The Information Content of Operational Efficiency

Abstract

We address whether and why a firm's operational efficiency has information content for investors and whether it is associated with prolonged price discovery at quarterly earnings announcements. We measure operational efficiency using the cash conversion cycle (CCC), where shorter CCC reflects better operational efficiency. We find that CCC has information content for investors in that shorter CCC is positively related to abnormal stock returns and trading volume at quarterly earnings announcements. We also find that shorter CCC is associated with higher future earnings and cash flows, which helps explain the positive announcement return and volume reactions. In addition, our findings reveal that CCC is associated with prolonged price discovery in that shorter CCC is associated with less timely and less efficient incorporation of information into stock prices and larger post-earnings-announcement drift. However, these findings largely are attributable to firms that announce bad earnings news.

JEL classification: G11, G12, G14, M41

Keywords: Operational efficiency; Information content; Price discovery

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1 Introduction

The questions we address are whether and why a firm's operational efficiency has information content for investors and whether information about operational efficiency prolongs price discovery at quarterly earnings announcements. We measure operational efficiency as the firm's Cash Conversion Cycle (hereafter, CCC). CCC reflects the average number of days it takes the firm to convert one dollar invested in inventory into a dollar collected from sales. Thus, the shorter is CCC, the more efficient are the firm's operations.[1] This efficiency enables firms with shorter CCC to generate earnings and cash flows faster. CCC varies not only across industries, but also across firms within an industry. We predict that these intra-industry differences are informative to investors because we expect that shorter CCC is predictive of higher future earnings and operating cash flows. We also predict that information about operational efficiency prolongs price discovery at quarterly earnings announcements. This is because investors likely require additional time to interpret the valuation implications of announced earnings in light of concurrently announced information about operational efficiency.

The motivation for our study stems from the observation that CCC comprises information on three key dimensions of a firm's operations—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 CCC and how it affects stock price discovery at earnings announcements. First, prior research predominantly focuses on studying the information content of earnings news at

[1] Section 3.1 provides the definition of our CCC measure, which we multiply by –1 to facilitate exposition and interpretation of our findings. Thus, higher values of our CCC measure reflect better operational efficiency. CCC also is known as the Net Operating Cycle.

quarterly earnings announcements, largely overlooking other important amounts and measures that can be calculated from financial statements. Hence, investigating the information content of CCC can shed light on the capital markets consequences and the availability of forward-looking fundamental information, particularly when firms report bad earnings news. Consistent with this reasoning, 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 this requirement is that firms are increasingly financing payments to suppliers through third parties and information about a firm's cash conversion cycle would allow investors to better predict the firm's future operating cash flows. In contrast, firms assert that the disclosure would be costly and not informative to investors. Hence, our study also informs this debate.

Second, CCC is not readily available from financial statements. Investors need to extract particular accounting amounts from financial statements to construct it, such as accounts receivable, accounts payable, and inventory. Prior research demonstrates that investors take time to incorporate fully into stock prices accounting information that is not readily available. Thus, by assessing the extent to which this phenomenon extends to CCC, our study enhances our understanding of how operational efficiency affects price discovery and provides insights into how financial statement transparency could be improved.

To address our first research question—whether and why a firm's operational efficiency has information content for investors—we first determine whether operational efficiency is informative to investors. We do so by testing whether the current level of, and most recent change in, CCC are positively associated with abnormal returns and trading volume at quarterly earnings announcements. If they are, we infer that CCC has information content for investors.

We then identify a reason why CCC is informative to investors. We do so by testing whether the return and trading volume reactions are positively associated with information reflected in CCC about future earnings and future operating cash flows. We also test whether the current level of, and most recent change in, CCC amplify the relation between firms' current quarter returns and next quarter's earnings. If we find the predicted relations, we infer that CCC is a channel through which investors obtain information about operational efficiency that is helpful to them in assessing firm value.

To address our second research question—whether operational efficiency prolongs price discovery at earnings announcements—we first test whether the current level of, and most recent change in, CCC are positively associated with the time it takes for, and the efficiency with which, stock prices reflect information in quarterly earnings announcements. We then test whether the current level of, and most recent change in, CCC are positively associated with post-earnings-announcement drift. If we find that CCC is associated with slower and less efficient incorporation of information into stock prices and larger post-earnings-announcement drift, we infer that CCC provides information about operational efficiency that prolongs price discovery at earnings announcements.

We address our research questions using a sample of 119,143 quarterly earnings announcements by 4,752 firms from 1988 to 2021. Regarding our first research question, our findings support our prediction that operational efficiency is informative to investors. In particular, we find that, on average, a one standard deviation higher level of CCC 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 higher change in CCC is associated with a 0.51% (2.57%) higher abnormal return (trading volume) reaction.

Regarding why a firm's operational efficiency as reflected in CCC is informative to investors, we find that a higher level of, and larger change in, CCC predicts higher future earnings and future operating cash flows. More importantly for our research question, we find that the future earnings and future operating cash flows reflected in CCC are positively associated with the stock price and trading volume reactions at quarterly earnings announcements. Relatedly, we also find that the current level of, and most recent change in, CCC amplify the relation between firms' current quarter returns and next quarter's earnings. Together, these findings reveal that CCC is a channel through which investors obtain information about operational efficiency that is helpful to them in predicting future earnings and future cash flows. To the best of our knowledge, we are the first to document these relations.

Regarding our second research question, we find that the current level of, and most recent change in, CCC are negatively associated with the speed and efficiency of price discovery at quarterly earnings announcements and positively associated with the magnitude of post-earnings-announcement drift. These findings are consistent with prior research that documents a positive association between shorter CCC and higher future stock returns. However, we find that the less timely and less efficient incorporation into stock prices of information about operational efficiency is concentrated in firms that announce bad earnings news. This finding suggests that when investors react to earnings announcements, they incorporate into stock prices bad earnings news more quickly than they incorporate the implications of changes in operational efficiency.

We extend and contribute to related research in two ways. First, we find that a firm's operational efficiency as reflected in CCC is informative to investors because a shorter CCC predicts higher future earnings and operating cash flows. In particular, we show that investors react to information reflected in both the current level of, and most recent change in, CCC and incorporate this information into stock prices. Second, we find that CCC is negatively associated with the speed and efficiency of price discovery at quarterly earnings announcements and positively associated with post-earnings-announcement drift. Thus, our findings reveal that investors do not incorporate into stock prices in a timely and efficient manner the forward-looking firm performance information reflected in CCC. However, these findings largely are attributable to firms that announce bad earnings news.

The paper proceeds as follows. Section 2 discusses related research and Section 3 explains 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 addresses whether and to what extent investors react to accounting information and incorporate it into stock prices. The second addresses whether accounting information has predictive power for stock returns and accounting performance measures such as earnings and cash flows.

Regarding the first strand, a vast literature beginning with Ball and Brown (1968) and Beaver (1968) studies the market reaction to accounting information. Focusing primarily on unexpected earnings, and to some extent other readily available financial statement line items 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). The literature also finds that stock prices do not fully reflect accounting information in a timely manner. Sloan (1996) shows that the price reaction to accounting information is incomplete in that investors fail to incorporate fully into prices the information about future earnings reflected in current accruals and cash flows. Relatedly, Israeli (2015) finds that investors fail to incorporate fully into 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 CCC, the information necessary to estimate this fair value-based net income is available in the financial statements, but not disclosed per se.

We contribute to this literature in two ways. First, we find that operational efficiency is informative to investors. Specifically, we find the current level of, and most recent change in, the firm's cash conversion cycle—which we measure using disclosed accounting amounts—are positively associated with abnormal stock price and trading volume reactions at earnings announcements. Second, we find that investors do not incorporate fully the information in operational efficiency in a timely or an efficient manner, particularly for firms with bad earnings news. These findings suggest that readily available information about operational efficiency could be helpful to investors.

Regarding the second strand of literature, there also is a vast literature documenting that particular accounting amounts have predictive ability for other accounting amounts and stock returns. Most relevant to our study is prior research that examines the predictive ability of accounting amounts used to construct CCC, namely inventory, accounts receivable, accounts payable, sales, and cost of goods sold. For example, Ou and Penman (1989) and Ou (1990) 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 CCC—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) demonstrate that financial statement analysis can help in equity valuation and prediction of fundamental performance, and Shin and Sonen (1998), Deloof (2003), and Rddatz (2006) show that effective working capital management reduces the need for external liquidity and enhances the firm's performance and shareholder value creation.

We contribute to this literature by assessing whether the predictive ability of these accounting amounts is attributable to inventory, sales, or other working capital amounts, per se, or to another construct that includes them as inputs, such as operational efficiency. We find that it is the latter by showing that CCC has predictive ability incremental to its components. This is important because CCC is the predominant metric to capture the efficiency of a firm's operations along its three key dimensions: investing in and selling inventory, collecting cash from customers, and paying suppliers.

Some studies focus on the role of CCC in predicting future operating cash flows and stock returns. Regarding future cash flows, Dechow et al. (1998) develops a model in which current earnings has predictive ability for future cash flows that is superior to that of current cash flows. In the model, the superior predictive ability of earnings is increasing in CCC. However, the model implicitly assumes that CCC is positive, which is not always the case. Thus, the study does not assess the extent to which negative CCC plays a role enhancing earnings' predictive ability. Regarding future stock returns, Wang (2019) finds that monthly hedge portfolios that buy (sell) stocks of firms with the shortest (longest) CCC, deliver abnormal returns that cannot be explained using known factors or equity return predictors, and concludes that CCC is associated with mispricing.[2]

We contribute to this literature in several ways. First, we find that operational efficiency as reflected in CCC contains forward-looking information about future earnings and cash flows. In particular, we find that shorter CCC is predictive of higher future earnings and future cash flows. Thus, our study establishes that CCC contains information about firms' future fundamental performance. Second, we find that operational efficiency prolongs the price discovery process at quarterly earnings announcements. We show that shorter CCC is associated with less timely and less efficient price discovery at quarterly earnings announcements and larger post-earnings-announcement drift. Our evidence reveals that the negative association between operational efficiency and price discovery is concentrated in firms with bad earnings news, which suggests that investors focus on the bad earnings news and take longer to process the news reflected in CCC.

3 Research design

3.1 Measuring operational efficiency

Addressing our research question requires measuring operational efficiency. We focus on a firm's cash conversion cycle, CCC, because textbooks often identify CCC as a proxy for how efficiently the firm manages its operations (Hanlon et al., 2020; Libby et al., 2021). The cash conversion cycle is the number of days it takes a firm to convert one dollar invested in inventory into one dollar collected from sales. Hence, a shorter cash conversion cycle indicates faster generation of cash from the firm's operating activities. Figure 1 presents the timeline of

[2] In contrast, Lin and Lin (2021) finds that CCC exhibits positive, not negative, correlations with future aggregate abnormal returns. However, Lin and Lin (2021) illustrates how biased beliefs of investors with respect to future cash flows can explain the seemingly contradictory findings between it and Wang (2019).

events in the cash conversion cycle. 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.

The cash conversion cycle typically is calculated as the sum of days inventory outstanding and days receivables outstanding minus days payables outstanding (Richards and Laughlin, 1980). Thus, we measure a firm's cash conversion cycle, *CCC*, as follows:[3]

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

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 payables outstanding, $DPO_t = 90 \times \frac{(AP_{t-1} + AP_t)/2}{COGS_t}$.[4] INV, $COGS$, AR, $SALES$, and AP denote inventory, cost of goods sold, accounts receivable, sales, and accounts payable.

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. Thus, to avoid this industry heterogeneity driving our inferences, we follow Wang (2019) and assign firms to Fama and French (1997) 48-industries and subtract from the firm's *CCC* the median *CCC* of the industry to which the firm belongs. The industry median that we subtract is based on firms' *CCC* values during the quarter prior to a firm's earnings announcement. This ensures that our industry-adjusted *CCC* measure is available to investors at the time of the firm's earnings announcement.[5] Because shorter cash conversion cycles reflect

[3] Section 6.1 reports findings from additional analyses that employ an alternative definition of *CCC* based on Lam and Larocque (2023). Those findings reveal the same inferences as the findings based on *CCC*.
[4] Following financial reporting practices, we define *AR* as accounts receivable, net. Defining *AR* as gross accounts receivable reveals the same inferences.
[5] Subtracting industry median *CCC* computed using firms' *CCC* values during the current quarter reveals the same inferences.

better operational efficiency, for ease of exposition, we multiply CCC by -1. Thus, higher values of CCC reflect better operational efficiency. Also for ease of exposition, we scale CCC by 100. i and t denote firms and quarters. All variable definitions appear in the Appendix.

Investors can calculate a firm's CCC 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 prior quarter. For example, Bassett's (NASDAQ: BSET) January 21, 2021 earnings announcement reveals that its cash conversion cycle is 79 days.[6] This number suggests that it takes Bassett, on average, 79 days to convert one dollar of investment in inventory into one dollar of cash collected from its customers. Bassett belongs to the Consumer Goods industry, which had a median CCC of 98 days in the previous quarter. Hence, Bassett's industry-adjusted CCC is negative ($-19 = 79 - 98$), which means that Bassett's operations are more efficient than those of the median firm in its industry.

For most firms, the raw, i.e., not industry-adjusted, CCC is positive. However, for some 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 reveals that its cash conversion cycle is –26 days, which means that Apple collects cash from sales on average 26 days before it pays its suppliers.[7] Apple is in the Electronic Equipment industry, and the median firm in this industry had a CCC of 94 days in the previous quarter. Thus, Apple's industry-adjusted CCC is even more negative ($-120 = -26 -$

[6] 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).

[7] 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).

94), which indicates that Apple's operations are substantially more efficient than other firms in its industry.

3.2 Informativeness of operational efficiency

To address the question of whether and why a firm's operational efficiency as reflected in its cash conversion cycle is informative to investors, we proceed in two main steps. First, we determine whether investors react to information reflected in *CCC*. We do so by testing whether the current level of, or most recent change in, *CCC* is positively associated with abnormal stock returns and trading volume at quarterly earnings announcements. We also test whether *CCC* is positively associated with future earnings and operating cash flows and whether the future earnings and operating cash flows associated with *CCC* 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 operational efficiency is positively associated with abnormal price or trading volume reactions to information in earnings announcements, we estimate several versions of the following equation.

$$REACT_{i,t} = \beta_1 CCC_{i,t} + \sum_k \beta_k \, Controls_{i,t} + \gamma_i + \delta_t + U_{i,t} \qquad \text{(1a)}$$

$REACT$ 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 $[-54, -5]$ relative to the quarter's earnings announcement

(Israeli et al., 2022). If operational efficiency 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 (Berkovitch et al., 2022; Israeli et al., 2022). These are absolute standardized unexpected earnings, $AbsSUE$; return on equity, ROE; an indicator variable for whether a firm reports a loss, $Loss$; operating accruals, $OAcc$; institutional ownership, $InstOwn$; analyst following, $Analyst$; log of equity market value, $Size$; log of equity book-to-market ratio, BTM; and return momentum, $Mom.$ 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 efficiency and result in variation in investor reactions to information in earnings announcements. 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 efficiency and the market reaction to information in quarterly earnings announcements relates to the most recent change in *CCC* rather than its level, we disaggregate CCC into the change in CCC during the quarter, ΔCCC, and the level of *CCC* in quarter $t-1$. This yields the following equation.

$$REACT_{i,t} = \beta_1 \Delta CCC_{i,t} + \beta_2 CCC_{i,t-1} + \sum_k \beta_k\, Controls_{i,t} + \gamma_i + \delta_t + U_{i,t} \qquad (1b)$$

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

3.2.2 Does CCC predict future earnings and operating cash flows?

We expect CCC is positively associated with future earnings and operating cash flows. To the extent that this is the case, we predict that the positive association between *CCC* and the price and volume reactions to quarterly earnings announcements are associated with this forward-looking information.

To test these predictions, we implement a two-stage least square (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 *CCC*—in equation (2a)—or most recent change in *CCC*—in equation (2b).

$$FuturePerf_{i,t+1} = \beta_1 CCC_{i,t} + \gamma_i + \delta_t + U_i \tag{2a}$$

$$FuturePerf_{i,t+1} = \beta_1 \Delta CCC_{t,i} + \beta_2 CCC_{i,t-1} + \gamma_i + \delta_t + U_i \tag{2b}$$

$FuturePerf$ 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 *CCC* in equation (1a) and for *ΔCCC* and CCC_{t-1} in equation (1b). These fitted values capture the information about future earnings or future operating cash flows reflected in *CCC*. Significantly positive coefficients on the fitted values in the second stage indicate that information reflected in *CCC* about future earnings and operating cash flows is a channel through which operational efficiency relates to returns and trading volume at quarterly earnings announcements. Following Chen et al. (2022), we use bootstrapping to adjust the second-stage standard errors for the first-stage estimation.

To provide additional evidence on the predictive ability of *CCC* for future earnings, we estimate equations (3a) and (3b).

$$\begin{aligned} RET_{i,t} = {} & \beta_1 EARN_{i,t+1} + \beta_2 \Delta EARN_{i,t} + \beta_3 CCC_{i,t} \\ & + \beta_4 CCC_{i,t} \times EARN_{i,t+1} + \beta_5 CCC_{i,t} \times \Delta EARN_{i,t} \\ & + \textstyle\sum_k \beta_k \, Controls_{i,t} + \gamma_i + \delta_t + U_{i,t} \end{aligned} \tag{3a}$$

$$\begin{aligned} RET_{i,t} = {} & \beta_1 EARN_{i,t+1} + \beta_2 \Delta EARN_{i,t} + \beta_3 \Delta CCC_{i,t} + \beta_4 CCC_{i,t-1} \\ & + \beta_5 \Delta CCC_{i,t} \times EARN_{i,t+1} + \beta_6 \Delta CCC_{i,t} \times \Delta EARN_{i,t} \end{aligned}$$

$$+\beta_7 CCC_{i,t-1} \times EARN_{i,t+1} + \beta_8 CCC_{i,t-1} \times \Delta EARN_{i,t}$$
$$+ \sum_k \beta_k \, Controls_{i,t} + \gamma_i + \delta_t + U_{i,t} \quad (3b)$$

RET is stock return for quarter *t*, beginning the last month of fiscal quarter *t* and ending two months after fiscal quarter *t* ends.[8] $Controls$ includes variables that prior research finds are determinants of returns associated with earnings and operational efficiency (Israeli et al., 2017), namely RET_{t+1}, $InstOwn$, $ATGROWTH$, $Loss$, and $Size$.[9] If *CCC* reflects information about future earnings, we expect β_5 in equation (3a) and β_6 in equation (3b) are positive.

3.3 Does information about operational efficiency prolong price discovery?

To address the question of whether a firm's operational efficiency, as reflected in its cash conversion cycle, prolongs price discovery at earnings announcements, we test whether *CCC* is negatively related to the timeliness and efficiency with which quarterly earnings announcement information is incorporated into stock prices and positively related to post-earnings-announcement drift.

3.3.1 Do stock prices timely and efficiently reflect information about operational efficiency?

To test whether investors incorporate information in *CCC* in a timely and efficient manner, we examine the association between *CCC* and measures of speed of price discovery at quarterly earnings announcements, by estimating several versions of the following equations.

$$IPX_{i,t} = \beta_1 CCC_{i,t} + \sum_k \beta_k \, Controls_{i,t} + \gamma_i + \delta_t + U_{i,t} \quad (4a)$$

$$IPX_{i,t} = \beta_1 \Delta CCC_{i,t} + \beta_2 CCC_{i,t-1} + \sum_k \beta_k \, Controls_{i,t} + \gamma_i + \delta_t + U_{i,t} \quad (4b)$$

[8] We use this window to compute *RET* to ensure that *RET* captures the price change during three-month period concurrent with a firms' quarterly earnings announcement. Measuring *RET* during the three months beginning two months before fiscal quarter *t* and ending one month after fiscal quarter *t* ends reveals the same inferences.

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

where IPX denotes either intraperiod timeliness, IPT, and intraperiod efficiency, IPE. $Controls$ comprises the same variables as in equations (1a) and (1b): $AbsSUE$, ROE, $Loss$, $OAcc$, $InstOwn$, $Analyst$, $Size$, BTM, and Mom with the addition of $CAR[-1,1]$ as controls for return reaction to information at quarterly earnings announcements.

Following prior research (Blankespoor et al., 2018; Berkovitch et al., 2022; Israeli et al., 2022), we measure IPT as:

$$IPT_{i,t} = \sum_{j=0}^{5} \frac{CAR_{i,t}[0,j]}{CAR_{i,t}[0,5]} + 0.5,$$

where $CAR[0,j]$ is the cumulative abnormal return for firm i from day zero through day j, relative to quarter *t*'s earnings announcement. Each $[0, j]$ 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:

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

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 *CCC*—in equation (4a)—and most recent change in *CCC*—in equation (4b).

If a firm's level of operational efficiency, as measured by its cash conversion cycle, is informative to investors but investors fail to incorporate fully the information in *CCC* into stock prices at the earnings announcement, we expect β_1 in equation (4a) is negative. If the recent change in *CCC* 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 (4b) is negative.

3.3.2 Is operational efficiency positively associated with post-earnings-announcement drift?

To test whether operational efficiency helps explain post-earnings-announcement drift, we estimate several versions of equations 5(a) and 5(b).

$$\begin{aligned} CAR[2,61]_{i,t} = {} & \beta_1 CAR[-1,1]_{i,t} + \beta_2 CCC_{i,t} + \beta_3 CCC_{i,t} \times CAR[-1,1]_{i,t} \\ & + \textstyle\sum_k \beta_k \, Controls_{i,t} + \gamma_i + \delta_t + U_{i,t} \end{aligned} \tag{5a}$$

$$\begin{aligned} CAR[2,61]_{i,t} = {} & \beta_1 CAR[-1,1]_{i,t} + \beta_2 \Delta CCC_{i,t} + \beta_3 CCC_{i,t-1} \\ & + \beta_4 \Delta CCC_{i,t} \times CAR[-1,1]_{i,t} + \beta_5 CCC_{i,t-1} \times CAR[-1,1]_{i,t} \\ & + \textstyle\sum_k \beta_k \, Controls_{i,t} + \gamma_i + \delta_t + U_{i,t} \end{aligned} \tag{5b}$$

$CAR[2,61]$ 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). $Controls_{i,t}$ in equations (5a) and (5b) comprise the same variables as in equations (4a) and (4b).

Equations (5a) and (5b) include $CAR[-1,1]$ as an explanatory variable and interacted with *CCC*. If the information reflected in *CCC* is associated with higher post-earnings-announcement drift, we expect β_3 in equation (5a) and β_4 in equation (5b) are positive.

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 January 1988 to December 2021.[10] We begin our sample in 1988 because this is the first full year with available cash flows information (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.

[10] As in Barth et al. (2022), we use Compustat exchange codes 11, 12, and 14 to identify these firms.

We exclude from our sample financial firms, i.e., 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 and end of quarter share price below $1. We also exclude observations with less than $10 million of cost of goods sold or sales because these amounts are 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 et al., 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.[11]

4.2 Descriptive statistics

Table 1 presents distributional statistics for CCC and its three components−*DIO*, *DSO*, and *DPO*−by industry. Consistent with Wang (2019), Table 1 reveals that operational efficiency varies substantially across industries.[12] The lowest (highest) median CCC is in the Restaurants, Hotels, and Motels (Electrical Equipment) industry. This is not surprising because firms in the Electrical Equipment industry tend to hold inventory and provide credit for more days (median *DIO* = 143 and median *DSO* = 71) than firms in the Restaurants, Hotels, and Motels industry (median *DIO* = 8 and median *DSO* = 7). Untabulated statistics indicate that the mean firm-by-firm AR(1) coefficient for *CCC* is 0.64 and for *ΔCCC* is −0.14.[13] These statistics reveal that

[11] Using unwinsorized variables in our analyses reveal the same inferences as our tabulated findings.
[12] Untabulated statistics reveal that *CCC* as well as its components also exhibit considerable variation within industries and across quarters.
[13] 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.

operational efficiency exhibits moderate, not high, persistence. Thus, it changes over time for a given firm.

Table 2 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, on average, industry median-adjusted *CCC* is -6.49 days. Untabulated statistics reveal that *CCC* comprises an average of 11.2 days inventory outstanding, 4.5 days sales outstanding, and 8.5 days payables outstanding. Panel A also reveals that during the earnings announcement window, i.e., 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). Stock prices reflect, on average, 59% of information in quarterly earnings announcements in an efficient manner (mean *IPE* = 0.59). Panel A also reveals that, on average, firms are profitable (mean *ROE* = 2%) with only 21% reporting losses (mean *Loss* = 0.21), are followed by more than seven analysts (mean *Analyst* = 7.13) and exhibit substantial institutional ownership (mean *InstOwn* = 0.58).

Panel B of Table 2 reveals that, consistent with operational efficiency being informative to investors, *CCC* is positively correlated with both abnormal returns and abnormal trading volume at quarterly earnings announcements. The Pearson (Spearman) correlation between *CCC* and $CAR[-1, 1]$ is 0.03 (0.03) and between *CCC* and *ATVol* is 0.01 (0.03). In addition, consistent with prior research, even though our measures of the speed with which stock prices reflect earnings information capture different aspects of the price discovery process, *IPT* and *IPE* exhibit sizable positive correlations (Pearson and Spearman corrs. = 0.44 and 0.56).

5 Findings

5.1 Information content of operational efficiency

5.1.1 Market reaction to information about operational efficiency

Table 3 presents summary statistics from estimating equations (1a) and (1b). Columns (1) and (2) present summary statistics from estimating the equations when $CAR[-1,1]$ is the dependent variable. These columns reveal that the current level of, and most recent change in, *CCC* are positively associated with abnormal returns at earnings announcements (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 (recent change in) *CCC* is associated with a 0.24% (0.51%) higher three-day earnings announcement return.[14]

Columns (3) and (4) present summary statistics from estimating equations (1a) and (1b) when *ATVol* is the dependent variable. These columns reveal inferences similar to those relating to $CAR[-1,1]$. In particular, the current level of, and most recent change in, *CCC* are significantly positively associated with abnormal trading volume (coefs. = 0.02 and 0.10; t-stats. = 1.96 and 4.94). These coefficients imply that a one standard deviation higher current level of (recent change in) *CCC* is associated with a 1.27% (2.57%) higher three-day earnings announcement abnormal trading volume.[15]

Taken together, the findings in Table 3 support the inference that operational efficiency is informative to investors.

5.1.2 Predictive ability of operational efficiency for earnings and operating cash flows

Table 4, panels A and B, present summary statistics from our two-stage tests of whether operational efficiency reflects information about future earnings, $EARN_{t+1}$, and future operating

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[14] 0.24% is $\frac{0.38}{100} \times 63.44$ and 0.51% is $\frac{1.98}{100} \times 25.69$, where 0.38 (1.98) is the estimated *CCC* (Δ*CCC*) coefficient and 63.44 (25.69) are the standard deviations of *CCC* (Δ*CCC*). Because in our regression analyses, for ease of exposition, we divide *CCC* by 100 when quantifying the effect of operational efficiency on capital market outcome we divide the coefficient estimates by the same amount.

[15] 1.27% is $(\frac{0.02}{100} \times 63.44) \times 100$ and 2.57% is $(\frac{0.1}{100} \times 25.69) \times 100$, where 0.02 (0.10) is the estimated *CCC* (Δ*CCC*) coefficient and 63.44 (25.69) are the standard deviations of *CCC* (Δ*CCC*). Because *ATVol* is defined as log of one plus abnormal trading volume, in addition to dividing the coefficient estimates by 100 we also multiply them by 100 to maintain the % interpretation.

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), reveal, as expected, that the current level of, and most recent change in, *CCC* 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 CCC 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 change in, *CCC* 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 *CCC* 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 5 presents summary statistics from estimating equations (3a) and (3b). The table reveals that the coefficients on the interaction between $EARN_{t+1}$ and *CCC* and the interaction between $EARN_{t+1}$ and ΔCCC 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 efficiency. This is not surprising in light of the Table 3 findings that operational efficiency is positively associated with price and trading volume reactions at quarterly earnings announcements and the Table 4 findings that these reactions are associated with information reflected in *CCC* about future earnings and future cash flow from operations. Thus, the findings in Table 5 support the inference that operational efficiency contains forward-looking information that, at least partially, is impounded into stock prices.[16]

5.2 Price discovery

Table 6 presents summary statistics from estimating equations (4a) and (4b). 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 change in, *CCC* 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). These findings indicate that an improvement in *CCC* reduces the speed with which stock prices reflect information in quarterly earnings announcements. Thus, investors do not incorporate fully into stock prices in a timely manner the information reflected in operational efficiency.

Columns (3) and (4) present summary statistics from estimating equations (4a) and (4b) when intraperiod efficiency, *IPE*, is the dependent variable. These columns reveal that the current level of, and most recent change in, *CCC* 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 *CCC* is associated with lower efficiency with which stock prices reflect information in quarterly earnings announcements.

[16] 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 5.

Table 7 presents summary statistics from estimating equations (5a) and (5b). As expected, and consistent with the findings in Table 6, Table 7 reveals that the current level of, and most recent change in, *CCC* are significantly positively related to post-earnings-announcement drift. In particular, the coefficients on the interactions between *CCC* and $CAR[-1,1]$ and between *ΔCCC* and $CAR[-1,1]$ are significantly positive (coefs. = 0.05 and 0.11; t-stats. = 4.13 and 3.03). The findings indicate that an improvement in the level of (change in) operational efficiency is associated with more post-earnings-announcement drift.

Together, the findings in Tables 4 through 7 support the inference that *CCC* reflects forward-looking information about earnings and cash flow from operations that predicts future stock returns. However, the findings also reveal that investors do not fully incorporate this information into stock prices in a timely or efficient manner. Thus, our findings help identify investors' incomplete and untimely reaction to information about operational efficiency as a source of stock return predictability documented in Wang (2019).

6. Additional analyses

6.1 When does the information in operational efficiency prolong price discovery?

To identify circumstances in which information about operational efficiency prolongs price discovery, we focus on instances when the firm announces bad earnings news. Specifically, we create two indicator variables, 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 and SUE_{BOT}, which equals 1 if the firm's *SUE* is in the bottom tercile and zero otherwise. We then estimate equations (4b) and 5(b), adding interactions between the most recent change in, and the prior quarter level of, *CCC* and SUE_{TOP} and SUE_{BOT}, as well as SUE_{TOP} and SUE_{BOT}. We refer to firm-quarter observations in the top (bottom) *SUE* tercile as releasing good (bad) earnings news.[17]

Table 8 presents summary statistics from estimating the revised equation (4b). Column (1) reveals that for good earnings news observations the association between the most recent change in *CCC* and *IPE* is not significant. Specifically, the coefficient on *ΔCCC* is -0.01 and that on *ΔCCC* interacted with 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 efficiency is not associated with the efficiency of price discovery.

In contrast, column (2) reveals that when the firm announces bad earnings news, the association between the most recent change in *CCC* and *IPE* is significantly negative. Specifically, the coefficient on *ΔCCC* is -0.001 and that on *ΔCCC* interacted with 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 efficiency is significantly negatively related to the efficiency of price discovery.

Columns (3) and (4) present summary statistics from estimating equation (5b) using two subsamples based on the terciles of *SUE*. The subsample underlying the summary statistics in column (3) (column (4)) have good (bad) earnings news. Column (3) reveals that when firms have good earnings news there is no significant relation between $CAR[2,61]$ and the interaction of *ΔCCC* and $CAR[-1,1]$. That is, consistent with the findings relating to *IPE* in column (1),

[17] 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*.

when firms have good earnings news, there is no significant relation between the most recent change in *CCC* and post-earnings-announcement drift. In contrast, and consistent with the findings relating to *IPE* in column (2), column (4) reveals that when firms have bad earnings news, the relation between $CAR[2, 61]$ and the interaction of *ΔCCC* and $CAR[-1, 1]$ is significantly positive (t-stat. = 1.93). These findings reveal that the significantly positive relation between *ΔCCC* and post-earnings-announcement drift in Table 7 is evident only for firms with bad earnings news.

Together, the Table 8 findings suggest that information reflected in operational efficiency prolongs price discovery only when firms announce bad earnings news. This evidence suggests that investors focus on the bad earnings news and fail to incorporate fully into stock prices the news regarding operational efficiency.

6.2 Information in components of operational efficiency

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

Thus, we estimate equations (1b) and (4b), with *IPE* as the dependent variable, replacing the most recent change in *CCC* and its previous level with the most recent change in each component of *CCC* and its previous level. Specifically, we sequentially estimate equations (1b) and (4b) using (i) the three components of *ΔCCC*−days inventory outstanding, *ΔDIO*; days sales outstanding, *ΔDSO*; and days payables outstanding, *ΔDPO*−separately, in place of *ΔCCC*, (ii) all three components together, in place of ΔCCC, and (iii) each component, separately, together with ΔCCC.[18] The first two estimations allow us to test which components of CCC have information content for investors. More importantly for our research question, the third set of estimations enables us to test whether CCC has information content incremental its components. For the sake of brevity, we tabulate only the analyses that examine the most recent changes in and lagged levels of the CCC components. Our inferences are the same when instead we use the current levels of CCC as in equations (1a) and (4a).

Table 9 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), reveal 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). Although the positive signs of the ΔDIO and ΔDSO coefficients are consistent with their roles in measuring ΔCCC, the positive sign of the ΔDPO coefficient is not.[19] 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. Notably, column (4) reveals that when the most recent change in, and previous level of, all three components are included together, they all are significantly related to $CAR[-1, 1]$ with signs consistent with their roles in measuring CCC.

More importantly for our research question, panel A, columns (5) through (7) reveal that ΔCCC is significantly positively related to $CAR[-1, 1]$ incremental to the most recent change in and previous level of each CCC component (t-stats. range from 3.05 to 11.11). These findings

[18] Because CCC is a linear combination of the three components, we cannot estimate a single equation with all three components and CCC together.
[19] Recall from Section 3.1 that $CCC = DIO + DSO - DPO$.

reveal that the information content of *CCC* subsumes the information content of some of its components, but not vice versa.

Panel B reveals inferences similar to those revealed by panel A. Most importantly, columns (5) through (7) reveal that *ΔCCC* is significantly positively related to *ATVol* incremental to the most recent change in and previous level of each *CCC* component (t-stats. range from 2.24 to 4.73).

Panel C presents summary statistics from estimating equation (4b) using *IPE* as the dependent variable. The results reveal that of the components, only the previous level of *DPO* consistently has a significant relation with *IPE* (t-stats. = 3.16, 3.58, and 2.65) and the signs of the coefficients are inconsistent with *DPO*'s role in measuring *CCC*. More importantly for our research question, columns (5) through (7) reveal that *ΔCCC* is significantly negatively associated with *IPE* incremental to all of its components (t-stats. = −1.95, −1.68, and −2.19). Taken together, the findings in Table 9 support the inferences we draw from Table 6.[20]

6.3 Robustness tests

6.3.1 Alternative measure of operational efficiency

A potential concern with our inferences is that they depend on our measure of CCC. To address this concern, we repeat our analyses using the Lam and Larocque (2022) measure of operational efficiency, *CCCDR*. This measure includes the number of days deferred revenue is outstanding, *DDRO*, to incorporate the time firms have cash advances from customers:

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

[20] We also re-estimate the equations underlying Table 7 using the specifications that include the *CCC* components. The untabulated findings reveal, consistent with our other component analyses, that *CCC* is significantly positively associated with post-earnings-announcement drift incremental to any of its components.

where $DDRO_t = 90 \times \frac{(DR+DR_{t-1})/2}{SALES_t}$ and DR is deferred revenue.

Table 10, panel A, presents findings from re-estimating equation (1b) in columns (1) and (2), and equation (4b), using *IPE* as the dependent variable, in column (3).[21] Consistent with Tables 3 and 8, columns (1) and (2) reveal that the coefficients on *ΔCCCDR* and *CCCDR* are significantly positive (t-stats. range from 1.91 to 11.90) and column (3) reveals they are significantly negative (t-stats. = −2.90 and −3.55). These findings mitigate the concern that our main findings are attributable to our choice of a particular operational efficiency measure.

6.3.2 Alternative industry classification

In our main analyses we define industries using the Fama and French (1997) 48-industry classification. We use this both for our measure of operational efficiency, when we subtract the industry median for each firm, and for the fixed effects structure in our estimating equations. A potential concern is that our findings could be sensitive to the choice of industry classification. Thus, we repeat our main analyses using three alternative industry classifications.

Table 10, panel B, presents findings from re-estimating our main analyses using these alternative industry classifications. In particular, columns (1) through (3) present findings based on the Fama and French (1997) 30-industry classification, columns (4) through (6) present findings based on two-digit SIC classification, and columns (7) through (9) present findings based on the Barth et al. (2005) industry classification. In each analysis we adjust the fixed effects structure to reflect the choice on industry classification. Panel B reveals the same inferences as our main tables, which mitigates concern that our inferences are sensitive to the choice of industry classification. Most importantly for our research questions, the coefficients on

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

ΔCCC are significantly positive when $CAR[-1,1]$ and *ATVol* are the dependent variables (t-stats. range from 4.80 to 11.96) and significantly negative with *IPE* is the dependent variable (t-stats. = -2.27, -2.04, and -2.00).

6.3.3 Information content of firm operational efficiency 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 and the 2008 financial crisis. Thus, we omit from the sample each of these periods separately and together and re-estimate our main analyses.

Table 10, panel C, presents the findings. Columns (1) through (3) present findings based on excluding 13,911 observations from 2,579 firms in both the Dot-Com crash and 2008 financial crisis, columns (4) through (6) present findings based on excluding 2,690 observations from 1,542 firms during the 2008 financial crisis, and columns (7) through (9) present finding based on excluding 11,221 observations from 2,166 firms during the Dot-Com crash. As with panels A and B, panel C reveals the same inferences as our main tables, 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 ΔCCC are significantly positive when $CAR[-1,1]$ and *ATVol* are the dependent variables (t-stats. range from 4.69 to 11.90) and significantly negative with *IPE* is the dependent variable (t-stats. = -1.85, -2.29, and -1.96).

7. Summary and concluding remarks

We address whether and why a firm's operational efficiency has information content for investors and how operational efficiency affects the price discovery process at quarterly earnings announcements. We measure operational efficiency using a firm's cash conversion cycle, CCC, where shorter CCC reflects better operational efficiency, i.e., how much time, in days, it takes a firm to convert a dollar invested in inventory into a dollar collected in sales.

Using a sample of 119,143 observations from 4,752 U.S. firms from 1988 to 2021, we find that operational efficiency is positively associated with measures of investor reaction to information in quarterly earnings announcements, namely abnormal stock returns and abnormal trading volume. We further show that operational efficiency contains forward-looking information regarding future earnings and cash flows. This forward-looking information helps explain why operational efficiency is positively associated with the market reaction to earnings announcements. We also show that the predictive ability of operational efficiency is not attributable to inventory, sales, or other working capital amounts, per se, but to a construct that includes them as inputs, i.e., CCC has predictive ability incremental to its components. This is important because CCC is the predominant metric capturing the efficiency of a firm's operations along its three key dimensions: investing in and selling inventory, collecting cash from customers, and paying suppliers.

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

Together, our findings shed light on an informative accounting-based measure that investors fail to incorporate into stock prices in a timely and efficient manner. These findings also shed light on the recent discussions between regulators and managers regarding the level of disclosure required by firms regarding their operating cash cycle. Our findings suggest that operational efficiency contains forward-looking information regarding future earnings and cash flows that also affects the speed and efficiency which information at quarterly earnings announcements is incorporated into prices—particularly for firms with bad earnings news. Thus, our study suggests that the new expanded disclosures could benefit investors who currently fail to incorporate fully the information in operational efficiency into stock prices in a timely and efficient manner and result in more informative stock prices. Whether this is the case is left for future research.

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Appendix: Variable definitions

Variable	Description
$Analyst$	Natural logarithm of 1 plus the number of analysts providing an earnings forecast calculated at the firm-quarter level.
$ATGROWTH$	Asset growth calculated as the change in total assets during the quarter from total assets at the prior quarter.
$ATVol$	Abnormal trading volume calculated as the natural logarithm of one plus the share turnover ratio for across days $[-1, 1]$, scaled by the average daily turnover ratio across days $[-54, -5]$ relative to the quarterly earnings announcement. Defined as $ATVol = ln(1+\frac{\frac{1}{3}\sum_{j=-1}^{1} TR_{i,t+j}}{\frac{1}{50}\sum_{j=5}^{54} TR_{i,t-j}})$. TR is the ratio between the number of shares traded and the number of shares outstanding, j represents 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 average time, in days, it takes a firm to convert a dollar invested in inventory to a dollar collected from sales during the quarter. It is calculated as days inventory outstanding plus days sales outstanding minus days payables outstanding $CCC = DIO + DSO - DPO$
$CCCDR$	An alternative definition of CCC that includes days deferred revenue outstanding in addition to the original components defined, calculated as: $CCC = DIO + DSO - DPO - DDRO$. $DDRO$ is defined as $90 \times \frac{(DR_{t-1}+DR_t)/2}{SALES_t}$ and DR indicates deferred revenue.
ΔCCC	The change in the CCC from the previous quarter to the current one.
$\Delta CCCDR$	An alternative definition of ΔCCC that includes days deferred revenue outstanding in addition to the components in our main specification. Defined as the change in $CCCDR$ from the prior to the current quarter.
CFO	The cash flow from operating activities, scaled by total assets.
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 period t, $COGS_t$ is the cost of goods sold of the firm at period 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.
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
$\Delta EARN$	Change in firm-level earnings before extraordinary items from the previous quarter, scaled by market value of equity
$InstOwn$	Percentage of shares owned by institutions at the most recent quarter-end.
IPE	Intraperiod efficiency of reported earnings, defined as: $IPE = 1 - \sum_{j=0}^{5} \frac{\lvert CAR[0,5]-CAR[0,j]\rvert}{\lvert CAR[0,5]\rvert}$, where j represents the trading day from 0 to 5 relative to the quarterly earnings announcement.
IPT	Intraperiod timeliness of reported earnings, defined as: $IPT = \sum_{j=0}^{4} \frac{CAR[0,j]}{CAR[0,5]} + 0.5$, where j represents 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.
Mom	Six-month cumulative stock return for ending one month prior to the quarter end date.
$OAcc$	Operating accruals, calculated as the difference between income before extraordinary items and cash flows from operating activities, divided by average total.
RET	Stock return measured during the three months starting from the last month of the fiscal quarter end 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 at the end of the quarter, measured as the difference between net income before extraordinary items of the last quarter and the 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 the standardized unexpected earnings is in the bottom tercile and 0 otherwise.
SUE_{TOP}	An indicator variable equal to 1 if the standardized unexpected earnings is in the top tercile and 0 otherwise.
ROE	Return on book value of equity during the quarter, measured as the ratio between net income before extraordinary items and average total assets for the quarter.

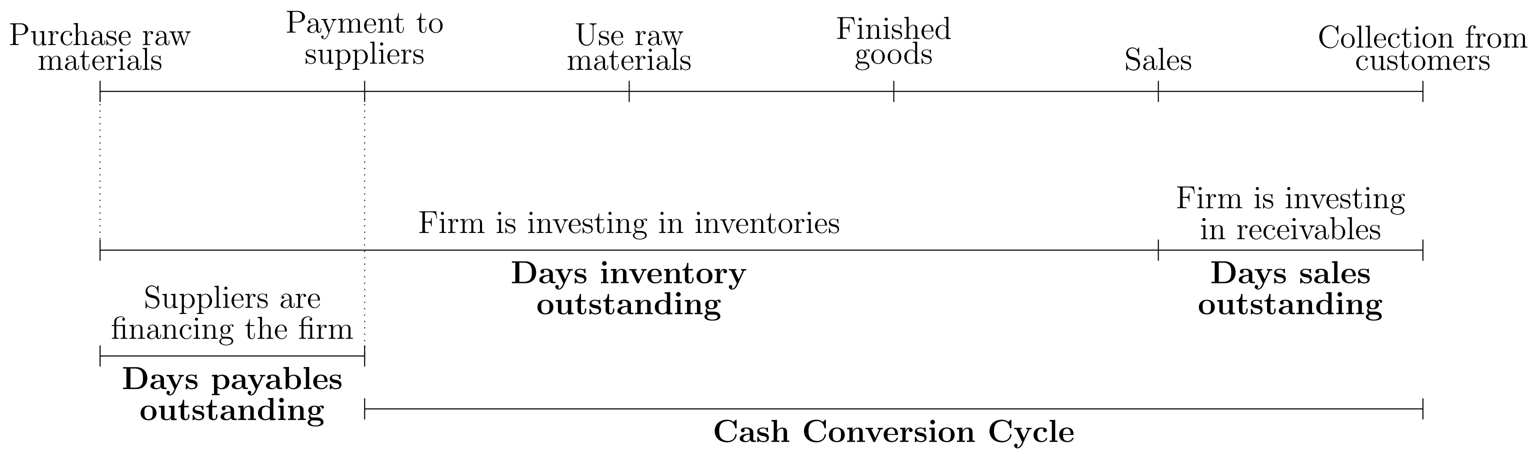

Figure 1: Graphic representation of a firm's cash conversion cycle

This figure presents the cash conversion cycle of a firm with a positive cycle. It begins with the purchase of raw materials or inventory, the firm then either produces final inventory or prepares it for sale, sells it, and the cycle finishes with collection of cash from sales. It is calculated as the sum of days inventory outstanding and days receivables outstanding minus days payables outstanding. All variables and components of the the cash conversion cycle are defined in the Appendix.

Table 1: Cash conversion cycle in days by industry

Industry	CCC	CCC_{sd}	DIO	DSO	DPO
Restaurants, Hotels, Motels	2	18	8	7	16
Entertainment	3	23	9	21	28
Petroleum and Natural Gas	14	19	22	58	59
Candy and Soda	17	39	45	37	60
Communication	20	11	6	54	47
Transportation	20	5	5	40	25
Utilities	21	9	20	45	45
Personal Services	30	32	16	36	28
Healthcare	42	8	4	54	19
Business Services	47	9	2	65	28
Food Products	52	10	57	30	31
Printing and Publishing	54	26	38	49	37
Shipping Containers	55	14	57	45	43
Retail	55	9	76	7	37
Business Supplies	60	9	56	44	39
Other	61	16	34	60	39
Coal	62	71	62	48	50
Wholesale	63	11	55	44	36
Automobiles and Trucks	72	14	54	57	41
Shipbuilding, Railroad Equipment	72	19	64	47	36
Precious Metals	77	44	97	28	49
Rubber and Plastic Products	79	13	65	52	38
Computers	86	18	69	62	44
Steel Works Etc	86	11	71	48	33
Chemicals	87	11	76	58	45
Non-Metallic and Industrial Metal Mining	87	28	73	51	34
Construction Materials	88	13	70	51	32
Beer and Liquor	89	60	92	45	52
Defense	95	33	65	59	33
Electronic Equipment	97	14	84	57	47
Consumer Goods	99	16	85	49	46
Construction	101	69	64	54	30
Fabricated Products	115	29	91	64	39
Textiles	115	20	94	53	32
Pharmaceutical Products	118	21	119	58	48
Apparel	121	23	110	51	38
Machinery	127	14	100	65	43
Recreation	130	29	100	75	42
Agriculture	131	190	125	57	52
Aircraft	135	23	103	63	38
Measuring and Control Equipment	145	21	121	68	42
Medical Equipment	149	16	133	64	43
Tobacco Products	165	106	190	19	43
Electrical Equipment	172	43	143	71	39

This table presents descriptive statistics for the cash conversion cycle, CCC, and its components in days by Fama and French (1997) 48-industry classification. DIO, DSO, and DPO are days inventory outstanding, days sales outstanding, and days payables outstanding. Each column reports the mean of the industry-year-quarter medians for each variable. CCC_{sd} is the standard deviation of the reported CCC mean. The sample comprises 119,143 observations from 4,752 U.S. firms from 1988 to 2021. See the Appendix for definitions of all variables.

Table 2: Descriptive statistics

Panel A: Distributional statistics

	Mean	Median	Std Dev
CCC	-6.49	0.20	63.44
ΔCCC	-0.09	-0.11	25.69
$CAR[-1,1]$	0.56	0.30	10.26
$ATVol$	2.00	1.62	1.50
IPT	4.02	4.06	2.28
IPE	0.59	0.66	0.29
SUE	0.03	0.01	0.08
ROE	0.02	0.02	0.07
$Loss$	0.21	0.00	0.41
$OAcc$	-0.01	-0.01	0.04
$InstOwn$	0.60	0.65	0.27
$Analyst$	1.71	1.79	0.94
$Size$	6.62	6.53	1.91
BTM	0.46	0.42	0.27
Mom	0.08	0.05	0.35

Table 2 (continued): Descriptive statistics

Panel B: Correlations

	CCC	Δ CCC	CAR[-1, 1]	ATVol	IPT	IPE	SUE	ROE	Loss	OAcc	InstOwn	Analysts	Size	BTM	Mom
CCC		0.22	0.03	0.01	−0.01	0.003	0.03	0.06	−0.05	−0.06	0.02	0.10	0.07	−0.12	0.06
ΔCCC	0.15		0.06	0.03	−0.001	−0.001	0.02	0.07	−0.06	−0.06	−0.003	−0.003	0.004	0.003	0.02
$CAR[-1,1]$	0.03	0.09		0.03	0.04	-0.01	0.09	0.11	-0.12	-0.02	-0.01	-0.01	-0.02	0.03	-0.01
ATVol	0.03	0.03	0.03		0.19	0.18	0.05	0.06	-0.05	0.01	0.01	0.01	-0.03	-0.02	0.03
IPT	−0.01	0.00	0.04	0.28		0.44	0.01	0.04	-0.03	0.01	0.09	0.06	0.03	-0.04	0.01
IPE	−0.01	-0.01	-0.01	0.30	0.56		0.02	0.07	-0.07	0.02	0.14	0.11	0.07	-0.10	0.02
SUE	0.06	0.04	0.20	0.09	0.02	0.01		0.38	-0.23	0.22	-0.01	-0.01	0.01	-0.09	0.15
ROE	0.11	0.09	0.15	0.12	0.05	0.09	0.38		-0.65	0.33	0.09	0.11	0.14	-0.22	0.17
Loss	−0.04	−0.05	-0.12	-0.07	-0.04	-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	-0.01	0.01	0.02	0.15	0.20	-0.22		-0.01	-0.05	0.01	-0.05	0.08
InstOwn	0.02	0.01	0.01	0.16	0.11	0.15	-0.01	0.09	-0.06	-0.02		0.41	0.13	-0.26	0.01
Analysts	0.12	-0.01	-0.01	0.15	0.08	0.13	-0.04	0.16	-0.09	-0.05	0.51		0.55	-0.31	-0.02
Size	0.12	0.00	-0.01	0.12	0.08	0.16	-0.01	0.28	-0.19	0.01	0.54	0.79		-0.20	0.02
BTM	-0.14	0.01	0.01	-0.13	-0.05	-0.09	-0.07	-0.43	0.18	-0.03	-0.25	-0.40	-0.52		-0.26
Mom	0.06	0.02	0.01	0.05	0.01	0.03	0.24	0.23	-0.18	0.07	0.05	0.01	0.13	-0.29	

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 observations from 4,752 U.S. firms from 1988 to 2021. See the Appendix for definitions of all variables.

Table 3: Informativeness of operational efficiency

	$CAR[-1,1]$		$ATVol$	
	(1)	(2)	(3)	(4)
CCC_t	0.38***		0.02*	
	(6.25)		(1.96)	
ΔCCC_t		1.98***		0.10***
		(11.50)		(4.94)
CCC_{t-1}		0.24***		0.01
		(3.93)		(1.22)
SUE	9.06***	9.11***		
	(13.64)	(13.68)		
$AbsSUE$			0.62***	0.62***
			(6.76)	(6.74)
ROE	11.70***	11.19***	1.50***	1.47***
	(13.28)	(12.65)	(10.84)	(10.74)
$Loss$	−2.27***	−2.23***	−0.13***	−0.12***
	(−17.52)	(−17.47)	(−6.95)	(−6.83)
$OAcc$	−18.39***	−17.60***	−0.43**	−0.39**
	(−12.07)	(−11.64)	(−2.59)	(−2.39)
$InstOwn$	0.13	0.12	−0.06*	−0.06*
	(0.79)	(0.72)	(−1.74)	(−1.76)
$Analyst$	0.21**	0.21**	0.17***	0.17***
	(2.50)	(2.52)	(10.49)	(10.50)
$Size$	−0.35***	−0.34***	−0.13***	−0.13***
	(−7.62)	(−7.50)	(−17.89)	(−17.86)
BTM	2.18***	2.11***	−0.13***	−0.13***
	(9.35)	(9.05)	(−3.72)	(−3.82)
Mom	−0.45***	−0.45***	0.10***	0.10***
	(−2.97)	(−2.99)	(5.61)	(5.60)
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	0.03	0.04	0.06	0.06

This table presents regression summary statistics from estimating equations (1a) and (1b) showing the association between current CCC, its lagged level and recent change in CCC and returns at earnings announcements, $CAR[-1,1]$, and 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 observations from 4,752 U.S. firms from 1988 to 2021. See the Appendix for definitions of all variables.

Table 4: Informativeness channel

Panel A: Future earnings

	$EARN_{t+1}$	$CAR[-1,1]$	$ATVol$	$EARN_{t+1}$	$CAR[-1,1]$	$ATVol$
	(1)	(2)	(3)	(4)	(5)	(6)
CCC_t	0.001***					
	(8.34)					
ΔCCC_t				0.004***		
				(12.27)		
CCC_{t-1}				0.001***		
				(5.99)		
$\widehat{EARN}_{t+1_{Levels}}$		3.19***	0.20*			
		(5.97)	(1.96)			
$\widehat{EARN}_{t+1_{Changes}}$					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}	$CAR[-1,1]$	$ATVol$	CFO_{t+1}	$CAR[-1,1]$	$ATVol$
	(1)	(2)	(3)	(4)	(5)	(6)
CCC_t	0.004***					
	(21.88)					
ΔCCC_t				0.01***		
				(13.57)		
CCC_{t-1}				0.004***		
				(20.18)		
$\widehat{CFO}_{t+1_{Levels}}$		0.90***	0.06*			
		(5.97)	(1.96)			
$\widehat{CFO}_{t+1_{Changes}}$					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

This table presents summary statistics from estimating a two-stage least square approach. Estimates are produced using the current level of CCC or the recent change in and lagged level of CCC to forecast future performance of the firm and the subsequent second stage where the fitted values are used in equations (2a) and (2b). Panel A uses future earnings, $EARN_{t+1}$, as the dependent variable and Panel B uses future cash flows, CFO_{t+1}, as the dependent variable in the first stage. 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 observations from 4,752 U.S. firms from 1988 to 2021. See the Appendix for definitions of all variables.

Table 5: Operational efficiency and the relation between current returns and future earnings

	RET_t	
	(1)	(2)
$CCC_t \times EARN_{t+1}$	0.18**	
	(2.28)	
$CCC_t \times \Delta EARN_t$	4.35	
	(0.91)	
$\Delta CCC_t \times EARN_{t+1}$		0.33**
		(2.24)
$\Delta CCC_t \times \Delta EARN_t$		−5.14
		(−0.76)
$CCC_{t-1} \times EARN_{t+1}$		0.18**
		(2.29)
$CCC_{t-1} \times \Delta EARN_t$		8.42
		(1.61)
CCC_t	0.01***	
	(5.83)	
ΔCCC_t		0.04***
		(9.31)
CCC_{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

This table presents summary statistics from estimating equations (3a) and (3b). Panel A presents results using lagged, current, and future levels of earnings. Panel B presents results using the recent change in earnings and the future level of earnings. 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 observations from 4,752 U.S. firms from 1988 to 2021. See the Appendix for definitions of all variables.

Table 6: Operational efficiency and the timeliness and efficiency of price discovery at earnings announcements

	IPT		IPE	
	(1)	(2)	(3)	(4)
CCC_t	-0.03^{***}		-0.004^{***}	
	(-2.69)		(-2.71)	
ΔCCC_t		-0.07^{**}		-0.01^{**}
		(-2.48)		(-2.41)
CCC_{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

This table presents regression summary statistics from equations (4a) and (4b) showing the association between the firms' current CCC, its lagged level and recent change in CCC and stock price informativeness denoted as IPT or as IPE. Industry fixed effects are defined according to 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 observations from 4,752 U.S. firms from 1988 to 2021. See the Appendix for definitions of all variables.

Table 7: Operational efficiency and post-earnings-announcement drift

	$CAR[2,61]$			
	(1)	(2)	(3)	(4)
$CCC_t \times CAR[-1,1]$		0.05***		
		(4.13)		
$\Delta CCC_t \times CAR[-1,1]$				0.11***
				(3.03)
$CCC_{t-1} \times CAR[-1,1]$				0.05***
				(3.80)
CCC_t	0.55***	0.54***		
	(5.11)	(5.10)		
ΔCCC_t			0.58*	0.62**
			(1.89)	(2.06)
CCC_{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

This table presents regression summary statistics from estimating equations (5a) and (5b) showing the association between the firms' current CCC, its lagged level and recent change in CCC and post earnings announcement returns, $CAR[2,61]$. Industry fixed effects are defined according to 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 observations from 4,752 U.S. firms from 1988 to 2021. See the Appendix for definitions of all variables.

Table 8: When does information about operational efficiency prolong price discovery?

	IPE		$CAR[2,61]$	
	(1)	(2)	(3)	(4)
	Full Sample	Full Sample	Top SUE Tercile	Bottom SUE Tercile
$\Delta CCC_t \times SUE_{TOP}$	0.02^{**}			
	(2.21)			
$CCC_{t-1} \times SUE_{TOP}$	0.005			
	(1.65)			
$\Delta CCC_t \times SUE_{BOT}$		-0.02^{**}		
		(-2.27)		
$CCC_{t-1} \times SUE_{BOT}$		-0.004		
		(-1.52)		
$\Delta CCC_t \times CAR[-1,1]$			0.09	0.09^{*}
			(1.36)	(1.93)
$CCC_{t-1} \times CAR[-1,1]$			0.05^{*}	0.06^{***}
			(1.81)	(3.02)
ΔCCC_t	-0.01^{***}	-0.001	0.88	0.88
	(-3.50)	(-0.24)	(1.53)	(1.60)
CCC_{t-1}	-0.01^{***}	-0.002	0.70^{***}	0.49^{***}
	(-2.97)	(-1.31)	(2.78)	(2.66)
SUE_{TOP}	-0.002			
	(-1.01)			
SUE_{BOT}		0.003^{*}		
		(1.78)		
$CAR[-1,1]$	-0.001^{***}	-0.001^{***}	0.13^{***}	0.08^{***}
	(-4.53)	(-4.41)	(6.41)	(4.29)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	119,143	119,143	39,719	39,756
Adjusted R^2	0.05	0.05	0.03	0.04

This table presents regression summary statistics from estimating equations (4b) and (5b). Columns (1) and (2) present results for equation (4b) with the addition of an interaction variable between ΔCCC and an indicator variable for the top (bottom) tercile of earnings surprise, SUE. Columns (3) and (4) present results for equation (5b) after partitioning the sample based on the top (bottom) tercile of earnings surprise, SUE. Industry fixed effects are defined according to 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 observations from 4,752 U.S. firms from 1988 to 2021. See the Appendix for definitions of all variables.

Table 9: Information content of CCC incremental to its components

Panel A: Components of changes in CCC 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)	
ΔDPO_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)
ΔCCC_t					1.95***	1.04***	1.95***
					(8.97)	(5.73)	(11.11)
CCC_{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 CCC 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)	
ΔDPO_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)
ΔCCC_t					0.06***	0.07***	0.09***
					(2.70)	(3.02)	(4.73)
CCC_{t-1}					0.04**	0.01	0.01
					(2.24)	(0.80)	(0.89)
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

Table 9 (continued): Information content of CCC incremental to its components

Panel C: Components of changes in CCC and IPE

	IPE						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔDIO_t	-0.01			-0.01	0.002		
	(-1.43)			(-1.25)	(0.36)		
DIO_{t-1}	-0.001			-0.003	0.01^{*}		
	(-0.64)			(-1.38)	(1.74)		
ΔDSO_t		-0.01		-0.01		-0.001	
		(-1.18)		(-1.02)		(-0.14)	
DSO_{t-1}		-0.0004		-0.004		0.003	
		(-0.09)		(-0.90)		(0.72)	
ΔDPO_t			0.003	0.01			0.003
			(0.57)	(1.44)			(0.57)
DPO_{t-1}			0.01^{***}	0.01^{***}			0.01^{***}
			(3.16)	(3.58)			(2.65)
ΔCCC_t					-0.01^{*}	-0.01^{*}	-0.01^{**}
					(-1.95)	(-1.68)	(-2.19)
CCC_{t-1}					-0.01^{***}	-0.004^{**}	-0.003
					(-2.87)	(-2.48)	(-1.57)
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	0.05	0.05	0.05	0.05	0.05	0.05	0.05

This table presents summary statistics from estimating equations (1b) and (4b) using the components of CCC disaggregated into recent changes and lagged levels. DIO is days inventory turnover, DSO is days sales turnover, and DPO is days payables turnover. Panel A presents statistics using earnings announcement returns, $CAR[-1, 1]$, as the dependent variable and Panel B presents statistics using abnormal trading volume, $ATVol$, as the dependent variable, and Panel C presents results using intraperiod price efficiency, IPE. Industry fixed effects are defined according to 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 observations from 4,752 U.S. firms from 1988 to 2021. See the Appendix for definitions of all variables.

Table 10: Robustness tests

Panel A: Alternative measure of operational efficiency

	$CAR[-1,1]$	$ATVol$	IPE
	(1)	(2)	(3)
$\Delta CCCDR_t$	1.71***	0.07***	−0.01***
	(11.90)	(4.33)	(−2.90)
$CCCDR_{t-1}$	0.28***	0.02*	−0.01***
	(5.67)	(1.91)	(−3.55)
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Calendar-Quarter FE	Yes	Yes	Yes
Observations	119,143	119,143	119,143
Adjusted R^2	0.04	0.06	0.05

Panel B: Alternative industry classifications

	FF30			SIC 2 Dig.			BBHL		
	$CAR[-1,1]$	$ATVol$	IPE	$CAR[-1,1]$	$ATVol$	IPE	$CAR_{[-1,1]}$	$ATVol$	IPE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔCCC_t	2.01***	0.09***	−0.01**	2.02***	0.10***	−0.01**	2.07***	0.10***	−0.01**
	(11.63)	(4.80)	(−2.27)	(11.96)	(5.25)	(−2.04)	(11.89)	(5.23)	(−2.00)
CCC_{t-1}	0.20***	0.002	−0.003*	0.25***	0.01	−0.003*	0.23***	0.02*	−0.003*
	(3.38)	(0.19)	(−1.94)	(4.11)	(0.71)	(−1.91)	(4.00)	(1.77)	(−1.82)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	119,143	119,143	119,143	119,143	119,143	119,143	119,143	119,143	119,143
Adjusted R^2	0.04	0.06	0.05	0.04	0.06	0.05	0.04	0.06	0.05

Table 10 (continued): Robustness tests

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

	Exc. Both			Exc. 2008			Exc. Dot-Com		
	$CAR[-1,1]$	$ATVol$	IPE	$CAR[-1,1]$	$ATVol$	IPE	$CAR[-1,1]$	$ATVol$	IPE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ΔCCC_t	2.00***	0.10***	−0.01*	1.90***	0.10***	−0.01**	2.09***	0.10***	−0.01*
	(11.90)	(4.83)	(−1.85)	(11.39)	(5.08)	(−2.29)	(11.94)	(4.69)	(−1.96)
CCC_{t-1}	0.22***	0.01	−0.004**	0.25***	0.01	−0.004**	0.20***	0.01	−0.003*
	(3.52)	(0.92)	(−1.99)	(4.11)	(1.17)	(−2.42)	(3.33)	(0.98)	(−1.91)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105,232	105,232	105,232	116,453	116,453	116,453	107,922	107,922	107,922
Adjusted R^2	0.04	0.06	0.05	0.04	0.06	0.05	0.04	0.06	0.05

This table presents regression summary statistics for robusteness tests. Panel A presents summary statistics from equations (4b) and (5b) with an alternative definition of CCC that includes deferred revenue, $CCCDR$. Industry fixed effects are defined according to the Fama and French (1997) 48-industry classification. Panel B presents results of estimating equations (1b) and (4b) using alternative industry classifications. In columns (1) through (3) we use Fama and French (1997) 30-industry classification, in columns (4) through (6) we use SIC 2 digit classification, and in columns (7) through (9) we use the Barth et al. (2005) industry classification. In all columns industry fixed effects are calculated according to the industry classification used in the definition of the variable. Panel C presents results of estimating equations (1b) and (4b) excluding: the 2008 financial crisis and the Dot-Com crisis, in columns (1) through (3), only the 2008 crisis, in columns (4) through (6), and only the Dot-Com crisis, in columns (7) through (9). Industry fixed effects are defined according to 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 observations from 4,752 U.S. firms from 1988 to 2021. See the Appendix for definitions of all variables.