our inferences is that we could be attributing our findings to operational effectiveness as reflected in *OpEff* when they are attributable to components of operational effectiveness. Conversely, as Section 2 explains, prior research examines the extent to which various accounting amounts used to construct *OpEff* explain future earnings and stock returns. However, this research does not assess the extent to which this explanatory power is attributable to the amounts themselves or to another construct that includes them as inputs, such as operational effectiveness.

Thus, we estimate Equation (1b) including various combinations of the most recent quarterly change in each of the three components of *OpEff* and each component's previous level—ΔDIO and DIO_{t-1}, ΔDSO and DSO_{t-1}, and ΔDPO and DPO_{t-1}—with and without the most recent quarterly change in *OpEff* and its previous level—$\Delta OpEff$ and $OpEff_{t-1}$.[27] The first (second) version includes each (all) pair(s) of component variables separately (together) and comprises three equations (one equation). Neither version includes $\Delta OpEff$ and $OpEff_{t-1}$. Estimating these two versions allows us to test whether any individual component of *OpEff*—on its own—has information content for investors. As in the first version, the third version includes each pair of component variables separately and comprises three equations. More importantly for our research question, the third version also includes $\Delta OpEff$ and $OpEff_{t-1}$.[28] Thus, estimating the third version enables us to test whether *OpEff* has information content incremental to each of its components.

Table 8 presents the findings. Panel A (Panel B) presents summary statistics from estimating Equation (1b) using $CAR[-1, 1]$ (*ATVol*) as the dependent variable. Panel A, Columns (1) through (3), reveals that ΔDIO, ΔDSO, and ΔDPO considered separately are all significantly positively related to $CAR[-1, 1]$ (*t*-stats. = 9.38, 12.57, and 5.10). The positive coefficients on ΔDIO and ΔDSO are consistent with their roles in measuring $\Delta OpEff$, but the positive coefficient on ΔDPO is not.[29] Columns (1) through (3) also reveal that DIO_{t-1} and DSO_{t-1} are significantly positively related to $CAR\,[-1, 1]$ (*t*-stat. = 1.80 and 3.05), but DPO_{t-1} is not (*t*-stat. = 1.80 and 3.05). Strikingly, Column (4) reveals that when the most recent quarterly change in, and previous level of, all three components are included together, each of their coefficients is significantly related to $CAR[-1, 1]$ with signs consistent with their roles in measuring *OpEff*.

More importantly for our research question, Panel A, Columns (5) through (7), reveals that $\Delta OpEff$ is significantly positively related to $CAR[-1, 1]$ incremental to the most recent quarterly change in, and previous level of, each *OpEff* component (*t*-stats. range from 3.05 to 11.11). Panel B reveals inferences similar to those revealed by Panel A. Most importantly, Columns (5) through (7) reveal that $\Delta OpEff$ is significantly positively related to *ATVol* incremental to the most recent quarterly change in and previous level of each *OpEff* component (*t*-stats. range from 2.24 to 4.73).

Taken together, the findings in Table 8 support the inferences we draw from Table 2 that operational effectiveness as reflected in *OpEff* has information content for investors.[30] The findings also support the inference that the information content of *OpEff* subsumes the information content of some of its components, but not vice versa. Thus, our inferences are attributable to *OpEff* as a measure of operational effectiveness, not to any of its separate components—namely, inventory management, collection of accounts receivable, or financing terms with suppliers.

6.2 | Robustness Tests

6.2.1 | Alternative Measures of Operational Effectiveness

A potential concern with our inferences is that they depend on our measure of operational effectiveness, that is, OpEff. To address this concern, we repeat our analyses based on Equation (1b) using the Lam and Larocque (2022) measure of operational effectiveness, OpEffDR.[31] This measure includes the number of days deferred revenue is outstanding, *DDRO*, to incorporate the time that firms have cash advances from customers. The addition of days deferred revenue changes the way the CCC is calculated. In particular, CCCDR is calculated as follows:

$$CCCDR_{i,t} = DIO_{i,t} + DSO_{i,t} - DPO_{i,t} - DDRO_{i,t}, \tag{6}$$

where $DDRO_t = 90 \times \frac{(DR_t + DR_{t-1})/2}{SALES_t}$ and *DR* is deferred revenue. We then calculate *CCCDR* based on Equation (6). We construct a new measure of *OpEff* based on CCCDR instead of CCC, but using the same procedure. In particular, as with *OpEff*, we industry-adjust CCCDR, multiply it by −1, and scale it by 100 to obtain a measure of operational effectiveness that incorporates *DR* and is interpreted in the same way as is *OpEff*.

Table 9, Panel A, presents findings from re-estimating Equation (1b) in Columns (1) and (2).[32] Consistent with Table 2, Columns (1) and (2) reveal that the coefficients on $\Delta OpEffDR$ and $OpEffDR_{t-1}$ are significantly positive (*t*-stats. range from 1.91 to 11.90).

Another construct that might reflect information about operational effectiveness is asset turnover, *AT*, which is the ratio of total sales to average total assets (Wang 2019). This measure is designed to capture the effectiveness with which a firm generates sales, relative to its assets in place, during a period. Notably for our analyses, *AT* is a component of *ROE*, which we include as a control variable in Equations (1b), (4b), and (5b).[33] Moreover, unlike *OpEff*, whose components comprise only items from financial statements that pertain to operations (i.e., sales, cost of goods sold, accounts receivable, accounts payable, and inventory), the denominator of *AT* is total assets, which comprises non-operating as well as operating assets. Thus, it is not clear that *AT* can be an appropriate measure of a firm's operational effectiveness. Nevertheless, untabulated findings reveal that including *AT* as an additional control variable in Equations (1b), (4b), and (5b) yield the same inferences as our tabulated findings.

Findings from these two analyses mitigate the concern that our inferences regarding the informativeness and price discovery implications of a firm's operational effectiveness are attributable to our choice of a particular measure of operational effectiveness, that is, *OpEff*.

6.2.2 | Alternative Industry Classification

In our analyses, we define industries using the Fama and French (1997) 48-industry classification. We use this classification both for computing the industry-adjusted measure of operational effectiveness—when we subtract the industry median for each firm—and for identifying the industry fixed effects in our estimating equations. A potential concern is that our inferences are sensitive to the choice of industry classification. Thus, we repeat our analyses based on Equation (1b) using three alternatives.

Table 9, Panel B, presents summary statistics from re-estimating Equation (1b) using these alternative industry classifications. Columns (1) and (2) present statistics based on the Fama and French (1997) 30-industry classification (FF30), Columns (3) and (4) present statistics based on two-digit SIC classification (SIC 2 Digit), and Columns (5) and (6) present statistics based on

TABLE 8 | Information content of *OpEff* incremental to its components.

Panel A: Components of changes in *OpEff* and earnings announcement returns

	$CAR\,[-1,1]$						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
ΔDIO_t	1.74***			1.16***	0.05		
	(9.38)			(5.40)	(0.20)		
DIO_{t-1}	0.13*			0.17**	−0.16		
	(1.80)			(2.25)	(−1.49)		
ΔDSO_t		4.34***		4.12***		3.14***	
		(12.57)		(11.07)		(8.72)	
DSO_{t-1}		0.44***		0.47***		0.26	
		(3.05)		(3.19)		(1.65)	
ΔPO_t			0.92***	−1.07***			0.77***
			(5.10)	(−4.75)			(4.13)
DPO_{t-1}			−0.07	−0.18*			0.04
			(−0.73)	(−1.87)			(0.44)
$\Delta OpEff_t$					1.95***	1.04***	1.95***
					(8.97)	(5.73)	(11.11)
$OpEff_{t-1}$					0.34***	0.21***	0.25***
					(3.92)	(3.05)	(3.87)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	119,143	119,143	119,143	119,143	119,143	119,143	119,143
Adjusted R^2	0.04	0.04	0.03	0.04	0.04	0.04	0.04

Panel B: Components of changes in *OpEff* and trading volume at earnings announcements

	ATVol						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
ΔDIO_t	0.11***			0.09***	0.05		
	(4.29)			(3.20)	(1.64)		
DIO_{t-1}	−0.002			0.003	−0.03*		
	(−0.17)			(0.18)	(−1.70)		
ΔDSO_t		0.17***		0.13***		0.09**	
		(4.46)		(2.81)		(2.03)	
DSO_{t-1}		0.03		0.05*		0.02	
		(1.31)		(1.71)		(0.89)	
$\Delta\ DPO_t$			0.06**	−0.04			0.05**
			(2.47)	(−1.42)			(2.15)
DPO_{t-1}			−0.03*	−0.04**			−0.03
			(−1.81)	(−2.26)			(−1.47)
$\Delta OpEff_t$					0.06***	0.07***	0.09***
					(2.70)	(3.02)	(4.73)
$OpEff_{t-1}$					0.04**	0.01	0.01
					(2.24)	(0.80)	(0.89)

(Continues)

TABLE 8 | (Continued)

Panel B: Components of changes in *OpEff* and trading volume at earnings announcements							
	ATVol						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	119,143	119,143	119,143	119,143	119,143	119,143	119,143
Adjusted R^2	0.06	0.06	0.06	0.06	0.06	0.06	0.06

Note: This table presents summary statistics from estimating Equations (1b) using the components of *OpEff* disaggregated into recent quarterly changes and one-quarter lagged levels. *DIO* is days inventory outstanding, *DSO* is days sales outstanding, and *DPO* is days payables outstanding. Panel A (Panel B) presents statistics using earnings announcement returns, *CAR* [−1, 1], (abnormal trading volume, *ATVol*) as the dependent. Industry fixed effects are based on the Fama and French (1997) 48-industry classification. *t*-statistics based on standard errors clustered by firm and year-quarter appear in parentheses. *, **, *** indicate significance at 10%, 5%, and 1%. The sample comprises 119,143 quarterly earnings announcements by 4,752 firms from the fourth calendar quarter of 1987 to the first calendar quarter of 2022. See the Appendix for definitions of all variables.

the Barth et al. (2005) industry classification (BBHL). In each analysis, we base industry fixed effects on the alternative industry classification. Panel B reveals the same inferences as revealed by Table 2, which mitigates concern that our inferences are sensitive to the choice of industry classification. Most importantly for our research questions, the coefficients on Δ*OpEff* are significantly positive when *CAR*[−1, 1] and *ATVol* are the dependent variables (*t*-stats. range from 4.80 to 11.96).

6.2.3 | Information Content of Firm Operational Effectiveness and Periods of Financial Stress

Another potential concern with our inferences is that our sample includes periods of financial stress, such as the Dot-Com crash of the early 2000s, the 2008 financial crisis, and the COVID-19 downturn in 2020. Thus, we omit from the sample each of these periods separately and re-estimate Equation (1b). We use NBER's identification of recession periods to determine when these periods of financial stress begin and end. NBER determines that the Dot-Com crash begins in Q1 2001 and ends in Q3 2002, the 2008 financial crisis begins in Q1 2008 and ends in Q2 2009 (Barth et al. 2025), and the COVID-19 downturn begins in Q1 2020 and ends in Q2 2020.[34]

Table 9, Panel C, presents the findings. Columns (1) and (2) present summary statistics based on excluding from the full sample 11,221 observations from 2,166 firms during the Dot-Com crash. Columns (3) and (4) present summary statistics based on excluding 2,690 observations from 1,542 firms during the 2008 financial crisis, and Columns (5) and (6) present summary statistics based on excluding 1,136 observations from 982 firms during the COVID downturn. As with Panels A and B, Panel C reveals the same inferences as Table 2 reveals, which mitigates concern that our inferences are sensitive to the sample including periods of financial stress. Most importantly for our research questions, the coefficients on Δ*OpEff* are significantly positive when *CAR*[−1, 1] and *ATVol* are the dependent variables (*t*-stats. range from 4.69 to 11.94).

6.2.4 | The Role of Operating Liability Leverage

Operating liability leverage is linked to firms' business model choices and thus might weaken the relation between operating effectiveness and expected returns. This is because operating liability leverage is associated with at least one component of *OpEff*, that is, *DPO*, through the credit provided by suppliers. To confirm that our inferences are not attributable to operating liability leverage, we re-estimate Equations (1a) and (1b) after including a control for operating liability leverage, *OpLev*, and interacting it with our main variables of interest, that is, *OpEff* or Δ*OpEff* and $OpEff_{t-1}$. We follow Nissim and Penman (2001) and Nissim (2024) and calculate *OpLev* as the ratio of operating liabilities to net operating assets. Operating liabilities is total current liabilities minus debt included in current liabilities, and net operating assets are operating assets minus operating liabilities.

Untabulated findings reveal that including a control for operating liability leverage has no effect on our inferences. The findings based on Equation (1a) reveal that the coefficient on *OpEff* is significantly positive (coef. = 0.47; *t*-stat. = 7.10) and the coefficient on *OpEff* × *OpLev* is not significantly different from zero (coef. = – 0.001, *t*-stat. = −0.11), as is the coefficient on *OpLev* (coef. = 0.01 , *t*-stat. = 1.17). The findings based on Equation (1b) reveal that the coefficients on Δ*OpEff* and $OpEff_{t-1}$ are both significantly positive (coefs. = 2.09 and 0.31; *t*-stats. = 11.08 and 4.75) and the coefficients on *OpLev* × Δ*OpEff* and *OpLev* × $OpEff_{t-1}$ are not significantly different from zero (coefs. = −0.001 and −0.002; *t*-stats. = −0.02 and −0.24). These findings indicate that operating liability leverage does not weaken the relation between operational effectiveness and abnormal returns.

6.2.5 | Investor Inattention and Prolonged Price Discovery

One might question whether our inference that investors do not incorporate fully the information about operational effectiveness into stock prices is attributable to limited investor attention to earnings announcements when firms announce bad earnings news. This might occur when firms release bad earnings news

TABLE 9 | Robustness tests.

Panel A: Alternative measure of operational effectiveness

	CAR [−1, 1]	*ATVol*
	(1)	**(2)**
$\Delta OpEffDR_t$	1.71***	0.07***
	(11.90)	(4.33)
$OpEffDR_{t-1}$	0.28***	0.02*
	(5.67)	(1.91)
Controls	Yes	Yes
Industry FE	Yes	Yes
Calendar-Quarter FE	Yes	Yes
Observations	119,143	119,143
Adjusted R^2	0.04	0.06

Panel B: Alternative industry classifications

	FF30		**SIC 2 Digit**		**BBHL**	
	CAR [−1, 1]	*ATVol*	*CAR* [−1, 1]	*ATVol*	*CAR* [−1, 1]	*ATVol*
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$\Delta OpEff_t$	2.01***	0.09***	2.02***	0.10***	2.07***	0.10***
	(11.63)	(4.80)	(11.96)	(5.25)	(11.89)	(5.23)
$OpEff_{t-1}$	0.20***	0.002	0.25***	0.01	0.23***	0.02*
	(3.38)	(0.19)	(4.11)	(0.71)	(4.00)	(1.77)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	119,143	119,143	119,143	119,143	119,143	119,143
Adjusted R^2	0.04	0.06	0.04	0.06	0.04	0.06

Panel C: Information content of operational effectiveness in different time periods

	Exc. Dot-Com		**Exc. 2008**		**Exc. COVID-19**	
	CAR [−1, 1]	*ATVol*	*CAR* [−1, 1]	*ATVol*	*CAR* [−1, 1]	*ATVol*
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$\Delta OpEff_t$	2.09***	0.10***	1.90***	0.10***	1.97***	0.10***
	(11.94)	(4.69)	(11.39)	(5.08)	(11.37)	(4.86)
$OpEff_{t-1}$	0.20***	0.01	0.25***	0.01	0.24***	0.01
	(3.33)	(0.98)	(4.11)	(1.17)	(3.93)	(1.17)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	107,922	107,922	116,453	116,453	118,007	118,007
Adjusted R^2	0.04	0.06	0.04	0.06	0.04	0.06

Note: This table presents regression summary statistics for robusteness tests. Panel A presents summary statistics from Equation (1b) with an alternative definition of *OpEff* that includes deferred revenue, *OpEffDR*. Industry fixed effects are based on the Fama and French (1997) 48-industry classification. Panel B presents summary statistics from estimating Equation (1b) using the alternative industry classifications. In Columns (1) and (2) we use the Fama and French (1997) 30-industry classification (FF30), in Columns (3) and (4) we use the SIC 2 digit classification (SIC 2 Digit), and in Columns (6) and (7) we use the Barth et al. (2005) industry classification (BBHL). In all columns industry fixed effects are calculated based on the alternative industry classification listed in the column heading. Panel C presents summary statistics from estimating Equation (1b) excluding: the Dot-Com crisis, in Columns (1) and (2); the 2008 financial crisis, in Columns (3) and (4); and the COVID-19 downturn, in Columns (5) and (6). In panel C, industry fixed effects are based on the Fama and French (1997) 48-industry classification. In all panels, *t*-statistics based on standard errors clustered by firm and year-quarter appear in parentheses. *, **, *** indicate significance at 10%, 5%, and 1%. The sample comprises 119,143 quarterly earnings announcements by 4,752 firms from the fourth calendar quarter of 1987 to the first calendar quarter of 2022. See the Appendix for definitions of all variables.

on busy earnings announcement days, that is, when many other firms release earnings news concurrently.

To address this concern, we include in Equation (1b) an additional control variable, *NumRepFirms*. *NumRepFirms* is either the number of firms announcing earnings on the same day as the firm in a particular quarter or an indicator variable that equals 1 if the number of firms announcing earnings on the same day as the firm is larger than the overall median number of firms announcing earnings on each day during our sample period.

Untabulated findings reveal the same inferences as revealed by the tabulated findings regardless of which definition of *NumRepFirms* we use. These findings suggest that our inferences regarding the price discovery implications of information about operational effectiveness are not driven by limited investor attention on earnings announcement days, but rather by the positive information about operational effectiveness released to the market concurrently with bad earnings news.

7 | Summary and Concluding Remarks

We address whether and why a firm's operational effectiveness has information content for investors and what role that information plays in the price discovery process at quarterly earnings announcements. We define operational effectiveness, *OpEff*, as a firm's CCC, multiplied by −1 such that larger values of *OpEff* reflect higher operational effectiveness. CCC measures how much time, in days, it takes the firm to convert $1 invested in inventory into $1 collected in sales.

Using a sample of 119,143 quarterly observations from 4,752 firms from the fourth calendar quarter of 1987 to the first calendar quarter of 2022, we find that *OpEff* is positively associated with measures of investor reaction to information in quarterly earnings announcements, namely abnormal stock returns and abnormal trading volume. We further find that *OpEff* is positively associated with future earnings and cash flows and, thus, *OpEff* serves as a channel through which investors obtain this information. This finding helps explain why operational effectiveness is positively associated with the price and volume reactions to earnings announcements. We also find that *OpEff* has information content incremental to its separate components, which indicates that it is operational effectiveness itself—and not information about particular components of operational effectiveness—that conveys information about a firm's future earnings and cash flows. This finding reinforces the observation that *OpEff* reflects the effectiveness of a firm's operations along its three key dimensions: obtaining credit from suppliers, producing and selling inventory, and providing credit to customers.

We also find that investors do not incorporate fully the information in operational effectiveness into stock prices in a timely manner. Specifically, we find that operational effectiveness is positively associated with post-earnings-announcement drift and negatively associated with the speed of incorporation of information in quarterly earnings announcements into stock prices. We find that this effect is concentrated in firms that release positive information about operational effectiveness and bad earnings news, that is, investors take longer to incorporate the positive information in *OpEff* when the firm announces bad earnings news.

Together, our findings show that investors fail to incorporate fully into stock prices in a timely manner an informative accounting-based measure of operational effectiveness. These findings inform recent discussions between accounting standard setters and firm managers regarding the disclosure that a firm should provide about its operating cash cycle. Specifically, our findings suggest that operational effectiveness contains information regarding future earnings and future cash flows that is not incorporated fully into prices in a timely manner, particularly for firms with positive information about operational effectiveness and bad earnings news. Thus, our study suggests that the new expanded disclosures required by the FASB regarding the structure of a firm's payments to suppliers could benefit investors and help improve the informativeness of stock prices. Whether this is, in fact, the case is left for future research.

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Data Availability Statement

The data that support the findings of this study are available from Wharton Research Data Services. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the author(s) with the permission of Wharton Research Data Services.

Endnotes

[1] CCC is also known as the net operating cycle.

[2] Our interpretation of the CCC as reflecting the effectiveness with which a firm manages its working capital components—accounts receivable, inventory, and accounts payable—to support ongoing operations is consistent with Wang (2019).

[3] Another stream of literature that is potentially related to our study deals with the relation between accruals and earnings management. That literature focuses on identifying normal and abnormal levels of accruals and on the possibility of earnings management affecting accruals (Jones 1991; Dechow et al. 1995; Peasnell et al. 2000; Stubben 2010). Because our measure of operational effectiveness is based on accounting amounts, a question arises as to whether the potential for earnings management can alter our inferences. Findings from untabulated analyses confirm that neither the level of accruals (Zang 2012) nor the proximity of reported earnings to analyst forecasts (Bartov et al. 2002)—two commonly used proxies for earnings management—alters our inferences. However, we leave it to future research to distinguish between normal and abnormal levels of OpEff and to explore the potentially distinct informational content of each component.

[4] Dickinson (2011) introduces a cash flow-based proxy for firm life cycle stages—introduction, growth, maturity, shake-out, and decline—and highlights how firms' strategy, resource allocation, and financial behavior differ across stages. These differences suggest that the information content of *OpEff*, as measured by CCC, could vary with life cycle stage. For example, CCC might be longer and more volatile for early stage firms because they invest more in working capital than mature firms. We leave it to future research to determine whether and how a firm's life cycle stage affects the information content of *OpEff*.

[5] In contrast to Wang (2019), Lin and Lin (2021) find that market-wide aggregate operational effectiveness exhibits positive, not negative, correlation with future aggregate abnormal returns. Lin and Lin (2021) say that investors' biased beliefs with respect to future cash flows can explain the seemingly contradictory findings with Wang (2019).

[6] Figure 1 presents a case of a firm with a positive CCC, which means the firm has a positive investment in inventory. This is not always the case; firms can exhibit a negative CCC when suppliers finance the firm's operations.

[7] Following financial reporting practices, we define *AR* as accounts receivable, net. Untabulated findings based on defining *AR* as gross accounts receivable reveal the same inferences.

[8] Our sample comprises US firms that apply US Generally Accepted Accounting Principles (GAAP). However, the inputs and procedures for constructing CCC are the same if a firm applies International Financial Reporting Standards (IFRS). Thus, our inferences are relevant to both sets of accounting standards.

[9] Untabulated findings based on subtracting the industry median CCC calculated based on CCC from the current quarter reveal the same inferences.

[10] Section 6.2.1 reports findings from additional analyses that employ an alternative definition of CCC based on Lam and Larocque (2022), which includes deferred revenue as a component of CCC. Those findings reveal the same inferences as the findings based on our measure of *OpEff*.

[11] Bassett's CCC of 79 equals *DIO* of 101 plus *DSO* of 16, minus *DPO* of 38. These amounts are based on Bassett's quarterly *SALES* and *COGS* of \$118,383 and \$50,427 and end-of-quarter (beginning-of-quarter) *INV*, *AR*, and *AP* of \$54,886, \$22,340, and \$23,426 (\$58,601, \$19,099, and \$19,215).

[12] Apple's CCC of −26 equals *DIO* of 6 plus *DSO* of 39, minus *DPO* of 71. These amounts are based on Apple's quarterly *SALES* and *COGS* of \$111,439 and \$67,111 and end-of-quarter (beginning-of-quarter) *INV*, *AR*, and *AP* of \$4,973, \$58,620, and \$63,846 (\$4,061, \$37,445, and \$42,296).

[13] When *CAR* [−1, 1] is the outcome variable, we include *SUE* as a control for standardized unexpected earnings. When *ATVol* is the outcome variable, we include *SUE* for the same reason, except that—because *ATVol* is non-negative—we include *SUE* in its absolute form, that is, *AbsSUE*, rather than *SUE*.

[14] Breuer and deHaan (2024) explain that interpreting coefficient magnitudes from estimating equations that include fixed effects (FE) requires consideration of whether the within-FE variation of the variable of interest (e.g., *OpEff*) is economically smaller than its sample variance. In untabulated analyses, we follow Mummulo and Peterson (2018) to determine whether the within-FE variation of *OpEff* is economically different from the sample variation of *OpEff*. The untabulated findings reveal that the within-FE variance is 0.381, which is not economically different from the sample variance in Table 1 of $0.6344^2 = 0.402$. Thus, we use the sample variance of *OpEff* to interpret the magnitudes of the estimated coefficients.

[15] We compute *RET* over this window to ensure that *RET* captures the price change during the 3-month period concurrent with a firm's quarterly earnings announcement. Untabulated findings based on measuring *RET* during the 3 months beginning (ending) 2 months before (1 month after) the end of quarter *t* reveal the same inferences.

[16] We also estimate versions of Equations (3a) and (3b) in which we replace $\Delta EARN_t$ with $EARN_t$ and $EARN_{t-1}$. This approach allows us to include an explicit control for previous as well as current quarter earnings. The untabulated findings reveal the same inferences as our tabulated findings.

[17] As in Barth et al. (2025), we use Compustat exchange codes 11, 12, and 14 to identify these firms.

[18] We exclude firms with negative equity book value because their inclusion poses conceptual and empirical challenges that could undermine the validity of our analyses. For example, negative equity book value often indicates that the firm is experiencing financial distress, which suggests that these firms differ economically from the broader population. Untabulated statistics reveal that including them would add to our sample only 628 observations from 17 firms. More importantly, untabulated findings reveal that including them in the sample would not change any of our inferences.

[19] Our inferences are the same when we use unwinsorized variables instead.

[20] To calculate a firm's AR(1) coefficient, we require at least four quarterly observations. Thus, these statistics are based on a slightly smaller sample—4,286 firms versus 4,752—than the sample we use in our main analyses.

[21] 0.24% is $(0.38/100) \times 63.44$ and 0.51% is $(1.98/100) \times 25.69$, where 0.38 (1.98) is the estimated *OpEff* (Δ*OpEff*) coefficient and 63.44 (25.69) are the standard deviations of *OpEff* (Δ*OpEff*). Because, for ease of exposition, we divided *OpEff* by 100 when quantifying the effect of operational effectiveness on capital market outcomes, we divide the coefficient estimates by the same amount.

[22] 1.27% is $(0.02/100) \times 63.44 \times 100$ and 2.57% is $(0.1/100) \times 25.69 \times 100$, where 0.02 (0.10) is the estimated *OpEff* (Δ*OpEff*) coefficient and 63.44 (25.69) are the standard deviations of *OpEff* (Δ*OpEff*). Because *ATVol* is the natural logarithm of one plus abnormal trading volume, in addition to dividing the coefficient estimates by 100, we multiply them by 100 to maintain the % interpretation.

[23] Our inferences are not sensitive to using an alternative measure of firm profitability or adding a control for gross profit margin. We re-estimate two additional versions of Equations (1a) and (1b). In the first, we replace our profitability measure, *ROE*, with return on assets, *ROA*. In the second, we include gross profit margin, *GPM*, as an additional control variable. We calculate *ROA* as the ratio of net income to average total assets and *GPM* as gross profit scaled by total revenue. Untabulated findings reveal that in both versions the coefficients on our key variables, *OpEff* and Δ*OpEff*, are significantly positive and similar in magnitude to those in Table 2.

[24] Because we calculate *OpEff* on the basis of accruals, there is a possibility that our inferences could be attributable to the accrual anomaly. To alleviate this concern, we re-estimate Equations (1a) and (1b), including interactions between operating accruals and our measures of *OpEff*. Untabulated findings reveal that the coefficients on operating accruals and the interaction terms are not significantly different from zero, whereas the coefficients on measures of *OpEff* are significantly positive and similar in magnitude to those in Table 2.

[25] We also estimate modified versions of Equations (3a) and (3b) that include $EARN_t$ and $EARN_{t-1}$ in place of $\Delta EARN_t$. The untabulated findings reveal the same inferences as revealed by Table 4.

[26] Untabulated statistics reveal that of the 39,756 observations in the bottom tercile, only 204 have positive *SUE*—the remaining 39,502 have negative *SUE*.

[27] For the sake of brevity, we tabulate only versions of Equation (1b). Untabulated findings from estimating equations based on analogous versions of Equation (1a), which focuses on the current level of *OpEff*,

reveal the same inferences as those based on the findings from various versions of Equation (1b) in Table 8.

[28] Because *OpEff* is a linear combination of the three components, we cannot estimate a single equation with all three components and *OpEff* together.

[29] Recall from Section 3.1 that $CCC = DIO + DSO - DPO$.

[30] We also re-estimate the equations underlying Table 5 using the specifications that include the *OpEff* components. Untabulated findings reveal, consistent with our other component analyses, that *OpEff* is significantly positively associated with post-earnings-announcement drift incremental to any of its components.

[31] For brevity, this section discusses findings from estimating Equation (1b). However, estimations of our other specifications reveal the same inferences.

[32] Untabulated findings from estimating all other equations using the alternative definition of *OpEff* reveal inferences that are the same as those revealed by the tabulated findings.

[33] In the DuPont decomposition, $ROE = \frac{\text{Net income}}{\text{Sales}} \times \frac{\text{Sales}}{\text{Avg. total assets}} \times \frac{\text{Avg. total assets}}{\text{Avg. book equity}}$.

[34] https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions

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Appendix: Variable definitions

Variable	Description
Analyst	Natural logarithm of 1 plus the number of analysts providing an earnings forecast.
ATVol	Abnormal trading volume calculated as the natural logarithm of one plus the share turnover ratio for during days $[-1, 1]$, scaled by the average daily turnover ratio during days $[-54, -5]$ relative to the quarterly earnings announcement, calculated as $ATVol = ln(1 + \frac{\frac{1}{3}\sum_{d=-1}^{1} TR_{i,t+d}}{\frac{1}{50}\sum_{d=5}^{54} TR_{i,t-d}})$. TR is the ratio of the number of shares traded to the number of shares outstanding, d is the trading day relative to the quarterly earnings announcement.
BTM	Natural logarithm of the equity book-to-market ratio at the end of the fiscal quarter.
$CAR[a, b]$	Cumulative abnormal equity return during days $[a, b]$ relative to the quarter's earnings announcement, calculated as raw return minus the value-weighted return for a portfolio of firms matched on 5×5 sorts of equity market value and market-to-book ratio following Daniel et al. (1997).
CCC	The cash conversion cycle. Calculated as days inventory outstanding plus days sales outstanding minus days payables outstanding, $CCC = DIO + DSO - DPO$.
CCCDR	An alternative definition of the cash conversion cycle that includes deferred revenue, calculated as days inventory outstanding plus days sales outstanding minus days payables outstanding and minus days deferred revenue outstanding, $CCCDR = DIO + DSO - DPO - DDRO$.
CFO	Cash flow from operating activities, scaled by average total assets during the quarter.
$\widehat{CFO}_{t+1\text{Levels}}$	The fitted value from the estimation of Equation (2a) using CFO_{t+1} as the dependent variable. It represents the portion of future operating cash flow that is explained by the current level of *OpEff*.
$\widehat{CFO}_{t+1\text{Changes}}$	The fitted value from the estimation of Equation (2b) using CFO_{t+1} as the dependent variable. It represents the portion of future operating cash flow that is explained by the most recent change in *OpEff*.
DIO	Days inventory outstanding, calculated as: $90 \times \frac{(INV_{t-1}+INV_t)/2}{COGS_t}$. It reflects the number of days, on average, it takes the firm to sell its inventory during the quarter. INV_t is the inventory of the firm at the end of quarter t, $COGS_t$ is the cost of goods sold of the firm during quarter t.
DPO	Days payables outstanding, calculated as: $90 \times \frac{(AP_{t-1}+AP_t)/2}{COGS_t}$. *AP* is accounts payable and *COGS* is cost of goods sold. It reflects the number of days, on average, it takes the firm to pay its suppliers.
DDRO	Days deferred revenue outstanding, calculated as: $90 \times \frac{(DR_{t-1}+DR_t)/2}{SALES_t}$. *DR* is deferred revenue and *SALES* is total sales. It reflects the number of days, on average, customers pay the firm in advance.
DSO	Days sales outstanding, calculated as: $90 \times \frac{(AR_{t-1}+AR_t)/2}{SALES_t}$. *AR* is accounts receivable and *SALES* is total sales. It reflects the number of days, on average, it takes the firm to collect cash from its customers.
EARN	Firm-level earnings before extraordinary items, scaled by market value of equity.
Δ *EARN*	The most recent quarterly change in firm-level earnings before extraordinary items, scaled by market value of equity.
$\widehat{EARN}_{t+1\text{Levels}}$	The fitted value from the estimation of Equation (2a) using $EARN_{t+1}$ as the dependent variable. It represents the portion of future earnings that is explained by the current level of *OpEff*.
$\widehat{EARN}_{t+1\text{Changes}}$	The fitted value from the estimation of Equation (2b) using $EARN_{t+1}$ as the dependent variable. It represents the portion of future earnings that is explained by the most recent quarterly change in *OpEff*.

(Continues)

Variable	Description
InstOwn	Percent of shares owned by institutions– divided by 100–measured at the most recent quarter-end.
IPE	Intraperiod efficiency of reported earnings, calculated as: $IPE = 1 - \sum_{d=0}^{5} \frac{\lvert CAR[0,5]-CAR[0,d]\rvert}{\lvert CAR[0,5]\rvert}$, where d is the trading day from 0 to 5 relative to the quarterly earnings announcement.
IPT	Intraperiod timeliness of reported earnings, calculated as: $IPT = \sum_{d=0}^{4} \frac{CAR[0,d]}{CAR[0,5]} + 0.5$, where d is the trading day from 0 to 5 relative to the quarterly earnings announcement.
Loss	An indicator variable equal to 1 if the firm reports a loss for the quarter and zero otherwise.
Mom	Six-month cumulative stock return ending one month prior to the end of the quarter.
NumRepFirms	A measure of investor inattention. It is either the number of firms announcing earnings on the same day as the firm in a particular quarter or an indicator variable that equals 1 if the number of firms announcing earnings on the same day as the firm is larger than the overall median number of firms announcing earnings on each day during our sample period.
OAcc	Operating accruals, calculated as the difference between income before extraordinary items and cash flows from operating activities, divided by average total assets.
OpEff	A measure of operational effectiveness based on the quarterly Cash Conversion Cycle (CCC), calculated as $OpEff = -1 \times (CCC_{i,t} - CCC_{j,t-1}^{IndMed})/100$. The CCC of the firm in quarter t is days inventory outstanding plus days sales outstanding minus days payables outstanding, $CCC = DIO + DSO - DPO$. $CCC_{j,t-1}^{IndMed}$ is the median cash conversion cycle in industry j during quarter $t-1$, when firm i belongs to industry j.
ΔOpEff	The change in *OpEff* from quarter $t-1$ to quarter t, calculated as $\Delta OpEff = -1 \times (\Delta CCC_{i,t} - \Delta CCC_{j,t-1}^{IndMed})/100$. $\Delta CCC_{j,t-1}^{IndMed}$ is the change in median cash conversion cycle in industry j during quarter $t-1$, when firm i belongs to industry j.
OpEffDR	An alternative definition of *OpEff* based on a CCC that includes days deferred revenue outstanding in addition to the original components defined in *OpEff*. This CCC measure is calculated as: $CCCDR = -1 \times (DIO + DSO - DPO - DDRO)$. $DDRO$ is calculated as $90 \times \frac{(DR_{t-1}+DR_t)/2}{SALES_t}$ and DR indicates deferred revenue. We then subtract the industry median $CCCDR$ from quarter $t-1$ and multiply the remainder by -1.
OpLev	Operating liability leverage, calculated as the ratio of operating liabilities to operating assets. Operating liabilities are calculated as total current liabilities minus debt included in current liabilities and operating assets is calculated as total current assets minus cash, cash equivalents, and investments in short-term assets.
RET	Stock return measured during the three months beginning the last month of the quarter and ending two months after the fiscal quarter ends.
Size	Natural logarithm of market value of equity at the end of the quarter.
SUE	Standardized unexpected earnings for the quarter, calculated as net income before extraordinary items of the prior quarter minus net income before extraordinary items from four quarters ago, scaled by the stock price at the end of the quarter.
SUE_{BOT}	An indicator variable equal to 1 if *SUE* is in the bottom tercile of the distribution in quarter t and 0 otherwise.
SUE_{TOP}	An indicator variable equal to 1 if *SUE* is in the top tercile of the distribution in quarter t and 0 otherwise.
ROE	Return on book value of equity during the quarter, calculated as the ratio of net income before extraordinary items to average total assets for the quarter.