INVESTOR'S RELIANCE ON INDICATOR CONSISTENCY
AT EARNINGS ANNOUNCEMENTS:
EARNINGS PERSISTENCE OR INDICATOR PRECISION?

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ABSTRACT

I examine whether sales news and cash flow news are more informative in valuation when they are consistent with earnings news. Prior studies show that the earnings response coefficient (ERC), the stock price reaction per unit of unexpected earnings, is larger when the earnings surprise is consistent in sign with the sales surprise or the cash flow surprise because the consistency suggests higher earnings persistence. I provide new evidence that indicator consistency increases sales response coefficients and cash flow response coefficients as well as ERCs. This consistency effect for sales and cash flow cannot be explained by the standard persistence argument from prior studies. I propose a new argument that can explain the consistency effects for all three indicators, and other performance indicators more broadly. I posit that investors perceive consistent indicators to each be more precise and thus rely more on each indicator. Under this precision argument, I predict and show that indicator consistency is particularly useful when there is high uncertainty about indicator precision.

To Anthony, Olivia, and the rest of the family.

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CHAPTER 1

INTRODUCTION

I study whether and why investors use consistency among different news indicators in valuing sales and operating cash flow. I use the unexpected component of earnings, sales, and operating cash flow at the time of announcement (e.g., earnings surprise) as the news indicator and consider two news indicators to be consistent when they both convey good news or both convey bad news. The rapid growth in the frequency of analysts' forecasts of sales and operating cash flow along with expanded disclosures with non-earnings metrics suggests that investors increasingly rely on these non-earnings indicators in valuation. Therefore, it is important to understand how investors use multiple news indicators and their consistency patterns in valuing sales and operating cash flow in addition to earnings. Prior studies (e.g., Ghosh, Gu, and Jain, 2005) show that the earnings response coefficient (ERC), the abnormal stock return per unit of earnings news, is larger when the earnings news is consistent with the sales news or the operating cash flow news, and argue that this happens because earnings is more persistent when the earnings news is confirmed by other indicators. I provide new evidence that the sales response coefficient (SRC) and cash flow response coefficient (CFRC) are larger when the sales news or the operating cash flow news, respectively, is consistent with the earnings news. This new finding cannot be explained by the standard persistence argument and requires a new explanation. I propose that investors perceive consistent indicators to each be more precise, and thus, they rely more on each indicator. My indicator precision argument can explain consistency effects for multiple indicators beyond earnings.[1]

Ghosh, Gu, and Jain (2005), Rees and Sivaramakrishnan (2007), and Brown, Huang, and Pinello (2013) argue that the market perceives earnings to be more persistent when the earnings news is consistent with the sales news or the operating cash flow news, thereby increasing ERC. Earnings persistence can vary across time because earnings can (and often does) include non-recurring components such as restructuring charges. Moreover, accounting methods such as asset write-downs shift the timing of the recognition of earnings, making earnings less persistent in certain years. Therefore, investors would want to confirm whether current year's earnings includes less transitory components and they can infer that by looking at consistency between the earnings news and sales news (or the cash flow news).

Unlike earnings, however, sales and cash flow contain less non-recurring components. Moreover, sales and cash flow are much less affected by accounting methods that cause periodic distortions such as asset write-downs for earnings, and thus, are comparably more stable over time. Therefore, investors would be much less interested in confirming the persistence of sales or cash flow in the current year. Thus, the standard

[1] If an indicator is more informative in valuation when it is consistent in sign with another indicator, I call it a consistency effect. Empirically, consistency effects are present if the response coefficients are larger when the indicators are consistent rather than inconsistent. To be specific, a consistency effect for earnings implies that ERC is larger when the earnings surprise is consistent in sign with other surprises such as the sales surprise or the cash flow surprise. Similarly, a consistency effect for sales (operating cash flow) implies that SRC (CFRC) is larger when the sales (operating cash flow) surprise is consistent in sign with the earnings surprise.

persistence argument can only explain why indicator consistency is useful for valuing earnings but cannot predict or explain why indicator consistency can also be useful for valuing other indicators than just earnings. Also, I empirically show that sales and operating cash flow are not more persistent when the respective surprise is consistent with the earnings surprise, confirming that the standard persistence argument cannot explain the consistency effects for sales and operating cash flow.[2]

I propose instead that mutual information complementarity can explain consistency effects for additional indicators beyond earnings. Specifically, I argue that consistency patterns between indicators provide information about indicator precision that is likely unknown *ex ante*. If indicator precision is known, then investors will simply add multiple indicators with relative weights based on their precision, and consistency effects will not arise. In contrast, if indicator precision is unknown *ex ante* (i.e., investors do not know whether the indicators are precise or imprecise), then investors can only infer indicator precision from patterns in the announced values, such as indicator consistency. Suppose two indicators (e.g., earnings surprise and sales surprise) reflect the same underlying firm value with noise. When the two surprises contradict each other (i.e., are inconsistent), that suggests more noise in both indicators (i.e., lower precision) for predicting firm value. In contrast, when the two surprises confirm each other (i.e., are

[2] I directly test whether indicator consistency predicts higher persistence of earnings, sales, and operating cash flow. I find that earnings is more persistent when the earnings surprise is consistent with the sales surprise. However, sales and operating cash flow are not more persistent when the respective surprise is consistent with the earnings surprise. These results confirm that the standard persistence argument (partially) explains the consistency effect for earnings but does not explain similar effects for other indicators.

consistent), it suggests less noise in both indicators (i.e., higher precision). More precise indicators with small noise receive a proportionally greater weight in inferences (Banker, Basu, and Byzalov, 2017). Thus, investors will place a greater weight on each consistent indicator in valuation because consistency suggests higher precision.

I calculate surprises for earnings, sales, and operating cash flow from analysts' consensus forecasts and realizations in I/B/E/S for 1998–2019 and designate two concurrent surprises with the same sign as consistent. I find that sales response coefficient (SRC) is larger when the sales surprise is consistent with the earnings surprise. Similarly, cash flow response coefficient (CFRC) is larger when the operating cash flow surprise is consistent with the earnings surprise. The consistency effect for sales is almost twice as large as that for earnings, and the consistency effect for operating cash flow is more than three times as large as that for earnings. Thus, investors actively use indicator consistency in valuing sales and cash flow.

The consistency effects are stronger when more indicators are consistent with each other. For example, SRC increases more when the sales surprise is consistent with both the earnings surprise and the operating cash flow surprise than when it is consistent with only one of the two surprises. Also, the empirical results are robust to an alternative measure of indicator consistency that requires having not only the same sign but also similar magnitudes of surprises.

Under my precision argument, indicator consistency should be particularly useful when there is high uncertainty about indicator precision (i.e., investors are not sure how noisy the indicator is). In this case, indicator consistency can help resolve a lot of uncertainty about indicator precision. That is, when investors observe consistent (inconsistent) indicators, they become more confident that the indicators are precise (imprecise). In contrast, when investors are relatively certain about indicator precision (e.g., indicator precision is clearly high, or clearly medium, or clearly low), indicator consistency should be less useful because there is less uncertainty to be resolved.

Using three different tests, I show that consistency effects are stronger when the uncertainty about indicator precision is high, as predicted. First, I use the absolute magnitude of surprises to estimate the level of uncertainty about indicator precision and expect moderate surprises to have high uncertainty about their precision.[3] I find that the consistency effects are stronger for moderate surprises than for extremely small or extremely large surprises. Second, I show that the consistency effect for earnings is larger after SFAS 142 because the standard introduces more uncertainty about earnings precision. Lastly, I show that the consistency effect for earnings is weaker for high-intangible firms, where earnings is known to be imprecise and thus uncertainty about its precision is low.

I contribute to consistency effect research (e.g., Rees and Sivaramakrishnan, 2007) by providing a new explanation for why indicator consistency is useful. With the new indicator precision explanation, this paper extends prior studies by showing that indicator consistency affects investors' use of major non-earnings indicators such as sales

[3] Investors are relatively certain that extremely large surprises are imprecise and extremely small surprises are precise. In contrast, investors tend to be uncertain about the precision of moderate surprises (e.g., investors are not sure whether a moderate earnings surprise is precise or imprecise). Therefore, moderate (extremely small or extremely large) surprises reflect high (low) uncertainty about their precision.

and operating cash flow and not just earnings. I also extend the earnings precision literature (e.g., Subramanyam, 1996) by proposing and validating indicator consistency as another proxy for earnings precision. Furthermore, my precision explanation can generalize beyond accounting indicators and can apply to various other disciplines in which decision makers make inferences based upon multiple indicators.

I develop the hypotheses in Section 2, describe the research design and data in Section 3, present the empirical results in Sections 4 and 5, provide additional analyses and robustness checks in Sections 6, and conclude in Section 7.

CHAPTER 2

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1. Prior Studies on Indicator Consistency

A few accounting papers show that indicator consistency matters in various contexts. Harris and Neely (2016) show that donors rely more on charity ratings when nonprofits receive consistent ratings about their quality (either good or bad) from multiple charity rating agencies. Livingston and Zhou (2010) find that bonds with inconsistent ratings from Moody’s and S&P have higher bond yields than bonds with consistent ratings, suggesting that investors demand a higher yield premium for inconsistent bond ratings. Banker, Basu, and Byzalov (2017) show that accountants incorporate the consistency of multiple indicators—stock return, sales, and operating cash flow—when impairing assets. Guest (2021) documents that tone consistency between media articles and firms’ earnings news speeds up the market’s price reaction to the earnings news.

Several papers show that investors consider consistency in accounting metrics. Smith (2010) finds experimentally that investors trade more aggressively as the consistency of various accounting metrics (e.g., gross margin ratio, inventory turnover) increases. The stock market reacts more strongly to the earnings surprise of firms that consistently beat the analysts’ earnings forecasts or that have consistent patterns of increasing earnings over time (Barth, Elliott, and Finn, 1999; Lopez and Rees, 2002; He, Jackson, and Liang, 2019). The market reacts more strongly to the earnings surprise when the announced earnings is consistent with the analyst forecast revision before the earnings announcement (Bartov, Givoly, and Hayn, 2002; Caylor, Christensen, Johnson, and Lopez, 2015). Brown and Huang (2013) find that individual analysts' earnings forecasts and stock recommendations elicit a stronger market reaction when they are consistent with each other (i.e., both are above or both are below the consensus).

Outside accounting, various disciplines suggest that investors rely on indicator consistency when drawing inferences.[4] Decision-making theory in psychology suggests that information consistency increases individual's confidence in their judgement (Tversky and Kahneman, 1974; Peterson and Pitz, 1988; Gill, Swann, and Silvera, 1998). Signaling theory in management research shows that signal consistency can enhance signal effectiveness (Connelly, Certo, Ireland, and Reutzel, 2011; Fischer and Reuber, 2007). Statistically, when multiple indicators are consistent with each other, the measurement errors in the indicators are likely small and the indicators' precision is likely high (Banker et al., 2017).

2.2. Investors' Use of Non-earnings Indicators at Earnings Announcements

Investors have access to multiple performance indicators, including earnings, sales, and operating cash flow at earnings announcements. Stock prices change systematically around earnings announcements (e.g. Ball and Brown, 1968; Beaver, 1968). Because of the central role of earnings in valuation, the earnings response coefficient (ERC), which is the abnormal return per unit of unexpected earnings at the

[4] Prior research uses "signal" and "indicator" interchangeably. I use the term "indicator" to avoid potential confusion with the signaling theory in economics (e.g., Spence, 1973) that is not relevant to my argument.

earnings announcement, and its components have been studied extensively (e.g., Collins and Kothari, 1989; Easton and Zmijewski, 1989).

While earnings is still the primary performance indicator, its value relevance has declined in recent decades due to an increase in non-recurring items, negative earnings, high-technology firms, and intangible intensity (Collins, Maydew, and Weiss, 1997; Ely and Waymire, 1999; Francis and Schipper, 1999). However, earnings announcements are still the most important information source (Basu, Duong, Markov, and Tan, 2013), and the information content of earnings announcements as reflected in abnormal trading volume and return volatility has increased (Landsman and Maydew, 2002; Ball and Shivakumar, 2008; Beaver, McNichols, and Wang, 2018). Expanded disclosures with non-earnings metrics have contributed to the increased informativeness of earnings announcements (Francis, Schipper, and Vincent, 2002; Chen, DeFond, and Park, 2002; Beaver, McNichols, and Wang, 2020). Sales and operating cash flow are major non-earnings metrics that are often disclosed concurrently with earnings. In a survey, U.S. CFOs ranked revenue and operating cash flow as the second and third most important performance measures after earnings (Graham, Harvey, and Rajgopal, 2005). In fact, many firms supplement their earnings guidance with sales guidance and cash flow guidance (Wasley and Wu, 2006; Merkley, Bamber, and Christensen, 2013). A large increase in the supply of analyst forecasts for sales and operating cash flow in recent decades confirms the importance of sales and cash flow in valuation (DeFond and Hung, 2003; Bilinski and Eames, 2019).

Sales and operating cash flow provide information that is incremental to earnings. Sales is not perfectly correlated with earnings because of other earnings components such as expenses. Sales is more persistent than expenses because some components of expenses such as special items and restructuring charges are non-recurring (Ertimur, Livnat, and Martikainen, 2003). Sales is more homogeneous and more difficult to manipulate than expenses (Chandra and Ro, 2008). Similarly, cash flow is also not perfectly correlated with earnings because of accruals. Operating cash flow has different implications for valuing earnings than operating accruals because earnings performance that is primarily driven by the operating cash flow component is more persistent than earnings performance that is attributable to the operating accruals component (Sloan, 1996). Cash flow is less subject to estimation errors than earnings because accruals and deferrals reflect managers' judgments about future cash flows, and accordingly CFOs view large accruals as a red flag for detecting earnings management (DeFond and Hung, 2003; Dichev, Graham, Harvey, and Rajgopal, 2013). Accordingly, sales and operating cash flow are expected to be incrementally informative relative to earnings in valuation and many studies show that sales and operating cash flow help assess firm value (e.g., Hopwood and McKeown, 1985; Swaminathan and Weintrop, 1991; Jegadeesh and Livnat, 2006; Barth, Beaver, Hand, and Landsman, 1999; Melendrez, Schwartz, and Trombley, 2008)

2.3. Standard Persistence Explanation for the Consistency Effect for Earnings

Prior studies mostly assume independent additive effects of different performance indicators (i.e., they regress returns on the earnings, sales, and operating cash flow surprises without any interaction terms between these indicators). There are three notable exceptions. Ghosh et al. (2005) document higher quality earnings and larger ERCs for firms reporting sustained increases in both earnings and sales. Rees and Sivaramakrishnan (2007) and Brown et al. (2013) show that firms beating analysts' earnings forecasts have stronger market reactions and larger ERCs if they also beat analysts' sales forecasts and cash flow forecasts, respectively. Thus, these two studies suggest that investors use the consistency between earnings news and sales news and the consistency between earnings news and cash flow news, respectively, in valuing earnings. However, these studies do not consider the parallel consistency effects in valuing sales and cash flow.

These studies attribute their findings to higher earnings persistence in the consistence case. Ghosh et al. (2005) show that firms with revenue-supported increases in earnings have more persistent earnings and thus have larger ERCs. Rees and Sivaramakrishnan (2007) and Brown et al. (2013) argue, but do not test, that greater earnings persistence causes larger ERCs for the earnings surprises that are confirmed by the sales surprise or the cash flow surprise (i.e., the earnings news that is consistent with the sales/cash flow news).

The persistence argument in these prior studies posits that indicator consistency predicts higher persistence of earnings. Valuation models suggest that investors value permanent earnings more than temporary earnings because high earnings persistence is indicative of sustainable dividends.[5] Additionally, the value relevance of earnings persistence is well documented in prior research (Miller and Rock, 1985; Kormendi and Lipe, 1987; Collins and Kothari, 1989; Basu, 1997). Earnings often includes non-recurring expense components, such as special items and restructuring charges, which reduce the persistence of earnings. Also, certain accounting methods, such as asset impairment, introduce one-time shocks to earnings and make the current year's earnings less representative of future earnings (i.e., less persistent). As earnings can include major non-recurring components in some years but not in others, investors can look at the consistency of earnings with other indicators to determine whether the current year's earnings include non-recurring components.[6] In other word, when the sales news or the cash flow news confirms the earnings news, it suggests that the current year's earnings contains less transitory items and thus is more persistent.

However, the same logic does not apply to the other indicators. Unlike earnings, sales and operating cash flow rarely contain non-recurring components that shift the

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[5] In a valuation model, stock price represents the present value of expected future dividends, which can be forecasted using operating cash flow or earnings. Permanent shocks cause all future earnings and expected dividends to change while transitory shocks affect only current period earnings. Price-irrelevant shocks are unrelated to stock price and have no valuation implications (Ramakrishnan and Thomas, 1998).

[6] Although investors can look for non-recurring items in the financial statements, information about non-recurring items is often limited because many write-downs are not included as a single line item. For example, inventory write-downs are often included in cost of goods sold and goodwill impairments may be included as part of restructuring charges (Martin and Roychowdhury, 2013). Also, reported non-recurring items can be unreliable because firms often strategically disclose non-recurring items (Schrand and Walther, 2000).

recognition of sales and operating cash flow over time.[7] For example, asset write-downs shift potential future losses into a large one-time loss in the current period, causing periodic distortions into earnings (Richardson, Sloan, and Soliman, 2005). Due to this variation in earnings persistence across periods, investors may find indicator consistency useful for inferring whether the current period's earnings includes less non-recurring components. However, such accounting methods mostly govern bottom line earnings and do not affect sales and operating cash flow. Moreover, many transitory components are classified as gains and losses and excluded from revenue (e.g., accounts receivable can be written down without affecting the top line reported sales).Therefore, sales and operating cash flow are inherently more stable over time and investors are less eager to confirm the transitory nature of current period's sales or operating cash flow.Therefore, even if the earnings news confirms the sales news or the cash flow news, such consistency does not add much information about the persistence of sales or operatingcash flow. Accordingly, while the standard earnings persistence argument above predicts the consistency effect for earnings, it does not predict the consistency effects for other indicators.

2.4. A New Indicator Precision Explanation for the Consistency Effects

Given the growing roles of sales and operating cash flow in valuation, it is important to understand whether and to what extent investors use indicator consistency in processing the sales and operating cash flow news in addition to the earnings news. I

[7] Sales can include non-recurring components although they are much less common for sales than for earnings. Campbell, Gee, and Wiebe (2022) show that some firms adjust their revenue growth figures and provide non-GAAP revenue disclosures. Common reasons for such adjustment include changes in foreign exchange rates and changes to the firm through mergers or divestitures.

propose a new explanation for the consistency effects that generalize to these and other additional indicators beyond earnings.

Specifically, I argue that investors can look at indicator consistency to infer indicator precision which is unknown *ex ante*. Theoretical models typically assume that investors know the true model parameters, including the true precision of each indicator. However, investors are likely uncertain about indicator precision (i.e., investors do not know how noisy the indicator is) and they can only infer indicator precision from some attributes of the announced values (Subramanyam, 1996).[8] For example, when different surprises are reported at earnings announcements, investors observe only the value of the surprises but do not know (and thus need to infer) the precision of each surprise.

How does indicator consistency help investors infer indicator precision? Suppose that there are two indicators—earnings surprise and sales surprise—that predict true firm value (i.e., expected future cash flow). Both the earnings surprise and the sales surprise reflect the same underlying change in firm value with noise.[9] When the two surprises contradict each other (i.e., are inconsistent), that suggests that there is more noise (i.e., low precision) in both surprises. In contrast, when the two surprises confirm each other (i.e., consistent), it suggests that there is less noise (i.e., high precision). In other words, if different indicators are consistent (e.g., both the earnings surprise and the sales surprise

[8] This notion of inferring model parameters is not limited to just earnings precision. For example, traditional asset pricing models often assume that investors know the probability distribution of the expected returns when in fact the parameters have to be estimated using available data (Khan, Li, Rajgopal, and Venkatachalam, 2018).

[9] Noise here refers to variance of the signal that the indicator provides about true firm value (i.e., how widely spread the observed values are around the true value).

indicate good news), investors will infer that each indicator is relatively precise. In contrast, if the indicators are inconsistent (e.g., one of the two surprises provides good news and the other one provides bad news), investors will infer that each indicator is relatively imprecise.

Indicator precision is used to evaluate the indicators, and those with high precision receive a proportionally greater weight in inferences.[10] Therefore, investors should consider not only the value of the announced surprises but also their precision when assessing the surprises in valuation. Accordingly, when different indicators are consistent with each other, investors will infer that the indicators are more precise and will place a greater weight on each indicator in valuation. If investors know indicator precision, then I expect to observe only the additive effects but not the interactive consistency effects between different indicators because multiple indicators will be added with relative weights based on their precision without any interactions between the indicators (Winkler, 1972; Banker and Datar, 1989).

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[10] In Bayesian inferences for a multivariate Normal distribution, the optimal weight on each indicator is equal to the ratio of the indicator's precision to the total precision of all other indicators, including the prior distribution (Basilevsky, 1994; Banker et al., 2017). Investors' preference for more precise indicators should also hold in OLS-based inferences which are more common in accounting research. Suppose two indicators $X_1$and X_2 provide information about a firm's future cash flow and the two indicators are correlated but are not perfectly correlated, thus having incremental information for predicting future cash flow. OLS regressions estimate a conditional expectation of future cash flow conditional on the two indicators (i.e., E(Future cash flow|X_1) and E(Future cash flow|X_2). X_1 and X_2 predict true future cash flow with some noise. If X_1 has high noise and X_2 has low noise, investors will rely more on X_2 because it will estimate the conditional expectation of future cash flow with less error.

My precision argument relies on mutual information complementarity between indicators. This differs from the standard persistence argument, which relies on a specific property of earnings (i.e., persistence of earnings).[11] If my precision argument holds, then I should find the consistency effects for other indicators besides earnings. Conversely, if the standard earnings persistence explanation dominates, then I will only see the consistency effect for earnings. Thus, my main hypotheses are:

H1a: Sales response coefficient (SRC) is larger when the sales surprise is consistent with the earnings surprise.

H1b: Cash flow response coefficient (CFRC) is larger when the opearing cash flow surprise is consistent with the earnings surprise.

My predictions go beyond Rees and Sivaramakrishnan (2007) and Brown et al. (2013), who study the consistency effect for only earnings and assume constant response coefficients for sales and cash flow. Additionally, like the persistence argument of Rees and Sivaramakrishnan (2007) and Brown et al. (2013), my precision argument also predicts that ERC will be larger when the earnings surprise is consistent with the sales

[11] My precision argument and the standard persistence argument examine different channels through which indicator consistency affect valuation. In a simple AR1 model where future earnings is regressed on current earnings with noise (i.e., $Earnings_{t+1} = \beta_0 + \beta_1 Earnings_t + \varepsilon_t$), the persistence argument implies that β_1 will be larger when the earnings news is consistent with other news indicators while the precision argument implies that the variance of ε_t will be smaller when the earnings news is consistent rather than inconsistent.

surprise or the cash flow surprise. However, I do not state this as a formal hypothesis because it was tested in prior studies.[12]

My predictions may not hold if investors are subject to behavioral biases. For example, the anchoring and adjustment heuristic (Solvic 1972; Tversky and Kahneman 1974) suggests that investors' expectations are anchored by earnings, so investors might fixate on earnings and neglect other indicators (Hand, 1990; Sloan, 1996; Shi and Zhang, 2012). Also, my precision argument for the consistency effects assumes unknown indicator precision. As described above, if indicator precision is known, I should not observe any interactive effects between indicators because investors will simply add multiple indicators with relative weights on each indicator based on the known precision.

2.5. The Moderating Effect of Uncertainty About Indicator Precision

The more uncertain investors are about indicator precision, the more they will rely on indicator consistency to resolve this uncertainty. High uncertainty about indicator precision means that investors do not know how noisy the indicator is. In this case, indicator consistency is particularly useful because it can help resolve uncertainty about indicator precision, i.e., investors can infer high (low) precision from consistent (inconsistent) indicators. In contrast, when investors are relatively sure about the precision of indicators, i.e., investors know that the indicator is clearly precise or that it is clearly imprecise, indicator consistency should be less helpful in inferring the precision because indicator precision is already clear. This leads to my second hypothesis:

[12] However, unlike the prior studies, my expanded empirical model tests the consistency effect for earnings after controlling for the consistency effect for sales or operating cash flow.

H2: Investors will rely more on indicator consistency when there is high uncertainty about indicator precision.

I test this prediction using three different proxies for uncertainty about indicator precision: absolute magnitude of surprises, SFAS 142, and intangible intensity. I describe these empirical proxies in detail in Section 5.

CHAPTER 3

RESEARCH DESIGN AND DATA DESCRIPTION

3.1. Research Design

To examine whether investors use indicator consistency in valuation, I check whether indicator consistency increases ERC, SRC, and CFRC. I use extended ERC regression models that relate the stock market reactions to the earnings, sales, and operating cash flow surprises. I use financial analysts' consensus forecasts as a benchmark to calculate the surprises. I start with the basic ERC model (e.g., Brown, Hagerman, Griffin, and Zmijewski, 1987):

$$CAR_{iq} = \beta_0 + \beta_1 Earnings\ Surprise_{iq} + \sum Controls + \varepsilon_{iq} \qquad (1)$$

CAR is the three-day market-adjusted stock return around the date of the quarterly earnings announcement. *Earnings Surprise* is calculated as the difference between the actual quarterly EPS and the most recent median consensus forecast of quarterly EPS before the earnings announcement, scaled by start-of-quarter stock price. The coefficient β_1 on *Earnings Surprise* measures ERC. β_1 is expected to be positive if earnings is informative for valuation.

Ertimur et al. (2003) examine the incremental information content of sales by adding the sales surprise to the basic ERC model. Their extended ERC model takes the form:

$$CAR_{iq} = \beta_0 + \beta_1 Earnings\ Surprise_{iq} + \beta_2 Other\ Surprise_{iq} + \sum Controls + \varepsilon_{iq} \qquad (2)$$

Other Surprise in model (2) refers to either the sales surprise or the operating cash flow surprise.[13] The sales (operating cash flow) surprise is calculated as the actual quarterly sales (operating cash flow) less the most recent median consensus forecast of quarterly sales (operating cash flow) before the sales (operating cash flow) announcement, converted to a per-share basis and scaled by start-of-quarter stock price.[14] The coefficient β_1 on *Earnings Surprise* is ERC and the coefficient β_2 on *Other Surprise* is SRC (for sale surprise) or CFRC (for operating cash flow surprise). Both β_1 and β_2 are expected to be positive, reflecting the net information content of earnings and the other indicator (sales or operating cash flow) in valuation.

I study whether investors value consistent indicators more, which is an interaction effect between surprises that is different from the additive incremental effect in (2). Rees and Sivaramakrishnan (2007) add an interaction term between *Earnings Surprise* and a consistency dummy in model (2) to study how the consistency between earnings surprise and sales surprise affects ERC. Brown et al. (2013) use a similar specification to study how

[13] Ertimur et al. (2003) include the sales surprise variable rather than *Other Surprise* in their model. I call it *Other Surprise* to refer to both the sales surprise and the operating cash flow surprise. Also, Ertimur et al. (2003) regress returns on sales surprise and expense surprise instead of earnings surprise and sales surprise. My model specification is closer to Jegadeesh and Livnat (2006) who regress returns on earnings surprise and sales surprise.

[14] I/B/E/S publishes the announcement dates separately for earnings, sales, and cash flow. Most of my sample firms have the same announcement date for all three indicators. If the sales or cash flow announcement date is more than one day apart from the earnings announcement date, the firm-quarter is dropped from the sample. See the next section and Table 1 for more details.

the consistency between earnings surprise and operatin cash flow surprise affects ERC. This extended ERC model of Rees and Sivaramakrishnan (2007) is as follows:[15]

$$\begin{aligned} CAR_{iq} = \beta_0 &+ \beta_1 Earnings\ Surprise_{iq} \\ &+ \beta_2 Other\ Surprise_{iq} + \beta_3 Consistency_{iq} \\ &+ \beta_4 Earnings\ Surprise_{iq} * Consistency_{iq} + \sum Controls + \varepsilon_{iq} \end{aligned} \tag{3}$$

Earnings Surprise and *Other Surprise* are as defined in models (1) and (2). *Consistency* is a dummy variable that equals one if the earnings surprise has the same sign as the other surprise (i.e., the sales surprise or the operating cash flow surprise).[16] For example, in the tests of consistency between the earnings surprise and the sales surprise, *Consistency* is one if the earnings surprise and the sales surprise have the same sign (e.g., both are positive or both are negative). The same logic applies to the consistency between the earnings surprise and the operating cash flow surprise. The

[15] The model specifications in Rees and Sivaramakrishnan (2007) and Brown et al. (2013) are not identical to model (3), but their test objectives are conceptually very similar. Rees and Sivaramakrishnan (2007) differentiate all four groups (i.e., beating both earnings and sales forecasts, beating earnings but not sales, beating sales but not earnings, and missing both), and use the first available forecast instead of the most recent forecast when calculating the *Earnings Surprise* variable in model (3). Brown et al. (2013) mainly focus on good news earnings, so they compare good news earnings accompanied by good news cash flow to good news earnings accompanied by bad news cash flow. Also, Brown et al. (2013) include accrual surprise instead of cash flow surprise for the *Other Surprise* variable in model (3).

[16] Following prior studies, I use sign consistency as a main measure of indicator consistency and additionally use magnitude consistency in robustness checks. Even a simple sign consistency can be informative as long as indicators have some noise. For example, when two indicators both have zero noise, the two indicators must have the same sign. In contrast, when the two indicators involve some noise, the two indicators could have the same sign but with different magnitudes or have the opposite signs. As the noise level of the two indicators increases, more sign inconsistency is expected and thus even sign consistency can be useful to infer indicator precision.

coefficient β_4 on *Earnings Surprise * Consistency* captures the consistency effect for earnings. Rees and Sivaramakrishnan (2007) and Brown et al. (2013) document a positive β_4, indicating that ERC is larger when the earnings surprise is consistent with the sales surprise and the operating cash flow surprise, respectively.

Although these prior studies incorporate the consistency between the earnings surprise and the other surprises as a determinant of ERC in their models, they do not allow any consistency effects for these other surprises. Rather, they assume constant response coefficients for sales and operating cash flow. Hence, model (3) cannot provide any insight on how investors use indicator consistency in valuing sales and operating cash flow, which are becoming increasingly more important in valuation. I thus add an interaction term between *Other Surprise* and *Consistency* to model (3) to allow the response coefficients to vary with indicator consistency. If this interaction term is excluded when the consistency effects exist for the other surprises, the model can provide biased estimates. Accordingly, I include the full set of interactions between the surprise variables and the consistency variable in the full model as shown below:[17]

$$\begin{aligned} CAR_{iq} = \beta_0 &+ \beta_1 Earnings\ Surprise_{iq} + \beta_2 Other\ Surprise_{iq} + \beta_3 Consistency_{iq} \\ &+ \beta_4 Earnings\ Surprise_{iq} * Consistency_{iq} \\ &+ \beta_5 Other\ Surprise_{iq}\ Consistency_{iq} + \sum Controls + \varepsilon_{iq} \end{aligned} \tag{4}$$

The coefficient of interest is β_5 on *Other Surprise * Consistency*, which captures the effect of consistency between the earnings surprise and the sales (operating cash

[17] Ertimur et al. (2003) and Rees and Sivaramakrishnan (2007) do not include control variables. I add control variables as well as year-quarter and industry fixed effects.

flow) surprise on SRC (CFRC). H1a and H1b predict a positive β_5, which indicates that SRC and CFRC are larger when the sales or operating cash flow surprise is consistent with the earnings surprise. In other words, a positive β_5 suggests that investors find indicator consistency useful in valuing sales and operating cash flow.

Following the ERC literature (e.g., Collins and Kothari, 1989; Ferri, Zheng, and Zou, 2018), I include control variables and their interaction with surprise variables across all four models. Specifically, I include firm size (*Size*), market-to-book ratio (*MTB*), leverage (*Leverage*), firm beta (*Beta*), and a loss indicator (*Loss*). I also include industry fixed effects (using Fama-French 12 industries) and year-quarter fixed effects. I demean the control variables so that the response coefficients and the consistency effects are interpreted at the mean of all control variables. Moreover, I scale the surprise variables by their standard deviations to make the consistency effects for different indicators more comparable.

3.2. Sample Selection and Descriptive Statistics

I construct a sample of firm-quarters for the period 1998–2019 from the intersection of the I/B/E/S, CRSP, and Compustat databases. I begin with 1998 because I/B/E/S sales and cash flow forecasts before 1998 are scarce. I start with firm-quarters where forecasted and actual earnings are available from I/B/E/S. Those that lack stock return data from CRSP and control variables from Compustat are dropped. I also restrict the sample to non-financial industries because accounting metrics of financial firms are not comparable with those of industrial firms. After these steps, I have an initial sample of 176,338 firm-quarters.

Table 1
Sample selection

		Sales surprise sample	**Cash flow surprise sample**
Firm-quarters with forecasted and actual earnings available from I/B/E/S summary file from 1998 to 2019	346,965		
Less firm-quarters			
Lacking stock return data from CRSP	(18,721)		
Lacking control variables from Compustat and CRSP	(115,240)		
In financial industry	(41,031)		
Initial sample of firm-quarter		176,338	176,338
Lacking sales or cash flow forecasts from I/B/E/S		(27,807)	(128,683)
With earnings announcement dates more than one day apart from sales or cash flow announcement dates		(195)	(301)
Final sample of firm-quarters		148,336	47,354

The table describes the sample selection process. There are two main samples in this study depending on which pair of performance indicators is used to measure consistency. In the sales (cash flow) surprise sample), sign consistency between the earnings surprise and the sales (cash flow) surprise is used to measure consistency. The number of observations for these two samples differ because some firms have only sales forecasts available while others have only cash flow forecasts available.

Since analysts' operating cash flow forecasts are much less common than sales and earnings forecasts, I use two separate samples: one for the tests of consistency between the earnings surprise and the sales surprise (the "sales surprise sample") and another one for the tests of consistency between the earnings surprise and the operating cash flow surprise (the "cash flow surprise" sample). For the sales (cash flow) surprise sample, firm-quarters must have both actual and forecasted sales (operating cash flows) from I/B/E/S. To capture the market response to the different surprises that are concurrently available, I require the earnings announcement date to be no more than one day apart from the sales or cash flow announcement date (Brown et al. 2013). The final sales (cash flow) surprise sample includes 148,336 (47,354) firm-quarters. Table 1 describes the two samples.

Table 2, Panel A shows the number of firm-quarters for each possible combination of the signs of the surprises.[18] The principal diagonal displays the consistent firm-quarters (i.e., positive-positive and negative-negative) and the secondary diagonal displays the inconsistent firm-quarters (i.e., positive-negative and negative-positive). In the sales (cash flow) surprise sample, approximately 65% (57%) have consistent firm-quarters.[19] Among the consistent firm-quarters in the sales (cash flow) surprise sample, 71% (73%) have good news for both indicators and 29% (27%) have bad news for both indicators.[20] Among the inconsistent firm-quarters, positive earnings surprise with negative sales (operating cash flow) surprise accounts for 64% (68%) and negative earnings surprise with positive sales (operating cash flow) surprise accounts for 36% (32%). Table 2, Panels B and C show the proportion of consistent firm-quarters by year and industry, respectively. The proportion of consistent firm-quarters is almost evenly

[18] Following prior studies (e.g., Brown et al., 2013), I include zero surprises in the positive category. Thus, a positive surprise refers to a non-negative surprise throughout the paper.

[19] In both samples, although I see more consistent cases than inconsistent ones, a substantial proportion of firms (approximately 35% to 43%) have inconsistent indicators, showing that inconsistent firm-quarters are not unusual exceptions.

[20] In both samples, there are more positive surprises than negative surprises. In the sales surprise sample, the proportion of positive earnings (sales) surprise is 68% (59%). In the cash flow surprise sample, the proportion of positive earnings (cash flow) surprises is 71% (55%). Therefore, we are more likely to observe positive-positive pairs than negative-negative pairs.

distributed throughout different years and industries, suggesting that indicator consistency is not clustered in certain years or industries.[21] Table 2, Panel D shows Pearson correlations between the surprise variables and returns. While all three surprises are positively correlated, they are not perfectly correlated, which suggests that each surprise can provide incremental information about firm value. Earnings surprise is most highly related to returns among the three surprise variables.

[21] For the cash flow surprise sample, the proportion of consistent firm-quarters is large in the first few years, but the number of observations is very small. These first few firms with operating cash flow forecasts tend to be stable, mature firms, and therefore the large proportion of consistent case for these firms is not surprising.

Table 2
Summary statistics of indicator consistency

Panel A. Proportion of consistent firm quarters by the sign of surprises

Sales surprise sample

	Positive sales surprise	Negative sales surprise
Positive earnings surprise	68,546	33,076
Negative earnings surprise	18,469	28,245

Cash flow surprise sample

	Positive cash flow surprise	Negative cash flow surprise
Positive earnings surprise	19,692	13,998
Negative earnings surprise	6,452	7,212

Panel B. Proportion of consistent firm-quarters by year

	Sales surprise sample		Cash flow surprise sample	
Year	N	%	N	%
1998	907	60.8	1	100.0
1999	2,211	64.1	21	70.0
2000	2,828	66.6	20	66.7
2001	2,660	59.7	84	68.9
2002	3,296	64.0	149	69.6
2003	4,198	67.3	405	67.8
2004	4,759	69.0	500	64.6
2005	4,855	66.2	541	59.5
2006	4,988	65.2	648	70.4
2007	5,189	66.1	624	67.3
2008	5,024	64.8	1,159	61.0
2009	4,876	64.1	1,508	62.3
2010	5,223	69.0	1,902	57.8
2011	4,823	66.9	1,907	55.7
2012	4,615	63.7	1,960	56.3
2013	4,732	65.2	1,952	55.3
2014	5,026	65.5	2,134	53.5
2015	4,952	61.7	2,279	54.3
2016	5,069	62.8	2,314	54.7
2017	5,469	67.7	2,302	55.6
2018	5,468	65.9	2,218	54.5
2019	5,623	63.9	2,276	54.7
Total	96,791	65.3	26,904	56.8

Panel C. Proportion of consistent firm-quarters by industry

Industry	Sales surprise sample N	Sales surprise sample %	Cash flow surprise sample N	Cash flow surprise sample %
Consumer Nondurables	5,024	63.2%	1,330	53.8%
Consumer Durables	2,854	67.0%	626	55.2%
Manufacturing	11,083	64.7%	2,818	54.0%
Energy	4,183	63.9%	3,310	61.0%
Chemicals	2,559	60.5%	844	52.9%
Business Equipment	26,101	71.5%	5,600	58.5%
Telecom	2,479	59.6%	744	55.4%
Utilities	3,056	57.0%	1,760	57.1%
Shops	11,155	62.6%	3,321	56.1%
Healthcare	15,440	63.9%	2,554	56.4%
Other	12,857	63.6%	3,997	56.7%
Total	96,791	65.3%	26,904	56.8%

Panel D. Correlation matrix of surprises and return

	Earnings surprise	Sales surprise	Cash flow surprise
Sales surprise	0.196		
Cash flow surprise	0.100	0.029	
CAR	0.209	0.106	0.103

Panels A to C show the proportion of consistent firm-quarters. In the sales (cash flow) surprise sample, consistent firm-quarters refer to the firm-quarters where the earnings surprise and the sales (operating cash flow) surprise have the same sign. Panel A shows two by two matrix with different combinations of surprises. Panels B and C show distributions of consistent quarters by year and industry, respectively, and % firms with consistent indicators refer to the percentage of consistent firm-quarters in each year and industry. I use the Fama-French 12 industries to classify firms in Panel C. Panel D shows correlations among the surprise variables and returns.

CHAPTER 4

EMPIRICAL RESULTS ON THE CONSISTENCY EFFECTS

4.1. LOWESS Graphs of the Consistency Effects

I first show consistency effects using a locally weighted scatterplot smoothing (LOWESS) curve. LOWESS curves in Figure 1 non-parametrically depict the relationship between surprises and returns for consistent firm-quarters versus inconsistent firm-quarters.

In Panel A, I use the sales surprise sample and measure consistency as the same sign between the earnings surprise and the sales surprise. The graph on the left-hand side shows the relationship between earnings surprise and returns (i.e., ERC). The solid (dashed) line indicates the relationship when the indicators are consistent (inconsistent). The slope of the solid line is steeper than the slope of the dashed line, showing that ERC is larger when the earnings surprise is consistent with the sales surprise. This confirms the consistency effect for earnings documented in prior research (e.g., Rees and Sivaramakrishnan, 2007). Also, in line with prior studies (e.g., Freeman and Tse, 1992), the association between earnings surprise and returns is much weaker for extreme earnings surprises (i.e., the slope is close to flat at the two tails in the graph). The graph on the right-hand side shows the relationship between sales surprise and returns (i.e., SRC). The slope of the solid line is positive, indicating a positive SRC when the sales surprise is consistent with the earnings surprise. In contrast, the dashed line has negative and close-to-flat slope, suggesting a weak association between sales surprise and returns when the sales surprise is inconsistent with the earnings surprise. The steeper positive slope for consistent sales surprises suggests that investors use consistency in valuing sales, as predicted by H1a.

Figure 1
Relationship between surprises and returns, partitioned by indicator consistency

Panel A. Consistency between the earnings surprise and the sales surprise

Panel B. Consistency between the earnings surprise and the cash flow surprise

Figure 1 shows the relationship between returns and surprises using LOWESS (Locally Weighted Scatterplot Smoothing) graphs. In both Panels A and B, the red solid lines represent consistent announcements and the gold dashed lines represent inconsistent announcements. In Panel A, the earnings surprise and the sales surprise are classified as consistent (inconsistent) if the two surprises have the same (opposite) sign. In Panel B, the earnings surprise and the operating cash flow surprise are classified as consistent (inconsistent) if the two surprises have the same (opposite) sign. The surprise variables are calculated as the difference between the actual and the forecasted values for earnings, sales, and operating cash flow, scaled by stock price. See the Appendix for detailed variable definitions. Also, see section 4.1 for my explanation for the negative slopes in the graphs on the right-hand side.

I find similar patterns in the cash flow surprise sample in Panel B. The graph on the left-hand side shows that the ERC is larger when the earnings surprise is consistent with the cash flow surprise. The graph on the right-hand side shows that the CFRC for consistent cash flow surprise is positive and is much larger than that for the inconsistent case.

In both panels, the slope of the dashed lines on the right-hand side is negative, indicating negative SRC and CFRC for the inconsistent case. This could be because investors rely more on the earnings surprise than the sales or cash flow surprise when the earnings surprise is inconsistent with the other surprise.[22] It is also possible that other firm characteristics that are not incorporated into these graphs shift the slope to be negative. Therefore, I next use the regression models to directly incorporate multiple indicators in one model along with control variables that are known to affect the response coefficients.

4.2. Regression Results of the Consistency Effects

In Table 3 Panel A, I run the four models presented in Section 3 in the sales surprise sample. In the basic ERC model in column (1), the coefficient on *Earnings Surprise* is 3.267 (significant at 1%), consistent with positive ERC in prior studies. When

[22] For example, when a positive sales surprise is inconsistent, the earnings surprise must be negative. This suggests that there was a negative shock to earnings that was large enough to outweigh the positive sales surprise. Therefore, a positive sales surprise in the inconsistent case likely involves a larger negative shock to earnings that is large enough to produce a negative net earnings surprise despite the positive sales surprise. If investors rely more on this negative shock to earnings than on the positive sales surprise, then the slope can be negative.

the sales surprise is added in column (2), ERC decreases slightly but remains positive and significant. The coefficient on *Sales Surprise* is 1.3 (significant at 1%), consistent with positive SRC in prior studies. The Rees and Sivaramakrishnan (2007) model in column (3) tests the consistency effect for earnings. The coefficient on *Earnings Surprise * Consistency* is 0.636 (significant at 1%), suggesting that ERC is larger when the earnings surprise and the sales surprise are consistent. Overall, the results in columns (1) to (3) confirm the findings from prior studies and set a benchmark for my full model in column (4).

In column (4), I add *Sales Surprise * Consistency* to capture the consistency effect for sales. H1a predicts a positive coefficient on *Sales Surprise * Consistency*, suggesting that SRC is larger when the sales surprise is consistent with the earnings surprise. The coefficient on *Sales Surprise * Consistency* is positive and significant (1.315, significant at 1%), as predicted by H1a. This suggests that sales is more informative in valuation when the sales surprise is consistent with the earnings surprise. Moreover, the coefficient on *Sales Surprise* in model (3) is more than 4 times larger than the one in model (4), suggesting that interpreting the SRC without considering the consistency effect for sales can be misleading.

Comparison between the consistency effect for earnings and sales suggests that indicator consistency has a larger valuation impact on sales relative to earnings. Note that the surprise variables are scaled by their standard deviations. Therefore, the coefficient on *Sales Surprise * Consistency* shows that a one standard deviation change in the sales surprise is associated with 1.3 percentage point larger increase in CAR for the consistent sales surprise than for the inconsistent one. It is much larger than the coefficient on *Earnings Surprise * Consistency*, 0.694, which shows that a one standard deviation increase in the earnings surprise is associated with 0.7 percentage point larger increase in CAR for the consistent earnings surprise than for the inconsistent one. Therefore, the consistency effect for sales is almost double the consistency effect for earnings. I depict this point in a bar chart in Figure 2, Panel A.

Furthermore, as I incorporate the consistency effect for sales in my full model, the adjusted R-squared increased by 0.3% from the Rees and Sivaramakrishnan (2007) model.[23] In comparison, I find that the incremental R-squared of the consistency effect for earnings is 0.1%.[24] This suggests that we can understand investors' behavior better when we include the consistency effect for sales in the model.

The effects of firm characteristics on ERC (i.e., the coefficients on interaction terms between control variables and earnings surprise) are generally in line with prior studies. Larger firms have higher ERC and growth firms have lower ERC. Losses are negatively associated with ERC (Hayn, 1995; Basu, 1997). For interaction of control variables with sales surprise, I find that smaller firms, growth firms, and firms with a larger beta are associated with larger SRC. Loss firms have lower SRC.

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[23] The Likelihood Ratio test confirms that adding the interaction term for the consistency effect for sales significantly improved model fitness.

[24] For comparison purposes, I run a model that includes only the consistency effect for sales and excludes the consistency effect for earnings (i.e., full model without *Earnings Surprise * Consistency*). In this model that lacks the consistency effect for earnings, the adjusted R-squared is 6.8%. Thus, incorporating the consistency effect for earnings increases the adjusted R-squared by 0.1% (6.8% to 6.9% in my full model).

Table 3, Panel B shows similar results for the cash flow surprise sample. In my full model in column (4), the coefficient on *CF Surprise * Consistency* is positive and significant (1.266, significant at 1%), as predicted by H1b. Moreover, the consistency effect for operating cash flow is more than triple the consistency effect for earnings (see Figure 2, Panel B for a graphical presentation). *CF Surprise* is insignificant unlike in model (3), suggesting that the cash flow news is informative enough to trigger a market reaction only when it is consistent with the earnings news. I find that larger firms, growth firms, and firms with a larger beta are associated with larger ERC. Loss firms have lower ERC. For CFRC, firm size and firm beta are positively associated with CFRC while losses are inversely associated with CFRC.

Although I examine both the sales surprise and the cash flow surprise as an additional indicator, I use the sales surprise sample as my primary sample for the following reasons. First, while sales forecasts are available for most I/B/E/S firms, only a small subset has cash flow forecasts. Thus, the cash flow surprise sample is less representative of the I/B/E/S population. Second, operating cash flow might be more susceptible to transitory noise due to normal variation in working capital (Dechow, 1994), poor matching of expenditures with expected revenues (Dichev and Tang, 2008), and gradual adjustment of resources to economic shocks. Thus, sales is arguably a better indicator for future performance than operating cash flow (Banker et al., 2017).

TABLE 3
Consistency effects for earnings, sales, and operating cash flow

Models (1) – (4):

(1) Basic ERC Model

$CAR_{iq} = \beta_0 + \beta_1 Earnings\ Surprise_{iq} + \sum Controls + \varepsilon$

(2) Ertimur, Livnat, and Martikainen (2003) Model

$CAR_{iq} = \beta_0 + \beta_1 Earnings\ Surprise_{iq} + \beta_2 \boldsymbol{Other\ Surprise_{iq}} + \sum Controls + \varepsilon$

(3) Rees and Sivaramakrishnan (2007) Model

$CAR_{iq} = \beta_0 + \beta_1 Earnings\ Surprise_{iq} + \beta_2 Other\ Surprise_{iq} + \beta_3 Consistency_{iq} + \beta_4 \boldsymbol{Earnings\ Surprise_{iq} * Consistency_{iq}} + \sum Controls + \varepsilon$

(4) Full Model

$CAR_{iq} = \beta_0 + \beta_1 Earnings\ Surprise_{iq} + \beta_2 Other\ Surprise_{iq} + \beta_3 Consistency_{iq} + \beta_4 Earnings\ Surprise_{iq} * Consistency_{iq} + \beta_5 \boldsymbol{Other\ Surprise_{iq} * Consistency_{iq}} + \sum Controls + \varepsilon$

Panel A. Consistency between the earnings surprise and the sales surprise

		(1)	(2)	(3)	(4)
Earnings Surprise		3.267***	2.947***	2.538***	2.125***
		(30.44)	(28.28)	(23.15)	(19.81)
Sales Surprise			1.300***	1.086***	0.260***
			(15.77)	(13.50)	(3.13)
Consistency				1.072***	1.130***
				(20.06)	(21.24)
Earnings Surprise * Consistency	+			**0.636*** **	**0.694*** **
				(7.74)	**(8.56)**
Sales Surprise * Consistency	+				**1.315*** **
					(18.72)
*Earnings Surprise * Size*		0.317***	0.335***	0.329***	0.319***
		(8.69)	(9.33)	(9.19)	(9.12)
*Earnings Surprise * MTB*		-0.059**	-0.096***	-0.099***	-0.050**
		(-2.28)	(-3.82)	(-3.96)	(-1.99)
*Earnings Surprise * Lev*		-0.003	0.004	0.006	-0.000
		(-0.21)	(0.34)	(0.48)	(-0.00)
*Earnings Surprise * Beta*		0.073	0.022	0.025	0.037
		(1.28)	(0.39)	(0.44)	(0.66)
*Earnings Surprise * Loss*		-2.271***	-2.002***	-1.977***	-1.766***
		(-20.12)	(-17.94)	(-17.77)	(-16.35)
*Sales Surprise * Size*			-0.056***	-0.037*	-0.021
			(-2.81)	(-1.84)	(-1.03)

*Sales Surprise * MTB*		0.532***	0.478***	0.453***
		(7.51)	(7.05)	(7.05)
*Sales Surprise * Lev*		-0.022*	-0.018	-0.014
		(-1.82)	(-1.53)	(-1.22)
*Sales Surprise * Beta*		0.280***	0.239***	0.225***
		(4.88)	(4.22)	(4.06)
*Sales Surprise * Loss*		-0.148**	-0.139**	-0.131*
		(-2.17)	(-2.01)	(-1.91)
Size	-0.068***	-0.082***	-0.081***	-0.080***
	(-4.59)	(-5.57)	(-5.51)	(-5.44)
MTB	-0.045**	-0.060***	-0.072***	-0.064***
	(-2.53)	(-3.35)	(-4.06)	(-3.64)
Lev	0.029**	0.030**	0.034***	0.033***
	(2.52)	(2.54)	(2.87)	(2.78)
Beta	0.121**	0.096*	0.081	0.077
	(2.34)	(1.84)	(1.57)	(1.49)
Loss	-1.616***	-1.537***	-1.514***	-1.474***
	(-24.36)	(-23.27)	(-22.99)	(-22.43)
Intercept	0.178	0.218	-0.542**	-0.577***
	(0.80)	(0.99)	(-2.45)	(-2.61)
Industry F.E.	Yes	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes	Yes
Observations	148,336	148,336	148,336	148,336
Adj-R2	0.0535	0.0623	0.0659	0.0694

Panel B. Consistency between the earnings surprise and the operating cash flow surprise

		(1)	(2)	(3)	(4)
Earnings Surprise		2.679***	2.576***	2.399***	2.039***
		(20.22)	(19.76)	(16.54)	(14.42)
CF Surprise			0.754***	0.653***	-0.005
			(9.98)	(8.13)	(-0.05)
Consistency				0.270***	0.285***
				(3.38)	(3.59)
Earnings Surprise * Consistency	+			**0.305****	**0.341*****
				(2.43)	**(2.78)**
CF Surprise * Consistency	+				**1.266*****
					(10.55)
*Earnings Surprise * Size*		0.143***	0.135***	0.138***	0.153***
		(3.16)	(3.02)	(3.08)	(3.50)
*Earnings Surprise * MTB*		0.215***	0.208***	0.205***	0.220***
		(3.38)	(3.31)	(3.28)	(3.53)
*Earnings Surprise * Lev*		-0.003	-0.005	-0.005	-0.005

	(-0.23)	(-0.40)	(-0.40)	(-0.41)
*Earnings Surprise * Beta*	0.306***	0.297***	0.300***	0.276***
	(3.19)	(3.18)	(3.22)	(2.94)
*Earnings Surprise * Loss*	-1.642***	-1.587***	-1.565***	-1.475***
	(-12.64)	(-12.20)	(-11.99)	(-11.53)
*CF Surprise * Size*		0.077**	0.080**	0.076**
		(2.32)	(2.38)	(2.23)
*CF Surprise * MTB*		0.024	0.015	0.035
		(0.34)	(0.21)	(0.52)
*CF Surprise * Lev*		0.010	0.010	0.010
		(0.79)	(0.81)	(0.81)
*CF Surprise * Beta*		0.205**	0.189*	0.222**
		(2.10)	(1.94)	(2.25)
*CF Surprise * Loss*		-0.159	-0.177*	-0.216**
		(-1.52)	(-1.66)	(-2.05)
Size	-0.114***	-0.113***	-0.113***	-0.104***
	(-4.37)	(-4.33)	(-4.29)	(-3.97)
MTB	0.004	0.001	-0.002	0.016
	(0.14)	(0.04)	(-0.06)	(0.51)
Lev	0.014	0.014	0.014	0.014
	(1.18)	(1.15)	(1.16)	(1.20)
Beta	0.043	0.074	0.078	0.061
	(0.46)	(0.78)	(0.82)	(0.65)
Loss	-1.173***	-1.152***	-1.155***	-1.150***
	(-10.28)	(-10.16)	(-10.19)	(-10.17)
Intercept	0.002***	0.002***	-0.001	-0.001**
	(4.07)	(3.79)	(-0.93)	(-2.39)
Industry F.E.	Yes	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes	Yes
Observations	47,354	47,354	47,354	47,354
Adj-R2	0.0606	0.0672	0.0676	0.0719

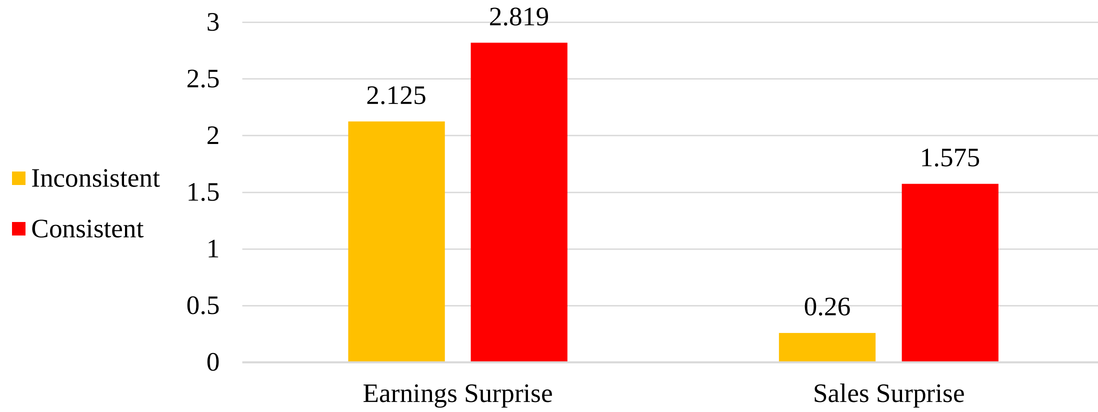
*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, in two-tailed tests.

The table presents pooled regression estimates with firm-quarter observations from 1998 to 2019. In Panel A (Panel B), consistency is measured using the sign of earnings and sales (operating cash flow) surprise so that it is consistent if the earnings surprise and the sales (operating cash flow) surprise have the same sign. The surprise variables are scaled by their standard deviation and the control variables are demeaned. Year-quarter fixed effects and industry fixed effects are included in all models. The *t*-statistics in parentheses are based on standard errors clustered by firm. The main coefficients of interest in the tests are in bold.

The variable definitions are provided in the Appendix A.

Figure 2
Comparison of consistency effects for earnings, sales, and operating cash flow

Panel A. ERCs and SRCs for consistent vs. inconsistent surprises



	ERCs	SRCs
Inconsistent surprise	2.125	0.260
Consistent surprise	2.819	1.575
Consistency effect	0.694	1.315

Panel B. ERCs and CFRCs for consistent vs. inconsistent surprises

	ERCs	CFRCs
Inconsistent surprise	2.039	-0.005
Consistent surprise	2.380	1.261
Consistency effect	0.341	1.266

Figure 2 plots ERCs, SRCs, and CFRCs for consistent and inconsistent surprises from Table 3, column (4). Yellow bars show the coefficients on *Earnings Surprise*, *Sales Surprise*, and *CF Surprise*. Red bars show: *Earnings Surprise* + *Earnings Surprise**Consistency*; *Sales Surprise* + *Sales Surprise**Consistency*; *CF Surprise* + *CF Surprise**Consistency*. The consistency effect is measured by the difference between the response coefficients for consistent and inconsistent cases.

Next, I examine whether more consistency is more informative. In Table 4, I use all three indicators concurrently in measuring consistency. The dummy variable *ES Consistent w/1* is one if the earnings surprise is consistent with either the sales surprise or the cash flow surprise but not both. The dummy variable *ES consistent w/2* is one if the earnings surprise is consistent with both the sales surprise and the cash flow surprise. Similarly, *SS consistent w/1* (*CFS consistent w/1)* is one if the sales (cash flow) surprise is consistent with only one of the two other surprises, and *SS consistent w/2* (*CFS consistent w/2*) is one if the sales (cash flow) surprise is consistent with both of the two other surprises.

Column (1) examines the consistency effect for earnings. The positive significant coefficients on *Earnings Surprise * ES consistent w/1* and *Earnings Surprise * ES consistent w/2* indicate that ERCs are larger when the earnings surprise is consistent with the other surprises. Moreover, the *F*-statistic at the bottom of the table shows that the coefficient on *Earnings Surprise * ES consistent w/2* (1.722) is significantly larger than *Earnings Surprise * ES consistent w/1* (1.067) (F=34.31). This suggests that investors find consistency more informative when the earnings surprise is consistent with both the sales surprise and the cash flow surprise than when it is consistent with just one of these two surprises. I find similar results for the consistency effects for sales and cash flow in columns (2) and (3). SRCs and CFRCs are larger for consistent surprises and the consistency effect is stronger when the surprise is consistent with two other indicators rather than just one other indicator.

In column (4), I use an extended model that incorporates all three surprises and their interactions with the consistency dummies. I continue to observe the consistency effects for earnings, sales, and cash flow. ERCs, SRCs, and CFRCs are all larger when the main surprise is consistent with one or two other surprises. The consistency effect for cash flow is strongest when the cash flow surprise is consistent with both the earnings surprise and the sales surprise. The coefficient on *CF Surprise * CFS consistent w/2* (1.449) is significantly larger than that on *CF Surprise * CFS consistent w/1* (0.659) (F=38.88).[25] The coefficient on *Earnings Surprise * ES consistent w/2* is also larger than that on *Earnings Surprise * ES consistent w/1*, but they are not significantly different (F=1.79). I plot the consistency effects for the three indicators in Figure 3.

Overall, Tables 3 and 4 show that indicator consistency matters not just in valuing earnings but also in valuing other indicators such as sales and cash flow. Moreover, consistency effects are stronger when more indicators are consistent with each other, confirming the informative role of indicator consistency.

[25] The coefficients on *Sales Surprise * SS consistent w/1* and *Sales Surprise * SS consistent w/2* are positive but the two are not significantly different from each other (F=0.74). I suspect that this model is too large with many correlated variables, causing the results to be weaker.

Table 4
Extended models with consistency between multiple indicators

	(1)	(2)	(3)	(4)
<u>Tests of consistency effect for earnings</u>				
Earnings Surprise (ES)	1.425***			1.684***
	(9.57)			(10.74)
Earnings Surprise*ES consistent w/ 1	**1.067*** **			**0.343** **
	(7.88)			**(2.20)**
Earnings Surprise*ES consistent w/ 2	**1.722*** **			**0.519*** **
	(11.35)			**(3.06)**
ES consistent w/ 1	0.689***			0.781***
	(6.89)			(6.76)
ES consistent w/ 2	1.467***			1.812***
	(12.95)			(11.01)
<u>Tests of consistency effect for sales</u>				
Sales Surprise (SS)		0.094		0.614***
		(0.36)		(2.90)
Sales Surprise * SS consistent w/ 1		**1.529*** **		**0.471*** **
		(12.45)		**(3.98)**
Sales Surprise * SS consistent w/ 2		**2.487*** **		**0.381*** **
		(16.19)		**(2.90)**
SS consistent w/ 1		0.333***		0.688***
		(3.36)		(6.11)
SS consistent w/ 2		1.206***		
		(10.92)		
<u>Tests of consistency effect for CF</u>				
CF Surprise (CFS)			-0.870***	-0.090
			(-8.13)	(-0.77)
CF Surprise * CFS consistent w/ 1			**1.728*** **	**0.659*** **
			(14.41)	**(4.79)**
CF Surprise * CFS consistent w/ 2			**3.264*** **	**1.449*** **
			(23.72)	**(9.36)**
CFS consistent w/ 1			-0.714***	
			(-7.29)	
CFS consistent w/ 2			0.412***	
			(4.01)	
*Earnings Surprise * Size*	0.128***			0.122***
	(2.82)			(2.88)
*Earnings Surprise * MTB*	0.192***			0.114**
	(3.12)			(2.00)

	(1)	(2)	(3)	(4)
*Earnings Surprise * Lev*	-0.002			-0.003
	(-0.18)			(-0.26)
*Earnings Surprise * Beta*	0.250***			0.186**
	(2.61)			(2.04)
*Earnings Surprise * Loss*	-1.512***			-1.365***
	(-11.85)			(-10.99)
*Sales Surprise * Size*		-0.126***		-0.062**
		(-3.93)		(-2.08)
*Sales Surprise * MTB*		1.021***		0.806***
		(4.08)		(4.11)
*Sales Surprise * Lev*		0.001		0.005
		(0.11)		(0.44)
*Sales Surprise * Beta*		0.322***		0.138
		(3.24)		(1.52)
*Sales Surprise * Loss*		-0.058		-0.022
		(-0.53)		(-0.21)
*CF Surprise * Size*			0.046	0.070**
			(1.32)	(2.07)
*CF Surprise * MTB*			0.090	0.026
			(1.38)	(0.40)
*CF Surprise * Lev*			0.005	0.007
			(0.45)	(0.60)
*CF Surprise * Beta*			0.291***	0.212**
			(2.87)	(2.15)
*CF Surprise * Loss*			-0.291***	-0.210**
			(-2.76)	(-2.04)
Size	-0.104***	-0.137***	-0.121***	-0.097***
	(-3.98)	(-5.29)	(-4.73)	(-3.71)
MTB	-0.025	-0.060*	-0.017	-0.031
	(-0.82)	(-1.82)	(-0.54)	(-0.98)
Lev	0.017	0.012	0.017	0.015
	(1.44)	(1.03)	(1.41)	(1.26)
Beta	0.050	0.174*	0.144	0.027
	(0.53)	(1.84)	(1.54)	(0.29)
Loss	-1.149***	-1.688***	-1.652***	-1.104***
	(-10.13)	(-14.96)	(-14.78)	(-9.81)
Intercept	-0.102	0.710**	1.018***	-0.609*
	(-0.35)	(2.40)	(3.51)	(-1.92)
Industry F.E.	Yes	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes	Yes
Observations	46,991	46,991	46,991	46,991
Adj-R2	0.0712	0.0466	0.0551	0.0832

	(1)	(2)	(3)	(4)
F-statistic for:				
*Earnings Surprise * ES consistent w/ 1* vs. *Earnings Surprise * ES consistent w/ 2*	34.31***			1.79
*Sales Surprise * SS consistent w/ 1* vs. *Sales Surprise * SS consistent w/ 2*		80.12***		0.74
*CF Surprise * CFS consistent w/ 1* vs. *CF Surprise * CFS consistent w/ 2*			196.28***	38.88***

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, in two-tailed tests.

The table shows the consistency effects when consistency between multiple indicators is used. Columns (1) to (3) test the consistency effect for earnings, sales, and operating cash flow, respectively, and column (4) tests all three effects concurrently. For interaction terms, I use abbreviations for the surprise variables (i.e., *ES* for *Earnings Surprise*, *SS* for *Sales Surprise*, and *CFS* for *Cash Flow Surprise*). *ES consistent w/1* is one if the earnings surprise has the same sign with either the sales surprise or the cash flow surprise. *ES consistent w/2* is one if the earnings surprise has the same sign with both the sales surprise and the cash flow surprise. *SS consistent w/1* is one if the sales surprise has the same sign with either the earnings surprise or the cash flow surprise. *SS consistent w/2* is one if the sales surprise has the same sign with both the earnings surprise and the cash flow surprise. *CFS consistent w/1* is one if the cash flow surprise has the same sign with either the earnings surprise or the sales surprise. *CFS consistent w/2* is one if the cash flow surprise has the same sign with both the earnings surprise and the sales surprise. The surprise variables are scaled by their standard deviation and the control variables are demeaned. Year-quarter fixed effects and industry fixed effects are included in all models. F-statistics to compare the two interaction terms are shown at the bottom of the table. In column (4), some of the stand-alone dummy variables are omitted because of perfect multicollinearity. When all three surprises have the same sign, all three variables−*ES consistent w/2*, *SS consistent w/2*, *CFS consistent w/2*−will be one, causing perfect multicollinearity between the three. Similarly, *CFS consistent w/1* has perfect multicollinearity with either *ES consistent w/1* or *SS consistent w/1*, and thus is omitted.

The variable definitions are provided in the Appendix A.

Figure 3
Graphical presentation of consistency effects with three indicators

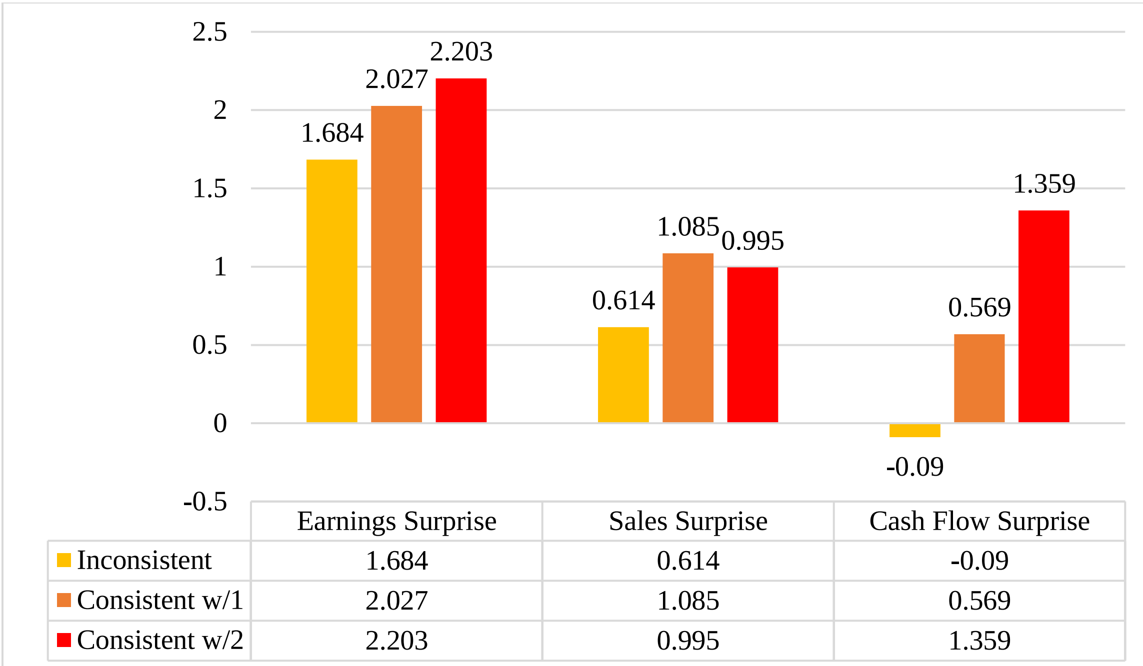


Figure 3 plots the coefficients on the surprise variables and their interaction terms with consistency from Table 4, column (4). Yellow bars show the response coefficients for inconsistent case. They are the coefficients on *Earnings Surprise*, *Sales Surprise*, and *CF Surprise*. Orange bars show the response coefficients for a case where the main surprise variable is consistent with one other surprise (e.g., earnings surprise is consistent with either sales surprise or cash flow surprise). They are the coefficients on *Earnings Surprise* + *Earnings Surprise*ES consistent w/1*; *Sales Surprise* + *Sales Surprise*SS consistent w/1*; *CF Surprise* + *CF Surprise*CFS consistent w/1*. Red bars show the response coefficients for a case where the main surprise variable is consistent with two other surprises (e.g., earnings surprise is consistent with both of sales surprise and cash flow surprise). They are the coefficients on *Earnings Surprise* + *Earnings Surprise*ES consistent w/2*; *Sales Surprise* + *Sales Surprise*SS consistent w/2*; *CF Surprise* + *CF Surprise*CFS consistent w/2*.

4.3. Direct Tests of the Standard Persistence Explanation for the Consistency Effects

Rees and Sivaramakrishnan (2007) and Brown et al. (2013) propose higher earnings persistence as the main reason for the consistency effect for earnings. In other words, they argue that earnings is more persistent when the earnings news is confirmed by the sales news or the operating cash flow news. I directly test this persistence argument by investigating whether earnings is more persistent when the earnings surprise is consistent with the sales surprise or the operating cash flow surprise.

Table 5 shows the results. I estimate earnings persistence with a seasonal random-walk-based model. In columns (1) and (2), I regress earnings at q+4 (same quarter in the next year) on the current quarter earnings and its interaction with the current quarter consistency.[26] In column (1), *Consistency with sales* is one if the earnings surprise has the same sign as the sales surprise. The positive and significant coefficient on *Earnings * Consistency with sales* in column (1) suggests that earnings is indeed more persistent when the earnings surprise is consistent with the sales surprise. In column (2), *Consistency with CF* is one if the earnings surprise has the same sign as the cash flow surprise. The coefficient on *Earnings * Consistency with CF* in column (2) is positive but not significant, suggesting that confirmation by the cash flow news does not necessarily indicate higher persistence of earnings.

In columns (3) and (4), I further examine whether indicator consistency relates to higher persistence of sales and cash flow. Like the earnings persistence model, I regress sales (or operating cash flow) at q+4 on the current quarter sales (or operating cash flow) and its interaction with the current quarter consistency. The coefficients on *Sales * Consistency with earnings* in column (3) and *CF * Consistency with earnings* in column (4) are small and statistically insignificant. This shows that consistent sales (or cash flow) surprises do not indicate higher persistence of sales (or operating cash flow), and

[26] In an untabulated model, I additionally control for negative earnings because negative earnings is known to be much less persistent than positive earnings (Hayn, 1995; Basu, 1997). I find qualitatively similar results.

accordingly the persistence argument cannot explain the consistency effects for sales and operating cash flow.[27]

[27] In an untabulated robustness test, I replace sales with sales growth and control for negative sales growth in the same model, and find similar results. The result for operating cash flow persistence is also qualitatively similar when I control for negative operating cash flow.

Table 5
Direct tests of the standard persistence explanation

	(1)	(2)	(3)	(4)
Dependent variable:	Future earnings		Future sales	Future CF
Tests of:	Persistence of earnings		Persistence of sales	Persistence of CF
Earnings	0.872***	0.915***		
	(95.68)	(71.82)		
Earnings * Consistency with sales	**0.033*****			
	(4.18)			
Earnings * Consistency with CF		**-0.003**		
		(-0.23)		
Sales			1.019***	
			(171.72)	
Sales * Consistency with earnings			**-0.003**	
			(-0.64)	
CF				0.810***
				(50.48)
CF * Consistency with earnings				**0.012**
				(0.75)
Consistency	-0.001	0.002	0.033	-0.102***
	(-0.31)	(0.31)	(1.26)	(-6.11)
Intercept	0.056***	0.070***	0.084**	0.304***
	(19.78)	(10.97)	(2.48)	(19.56)
Observations	115,345	41,178	115,218	35,617
Adj-R2	0.692	0.702	0.940	0.564

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, in two-tailed tests.

The table presents regression estimates to examine how indicator consistency is associated with the persistence of earnings, sales, and cash flow. In columns (1) and (2), the dependent variable is future earnings (i.e., earnings in the same quarter of the next year). *Consistency with sales* is one if the earnings surprise and the sales surprise have the same sign. *Consistency with CF* is one if the earnings surprise and the cash flow surprise have the same sign. In column (3), the dependent variable is future sales (i.e., sales of the same quarter in the next year) and *Consistency with earnings* is one if the sales surprise has the same sign with the earnings surprise. In column (4), the dependent variable is future cash flow (i.e., cash flow of the same quarter in the next year) and *Consistency with earnings* is one if the cash flow surprise has the same sign with the earnings surprise. The main coefficients of interest in the tests are in bold.

The variable definitions are provided in the Appendix A.

CHAPTER 5

UNCERTAINTY ABOUT INDICATOR PRECISION

5.1. Absolute Magnitude of Surprises

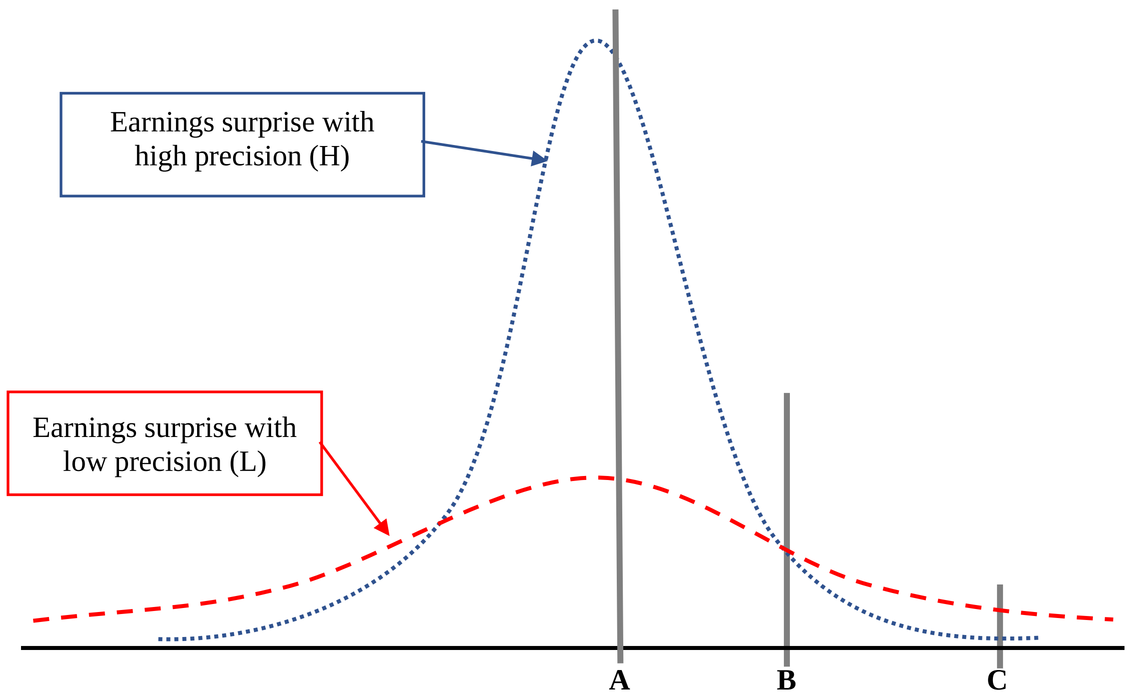
The absolute magnitude of the earnings surprise is a well-known proxy for earnings news precision. Subramanyam (1996) develops a model to show that the market assesses earnings news precision based on the realization of the earnings surprise and shows that the absolute magnitude of the earnings surprise is inversely related to the unknown precision.[28]

The absolute magnitude of the earnings surprise also reflects the degree of uncertainty about earnings precision. Consider the two hypothetical earnings surprise distributions in Figure 4. The blue dotted (red dashed) curve represents an earnings surprise with high (low) precision. Investors do not know *ex ante* whether the realized earnings surprise is drawn from the high precision distribution or the low precision distribution. When the realized earnings surprise is at point B where the two distributions have a comparable density, the earnings could have arisen from either the high precision distribution or the low precision distribution because the two are equally likely. Therefore, there is high uncertainty about indicator precision (i.e., investors are not sure whether the indicator is precise or not). In this case, investors can resolve this uncertainty

[28] As a result, the market discounts extreme earnings surprises because of their low precision, leading to a decline in ERC as the absolute value of the surprises increases. This nonlinear price response to the earnings surprise is empirically well documented (Freeman and Tse, 1992; Kinney, Burgstahler, and Martin, 2002; Burgstahler and Chuk, 2017).

about precision by examining the consistency between the earnings surprise and an additional surprise.

Figure 4
Magnitude of earnings surprise and uncertainty about its precision



	Very small surprise (A)	Moderate surprise (B)	Very large surprise (C)
Indicator precision (Distribution H/L)	Almost certainly high (Likely from H)	Can be high or low (Could be from H or L)	Almost certainly low (Likely from L)
Uncertainty about indicator precision	Low	High	Low

Figure 4 depicts two hypothetical distributions of earnings surprise. The blue dotted curve represents a distribution with high precision and the red dashed curve represents a distribution with low precision. If the realized earnings surprise is at point B (i.e., a moderate surprise), it could have arisen from either the high precision distribution or the low precision distribution. Therefore, point B indicates high uncertainty about indicator precision. In contrast, very small (very large) earnings surprises at point A (point C) almost certainly came from the high (low) precision distribution. Therefore, points A and C indicate low uncertainty about indicator precision.

In contrast, when investors observe an extremely large earnings surprise at point C, they are almost certain that it is drawn from the low precision distribution because the high precision distribution has very few extreme values. Similarly, when investors observe an extremely small earnings surprise at point A, they know that there is a very high chance that the earnings is drawn from the high precision distribution. Accordingly, at points A and C, there is low uncertainty about indicator precision as investors can confidently infer earnings precision from the realized earnings surprises. In this case, therefore, indicator consistency is not as useful for determining indicator precision.[29]

To estimate the precision of earnings news, I partition the sample into five quintiles across different absolute magnitudes of the earnings surprises. Table 6 shows the regression results of model (4) in the partitioned sample. Quintile 1 (quintile 5) contains the smallest (largest) earnings surprises in absolute value. Extremely small earnings surprises in quintile 1 have high indicator precision while extremely large earnings surprises in quintile 5 have low indicator precision. Thus, there is little uncertainty about indicator precision in these two groups (i.e., investors are reasonably sure that the earnings surprise is precise for quintile 1 and imprecise for quintile 5). Quintile 1 and Quintile 5 are comparable to point A and point C, respectively, in Figure 4. In contrast, the precision of the earnings surprises in the middle quintiles could be

[29] As described, I use the absolute magnitude of the earnings surprise as a proxy for earnings precision as well as uncertainty about earnings precision. Inferred earnings precision monotonically decreases with the absolute magnitude of the earnings surprise (i.e., A>B>C in terms of precision), while inferred uncertainty is non-monotonic (i.e., A<B and B>C in terms of uncertainty). See the summary table in Figure 4 for more details.

either high or low. This is like point B in Figure 4, where the surprise can be drawn from either the low precision distribution or the high precision distribution. Therefore, these middle quintiles have higher uncertainty about indicator precision (i.e., investors are not sure whether the earnings surprise is precise or imprecise) than the two end quintiles.

H2 predicts that the consistency effect for earnings is stronger for moderate earnings surprises than for extremely large or extremely small earnings surprises because moderate surprises have higher uncertainty about their precision. Therefore, I expect the coefficient on *Earnings Surprise * Consistency* to be larger in the middle three quintiles than in quintile 1 and quintile 5. The results are consistent with this prediction. First, in Table 6 Panel A, I use the sales surprise sample. As expected, the coefficient on *Earnings Surprise * Consistency* is significantly larger in the middle three quintiles than in quintiles 1 and 5. Specifically, the consistency effect for earnings is largest in quintile 4 (2.132, significant at 1% level), and the consistency effects in quintiles 2 and 3 are also larger than those in quintiles 1 and 5. [30] Next, in Panel B, I use the cash flow surprise sample and find similar but weaker results. The coefficient on *Earnings Surprise * Consistency* in quintile 1 (0.287, significant at 5% level) is significantly smaller than those in the middle three quintiles, as expected.[31] However, the consistency effect for earnings in quintile 5 is statistically not different from those in the middle three quintiles.

[30] The difference in the coefficients on *Earnings Surprise * Consistency* between quintile 1 and the middle three quintiles is statistically significant at the 1% level. The coefficient on *Earnings Surprise * Consistency* in quintile 5 is significantly smaller than that in quintile 2 (quintiles 3 and 4) at the 10% (1%) level.

[31] The coefficient on *Earnings Surprise * Consistency* in quintile 1 is significantly smaller than that in quintile 2 (at 5% level) and in quintile 4 (1% level).

By analogy to earnings, I use the absolute magnitude of the sales surprise to proxy for sales news precision and the absolute magnitude of the cash flow surprise to proxy for cash flow news precision. In Table 7, Panel A (Panel B), I partition the sample into five quintiles based on the absolute magnitude of the sales (cash flow) surprise. Like Table 6, the middle three quintiles have higher uncertainty about indicator precision than the two end quintiles. H2 predicts that the consistency effect for sales (cash flow) is stronger for moderate sales (cash flow) surprises than for extremely large or extremely small sales (cash flow) surprises. In Panel A, the coefficients on *Sales Surprise * Consistency* in quintile 1 and quintile 5 are significantly smaller than those in quintiles 2, 3, and 4, as predicted by H2.[32] In the cash flow surprise sample in Panel B, the coefficient on *CF Surprise * Consistency* in quintile 1 is significantly smaller than that in the middle three quintiles (all at 1% level), as expected. However, the consistency effect for cash flow in quintile 5 is not ranked lower than the middle three quintiles, and it is statistically not different from those in the middle three quintiles.

[32] The coefficient on *Sales Surprise * Consistency* in quintile 1 is significantly smaller than that in the middle three quintiles (at 1% level). The coefficient on *Sales Surprise * Consistency* in quintile 5 is smaller than that in the middle three quintiles, and the difference is statistically significant from quintile 3 (at 1% level) and from quintile 4 (at 5% level).

Table 6
Consistency effects across different magnitudes of earnings surprise

Panel A. Consistency between the earnings surprise and the sales surprise

	(1)	(2)	(3)	(4)	(5)
Abs(Earnings Surprise)	Quintile 1 (Smallest)	Quintile 2	Quintile 3	Quintile 4	Quintile 5 (Largest)
Indicator precision	Almost certainly high	Maybe high or maybe low	Maybe high or maybe low	Maybe high or maybe low	Almost certainly low
Uncertainty about indicator precision	Lowest	Higher	Higher	Higher	Lowest
Earnings Surprise	0.213***	0.625***	1.180***	1.850***	1.480***
	(2.85)	(7.68)	(13.08)	(17.30)	(9.76)
Sales Surprise	0.527***	0.561***	0.339*	0.334**	-0.188
	(3.32)	(3.42)	(1.86)	(2.20)	(-1.12)
Consistency	1.070***	0.250**	0.445***	0.451***	0.437***
	(10.65)	(2.46)	(4.01)	(3.95)	(3.18)
Earnings Surprise * Consistency	**0.800*** **	**1.626*** **	**1.918*** **	**2.132*** **	**1.139*** **
	(8.71)	**(14.71)**	**(16.12)**	**(16.04)**	**(6.23)**
*Sales Surprise * Consistency*	-0.078	-0.202**	-0.228**	-0.099	2.313***
	(-0.68)	(-2.15)	(-2.10)	(-0.77)	(12.23)
*Earnings Surprise * Size*	-0.044	-0.061**	-0.048	-0.051	0.318***
	(-1.54)	(-2.03)	(-1.47)	(-1.33)	(4.78)
*Earnings Surprise * MTB*	0.078**	0.133***	0.104***	0.076*	-0.127**
	(2.54)	(3.63)	(2.72)	(1.82)	(-2.53)
*Earnings Surprise * Lev*	-0.020	-0.056**	-0.046**	-0.077***	0.014
	(-0.68)	(-2.36)	(-2.01)	(-2.88)	(0.53)
*Earnings Surprise * Beta*	-0.031	0.020	0.418***	0.551***	0.258**
	(-0.29)	(0.18)	(4.07)	(5.53)	(2.11)
*Earnings Surprise * Loss*	-0.306*	-0.659***	-1.232***	-1.877***	-1.934***
	(-1.80)	(-4.44)	(-9.56)	(-14.64)	(-8.58)
*Sales Surprise * Size*	-0.053*	-0.089***	-0.062**	-0.127***	0.061
	(-1.85)	(-3.20)	(-2.46)	(-3.97)	(1.05)
*Sales Surprise * MTB*	0.382***	0.443***	0.283*	0.447***	0.293***
	(3.78)	(3.75)	(1.91)	(3.32)	(2.85)
*Sales Surprise * Lev*	0.031	-0.005	0.020	-0.011	-0.031
	(1.18)	(-0.22)	(1.20)	(-0.39)	(-1.29)
*Sales Surprise * Beta*	0.008	0.145	0.190**	0.270***	0.195
	(0.07)	(1.59)	(2.19)	(2.74)	(1.55)
*Sales Surprise * Loss*	0.068	0.082	0.018	-0.172	-0.368**

	(1)	(2)	(3)	(4)	(5)
	(0.48)	(0.54)	(0.13)	(-1.20)	(-2.36)
Size	-0.051*	0.016	-0.119***	-0.110***	-0.119**
	(-1.67)	(0.46)	(-3.38)	(-2.88)	(-2.41)
MTB	-0.181***	-0.154***	-0.085**	-0.015	-0.062
	(-4.70)	(-3.58)	(-2.04)	(-0.37)	(-1.16)
Lev	0.037	0.069**	-0.003	0.080***	0.033
	(1.54)	(2.45)	(-0.14)	(3.10)	(1.19)
Beta	-0.224*	-0.214*	-0.281**	-0.216**	0.358***
	(-1.88)	(-1.71)	(-2.37)	(-1.98)	(3.03)
Loss	-0.573***	-0.843***	-0.639***	-1.297***	-2.785***
	(-3.58)	(-5.03)	(-4.35)	(-9.97)	(-17.81)
Intercept	-1.832***	-1.920***	-2.547***	-1.463***	1.533***
	(-5.30)	(-5.67)	(-6.41)	(-4.20)	(3.40)
Industry F.E.	Yes	Yes	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes	Yes	Yes
Observations	29,668	29,669	29,667	29,665	29,667
Adj-R2	0.0290	0.0694	0.105	0.154	0.126

Panel B. Consistency between the earnings surprise and the operating cash flow surprise

	(1)	(2)	(3)	(4)	(5)
Abs(Earnings Surprise)	Quintile 1 (Smallest)	Quintile 2	Quintile 3	Quintile 4	Quintile 5 (Largest)
Indicator precision	Almost certainly high	Maybe high or maybe low	Maybe high or maybe low	Maybe high or maybe low	Almost certainly low
Uncertainty about indicator precision	Lowest	Higher	Higher	Higher	Lowest
Earnings Surprise	0.502***	1.066***	1.714***	1.911***	2.079***
	(5.13)	(8.54)	(12.70)	(12.32)	(8.60)
CF Surprise	0.265*	0.372***	0.284*	0.322*	-0.128
	(1.74)	(2.75)	(1.72)	(1.65)	(-0.54)
Consistency	0.267*	-0.033	-0.125	-0.206	-0.121
	(1.75)	(-0.21)	(-0.73)	(-1.15)	(-0.57)
Earnings Surprise * Consistency	**0.287****	**0.753*****	**0.570*****	**1.187*****	**0.762*****
	(2.19)	**(4.66)**	**(3.19)**	**(5.72)**	**(2.61)**
*CF Surprise * Consistency*	-0.096	-0.109	-0.216	0.049	1.699***
	(-0.53)	(-0.65)	(-1.04)	(0.22)	(5.17)
*Earnings Surprise * Size*	-0.029	-0.148***	-0.195***	-0.181***	0.061
	(-0.55)	(-2.77)	(-3.41)	(-3.07)	(0.72)
*Earnings Surprise * MTB*	0.049	0.247***	0.244***	0.214***	0.128

	(0.96)	(3.74)	(3.63)	(2.76)	(1.08)
*Earnings Surprise * Lev*	0.006	-0.019	-0.057**	-0.035	-0.003
	(0.25)	(-0.88)	(-2.30)	(-1.31)	(-0.12)
*Earnings Surprise * Beta*	0.116	-0.185	-0.012	0.259	0.759***
	(0.66)	(-1.02)	(-0.07)	(1.52)	(3.79)
*Earnings Surprise * Loss*	0.099	-0.389	-0.823***	-1.262***	-2.042***
	(0.37)	(-1.60)	(-3.54)	(-5.79)	(-7.43)
*Sales Surprise * Size*	0.013	0.005	0.058	-0.004	0.094
	(0.24)	(0.10)	(1.00)	(-0.07)	(1.08)
*Sales Surprise * MTB*	0.007	-0.078	-0.104	-0.008	0.044
	(0.06)	(-1.13)	(-1.10)	(-0.05)	(0.29)
*Sales Surprise * Lev*	0.001	0.002	0.005	-0.010	0.023
	(0.03)	(0.11)	(0.27)	(-0.37)	(0.94)
*Sales Surprise * Beta*	0.165	0.122	0.373**	0.225	0.390*
	(0.80)	(0.70)	(2.10)	(1.28)	(1.82)
*Sales Surprise * Loss*	-0.321	0.127	0.323	-0.216	-0.478*
	(-1.55)	(0.60)	(1.52)	(-1.06)	(-1.94)
Size	-0.069	0.013	-0.024	-0.144**	-0.110
	(-1.17)	(0.23)	(-0.38)	(-2.37)	(-1.61)
MTB	-0.078	-0.127*	-0.080	0.064	0.227**
	(-1.27)	(-1.67)	(-1.05)	(0.75)	(1.99)
Lev	0.003	0.017	0.025	0.022	0.041
	(0.12)	(0.60)	(0.89)	(0.79)	(1.53)
Beta	-0.266	-0.312	-0.127	-0.275	0.497**
	(-1.20)	(-1.39)	(-0.60)	(-1.34)	(2.47)
Loss	-0.436	-0.760***	-0.619**	-1.085***	-2.131***
	(-1.61)	(-2.65)	(-2.36)	(-4.58)	(-9.41)
Intercept	-1.308***	-1.638***	-1.680***	0.051	0.899
	(-2.97)	(-3.35)	(-3.70)	(0.10)	(1.21)
	-0.029	-0.148***	-0.195***	-0.181***	0.061
Industry F.E.	Yes	Yes	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes	Yes	Yes
Observations	9,471	9,471	9,471	9,476	9,465
Adj-R2	0.0165	0.0637	0.0858	0.127	0.134

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, in two-tailed tests.

The table presents regression estimates in five groups with differing level of the absolute earnings surprises. The absolute value of earnings surprise becomes larger from quintile 1 to quintile 5, where quintile 5 contains the most extreme values. In Panel A (Panel B), consistency is measured using the sign of the earnings surprise and the sales (operating cash flow) surprise so that it is consistent if the earnings surprise and the sales (operating cash flow) surprise have the same sign. The surprise variables are scaled by their standard deviation in each quintile and the control variables are demeaned within each quintile. The *t*-statistics in parentheses are based on standard errors clustered by firm. The main coefficients of interest in the tests are in bold.

Table 7
Consistency effects for different magnitudes of sales and operating cash flow surprise

Panel A. Consistency between the earnings surprise and the sales surprise

	(1)	(2)	(3)	(4)	(5)
Abs(Sales Surprise)	Quintile 1 (Smallest)	Quintile 2	Quintile 3	Quintile 4	Quintile 5 (Largest)
Indicator precision	Almost certainly high	Maybe high or maybe low	Maybe high or maybe low	Maybe high or maybe low	Almost certainly low
Uncertainty about indicator precision	Lowest	Higher	Higher	Higher	Lowest
Earnings Surprise	1.441***	1.005***	1.515***	1.805***	1.943***
	(7.45)	(6.08)	(8.20)	(10.58)	(8.66)
Sales Surprise	-0.260***	-0.384***	-0.244**	-0.144	-0.483***
	(-2.98)	(-4.02)	(-2.38)	(-1.35)	(-3.92)
Consistency	0.425***	0.430***	0.579***	0.493***	0.434***
	(3.76)	(3.64)	(4.96)	(4.28)	(3.49)
*Earnings Surprise * Consistency*	-0.120	-0.078	-0.267*	0.073	0.960***
	(-0.97)	(-0.56)	(-1.67)	(0.44)	(4.20)
Sales Surprise * Consistency	**1.768*** **	**2.954*** **	**3.436*** **	**3.352*** **	**2.772*** **
	(15.07)	**(23.96)**	**(25.37)**	**(24.29)**	**(17.19)**
*Earnings Surprise * Size*	0.084*	0.058	0.190***	0.184***	0.274***
	(1.66)	(1.21)	(3.62)	(3.43)	(3.70)
*Earnings Surprise * MTB*	-0.056*	-0.041	-0.154***	-0.061	-0.150**
	(-1.81)	(-1.23)	(-3.77)	(-1.14)	(-2.08)
*Earnings Surprise * Lev*	0.006	0.004	-0.047**	0.024	0.003
	(0.16)	(0.13)	(-1.99)	(1.04)	(0.13)
*Earnings Surprise * Beta*	0.043	0.131	0.001	0.151	0.150
	(0.46)	(1.54)	(0.01)	(1.25)	(1.16)
*Earnings Surprise * Loss*	-1.438***	-1.058***	-1.205***	-1.756***	-2.084***
	(-5.57)	(-5.99)	(-5.71)	(-9.35)	(-9.70)
*Sales Surprise * Size*	0.027	0.002	-0.118***	-0.181***	-0.134***
	(0.98)	(0.07)	(-3.77)	(-5.32)	(-3.33)
*Sales Surprise * MTB*	0.078***	0.248***	0.502***	0.455***	0.308***
	(2.73)	(6.69)	(10.16)	(6.76)	(2.81)
*Sales Surprise * Lev*	-0.022	-0.030	0.027	-0.059**	-0.026
	(-0.98)	(-1.13)	(1.13)	(-2.06)	(-1.04)
*Sales Surprise * Beta*	0.096	0.460***	0.500***	0.418***	0.455***
	(0.87)	(4.20)	(4.68)	(3.98)	(3.75)
*Sales Surprise * Loss*	0.177	-0.033	-0.116	0.081	-0.378**

	(1.29)	(-0.23)	(-0.79)	(0.57)	(-2.42)
Size	-0.050	-0.103***	-0.160***	-0.148***	-0.225***
	(-1.59)	(-3.35)	(-4.81)	(-4.17)	(-5.71)
MTB	-0.217***	-0.086**	-0.120**	-0.033	-0.166*
	(-7.30)	(-2.38)	(-2.27)	(-0.52)	(-1.79)
Lev	0.046*	0.057**	0.017	0.057**	0.018
	(1.85)	(2.21)	(0.63)	(1.97)	(0.72)
Beta	-0.115	-0.211*	-0.065	0.091	0.299***
	(-1.04)	(-1.87)	(-0.56)	(0.80)	(2.59)
Loss	-0.992***	-0.860***	-1.067***	-1.261***	-1.714***
	(-6.67)	(-5.90)	(-7.48)	(-9.01)	(-11.93)
Intercept	-1.955***	-2.500***	-1.264***	-1.093***	1.103**
	(-5.20)	(-6.15)	(-2.91)	(-3.03)	(2.53)
Industry F.E.	Yes	Yes	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes	Yes	Yes
Observations	29,668	29,667	29,667	29,667	29,667
Adj-R2	0.0415	0.0757	0.119	0.136	0.123

Panel B. Consistency between earnings and operating cash flow surprise

	(1)	(2)	(3)	(4)	(5)
Abs(CF Surprise)	Quintile 1 (Smallest)	Quintile 2	Quintile 3	Quintile 4	Quintile 5 (Largest)
Indicator precision	Almost certainly high	Maybe high or maybe low	Maybe high or maybe low	Maybe high or maybe low	Almost certainly low
Uncertainty about indicator precision	Lowest	Higher	Higher	Higher	Lowest
Earnings Surprise	1.055***	0.961***	1.360***	1.596***	1.816***
	(4.00)	(4.66)	(5.86)	(6.46)	(6.77)
CF Surprise	-0.817***	-1.049***	-0.710***	-0.409***	-0.400**
	(-5.98)	(-7.19)	(-4.74)	(-2.70)	(-2.02)
Consistency	0.388**	0.087	-0.191	-0.211	0.017
	(2.25)	(0.49)	(-1.08)	(-1.16)	(0.08)
*Earnings Surprise * Consistency*	-0.232	0.056	0.108	-0.446*	0.534*
	(-0.82)	(0.25)	(0.46)	(-1.71)	(1.71)
CF Surprise * Consistency	**2.080***	**2.813***	**2.819***	**2.947***	**2.817***
	(10.99)	**(13.56)**	**(13.26)**	**(14.22)**	**(10.09)**
*Earnings Surprise * Size*	0.042	-0.003	0.087	-0.034	0.067
	(0.61)	(-0.05)	(1.18)	(-0.48)	(0.73)
*Earnings Surprise * MTB*	0.029	-0.003	0.280***	0.023	0.164

	(0.32)	(-0.03)	(2.73)	(0.20)	(1.15)
*Earnings Surprise * Lev*	-0.031	-0.018	-0.031	-0.021	0.013
	(-1.35)	(-0.48)	(-1.06)	(-0.86)	(0.62)
*Earnings Surprise * Beta*	0.606***	0.435***	0.120	0.402**	0.466**
	(2.71)	(2.91)	(0.69)	(2.33)	(2.32)
*Earnings Surprise * Loss*	-0.531*	-0.995***	-0.939***	-1.254***	-2.094***
	(-1.75)	(-4.13)	(-4.42)	(-5.36)	(-7.32)
*Sales Surprise * Size*	-0.006	-0.022	-0.082	-0.011	0.112
	(-0.12)	(-0.45)	(-1.52)	(-0.20)	(1.48)
*Sales Surprise * MTB*	0.021	0.158***	0.171**	0.134	-0.218
	(0.43)	(2.98)	(2.48)	(1.53)	(-1.53)
*Sales Surprise * Lev*	0.028	-0.021	0.019	0.026	0.013
	(1.06)	(-0.90)	(0.74)	(1.07)	(0.52)
*Sales Surprise * Beta*	0.267	-0.045	0.054	0.332*	0.475**
	(1.43)	(-0.26)	(0.29)	(1.91)	(2.19)
*Sales Surprise * Loss*	0.131	0.165	-0.006	0.226	-0.497**
	(0.51)	(0.69)	(-0.02)	(1.01)	(-2.12)
Size	-0.148***	-0.159***	-0.127**	-0.240***	-0.216***
	(-2.74)	(-3.00)	(-2.41)	(-4.06)	(-3.05)
MTB	-0.098*	-0.027	-0.036	-0.031	-0.299**
	(-1.71)	(-0.47)	(-0.51)	(-0.35)	(-2.17)
Lev	0.037	-0.001	-0.009	0.000	0.038
	(1.48)	(-0.04)	(-0.35)	(0.01)	(1.45)
Beta	-0.185	-0.284	0.177	0.292	0.255
	(-0.91)	(-1.42)	(0.89)	(1.47)	(1.18)
Loss	-0.716***	-0.857***	-0.833***	-0.868***	-1.430***
	(-2.79)	(-3.40)	(-3.37)	(-3.63)	(-6.02)
Intercept	-0.106	-0.863*	-1.593***	-0.766	-1.599***
	(-0.18)	(-1.84)	(-3.31)	(-1.41)	(-2.66)
	0.042	-0.003	0.087	-0.034	0.067
Industry F.E.	Yes	Yes	Yes	Yes	Yes
Year-Quarter F.E.	Yes	Yes	Yes	Yes	Yes
Observations	9,471	9,471	9,471	9,476	9,465
Adj-R2	0.0165	0.0637	0.0858	0.127	0.134

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, in two-tailed tests.

The table presents regression estimates in five groups with differing level of the absolute sales (operating cash flow) surprises in Panel A (Panel B). The absolute magnitude of the sales or operating cash flow surprise becomes larger from quintile 1 to quintile 5 where quintile 5 contains most extreme values. In Panel A (Panel B), consistency is measured using the sign of the earnings surprise and the sales (operating cash flow) surprise so that it is consistent if the earnings surprise and the sales (operating cash flow) surprise have the same sign. The surprise variables are scaled by their standard deviation in each quintile and the control variables are demeaned within each quintile. The *t*-statistics in parentheses are based on standard errors clustered by firm. The main coefficients of interest in the tests are in bold.

Overall, the results in Tables 6 and 7 show that investors rely on consistent indicators more when the uncertainty about indicator precision is high because indicator consistency can help resolve the uncertainty about indicator precision. The results are generally weaker in the cash flow surprise sample. As mentioned above, only a subset of I/B/E/S firms have operating cash flow forecasts, and this selection issue could be more severe in this partitioned sample analysis.[33]

5.2. SFAS 142 and Uncertainty About Earnings Precision

Next, I use Statement of Financial Accounting Standards 142 (SFAS 142), *Goodwill and Other Intangible Assets*, to test H2. SFAS 142 significantly changed accounting rules for goodwill and other intangible assets.[34] Specifically, it eliminated amortization of goodwill and requires that goodwill be tested for impairment at least annually based on the estimated fair value. Therefore, impairment became the dominant method of accounting for goodwill after SFAS 142.

[33] In Table 6 Panel A (Panel B), the coefficient on *Sales Surprise * Consistency* (*CF Surprise * Consistency*) is positive and significant only in quintile 5. Similarly, in both panels in Table 7, the coefficient on *Earnings Surprise * Consistency* is positive and significant only in quintile 5. When I use a more sophisticated measure of consistency which considers not just the sign consistency but also the degree to which indicators are consistent (see more details in section 6), I find consistency effects throughout all five quintiles. This finding suggests that when surprise A is extremely large (in absolute value), simply having the same sign can be informative in inferring the precision of surprise B. However, if surprise A is non-extreme, having not just the same sign but also a similar magnitude is important to infer the precision of surprise B.

[34] Prior to SFAS 142, APB Opinion 17 and SFAS 121 addressed accounting for goodwill. APB Opinion 17 viewed goodwill as an asset with a finite life and required it to be amortized. SFAS 121 required impairment for goodwill in the event that the carrying amount of an asset may not be recoverable (i.e., carrying value of the asset is higher than the sum of expected undiscounted future cash flows).

I posit that indicator consistency becomes more useful in the post-SFAS 142 period because the standard introduced more uncertainty about earnings precision. Investors might have expected SFAS 142 to increase earnings precision. FASB argued that the new standard will improve financial reporting because impairing goodwill based on fair value will better reflect the underlying economics of those assets (FASB, 2001). Cheng, Cho, and Yang (2018) show that SFAS 142 improved firms' internal information environment as it induced managers to acquire additional information to estimate fair value of assets. If this is the case, earnings precision will increase in the sense that earnings will reflect future cash flow more precisely.

However, investors could believe that SFAS 142 reduces earnings precision. While amortization involves gradual and systematic reduction in asset value, goodwill impairment involves one-time large reductions in earnings and makes earnings less predictable. Also, managers can exercise discretion in estimating fair value (Ramanna and Watts, 2012; Li and Sloan, 2017). Fair value estimation requires many assumptions and estimates including forecasts of future cash flows, growth rates, and discount rates. Because it is difficult to verify fair value estimates for goodwill, managers may use discretion to avoid or delay impairment. Chen, Krishnan, and Sami (2015) document that analyst earnings forecasts are less accurate and more dispersed for firms with goodwill impairment charges, suggesting that goodwill impairment can make earnings less interpretable in valuing firms. In this case, earnings precision will decrease as earnings will reflect future cash flows with more noise.

Because it is unclear whether earnings precision after SFAS 142 will be higher or lower, SFAS 142 likely increased uncertainty about earnings precision (i.e., investors are more unsure about earnings precision after SFAS 142 than before). Therefore, I predict that indicator consistency is more useful in the post-SFAS 142 period because indicator consistency can resolve the increased uncertainty about earnings precision. To test this prediction, I add a three-way interaction term, *Earnings Surprise * Consistency * Post-SFAS 142*, in the full model. I expect a positive coefficient on this interaction, indicating that the consistency effect for earnings is larger after SFAS 142.

SFAS 142 became effective for fiscal years beginning after December 15, 2001. Following Li and Sloan (2017), I exclude data between 2001 and 2003 to eliminate potential confounding effects during the transition. Hence, the pre-SFAS 142 period is from 1998 to 2000 and the post-SFAS 142 period is from 2004 to 2006. I limit this analysis to the sales surprise sample because there are very few observations with cash flow surprises in these early years. Treatment (control) firms are those that (do not) have a positive goodwill balance on the balance sheet at the beginning of the fiscal year.[35] My prediction should hold only for the treatment firms but not for the control firms because the standard has very little impact on firms that do not have any goodwill balance to write down.

[35] Additionally, I define treatment firms as those with a goodwill balance that is over 1 percent (or 5 percent) of total assets. The results are stronger with these alternative definitions of treatment group likely because firms with a very small goodwill balance are less affected by the standard.

Table 8 shows the regression results. As expected, the consistency effect for earnings is significantly larger after SFAS 142 for the treatment firms in column (1) but not for the control firms in column (2). The coefficient on *Earnings Surprise * Consistency * Post-SFAS 142* in column (1) is 1.222 (significant at 10% level), indicating the incremental consistency effect for post-SFAS 142. The negative coefficient on *Earnings Surprise * Post-SFAS 142* (-1.311, significant at 10% level) in column (1) suggests that the increase in the consistency effect from before to after SFAS 142 for the treatment firms is driven by inconsistent earnings surprises being viewed as more imprecise after SFA142 than before. These results suggest that investors find indicator inconsistency more useful after SFAS 142 because the inconsistency helps investors filter out low precision earnings in the environment with high uncertainty about earnings precision.

Table 8
Consistency effect for earnings after SFAS 142

	(1) Treatment	(2) Control
Earnings Surprise	3.701***	1.298***
	(4.98)	(2.96)
*Earnings Surprise * Post-SFAS 142*	-1.311*	0.319
	(-1.93)	(0.72)
*Earnings Surprise * Consistency*	-0.592	1.258***
	(-0.86)	(2.79)
Earnings Surprise * Consistency * Post-SFAS 142	1.222*	-0.427
	(1.68)	(-0.77)
Sales Surprise	0.772***	-0.255
	(2.89)	(-0.85)
*Sales Surprise * Post-SFAS 142*	-0.212	0.384
	(-0.80)	(1.24)
*Sales Surprise * Consistency*	0.485*	1.530***
	(1.89)	(4.79)
*Sales Surprise * Consistency * Post-SFAS 142*	0.961***	-0.072
	(2.97)	(-0.18)
Consistency	0.060	1.539***
	(0.15)	(4.97)
Post-SFAS 142	-5.420***	-2.123*
	(-3.48)	(-1.71)
*Consistency * Post-SFAS 142*	1.262***	-0.412
	(2.99)	(-1.09)
*Earnings Surprise * Size*	0.185**	0.113
	(2.01)	(1.05)
*Earnings Surprise * MTB*	0.047	0.127*
	(0.32)	(1.70)
*Earnings Surprise * Lev*	-0.002	0.038
	(-0.08)	(0.81)
*Earnings Surprise * Beta*	0.334*	0.202
	(1.86)	(1.13)
*Earnings Surprise * Loss*	-2.264***	-1.871***
	(-7.08)	(-4.87)
*Sales Surprise * Size*	-0.124***	-0.103*
	(-2.62)	(-1.72)
*Sales Surprise * MTB*	1.054***	0.356***

	(6.47)	(3.18)
*Sales Surprise * Lev*	0.005	-0.065
	(0.14)	(-1.13)
*Sales Surprise * Beta*	0.024	0.392**
	(0.15)	(2.05)
*Sales Surprise * Loss*	0.057	-0.500**
	(0.29)	(-2.19)
Size	0.058	0.123**
	(1.51)	(2.05)
MTB	-0.207***	-0.099*
	(-3.26)	(-1.87)
Lev	0.038	-0.057
	(1.12)	(-0.97)
Beta	-0.170	-0.246
	(-1.38)	(-1.47)
Loss	-1.461***	-1.238***
	(-7.89)	(-5.43)
Intercept	3.760**	-1.525***
	(2.42)	(-3.06)
Industry F.E.	Yes	Yes
Year-Quarter F.E.	Yes	Yes
Observations	18,779	12,282
Adj-R2	0.0774	0.0493

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, in two-tailed tests.

The table presents regression estimates to show differential consistency effect for earnings after SFAS 142. I reordered the variables so that the variables for ERC (i.e., *Earnings Surprise* and the interaction terms with *Earnings Surprise*) and the variables for SRC (i.e., *Sales Surprise* and the interaction terms with *Sales Surprise*) are grouped. The treatment group includes firm-quarters with a goodwill balance larger than 1 percent of total assets at the beginning of each fiscal year. The control group includes firm-quarters with no outstanding goodwill balance at the beginning of each fiscal year. The sample period for this analysis comprises 1998 to 2000 (before SFAS 142) and 2004 to 2006 (after SFAS 142). Consistency is one if the earnings surprise and the sales surprise have the same sign. Post-SFAS 142 is one if the firm-quarters belong to years 2004 to 2006. Control variables and their interactions with surprise variables are included. Year-quarter fixed effects and industry fixed effects are included in all models. The *t*-statistics in parentheses are based on standard errors clustered by firm. The main coefficients of interest in the tests are in bold.

Because SFAS 142 directly addresses only earnings but not sales or operating cash flow, I do not have clear expectations as to how SFAS 142 will change the precision of the sales and operating cash flow news and uncertainty about their precision. Thus, I do not have predictions for the consistency effect for sales and cash flow. Empirically, the results show that the consistency effect for sales is larger after SFAS 142. One potential explanation is that earnings after SFAS 142 is more informative in valuing sales because managers are likely to have better quality inputs for forecasting sales as they will actively interact with the sales team to calibrate their impairment models during annual impairment testing, and as a result, earnings will be more in line with sales in predicting future firm value. Therefore, consistency between the earnings surprise and the sales surprise is more indicative of high precision for the sales news after SFAS 142 than before.

5.3. The Moderating Role of Intangible Intensity

I investigate whether the consistency effect for earnings varies with intangible intensity. Many studies have documented that earnings is volatile and unreliable in high-intangible firms.[36] Instead, revenue-based measures are more commonly used in valuing such firms (Chandra and Ro, 2008; Kama, 2009). This suggests that there is not much uncertainty about earnings precision for high-intangible firms (i.e., earnings is known to be imprecise). Therefore, I expect the consistency effect for earnings to be weaker for high-intangible firms, where uncertainty about earnings precision is low.

[36] Firms in the technology sector have more volatile earnings because of mismatching of start-up costs and other transitory expenditures (Amir and Lev, 1996). Earnings of R&D-intensive firms are more difficult to process because R&D is expensed but may be regarded as assets by the market (Lev and Sougiannis, 1996). Investors pay more attention to sales than earnings for growth firms because building market share is more important than expense reduction (Ertimur et al., 2003).

TABLE 9
Consistency effect for earnings in high-intangible firms

	(1)	(2)	(3)
	Intangible Intensity Proxy		
	High-tech Industry	R&D over 5%	SG&A top 30%
Earnings Surprise	2.079***	2.047***	2.436***
	(17.30)	(17.05)	(15.97)
*Earnings Surprise * High-Intangible*	-0.001	0.068	-0.123
	(-0.01)	(0.54)	(-0.76)
*Earnings Surprise * Consistency*	0.874***	0.853***	0.904***
	(7.54)	(7.31)	(5.97)
Earnings Surprise*Consistency*High-Intangible	**-0.411*** **	**-0.354** **	**0.016**
	(-2.61)	**(-2.22)**	**(0.08)**
Sales Surprise	0.243***	0.264***	0.493***
	(2.88)	(3.06)	(4.29)
*Sales Surprise * High-Intangible*	0.050	-0.112	0.190
	(0.26)	(-0.60)	(1.00)
*Sales Surprise * Consistency*	1.239***	1.253***	1.270***
	(17.13)	(17.39)	(15.51)
*Sales Surprise * Consistency * High-Intangible*	0.463**	0.508**	0.631***
	(2.03)	(2.07)	(2.70)
Consistency	0.813***	0.741***	0.720***
	(13.61)	(12.41)	(10.55)
High-Intangible	-0.719***	-0.666***	-0.718***
	(-6.26)	(-6.03)	(-6.77)
*High-Intangible * Consistency*	0.988***	1.147***	1.231***
	(8.20)	(9.88)	(10.15)
*Earnings Surprise * Size*	0.311***	0.315***	0.353***
	(8.83)	(8.91)	(7.85)
*Earnings Surprise * MTB*	-0.035	-0.045*	0.104*
	(-1.41)	(-1.76)	(1.90)
*Earnings Surprise * Lev*	-0.002	0.000	-0.002
	(-0.13)	(0.00)	(-0.13)
*Earnings Surprise * Beta*	0.039	0.032	0.073
	(0.70)	(0.58)	(1.04)
*Earnings Surprise * Loss*	-1.725***	-1.737***	-1.995***
	(-15.89)	(-15.97)	(-16.13)
*Sales Surprise * Size*	-0.002	-0.010	0.018
	(-0.12)	(-0.49)	(0.74)
*Sales Surprise * MTB*	0.430***	0.439***	0.683***

	(6.63)	(6.79)	(7.32)
*Sales Surprise * Lev*	-0.012	-0.013	0.001
	(-0.99)	(-1.15)	(0.06)
*Sales Surprise * Beta*	0.213***	0.223***	0.223***
	(3.86)	(4.02)	(3.65)
*Sales Surprise * Loss*	-0.192***	-0.193***	-0.301***
	(-2.77)	(-2.77)	(-3.88)
Size	-0.086***	-0.087***	-0.097***
	(-5.80)	(-5.89)	(-5.96)
MTB	-0.065***	-0.069***	-0.093***
	(-3.64)	(-3.81)	(-4.29)
Lev	0.032***	0.032***	0.034***
	(2.71)	(2.76)	(2.66)
Beta	0.079	0.070	0.069
	(1.52)	(1.36)	(1.21)
Loss	-1.453***	-1.482***	-1.492***
	(-21.87)	(-21.90)	(-20.48)
Intercept	-0.349	-0.423*	-0.443*
	(-1.51)	(-1.88)	(-1.74)
Controls	Yes	Yes	Yes
Controls * Surprises	Yes	Yes	Yes
Observations	148,336	148,336	129,056
Adj-R2	0.0702	0.0704	0.0792

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, in two-tailed tests.

The table presents regression estimates to show differential consistency effect for earnings for firms with high intangible intensity. I reordered the variables so that the variables for ERC (i.e., *Earnings Surprise* and the interaction terms with *Earnings Surprise*) and the variables for SRC (i.e., *Sales Surprise* and the interaction terms with *Sales Surprise*) are grouped. *High-Intangible* indicates firm-quarters in high-tech industry in column (1), firm-quarters with R&D to revenue ratio higher than 5% in column (2), firm-quarters with SG&A costs in the top 30% distribution in column (3). Consistency is one if the earnings surprise and the sales surprise have the same sign. Control variables and their interactions with surprise variables are included. Year-quarter fixed effects and industry fixed effects are included in all models. The *t*-statistics in parentheses are based on standard errors clustered by firm. The main coefficients of interest in the tests are in bold.

Table 9 shows the regression results. I use three proxies for intangible intensity: whether the firm is in a high-tech industry (Francis, Philbrick, and Schipper, 1994; Francis and Schipper, 1999), whether the firm has an R&D to revenue ratio higher than

5% (Kama, 2009), and whether the firm's SG&A expenses to revenue ratio falls in the top 30% of the distribution (Srivastava, 2014). The interaction term *Earnings Surprise * Consistency * High Intangible* captures the incremental consistency effect for earnings in high-intangible firms. I expect negative coefficients on this interaction term, indicating that the consistency effect for earnings is weaker for high-intangible firms. As expected, the coefficients on *Earnings Surprise * Consistency * High Intangible* are generally negative and significant (except in column (3)).[37] This shows that the consistency effect for earnings is significantly larger for low-intangible firms than for high-intangible firms, as predicted by H2.

While earnings is known to be less precise for high-intangible firms than for low-intangible firms, there is no such expectation for sales. Prior studies only suggest that sales is a better measure than earnings in valuing high-intangible firms, but they do not suggest that sales of high-intangible firms is more reliable than sales of low-intangible firms. Because it is unclear whether uncertainty about sales precision varies with intangible intensity, I do not have predictions for the consistency effect for sales. The empirical results show that the consistency effect for sales is stronger for high-intangible firms than for low-intangible firms. The coefficients on *Sales Surprise * Consistency * High-Intangible* are positive and significant in all three columns. This may be because it

[37] Unlike high-tech industry and R&D intensity which mostly refer to firms with large R&D expenses (which make earnings less precise in predicting future performance), SG&A intensity is a noisier proxy for intangible intensity because mature consumer goods firms can also have large SG&A costs. This can explain why I do not find the expected result in column (3) where I use SG&A intensity as a proxy for intangible intensity.

is less common and more difficult to have good news in both earnings and sales for high intangible firms and thus the market finds the consistency more useful for inferring sales precision for high intangible firms. [38]

[38] Unlike sales, there is no clear anticipation that cash flow is more useful than earnings for high-intangible firms because R&D costs are treated as operating expenses and thus is deducted from operating cash flow. Thus, I limit this analysis to the sales surprise sample. When I run the same regression for the cash flow surprise sample, I do not find differential consistency effect for earnings for high-intangible firms.

CHAPTER 6

ADDITIONAL ANALYSES AND ROBUSTNESS CHECKS

6.1. Consistency Between Non-GAAP Earnings Surprise and GAAP Earnings Surprise

Many studies show that investors rely more on non-GAAP earnings than GAAP earnings in valuation because non-GAAP earnings excludes transitory or unusual components from GAAP earnings, thereby increasing the value relevance of earnings (e.g., Bradshaw and Sloan, 2002; Bhattacharya, Black, Christensen, and Larson, 2003; Brown and Sivakumar, 2003; Huang and Skantz, 2016).[39] However, non-GAAP earnings can be defined differently across firms, raising concerns that managers can opportunistically report non-GAAP earnings (e.g., to meet or beat analysts' forecasts). Many studies document that non-GAAP earnings can be misleading because managers and analysts often exclude items that are not transitory and thus are useful in valuation when calculating non-GAAP earnings (Doyle, Lundholm, and Soliman, 2003; Gu and Chen, 2004; Black and Christensen, 2009; Doyle, Jennings, and Soliman, 2013).

GAAP earnings can be useful to investors especially when used jointly with non-GAAP earnings because the difference between the two provides information about disaggregated earnings (Bradshaw, Christensen, Gee, and Whipple, 2018). Moreover,

[39] Non-GAAP earnings is often interchangeably called as pro-forma earnings, street earnings, or core earnings. All these terms refer to GAAP earnings that is adjusted for certain items that managers consider transitory or non-representative of future performance.

given the controversy over the informativeness of non-GAAP earnings, consistency between GAAP and non-GAAP earnings can be useful for inferring precision of the earnings news because it is much more difficult to strategically adjust both GAAP and non-GAAP earnings (i.e., measurement errors are likely smaller when the two indicators are consistent). Therefore, I examine whether the consistency between GAAP earnings surprise and non-GAAP earnings surprise is informative in valuation.

Similar to the main analysis, GAAP earnings surprise is measured as the difference between the actual and forecasted GAAP earnings from I/B/E/S. In Table 10, I repeat the analysis from Table 3 using consistency between the GAAP and non-GAAP earnings surprises.[40] I find the consistency effects for both GAAP and non-GAAP earnings. That is, consistency between the two helps investors interpret both GAAP and non-GAAP earnings in predicting a firm's future cash flow. Specifically, a one standard deviation change in non-GAAP earnings surprise is associated with a 0.4 percentage point larger market reaction for the consistent case than for the inconsistent case. Similarly, a one standard deviation change in GAAP earnings surprise is associated with 0.3 percentage point larger market reaction for the consistent case than for the inconsistent one.

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[40] In this sample, there are approximately 65% consistent firm-quarters and 35% inconsistent firm-quarters. While I see more consistent cases than inconsistent ones, inconsistency between the GAAP and non-GAAP earnings surprise is also quite common.

Table 10
Consistency between Non-GAAP earnings surprise and GAAP earnings surprise

		(1)	(2)	(3)	(4)
Non-GAAP Surprise		3.425***	3.381***	3.072***	2.997***
		(24.56)	(23.36)	(14.76)	(14.27)
GAAP Surprise			0.498***	0.410***	0.219
			(3.64)	(3.00)	(1.31)
Consistency				-0.143	-0.102
				(-1.54)	(-1.11)
Non-GAAP Surprise * Consistency	+			**0.404****	**0.438****
				(2.20)	**(2.39)**
GAAP Surprise * Consistency	+				**0.308****
					(2.14)
*Non-GAAP Surprise * Size*		0.265***	0.278***	0.273***	0.274***
		(5.78)	(5.93)	(5.83)	(5.87)
*Non-GAAP Surprise * MTB*		0.350***	0.419***	0.407***	0.418***
		(3.39)	(3.61)	(3.55)	(3.62)
*Non-GAAP Surprise * Lev*		-0.015	-0.013	-0.013	-0.012
		(-1.06)	(-0.86)	(-0.83)	(-0.81)
*Non-GAAP Surprise * Beta*		0.085	0.161	0.175	0.166
		(0.83)	(1.50)	(1.64)	(1.55)
*Non-GAAP Surprise * Loss*		-1.642***	-1.539***	-1.561***	-1.618***
		(-10.73)	(-9.77)	(-9.94)	(-10.18)
*GAAP Surprise * Size*			-0.033	-0.016	-0.009
			(-0.90)	(-0.42)	(-0.23)
*GAAP Surprise * MTB*			-0.187**	-0.179**	-0.189**
			(-2.17)	(-2.12)	(-2.20)
*GAAP Surprise * Lev*			-0.008	-0.008	-0.009
			(-0.52)	(-0.55)	(-0.65)
*GAAP Surprise * Beta*			-0.223**	-0.236**	-0.235**
			(-2.18)	(-2.32)	(-2.30)
*GAAP Surprise * Loss*			-0.756***	-0.672***	-0.612***
			(-3.89)	(-3.50)	(-3.12)
Size		-0.108***	-0.112***	-0.112***	-0.113***
		(-3.73)	(-3.85)	(-3.85)	(-3.87)
MTB		0.036	0.019	0.021	0.019
		(0.86)	(0.45)	(0.49)	(0.46)
Lev		0.007	0.005	0.005	0.005
		(0.39)	(0.27)	(0.29)	(0.29)
Beta		-0.017	-0.088	-0.089	-0.085

	(-0.16)	(-0.84)	(-0.84)	(-0.81)
Loss	-1.268***	-1.163***	-1.134***	-1.127***
	(-10.85)	(-9.27)	(-8.99)	(-8.94)
Intercept	0.538**	0.384	0.483*	0.445
	(2.01)	(1.42)	(1.75)	(1.61)
Observations	43,929	43,929	43,929	43,929
Adj-R2	0.0722	0.0734	0.0736	0.0737

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, in two-tailed tests.

In this table, consistency is measured using the sign of non-GAAP earnings surprise and GAAP earnings surprise so that it is consistent if the two surprises have the same sign. *Non-GAAP Surprise* variable in this table is the same as *Earnings Surprise* in other tables but I call it *Non-GAAP Surprise* here to differentiate it from GAAP earnings. The surprise variables are scaled by their standard deviation and the control variables are demeaned. Year-quarter fixed effects and industry fixed effects are included in all models. The t-statistics in parentheses are based on standard errors clustered by firm. The main coefficients of interest in the tests are in bold.

6.2. Consistency Between Earnings Surprise and Gross Margin Surprise

Prior studies suggest that gross margin has information content in valuation and in forecasting other metrics such as sales (Lento and Sayed, 2015; Kesavan, Gaur, and Raman, 2010). Thus, I consider gross margin as an additional firm performance indicator and examine whether consistency between earnings surprise and gross margin surprise is informative in valuation. I define gross margin surprise as the difference between the actual gross margin and the median analyst forecast of quarterly gross margin. Both the actual and forecasted gross margin are taken from the I/B/E/S summary file. In Table 11, I repeat the analysis from Table 3 using consistency between the earnings surprise and the gross margin surprise and find qualitatively similar results. Specifically, a one standard deviation change in earnings surprise is associated with 0.6 percentage point larger market response to a consistent earnings surprise than to an inconsistent one. I also find the consistency effect for gross margin. A one standard deviation change in gross margin surprise is associated with a 1.0 percentage point larger market response to consistent gross margin surprise than to an inconsistent one.

6.3. Magnitude Consistency

Following prior research (Rees and Sivaramakrishnan, 2007; Brown, Huang, and Pinello, 2013), I use sign consistency as my main measure of indicator consistency. Additionally, I use a consistency measure that is based on both the sign and the magnitude of the surprises. Specifically, when defining indicator consistency, I consider not only having the same sign but also the degree to which the indicators are consistent. Magnitude consistency is measured as follows. First, I classify firm-quarters into 5 quintiles by the size of each surprise, separately for positive and negative surprises. Next, I compare the quintile rank of different surprises. For example, if both the earnings surprise and the sales surprise have the same sign and are in the same rank, this pair is classified as most consistent. If the earnings surprise and the sales surprise have the same sign but have the maximum possible difference in their quintile ranking, this pair is regarded the least consistent among the pairs with the same sign. However, it is still more consistent than other pairs with divergent signs. If the earnings surprise and the sales surprise have the opposite signs and their ranking gap is also maximum, this pair is regarded the least consistent among all. The empirical results are qualitatively similar when the magnitude consistency is used instead of the sign consistency (see Table 12). Therefore, my findings are robust to this alternative measure of consistency.

Table 11
Consistency between earnings surprise and gross margin surprise

		(1)	(2)	(3)	(4)
Earnings Surprise		4.037***	3.923***	3.522***	3.195***
		(29.89)	(29.16)	(22.75)	(20.65)
GM Surprise			0.400***	0.313***	-0.322***
			(10.82)	(8.06)	(-5.69)
Consistency				0.073	0.119*
				(1.06)	(1.74)
Earnings Surprise * Consistency	+			**0.598*** **	**0.656*** **
				(4.88)	**(5.39)**
GM Surprise * Consistency	+				**1.041*** **
					(12.64)
*Earnings Surprise * Size*		0.373***	0.383***	0.384***	0.343***
		(8.37)	(8.61)	(8.69)	(7.85)
*Earnings Surprise * MTB*		0.107**	0.092*	0.104**	0.072
		(2.12)	(1.86)	(2.12)	(1.52)
*Earnings Surprise * Lev*		-0.017	-0.016	-0.017	-0.016
		(-1.11)	(-1.05)	(-1.11)	(-1.09)
*Earnings Surprise * Beta*		0.155*	0.134	0.120	0.137*
		(1.88)	(1.59)	(1.44)	(1.67)
*Earnings Surprise * Loss*		-2.452***	-2.421***	-2.400***	-2.398***
		(-17.80)	(-17.37)	(-17.26)	(-17.40)
*GM Surprise * Size*			-0.085***	-0.057***	-0.034*
			(-4.50)	(-2.93)	(-1.71)
*GM Surprise * MTB*			0.022	0.037	0.039
			(0.94)	(1.58)	(1.64)
*GM Surprise * Lev*			-0.006	-0.005	-0.006
			(-0.41)	(-0.39)	(-0.44)
*GM Surprise * Beta*			0.114	0.118*	0.101
			(1.60)	(1.67)	(1.41)
*GM Surprise * Loss*			-0.135	-0.165*	-0.160*
			(-1.60)	(-1.95)	(-1.87)
Size		-0.123***	-0.123***	-0.123***	-0.132***
		(-6.12)	(-6.07)	(-6.07)	(-6.51)
MTB		-0.002	-0.010	-0.014	-0.018
		(-0.08)	(-0.38)	(-0.52)	(-0.67)
Lev		0.023	0.024	0.025*	0.026*
		(1.50)	(1.57)	(1.66)	(1.72)
Beta		0.262***	0.255***	0.249***	0.255***
		(3.41)	(3.32)	(3.25)	(3.32)
Loss		-1.407***	-1.363***	-1.367***	-1.354***

	(-14.95)	(-14.50)	(-14.55)	(-14.43)
Intercept	0.346	0.341	0.300	0.220
	(1.30)	(1.29)	(1.12)	(0.82)
Observations	78,531	78,531	78,531	78,531
Adj-R2	0.0780	0.0799	0.0806	0.0830

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, in two-tailed tests.

In this table, consistency is measured using the sign of earnings surprise and gross margin surprise so that it is consistent if the two surprises have the same sign. The surprise variables are scaled by their standard deviation and the control variables are demeaned. Year-quarter fixed effects and industry fixed effects are included in all models. The t-statistics in parentheses are based on standard errors clustered by firm. The main coefficients of interest in the tests are in bold.

The variable definitions are provided in the Appendix.

Table 12
Consistency effects with magnitude consistency

Panel A. Consistency between the earnings surprise and the sales surprise

		Full Model
		(1)
Earnings Surprise		1.874***
		(16.00)
Sales Surprise		-0.060
		(-0.64)
Magnitude Consistency		0.109***
		(15.78)
Earnings Surprise * Magnitude Consistency	+	**0.070*** **
		(8.56)
Sales Surprise * Magnitude Consistency	+	**0.127*** **
		(18.27)
*Earnings Surprise * Size*		0.324***
		(9.19)
*Earnings Surprise * MTB*		-0.039
		(-1.55)
*Earnings Surprise * Lev*		-0.001
		(-0.10)
*Earnings Surprise * Beta*		0.036
		(0.64)
*Earnings Surprise * Loss*		-1.725***
		(-15.97)
*Sales Surprise * Size*		-0.002
		(-0.11)
*Sales Surprise * MTB*		0.459***
		(7.12)
*Sales Surprise * Lev*		-0.014
		(-1.21)
*Sales Surprise * Beta*		0.214***
		(3.88)
*Sales Surprise * Loss*		-0.172**
		(-2.46)
Size		-0.099***
		(-6.69)
MTB		-0.074***
		(-4.17)
Lev		0.033***

		(2.81)
Beta		0.077
		(1.49)
Loss		-1.441***
		(-21.89)
Intercept		-0.951***
		(-4.14)
Observations		148,336
Adj-R2		0.0683

Panel B. Consistency between the earnings surprise and the operating cash flow surprise

		Full Model (1)
Earnings Surprise		1.927***
		(12.61)
CF Surprise		-0.221*
		(-1.81)
Magnitude Consistency		0.010
		(0.96)
Earnings Surprise * Magnitude Consistency	+	**0.035*** **
		(3.15)
CF Surprise * Magnitude Consistency	+	**0.113*** **
		(9.38)
*Earnings Surprise * Size*		0.162***
		(3.70)
*Earnings Surprise * MTB*		0.225***
		(3.59)
*Earnings Surprise * Lev*		-0.005
		(-0.40)
*Earnings Surprise * Beta*		0.266***
		(2.83)
*Earnings Surprise * Loss*		-1.475***
		(-11.51)
*CF Surprise * Size*		0.087**
		(2.54)
*CF Surprise * MTB*		0.037
		(0.53)
*CF Surprise * Lev*		0.009
		(0.79)
*CF Surprise * Beta*		0.220**

	(2.23)
*CF Surprise * Loss*	-0.244**
	(-2.30)
Size	-0.104***
	(-3.99)
MTB	0.015
	(0.47)
Lev	0.014
	(1.16)
Beta	0.059
	(0.63)
Loss	-1.156***
	(-10.20)
Intercept	0.574*
	(1.92)
Observations	148,336
Adj-R2	0.0683

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, in two-tailed tests.

The table presents the regression results of my full model when consistency is measured using sign and magnitude instead of only sign. In Panel A (Panel B), consistency is measured using the sign of earnings and sales (cash flow) surprise so that it is consistent if the earnings surprise and the sales (cash flow) surprise have the same sign. *Magnitude Consistency* ranges from 1 (least consistent) to 14 (most consistent) based on the degree to which the two surprises are consistent. The surprise variables are scaled by their standard deviation and the control variables are demeaned. Year-quarter fixed effects and industry fixed effects are included in all models. The *t*-statistics in parentheses are based on standard errors clustered by firm. The main coefficients of interest in the tests are in bold.

6.4. Different Specification of CAR

Following prior studies (e.g., Ferri et al., 2018; Gipper et al., 2020), I use market-adjusted 3-day returns as the main CAR variable. Additionally, I use the 3-day CAR computed from the market model, Fama-French three-factor model, and Carhart four-factor model, and find qualitatively similar results. See Table 13 for details.

Table 13

Robustness test: Different specification of CAR

Panel A. Different specification for CAR in the sales surprise sample

		CAR from market model (1)	CAR from Fama French 3-factor model (2)	CAR from Carhart 4-factor model (3)
Earnings Surprise		2.138***	2.137***	2.139***
		(20.00)	(20.05)	(20.18)
Sales Surprise		0.219***	0.204**	0.202**
		(2.67)	(2.50)	(2.48)
Consistency		1.103***	1.108***	1.095***
		(20.83)	(21.00)	(20.78)
Earnings Surprise * Consistency	+	**0.660*** **	**0.672*** **	**0.678*** **
		(8.09)	**(8.28)**	**(8.34)**
Sales Surprise * Consistency	+	**1.273*** **	**1.286*** **	**1.284*** **
		(18.27)	**(18.35)**	**(18.28)**
*Earnings Surprise * Size*		0.326***	0.332***	0.336***
		(9.29)	(9.37)	(9.53)
*Earnings Surprise * MTB*		-0.035	-0.040	-0.042
		(-1.34)	(-1.51)	(-1.59)
*Earnings Surprise * Lev*		-0.004	-0.006	-0.006
		(-0.31)	(-0.52)	(-0.50)
*Earnings Surprise * Beta*		0.048	0.046	0.034
		(0.84)	(0.79)	(0.59)
*Earnings Surprise * Loss*		-1.721***	-1.731***	-1.725***
		(-16.01)	(-16.09)	(-16.09)
*Sales Surprise * Size*		-0.017	-0.017	-0.017
		(-0.85)	(-0.84)	(-0.85)
*Sales Surprise * MTB*		0.404***	0.400***	0.396***
		(6.32)	(6.29)	(6.27)
*Sales Surprise * Lev*		-0.014	-0.012	-0.010
		(-1.18)	(-1.03)	(-0.90)
*Sales Surprise * Beta*		0.248***	0.257***	0.263***
		(4.47)	(4.67)	(4.74)
*Sales Surprise * Loss*		-0.129*	-0.134**	-0.141**
		(-1.88)	(-1.96)	(-2.06)
Size		-0.087***	-0.091***	-0.094***
		(-5.88)	(-6.13)	(-6.35)
MTB		-0.187***	-0.177***	-0.178***
		(-10.24)	(-9.73)	(-9.75)
Lev		0.024**	0.025**	0.025**

		(2.05)	(2.14)	(2.17)
Beta		0.127**	0.130**	0.148***
		(2.45)	(2.50)	(2.85)
Loss		-1.322***	-1.325***	-1.311***
		(-20.15)	(-20.24)	(-20.00)
Intercept		-0.416*	-0.496**	-0.378*
		(-1.87)	(-2.24)	(-1.70)
Observations		148,336	148,336	148,336
Adj-R2		0.0657	0.0655	0.0649

Panel B. Different specification for CAR in the operating cash flow surprise sample

		CAR from market model (1)	CAR from Fama French 3-factor model (2)	CAR from Fama French 4-factor model (3)
Earnings Surprise		2.004***	1.998***	2.001***
		(14.14)	(14.13)	(14.09)
CF Surprise		-0.020	-0.033	-0.026
		(-0.21)	(-0.35)	(-0.27)
Consistency		0.295***	0.288***	0.299***
		(3.73)	(3.66)	(3.81)
Earnings Surprise * Consistency	+	**0.346*** **	**0.380*** **	**0.373*** **
		(2.80)	**(3.10)**	**(3.04)**
CF Surprise * Consistency	+	**1.280*** **	**1.263*** **	**1.265*** **
		(10.75)	**(10.69)**	**(10.70)**
*Earnings Surprise * Size*		0.156***	0.158***	0.157***
		(3.59)	(3.63)	(3.60)
*Earnings Surprise * MTB*		0.217***	0.224***	0.219***
		(3.46)	(3.63)	(3.56)
*Earnings Surprise * Lev*		-0.005	-0.005	-0.005
		(-0.46)	(-0.42)	(-0.42)
*Earnings Surprise * Beta*		0.236**	0.231**	0.211**
		(2.55)	(2.46)	(2.24)
*Earnings Surprise * Loss*		-1.416***	-1.425***	-1.429***
		(-11.28)	(-11.35)	(-11.34)
*CF Surprise * Size*		0.081**	0.081**	0.082**
		(2.38)	(2.37)	(2.40)
*CF Surprise * MTB*		0.030	0.021	0.022
		(0.44)	(0.32)	(0.34)
*CF Surprise * Lev*		0.010	0.011	0.010
		(0.86)	(0.90)	(0.89)
*CF Surprise * Beta*		0.203**	0.194*	0.200**

	(2.04)	(1.95)	(2.00)
*CF Surprise * Loss*	-0.225**	-0.246**	-0.264**
	(-2.12)	(-2.33)	(-2.49)
Size	-0.128***	-0.135***	-0.134***
	(-4.98)	(-5.27)	(-5.19)
MTB	-0.077**	-0.074**	-0.075**
	(-2.51)	(-2.37)	(-2.41)
Lev	0.011	0.011	0.012
	(0.91)	(0.92)	(1.04)
Beta	0.141	0.139	0.128
	(1.52)	(1.49)	(1.38)
Loss	-1.024***	-1.043***	-1.033***
	(-9.11)	(-9.31)	(-9.22)
Intercept	0.564**	0.366	0.216
	(1.97)	(1.30)	(0.77)
Observations	47,354	47,354	47,354
Adj-R2	0.0692	0.0697	0.0690

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, in two-tailed tests.

The table presents robustness checks for the full model in Table 3. I use CAR from the market model, CAR from the Fama French 3-factor model, and CAR from the Carhart 4-factor model in columns (1), (2), and (3), respectively. The *t*-statistics in parentheses are based on standard errors clustered by firm. The main coefficients of interest in the tests are in bold.

6.5. Alternative Sample Period

There are very few observations in each quarter before 2003 especially in the cash flow surprise sample. As a robustness check, I start the sample period in 2003 so that there are at least 100 observations in each quarter. I find qualitatively similar results in this restricted period. Moreover, sales forecasts and cash flow forecasts became more common in recent years. To examine whether consistency effects mainly exist in recent years, I run the main regression separately for years 1998 to 2009 and years 2010 to 2019. In both periods, there exist significant consistency effects for earnings, sales, and cash flow. See Table 14 for details.

6.6. Fixed Effects for the Response Coefficients

In the main regression tables, I include industry fixed effects and year-quarter fixed effects to control for systematic differences in CAR across industry and time. Additionally, I add interaction terms between surprise variables and the fixed effects to account for differences in ERCs, SRCs, and CFRCs across industry and time. The results are qualitatively similar. See Table 15 for details.

Table 14
Robustness test: Alternative sample period

Panel A. Alternative sample periods in the sales surprise sample

		2003 to 2019	1998 to 2009	2010 to 2019
		(1)	(2)	(3)
Earnings Surprise		2.110***	2.076***	2.190***
		(19.01)	(13.58)	(15.51)
Sales Surprise		0.470***	0.084	0.482***
		(4.29)	(0.79)	(3.67)
Consistency		1.145***	1.196***	1.089***
		(20.61)	(15.55)	(15.77)
Earnings Surprise * Consistency	+	**0.635*** **	**0.807*** **	**0.545*** **
		(7.49)	**(6.30)**	**(5.35)**
Sales Surprise * Consistency	+	**1.355*** **	**1.324*** **	**1.267*** **
		(17.28)	**(14.79)**	**(12.18)**
*Earnings Surprise * Size*		0.312***	0.285***	0.343***
		(8.59)	(5.65)	(7.43)
*Earnings Surprise * MTB*		-0.070***	0.050	-0.110***
		(-2.77)	(1.20)	(-3.52)
*Earnings Surprise * Lev*		-0.005	0.006	-0.001
		(-0.38)	(0.30)	(-0.08)
*Earnings Surprise * Beta*		0.038	0.050	0.024
		(0.65)	(0.55)	(0.34)
*Earnings Surprise * Loss*		-1.787***	-1.846***	-1.669***
		(-15.98)	(-11.72)	(-12.01)
*Sales Surprise * Size*		-0.030	-0.022	-0.038
		(-1.27)	(-0.88)	(-1.27)
*Sales Surprise * MTB*		0.595***	0.440***	0.459***
		(6.55)	(5.39)	(4.38)
*Sales Surprise * Lev*		-0.016	-0.008	-0.019
		(-1.24)	(-0.42)	(-1.18)
*Sales Surprise * Beta*		0.206***	0.185**	0.171**
		(3.24)	(2.51)	(2.04)
*Sales Surprise * Loss*		-0.080	-0.162*	-0.126
		(-1.05)	(-1.71)	(-1.26)
Size		-0.083***	-0.019	-0.127***
		(-5.37)	(-0.85)	(-6.54)
MTB		-0.060***	-0.161***	0.016
		(-3.20)	(-5.78)	(0.73)
Lev		0.034***	0.056***	0.023
		(2.79)	(2.82)	(1.61)
Beta		0.064	0.042	0.138*

		(1.20)	(0.58)	(1.91)
Loss		-1.455***	-1.402***	-1.588***
		(-21.11)	(-14.64)	(-17.95)
Intercept		-0.655***	-0.667***	-0.519**
		(-2.96)	(-2.86)	(-2.29)
Observations		129,545	70,115	78,221
Adj-R2		0.0769	0.0608	0.0793

Panel B. Alternative sample periods in the operating cash flow surprise sample

		2003 to 2019	1998 to 2009	2010 to 2019
		(1)	(2)	(3)
Earnings Surprise		2.048***	2.187***	2.046***
		(14.41)	(7.02)	(13.35)
CF Surprise		0.005	-0.485*	0.063
		(0.05)	(-1.95)	(0.59)
Consistency		0.282***	0.682***	0.208**
		(3.54)	(3.82)	(2.35)
Earnings Surprise * Consistency	+	**0.323***	**0.639**	**0.262**
		(2.62)	**(2.17)**	**(1.99)**
CF Surprise * Consistency	+	**1.271***	**0.992***	**1.331***
		(10.53)	**(3.71)**	**(10.25)**
*Earnings Surprise * Size*		0.147***	0.193**	0.153***
		(3.34)	(2.54)	(3.01)
*Earnings Surprise * MTB*		0.217***	0.493***	0.185***
		(3.48)	(2.99)	(2.86)
*Earnings Surprise * Lev*		-0.004	0.018	-0.009
		(-0.35)	(0.54)	(-0.70)
*Earnings Surprise * Beta*		0.258***	0.327*	0.270***
		(2.70)	(1.68)	(2.58)
*Earnings Surprise * Loss*		-1.479***	-1.432***	-1.463***
		(-11.47)	(-5.79)	(-10.06)
*CF Surprise * Size*		0.078**	-0.066	0.109***
		(2.31)	(-0.86)	(2.96)
*CF Surprise * MTB*		0.034	-0.290*	0.078
		(0.50)	(-1.77)	(1.03)
*CF Surprise * Lev*		0.009	-0.016	0.013
		(0.75)	(-0.59)	(1.00)
*CF Surprise * Beta*		0.212**	0.141	0.263**
		(2.13)	(0.61)	(2.39)
*CF Surprise * Loss*		-0.194*	-0.049	-0.259**
		(-1.83)	(-0.21)	(-2.23)
Size		-0.108***	-0.099*	-0.104***

	(1)	(2)	(3)
	(-4.11)	(-1.83)	(-3.53)
MTB	0.019	-0.191**	0.048
	(0.59)	(-2.05)	(1.47)
Lev	0.015	0.037	0.012
	(1.23)	(1.01)	(0.95)
Beta	0.045	-0.196	0.135
	(0.47)	(-1.04)	(1.25)
Loss	-1.159***	-0.713***	-1.260***
	(-10.19)	(-2.62)	(-10.15)
Intercept	0.486*	-1.467***	0.552*
	(1.71)	(-3.82)	(1.92)
Observations	46,957	8,845	38,509
Adj-R2	0.0722	0.0725	0.0725

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, in two-tailed tests.

The table presents robustness checks for the full model in Table 3. I use different years for sample periods in columns (1) through (3): 1998 to 2019 in column (1); 1998 to 2009 in column (2); 2010 to 2019 in column (3). The *t*-statistics in parentheses are based on standard errors clustered by firm. The main coefficients of interest in the tests are in bold.

TABLE 15
Robustness test: Fixed effects for the response coefficients

Panel A. Consistency between the earnings surprise and the sales surprise

		Full Model (1)
Earnings Surprise		2.980***
		(11.50)
Sales Surprise		1.785***
		(5.49)
Consistency		1.114***
		(21.00)
Earnings Surprise * Consistency	+	**0.539*** **
		(6.74)
Sales Surprise * Consistency	+	**1.155*** **
		(16.51)
*Earnings Surprise * Size*		0.359***
		(9.89)
*Earnings Surprise * MTB*		-0.030
		(-1.15)
*Earnings Surprise * Lev*		0.002
		(0.15)
*Earnings Surprise * Beta*		0.114*
		(1.88)
*Earnings Surprise * Loss*		-1.685***
		(-15.86)
*Sales Surprise * Size*		0.032
		(1.33)
*Sales Surprise * MTB*		0.406***
		(6.29)
*Sales Surprise * Lev*		-0.003
		(-0.29)
*Sales Surprise * Beta*		0.108*
		(1.75)
*Sales Surprise * Loss*		-0.213***
		(-3.00)
Size		-0.087***
		(-5.85)
MTB		-0.067***
		(-3.77)
Lev		0.031***
		(2.67)
Beta		0.057
		(1.10)

Loss		-1.441***
		(-21.84)
Intercept		-0.575***
		(-2.62)
Industry F.E.		Yes
Year-Quarter F.E.		Yes
Surprises*Industry F.E.		Yes
Surprises*Year-Quarter F.E.		Yes
Observations		148,336
Adj-R2		0.0759

Panel B. Consistency between the earnings surprise and the operating cash flow surprise

		Full Model (1)
Earnings Surprise		2.894***
		(6.84)
CF Surprise		0.448
		(1.35)
Consistency		0.290***
		(3.64)
Earnings Surprise * Consistency	+	**0.342*** **
		(2.70)
CF Surprise * Consistency	+	**1.213*** **
		(10.19)
*Earnings Surprise * Size*		0.135***
		(2.94)
*Earnings Surprise * MTB*		0.263***
		(3.62)
*Earnings Surprise * Lev*		-0.003
		(-0.21)
*Earnings Surprise * Beta*		0.315***
		(3.01)
*Earnings Surprise * Loss*		-1.346***
		(-10.56)
*CF Surprise * Size*		0.102***
		(2.95)
*CF Surprise * MTB*		0.030
		(0.42)
*CF Surprise * Lev*		0.012
		(1.04)
*CF Surprise * Beta*		0.208*

	(1.94)
*CF Surprise * Loss*	-0.259**
	(-2.39)
Size	-0.103***
	(-3.93)
MTB	0.010
	(0.32)
Lev	0.012
	(1.05)
Beta	0.024
	(0.25)
Loss	-1.151***
	(-10.20)
Intercept	0.335
	(1.16)
Industry F.E.	Yes
Year-Quarter F.E.	Yes
Surprises*Industry F.E.	Yes
Surprises*Year-Quarter F.E.	Yes
Observations	148,336
Adj-R2	0.0759

*, **, *** Indicate significance at the 10, 5, and 1 percent levels, respectively, in two-tailed tests.

The table presents the regression results of my full model when consistency is measured using sign and magnitude instead of onlysign. In Panel A (Panel B), consistency is measured using the sign of earnings and sales (cash flow) surprise so that it is consistent if the earnings surprise and the sales (cash flow) surprise have the same sign. *Magnitude Consistency* ranges from 1 (least consistent) to 14 (most consistent) based on the degree to which the two surprises are consistent. The surprise variables are scaled by their standard deviation and the control variables are demeaned. Year-quarter fixed effects, industry fixed effects, and interactions between surprise variables and fixed effects are included in all models. The *t*-statistics in parentheses are based on standard errors clustered by firm. The main coefficients of interest in the tests are in bold.

CHAPTER 7

CONCLUSION

I examine whether and why investors rely on the consistency of different indicators in valuing sales and operating cash flow. I argue that indicator consistency provides information about indicator precision and accordingly it can be useful in valuation. Investors likely do not know *ex ante* whether a given indicator is precise or imprecise, and they can only try to infer indicator precision from available information. To be specific, when different indicators are consistent, investors will infer that the indicators are more precise and will place a greater weight on each indicator in valuation. My precision explanation for the consistency effects generalizes to sales and operating cash flow in addition to earnings because it relies on mutual information complementarity between indicators. In other words, when the earnings news and the sales (operating cash flow) news are consistent with each other, this indicates higher precision for both the earnings news and the sales (operating cash flow) news.

As expected, I find that indicator consistency increases the informativeness of all three indicators−earnings, sales, and operating cash flow. Empirically, I show that the sales (cash flow) response coefficient is significantly larger when the sales (operating cash flow) surprise is consistent in sign with the earnings surprise. Additional tests indicate that these consistency results extend to GAAP earnings and gross margin. These consistency effects are not predicted by nor empirically consistent with the standard persistence argument in prior research.

I also posit that indicator consistency is particularly useful when there is high uncertainty about indicator precision because indicator consistency can help resolve the uncertainty. This prediction holds for three different proxies for uncertainty about indicator precision—absolute magnitude of surprises, SFAS 142, and intangible intensity.

This dissertation has implications that generalize beyond earnings announcements. Other users of financial statements, such as creditors or analysts, may find indicator consistency informative when they evaluate firm performance indicators. Additionally, managers are likely to rely on indicator consistency in making decisions, such as when reviewing compensation plans for executives or when evaluating potential target firms in mergers. Hence, the usefulness of indicator consistency is not restricted to accounting studies. There are many situations where decision makers need to evaluate and decide on an agenda based on information provided by multiple indicators. For example, researchers in human resource management can examine how consistency between different performance metrics of job applicants or employees affects the hiring and training process at the workplace. Researchers in risk management can study whether firms consider consistency between different risk indicators in assessing enterprise risk. Therefore, I expect my study to benefit researchers in many areas.

In my dissertation study, I focus on consistency between multiple indicators that are concurrently available to the market and examine how investors combine multiple pieces of information received simultaneously. Consistency can also be measured overtime. For example, having positive surprises consistently overtime could have different market implications than having mixed surprises overtime. Repeated indicator consistency overtime might have stronger consistency effects than less frequent indicator consistency in time series. I leave these dynamic analyses to future research.

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APPENDIX A

VARIABLE DEFINITIONS

CAR	A firm's three-day market-adjusted stock return around the quarterly earnings announcement date (in percentage).
Earnings surprise	The difference between the actual quarterly EPS and the median analyst forecast of quarterly EPS, scaled by beginning-of-quarter stock price. Both the actual and forecasted earnings are taken from I/B/E/S summary file. For forecasted earnings, I use the most recent consensus prior to the earnings announcement.
Sales surprise	The difference between the actual quarterly sales and the median analyst forecast of quarterly sales, converted to a per-share basis and scaled by beginning-of-quarter stock price. Both the actual and forecasted sales are taken from I/B/E/S summary file. For forecasted sales, I use the most recent consensus prior to the earnings announcement. I use SAL from I/B/E/S for sales information.
CF surprise	The difference between the actual quarterly operating cash flow per share and the median analyst forecast of quarterly operating cash flow per share, scaled by beginning-of-quarter stock price. Both the actual and forecasted operating cash flow are taken from I/B/E/S summary file. For forecasted operating cash flow, I use the most recent consensus prior to the earnings announcement. I use CPS from I/B/E/S for cash flow information.
Consistency	An indicator variable that equals one if different surprises have the same sign, and zero otherwise. In sales surprise sample, *Consistency* is one if the earnings surprise and the sales surprise have the same sign (e.g., both positive or both negative). In cash flow surprise sample, *Consistency* is one if the earnings surprise and the operating cash flow surprise have the same sign.
ES Consistent w/1	An indicator variable that equals 1 if the earnings surprise has the same sign as either the sales surprise or the operating cash flow surprise but not both.
ES Consistent w/2	An indicator variable that equals 1 if the earnings surprise has the same sign as both the sales surprise and the operating cash flow surprise.

SS Consistent w/1	An indicator variable that equals 1 if the sales surprise has the same sign as either the earnings surprise or the operating cash flow surprise but not both.
SS Consistent w/2	An indicator variable that equals 1 if the sales surprise has the same sign as both the earnings surprise and the operating cash flow surprise.
CFS Consistent w/1	An indicator variable that equals 1 if the operating cash flow surprise has the same sign as either the earnings surprise or the sales surprise but not both.
CFS Consistent w/2	An indicator variable that equals 1 if the operating cash flow surprise has the same sign as both the earnings surprise and the sales surprise.
Size	Natural log of market cap measured at the end of each quarter. Market cap equals the share price multiplied by the number of shares reported by Compustat.
MTB	Ratio of market value of total assets to book value of total assets, both measured at the end of each fiscal quarter.
Lev	Ratio of total debt to total book value of equity, measured at the end of each fiscal quarter.
Beta	Slope coefficient of market model regression, estimated over 200 trading days (with minimum 70 days) prior to the earnings announcement period.
Loss	An indicator that equals 1 if the earnings per share excluding extraordinary items (from Compustat) is negative, and 0 otherwise.
Post-SFAS 142	An indicator that equals 1 if years belong to 2004, 2005, and 2006.
High-Intangible	I use three proxies for high intangible firms: (1) firm-quarters in high-tech industry, (2) firm-quarters with R&D to revenue ratio higher than 5%, (3) firm-quarters with market-to-book ratio in the top 25%.
High-tech industry	An indicator variable that equals one if the three digit SIC code falls in one of the following: 283, 357, 360, 361, 362, 363, 364, 365, 366, 367, 368, 481, 737, 873, and zero otherwise.

R&D over 5%	An indicator variable that equals one if the R&D to revenue ratio is higher than 5%, and zero otherwise.
SG&A top 30%	An indicator variable that equals one if the SG&A ratio belongs to the top 30% in sample, and zero otherwise.
Non-GAAP Surprise	The difference between the actual quarterly GPS (I/B/E/S data item) and the median analyst forecast of quarterly GPS, scaled by beginning-of-quarter stock price.
GM Surprise	The difference between the actual quarterly GRM (I/B/E/S data item) and the median analyst forecast of quarterly GRM, scaled by beginning-of-quarter stock price.
Magnitude Consistency	A rank variable that ranges from 1 (least consistent) to 14 (most consistent). I rank each surprise into five groups by their size, separately for positive and negative surprises. For a pair of two surprises, I compare their signs as well as their rank gap. Ranges 1 to 9 are the cases where the two surprises have the opposite signs. It is coded 1 (9) when the rank gap between the two surprises is maximum (minimum) and the rank gap monotonically reduces from 1 to 9. For example, it is coded 1 if the earnings surprise is positive and in the top rank and the sales surprise is negative and in the bottom rank. Ranges 10 to 14 are the cases where the two surprises have the same sign. It is coded 10 if the two surprises are in the same sign but have the maximum rank gap, then it increases to 14 where the two surprises have the same sign and are in the same rank.