Key Performance Indicators: The Incremental News in Their Disclosures and the Properties of Their Analyst Forecasts

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Abstract

We assess the incremental news in the disclosures of key performance indicators (KPIs), the properties of their forecasts by analysts, and the determinants of analysts' decisions to forecast KPIs. Our findings show that after controlling for other concurrent public information, unexpected realizations of the most frequently forecasted KPIs have an economically significant association with announcement returns. Further, they induce revisions in analysts' forecasts of earnings and revenue. The information content of a KPI is diminished by its lack of disclosure about the measurement of the KPI and computational inconsistency over time. Analysts' decisions on whether to issue a KPI forecast depend primarily on the information content of the KPI. KPI forecasts are more accurate than earnings forecasts, and they outperform random walk forecasts for both short- and long-term forecast horizons. Finally, we find that, contrary to the documented optimism of earnings forecasts made early in the forecast period, analysts' KPI forecasts display a slight pessimistic bias.

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1. Introduction

The operating performance of firms in many industries is often evaluated by industry-specific measures referred to as *key performance indicators* (KPIs). These measures, in most cases, cannot be derived from financial statements. They include, among others, the average daily production of oil (in barrels) of an oil and gas company, same-store sales growth of a retail chain, and the passenger load factor of an airline.

Managers use these measures extensively to assess the performance of the company as a whole or some of its internal units. The role of KPIs in evaluating firm performance led the SEC to encourage companies to disclose and discuss their KPIs in financial reports (SEC, 2003). Many companies already disclose and discuss them in their earnings press releases and 10-Q/K filings. This voluntary disclosure, which is often made prominently[1], is likely to be used by investors. Analysts often refer to KPI in their research reports, and usually consider them in their earnings forecasts and stock recommendations. Further, because of their importance, some KPIs are forecasted by analysts on a regular basis.

There is abundant anecdotal evidence indicating the importance of KPIs to market participants. For example, the earnings announcement of Nordstrom Inc. for the first quarter of fiscal year 2017 constituted a positive surprise: Both pro forma EPS and net sales revenue exceeded analysts' expectations. Yet, the market response was negative (share price decreased by 3% in extended trading). This drop in price was attributed to a disappointing KPI—a growth rate in same-store sales of −0.8% versus expectations of no growth (Garber 2017). In another example, Southwest Airlines Co. suffered a drop of 9% in its share price immediately after it announced on May 19, 2015, that its passenger revenue per available seat–mile was expected to drop by 3%.

[1] For example, in its earnings announcement on January 29, 2016, American Airlines Group mentions ASM—available seat miles—fifty-seven times.

KPIs are used extensively in both business and practitioner literature.[2] There is also some empirical research on the relevance of these indicators for stock valuation. This research includes Amir and Lev (1996) and Rajgopal, Venkatachalam, and Kotha (2003b); who show that KPIs contribute to the explanation of the cross-sectional variation of stock valuation in, respectively, the wireless and e-commerce industries. Similarly, Francis, Schipper, and Vincent (2003) find that KPI information in several industries is incremental (in terms of its association with annual stock returns) to earnings. Tests of the association between annual return and various measures of the firm's performance for the year are informative. However, they cannot tell us about the timeliness of the information contained in the measures. Further, because of the length of the interval over which the association is measured, the likely presence of correlated omitted information related to the firm's performance makes it difficult to assess the incremental contribution of the different measures.

Consistent with their importance, analysts routinely follow and forecast key KPIs. A large body of research deals with the properties of analyst earnings forecasts, their accuracy, bias, and dispersion, as well as their relationship to revenue and cash flow forecasts. Very little is known, however, about the properties of KPI forecasts, the factors that influence analysts to produce such forecasts, and the extent to which their production enhances the accuracy of the analyst's earnings and revenue forecasts.

In this paper, we first extend the evidence provided by past research on the valuation relevance of KPIs. We do so by using a much larger set of KPIs in a number of industries, and by testing the information content of KPIs based on the market response to the "innovation" contained in KPIs upon their release, using analyst KPI forecasts as a proxy for market expectations. In

[2] A search on Amazon.com yields more than 300 book titles dealing with or relating to "key performance indicators." The popularity of the subject is apparently at such a high level that it warranted the publication of yet another book, "Key Performance Indicators for Dummies" (March, 2015).

addition to these market tests, we gauge the informativeness of KPI news by examining its effect on analysts' earnings and revenue forecasts.

Next, we observe considerable variability in analyst coverage of KPIs across KPIs and firms, and we study the determinants of analysts' production of KPI forecasts. Among the determinants that we consider are (i) the information content of the KPI obtained from our first set of tests and (ii) the factors that tend to reduce the predictive ability of earnings numbers, such as presence of losses and the magnitude of accruals. We then turn our attention to the properties of KPI forecasts and the extent to which their production helps analysts produce more accurate earnings and revenue forecasts.

One issue that arises when studying the informativeness of KPIs and their forecasts is that, due to their voluntary disclosure, the measurement of some of them may vary across firms and may change over time for a given firm.[3] Indeed, in a recent concept release (SEC, 2016), the SEC seeks comments and advice from the public on the cost and benefits of mandating the disclosure of standardized, industry-specific KPIs. In order to address this issue, we hand-collect data from the MD&A section of 10-K filings for one important KPI in the retail industry, same-store sales, which is the growth rate in sales from the same period (quarter or month) in the previous year to the current period, of stores that were in existence for some specified interval. This interval is defined by the company, but it is at least 12-month long. We analyze this sample for the degree of variability across firms and consistency over time in the definition of this KPI, as well as the effect of such variability and consistency on the information content of KPI forecasts.

[3] The measurement of some KPIs, particularly financial ones, are uniformly defined and measured. For example, KPIs such as "exploration expense" or "production expense" in the oil and gas industry are uniformly based on GAAP. The measurement of other KPIs may be determined by the regulator. For example, the value of "Capital Tier 1" is dictated by bank regulators, and the measurement of "proved reserves" in the oil & gas industry is prescribed in great detail by the SEC). The measurement of other KPIs may sometimes vary across firms and over time (e.g., same-store sales in the retail industry).

Using new I/B/E/S data on forecasts and realizations of KPIs over the period ranging from 2005 to 2016 (depending on the industry), we identify 28 industry-specific KPIs in four industries that are followed frequently by analysts: *airline*, *oil & gas*, *pharmaceutical*, and *retail*.[4]

We find significant market responses to unexpected values of the KPIs for 12 out of the 28 KPIs in our tests at the firm–quarter–KPI level (with 9 of the 16 insignificant responses having the predicted direction). Further, after controlling for contemporaneous earnings and revenue surprises, we find a significant market response to KPI surprises that are related to the most frequently forecasted KPIs in the industry. These results indicate that KPI news is incrementally informative.

In addition to quarterly KPI, we also examine the market response to the release of an important KPI in the retail industry, SSS^M, which is the monthly rate of growth in same-store sales relative to the same month in the previous year. In contrast to the disclosures of other KPIs, which are made only as part of the quarterly earnings press releases, many firms in the retail industry also issue monthly SSS announcements. Except for very few cases, $\mathrm{SSS^M}$ announcements do not coincide with the quarterly press releases.

Using this sample alleviates the need to control for information contained in earnings press releases, thus enhancing the reliability of our inferences regarding the incremental value of these KPIs. We find that market reaction to the "stand-alone" $\mathrm{SSS^M}$ surprises is positive and highly significant, which is consistent with the findings on the incremental information content of KPI announcements made concurrently with the earnings announcement. This finding also highlights the value of *the more timely* KPI announcements that pre-empt some of the news in subsequent earnings releases. We also exploit the fact that monthly SSS data are available for both the firm and its segments to show that one segment's SSS is incrementally informative to both that of the

[4] These four industries are the only nonfinancial industries that have a sufficient number of observations.

contemporaneously reported SSS of another segment of the firm as well as that of the SSS for the firm as a whole.

Using analysts' reactions to KPI surprises as an alternative gauge for the informativeness of KPIs, we find evidence consistent with the results from our market tests in showing that analysts' revisions of next-quarter earnings and revenue forecasts are positively and significantly associated with the recent KPI surprise. Using monthly SSS announcements, we also find that analysts' forecast revisions for the current- and next-quarter earnings and revenue are positively associated with the stand-alone SSS^M surprises.

The information content of a KPI appears to be affected by the disclosure of how the KPI is computed, the uniformity of its computation across firms, and the consistency over time in this computation by the firm. For example, we observe from manually collected KPI disclosures that the computation of SSS is not uniform across firms and over time.[5] We also observe that about 14% of the firms do not disclose how they compute this KPI. We find a diminished information content of the SSS of firms that do not provide these computational details and, among firms that do disclose the calculations, we find reduced information content of this KPI for years in which the firm changes the calculation. This finding is based on either market response to KPI disclosures or analyst forecast revisions as gauges of information content.

From our tests on the determinants of analysts' decisions to produce KPI forecasts, we learn that the most important determinant of analysts' decisions to forecast a KPI for a firm is the information content of that KPI, which reflects investors' demand for these forecasts. Consistent with the demand effect, we also find that more analysts issue KPI forecasts in periods when the company reports a loss, thus rendering the earnings number less informative (Hayn, 1995), and in

[5] The most common version of the measure (under which "same-store" is defined as a store that has been open for at least 12 months), is used by only 46% of the firms. Further, in 10% of the firm-years there is a change (relative to the previous year) in this parameter.

cases with large absolute accruals, i.e., situations with a large discrepancy between earnings and cash flow from operations.

Our next set of tests focuses on the properties of analysts' forecasts of KPI. We find that the average accuracy of KPI forecasts is comparable to or, in some cases, greater than that of EPS forecasts, which suggests that either (i) KPIs are relatively easy to forecast or (ii) analysts exert effort to make accurate KPI forecasts. In contrast to the finding of prior research that early-in-the-period EPS forecasts are optimistic (Brown, 2001; Bartov, Givoly, and Hayn, 2002; Matsumoto, 2002; Richardson et al., 2004), we find that KPI forecasts made early in the period are pessimistic, on average. However, consistent with the pattern found for earnings, we do find a pattern of "walk-downs" of KPI expectations, in which the fraction of forecasts that are pessimistic increases as the period progresses. We find only weak evidence that analysts who issue KPI forecasts provide more accurate earnings and revenue forecasts than those who do not issue such forecasts.

Finally, additional analyses reveal the following. First, similar to short-term EPS forecasts, forecasts of KPI are more accurate than random walk models, and the market reacts more strongly to surprises based on these forecasts. However, in contrast to the findings of Bradshaw, Drake, Myers, and Myers (2012) regarding analysts' *earnings* forecasts, we find that analysts' KPI forecasts for 2- and 3-year-ahead are superior to a naïve extrapolation of analysts' KPI forecasts for the current year to 2- and 3-year-ahead horizons.

Second, using hand-collected data on SSS disclosures in the quarterly press releases, we find that the importance that management attributes to a particular KPI, as captured by the number of its mentions in the press release, is a determinant in analysts' decisions to forecast that KPI.

Our study extends previous empirical studies on the value-relevance of individual KPIs (Amir and Lev, 1996; Francis et al., 2003; Rajgopal et al., 2003b; Patatoukas, Sloan, and Zha, 2015). We extend these studies in three ways. First, we examine if KPI disclosures are informative and timely in that they lead to investor reaction. Next, we extend the examination to a large set of KPIs in different industries. Last, we capture informativeness and timeliness by a non-return measure—specifically, the extent to which KPI disclosures affect analysts' revisions in their earnings and revenue forecasts.

Our study contributes to a number of strands of research. First, by modeling and testing the determinants of analysts' decisions to issue KPI forecasts, we contribute to the research on the effect of value relevance of information to investors on the supply of products by analysts (e.g., forecasts) (see, for example, Chapman and Green, 2015; DeFond and Hung, 2003; Ehinger, Lee, Somberg, and Towrey, 2017; and Ertimur and Stubben, 2005). Second, we contribute to the literature on analysts' forecasts (for recent reviews, see Bradshaw, 2011; and Kothari, So, and Verdi, 2016). By examining the properties of analysts' forecasts of KPI as compared to their earnings and revenue forecasts, this paper enhances our understanding of analysts' activities and the information they produce.[6] Last, our study contributes to the literature on the role of voluntary disclosures in equity valuation. In contrast to mandated financial reporting and disclosures, there are no requirements to disclose KPIs and no guidelines for computing and reconciling them with GAAP measures. As a result, the usefulness of KPI disclosures, which are not audited, is potentially impaired by reduced comparability and greater susceptibility to opportunistic reporting by management. Our findings show that, despite these limitations, KPIs have incremental information. However, our findings also show the importance of transparency and consistency regarding the measurement of KPI. A KPI's usefulness and information content are detracted by a lack of detailed disclosure about a KPI's computation or by changes in its calculation. These findings are

[6] Prior research examines forecasts of financial statement variables, including forecasts of earnings, revenue, cash flows, and income taxes. For reviews of the early analyst forecast literature, see Givoly and Lakonishok (1979), Schipper (1991), and Brown 1993. More recent research is reviewed by Ramnath, Rock and Shane (2008), Bradshaw (2011), and Kothari, So, and Verdi (2016).

relevant to the ongoing debate about the reliability and usefulness of mandated disclosures of companies' intangibles and nonfinancial performance measures (for examples of such proposed disclosures, see Lev, 2001).

The remainder of this paper is organized as follows. Section 2 discusses related research and disclosure issues. Section 3 discusses the sample data, variables, and research design. Section 4 presents descriptive statistics and empirical results. Section 5 summarizes and concludes.

2. Investor and Regulatory Interest and Related Research

2.1 Investor and Regulatory Interest in KPI Disclosures

There is a broad consensus in the investment community that disclosures of industry-specific KPIs are important to the decision-making process. An Ernst & Young (2015) survey conducted by Institutional Investor Research (IIR) shows that almost three-quarters of institutional investors considered industry-specific reporting and KPI to be very, or somewhat, beneficial.[7] As one analyst stated, "To truly understand the company, it's important to have not only top and bottom line guidance, but also a clear description of the KPIs that drive the growth and success of the business" (Gaertner, 2016).

The growing interest in KPI information has drawn attention from regulators, which is in line with the interest of the investor community in KPI information (FASB, 2001; AAA Financial Accounting Standards Committee, 2002; SEC, 2003, 2008, and 2016). In its guidance regarding MD&A, the SEC expects companies to identify and discuss KPIs, including nonfinancial measures that management uses to manage the business (SEC, 2003).[8] Doing so should allow investors to view the company through the eyes of its management. Since KPIs vary by industry, and

[7] The survey covered more than 200 institutional investors, including portfolio managers, equity analysts, chief investment officers, and managing directors.
[8] Similar guidance is offered by the EU Directive (2003) and by the IASB (see IASB, 2010).

sometimes by company, the SEC suggests that companies should discuss key variables, both financial and nonfinancial, that are specific to their industry or company.

While in principle, companies should disclose all material information, including all material industry-specific measures of performance, there are no specific requirements for KPI disclosure. The SEC may ask a company to disclose and discuss KPIs in its SEC filings when those metrics are included in the company's communication with investors outside the SEC filings (e.g., a press release or a website). Further, when a company refers to a KPI when analyzing its performance in the MD&A section of the 10-K, the SEC staff often asks it to define the KPI and discuss its computations and limitations. So, as it stands now, the disclosure of KPIs is largely voluntary. Even when KPIs are disclosed and discussed by the company, there are no standards that assure comparability across companies and consistency over time within a company.

The SEC Committee on Improvements in Financial Reporting (SEC, 2008) recommends the development of industry-wide KPIs that are consistently defined and disclosed so investors can more easily interpret them and compare them across companies. Consistent with this recommendation, the SEC is considering the development of rules and guidelines concerning KPI disclosures. In its Concept Release on April 13, 2016 (SEC, 2016), the SEC requested public comments on whether registrants should be required to disclose and comment on KPIs important to their business, what types of users are likely to benefit from such information, and how to identify those industry KPIs that should be standardized.[9,10]

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[9] Our reading of comment letters suggests the following. While there seems to be general support for a principle-based approach that emphasizes materiality; the majority of respondents, including Big 4 auditors, did not recommend prescriptive requirements for disclosure of specific KPIs. Their concerns included a potential reduction in the flexibility for the registrants to select variables that they consider most important, and difficulties in identifying KPIs that apply to all firms in the industry.

[10] Regulatory bodies abroad are equally concerned about the disclosure and standardization of KPIs, and these bodies either require or suggest adequate disclosures of them (see, for example, IASB, 2010; the EU Accounts Modernization Directive, 2003; and Section 417 of the Companies Act of 2006 in the UK, 2006).

2.2 Related Research

Several studies examine the role of certain individual KPIs in explaining company valuations and predicting future financial performance. Amir and Lev (1996) find that in the wireless industry, the size of the population in the specific area where wireless services are available and the penetration rate (i.e., the ratio of the number of subscribers to the total population in that area), help explain the cross-sectional variability of the market values of firms in this industry. Ittner and Larcker (1998a) examine the information content of customer satisfaction scores. These scores, unlike other KPIs, are not developed and disclosed by the firms but rather produced by a third party (the National Quality Research Center) and published by *Fortune* magazine. Ittner and Larcker (1988a) find that these scores are positively associated with firm market values and future financial performance and that investors respond to their releases.

Francis, Schipper, and Vincent (2003) examine the association between annual returns and different measures of performance: earnings, EBITDA, cash flow from operations (CFO), as well as selected KPIs. They conduct their examination within industries for which respondents to a survey by PricewaterhouseCoopers (PwC) have identified their preferred performance measure. Their results suggest the superiority of earnings as a measure of performance over other measures (even for some of the industries for which the survey results point to EBITDA or CFO as superior). Other researchers examine and document the value relevance of Web traffic (Trueman, Wong, and Zhang, 2001; Rajgopal, Venkatachalam, and Kotha, 2003b), order backlog (Rajgopal, Shevlin, and Venkatachalam, 2003a), and discounted cash flow estimates of oil and gas royalty trusts (Patatoukas, Sloan, and Zha, 2015). Curtis, Lundholm, and McVay (2015) show that components of sales (e.g., growth in same-store sales, the number of existing stores, and new stores open) are useful in predicting future sales.

We extend the research on the value relevance of KPIs by examining a broader set of KPIs in multiple industries. Rather than using market valuation tests to assess the information relevance of firm-produced KPIs, we rely on the market response to news on economically important KPIs (as captured by the size of their analyst following). The use of an event-study methodology improves the reliability of the inferences by alleviating the need to control for a multitude of valuation drivers, many of which are highly correlated. We further consider an alternative measure of the informativeness of KPIs that is not return based, in the form of analysts' responses to KPI news. We find that KPI surprises induce revisions in analyst forecasts of earnings and revenue, a finding that reinforces our conclusion on the information content of KPIs based on the market response to these surprises. Our paper also extends the literature on the properties of analysts' forecasts by analyzing the accuracy and bias of KPI forecasts and contrasting them with analysts' revenue and earnings forecasts.

The paper includes an examination of the effect of the cross-sectional uniformity and consistency over time in defining and measuring a KPI on the information content of the KPI. It is generally recognized that a lack of uniformity in voluntarily disclosed measures and inconsistency over time in the definition and computation of a KPI diminish the informativeness of these measures. A number of studies point to the need to standardize voluntary disclosures in other areas, such as intangibles (Lev, 2001), corporate social responsibility (CSR), and sustainability (Langer, 2006). With respect to voluntary disclosure of KPIs, Elzahar, Hussainey, Mazzi, and Tsalavoutas (2015) develop a model for the quality of such disclosures in which quality includes the characteristics of year-to-year consistency and calculation comparability.

The lack of standards and regulation make KPI measurement also susceptible to manipulation. For example, Schilit and Perler (2010) note that companies can manipulate SSS by changing the definition of *existing stores*. For example, one definition of an *existing store* may be a store that exists for at least 12 months, but this definition may be revised so that an *existing store* must be open for 18 months instead. The authors also give examples of companies that stopped disclosing SSS when the indicator showed worsening performance (e.g., Starbucks in 2007).

For completeness, we should mention that past research also examines the efficiency of market prices and analyst EPS forecasts with respect to KPI information, an issue that we do not examine in this paper. Rajgopal et al. (2003a) find that investors overvalue firms with high order backlog, while analysts correctly incorporate backlog information in their earnings forecasts. Simpson (2010) finds that in the wireless industry, analyst earnings forecasts do not fully incorporate the information contained in several KPI measures, namely, customer acquisition cost, number of subscribers, and average revenue per user. However, this inefficient forecasting is observed only in forecasts for firms that disclose these three KPIs sporadically. Analysts' earnings forecasts correctly incorporate KPI disclosures by firms that persistently disclose such information.

3. Sample Data, Variable Measurement, and Research Design

3.1 Sample Selection and Distribution

We obtained quarterly and monthly forecasts of industry-specific KPIs, quarterly earnings and revenue forecasts, as well as the actual values of these forecasts from the respective I/B/E/S detail files.[11] Stock prices and returns are obtained from CRSP, and company financial data are obtained from Compustat.

Table 1 presents details of the sample construction. As the table shows, the initial sample consists of all industry-specific KPIs available from the I/B/E/S KPI database for nonfinancial

[11] The KPI data were obtained directly from Thomson Reuters in February 2016.

industries.[12,13] This initial sample consists of 615,635 analyst forecasts of quarterly KPIs for 1,215 firms. We define the median of the contemporaneous individual forecasts as the *consensus forecast*. We exclude from the consensus measure *stale* KPI forecasts, defined as forecasts issued more than 90 days before the announcement date,[14] and we omit observations that have missing KPIs or lack any of the necessary financial data. Finally, to be included in the final sample, we require each KPI to have at least 100 firm–quarter observations with available values for both the forecasted and the realized KPI. This requirement is designed to ensure that the KPI is of a sufficient economic importance to be widely followed by analysts.[15] Our final sample contains 28 KPIs; 129,184 KPI-firm–quarter analyst forecasts; and 17,018 KPI–firm–quarter consensus forecasts for 659 distinct firms. Appendix A contains a description of KPI measures and variable definitions.

Table 2 Panel A presents the distribution of sample observations by industry. The sample includes four I/B/E/S industries: *airline*, *oil & gas*, *pharmaceutical*, and *retail*.[16] The largest number of sample observations are found in the retail and the oil & gas industries. To accommodate the inter-industry differences, we conduct empirical tests for the entire (all-industry) sample as well as for each industry separately. On average, sample firms in the pharmaceutical (retail) industry are the largest (smallest), with a median market capitalization of $12.741 ($2.008) billion.

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[12] I/B/E/S non-industry-specific KPIs relate to financial statement items (e.g., cost of goods sold, R&D expense, cash flow from operations), financial ratios (e.g., price-to-sales ratio, return on capital), and other variables not specific to any particular industry (e.g., free cash flow, number of shares outstanding). These "KPIs" are excluded because they do not represent information beyond that which is available, or directly derived, from the financial statements.

[13] We exclude the financial industry because the majority of KPIs provided by I/B/E/S for that industry can be directly inferred from financial statements. For example, the three most forecasted KPIs in the financial industry are net *interest income*, *loan loss provisions*, and *non-interest expense*, all of which can be directly inferred from financial statements.

[14] The results are very similar when we do not delete stale forecasts.

[15] The requirement eliminates approximately 2.7% of KPI–firm–quarter observations. The five most populated KPIs excluded from our analysis are *revenue per passenger mile* in the airline industry, *capacity for refining crude oil* (measured in barrels per day), *upstream income*, *refining income*, and *downstream income* in the oil & gas industry.

[16] Excluding financial industries, I/B/E/S reports industry KPIs for five industries: airline, oil & gas, pharmaceutical, retail, and technology. I/B/E/S uses a proprietary industry classification to construct these five industries. The oil & gas industry includes integrated oil & gas, oil & gas exploration & production, and oil & gas refining & marketing. The retail industry includes retail stores and restaurants. None of KPIs in the technology industry have 100 firm–quarters with analyst forecasts; therefore, we exclude them from our analyses.

Firms in the oil & gas industry have the highest book-to-market ratios (i.e., they are value firms), and firms in the pharmaceutical industry have the lowest book-to-market ratios (i.e., they are growth firms).

The available KPI forecast data for different industries (see Table 2 Panel B) spans over somewhat different time periods. The airlines sample covers 2013–2016, oil & gas covers 2012–2016, retail covers 2008–2016, and pharmaceutical covers 2005–2016. With the exception of the pharmaceutical industry, the number of analyst KPI forecasts grows over time (the numbers for 2016 relate to the early part of the year), which is consistent with these performance measures becoming more popular. The coverage of KPI forecasts available on I/B/E/S database for the pharmaceutical industry is quite erratic (likely due to the fact that the collected data were obtained in part through acquisitions of other data providers), with a discontinuity in coverage in 2011 and considerably reduced coverage in later years.[17]

Table 2 Panel C shows the available sample size for each KPI in terms of firm–quarters, number of firms, number of analysts, and number of forecasts. The individual KPI with the largest number of available firm–quarter observations are *available seat miles* (ASM) in the airline industry, *distributable cash flow* (DCF) in the oil & gas industry, *pharmaceutical sales* (SAL) in the pharmaceutical industry, and the rate of growth in *same-store sales* (SSS) in the retail industry. The number of firms in our sample that disclosed a given KPI varies from 13 (revenue per available seat mile (RASM)) to 231 (distributable cash flow (DCF)), and the number of analysts who issued forecasts for a given KPI ranges from 17 (revenue per available seat mile (RASM)) to 524 (same-store sales growth rate (SSS)).

[17] Our inferences remain intact when we delete observations in 2010–2016 in the pharmaceutical industry or when we exclude the pharmaceutical industry from the sample.

3.2 Surprise Measures

We define the *KPI surprise* (the *KPI news*), $SURP\_KPI_{ijt}$, for firm *j* that belongs to industry *i* in quarter *t*, as the forecast error. That error is calculated as the realized KPI announced by firm *j* for quarter *t* minus the corresponding analyst consensus forecast, scaled by the average absolute value of the two variables.[18] *Analyst consensus forecast* is calculated as the median of the most recent forecasts made by individual analysts at the time of the KPI announcement. We exclude from the consensus forecast those forecasts that were made more than 90 days before the KPI announcement.

For each KPI, we rank KPI surprises across all firm–quarter observations in industry *i*, and we assign the rank values of 0, 0.5, and 1 to observations in the bottom (i.e., the most negative), middle, and top (i.e., the most positive) terciles, respectively. The resulting variable is denoted $SURP^{rank}\_KPI_{ijt}$. Using these rank scores mitigates the influence of extreme surprises. It also facilitates the interpretation of the regression coefficient on $SURP^{rank}\_KPI$ as the increase in the dependent variable (e.g., the announcement period return) as the KPI surprise moves from the bottom to the top tercile of the KPI surprise distribution.[19]

To determine whether the surprises of important KPIs in an industry have, collectively, information content incremental to that of earnings and revenue surprises, we first identify for each industry the KPIs that are likely to be important to market participants. Specifically, for each industry, we select the three KPIs that are most followed by analysts, based on the number of firm–quarter forecasts for the KPI in the industry. We then average in each firm–quarter the surprises

[18] Many KPI, such as Available Seat Miles and Oil Production per Day, are measured in unscaled non-monetary numbers; others such as Same Store Sales and Passenger Load Factor are measured as a growth rate or a ratio; while others—such as Distributable Cash Flow—reflect dollar amounts. Given this heterogeneity, scaling by average absolute value of the actual and forecasted value makes more sense than scaling by share price as is typically done for earnings and revenue surprises.

[19] We use terciles rather than deciles to ensure a sufficient number of sample observations in each KPI surprise group, as some KPI have a relatively small number of observations. The results are robust to using deciles or quintiles.

of these three KPI surprises and, similar to the construction of *SUPR*^{rank}*_KPI*, we rank the average surprises across all firm–quarter observations in industry *I*, and we assign the rank values of 0, 0.5, and 1 to observations in the bottom (i.e., the most negative), middle, and top (i.e., the most positive) terciles of the distribution of this average surprise, respectively. We denote the resulting measure as *SURP*^{rank}*_3-KPI*, and use it to test for the collective information content of these potentially important industry KPIs.[20] We use *SURP*^{rank}*_3-KPI* to conduct tests at the industry level and for the entire (all-industry) sample.

We calculate earnings (revenue) surprise as the difference between the actual number announced by the company and the latest analyst consensus forecast before the earnings (revenue) announcements, scaled by the stock price (total market value of equity) at the end of the fiscal quarter. Similar to the ranking of the KPI surprises, we rank the earnings and revenue surprises into terciles and assign them scores of 0, 0.5, and 1 to form *SURP*^{rank}*_EPS* and *SURP*^{rank}*_REV*, respectively.

One of our KPIs, SAL (i.e., sales per drug, in the pharmaceutical industry), is reported for individual drugs rather than for the company as a whole. When there is more than one drug with available forecast and actual (thus more than one drug with a SAL surprise), we use the SAL surprise in our analysis for the drug that has the largest number of analyst forecasts, which presumably indicates that sales of that drug are likely to be most important to market participants.

3.3 Testing the Information Content of KPI News Based on Stock Price Response

Most KPIs are announced quarterly, concurrently with earnings announcements. We estimate the incremental information content of KPI announcements through the following pooled

[20] Aside from capturing the collective information content of the industry KPIs, using the average surprise has the advantage of alleviating the difficulty (created by the high correlation between the industry KPI surprises) of identifying the incremental information content of individual KPIs.

regression of announcement returns estimated from all firm–quarter observations within a given industry or across industries:

$$CAR(-1,+1)_{jt} = \alpha_1 + \beta_1\, SURP^{rank}\_KPI_{jt} \text{ (or } SURP^{rank}\_3\text{-}KPI_{ijt}) + \beta_2\, SURP^{rank}\_EPS_{jt} + \beta_3\, SURP^{rank}\_REV_{jt} + \varepsilon_{jt}, \quad (1)$$

where *CAR(-1,+1)* is the cumulative abnormal return over the 3-day window centered on the announcement date. Appendix A contains definitions of all variables and KPI measures. We control for the revenue surprise in addition to our control for the earnings surprise, since prior research indicates that investors react more strongly to a revenue surprise than to an expense surprise of the same magnitude (Ertimur, Livnat, and Martikainen, 2003).

Some KPIs reflect favorable aspects of performance, while others reflect expenses (i.e., cost per seat miles (CPA), maintenance CapEx (MCX), lease operating expense (LOE), exploration expense (EXP), production tax (PTX), and production expense (PEX)) or unfavorable developments (i.e., number of stores closed/relocated (NSC)). To allow for a uniform interpretation of the sign for all KPIs, we multiply these unfavorable surprises by −1 before estimating Regression (1) and subsequent related tests.[21] We expect the coefficients on earnings and revenue surprises to be positive. If KPI surprises have incremental information content to that contained in earnings and revenue surprises, we expect the coefficient on $SURP^{rank}\_KPI$ (or on $SURP^{rank}\_3\text{-}KPI$) to be positive as well.

3.4 Testing the Information Content of KPI News Based On Analysts' Revisions of Earnings and Revenue Forecasts

To provide further evidence on the information content of KPI surprises, we use an additional measure of informativeness, namely, the extent of analysts' responses to KPI surprises

[21] Higher maintenance CapEx (MCX) and higher production tax (PTX) may convey positive information to investors, so there might be some ambiguity about the expected signs for these KPIs.

when revising their EPS and revenue forecasts. We estimate the following regression from all firm–quarter observations within a given industry, as well as across industries:

$$EPS\ (REV)\ Forecast\ Revision_{jt+1} = \alpha_1 + \beta_1\ SURP^{rank}\_3\text{-}KPI_{ijt} + \beta_2\ SURP^{rank}\_EPS_{jt} + \beta_3\ SURP^{rank}\_REV_{jt} + \varepsilon_{jt}, \quad (2)$$

where *EPS (REV) Forecast Revision*$_{jt+1}$ is the median analyst forecast for firm j quarter $t+1$ EPS (revenue) issued within 10 days after the quarter t earnings announcement date minus the median of the latest analyst EPS (revenue) forecast for firm j quarter $t+1$ (revenue), issued within 90 days before the quarter t earnings announcement date, scaled by the stock price (market value of equity) at the end of quarter t, and multiplied by 100.

If analysts respond incrementally to KPI surprises when revising their forecasts of next-quarter EPS and revenue, we expect β_1 to be positive and significant. KPI surprises are likely to be correlated with earnings surprises (and possibly with revenue surprises), thus we expect them to induce revisions in the forecasts of these variables. In fact, past research suggests that some KPIs (e.g., same-store sales, change in number of stores) can be, and indeed are, used in a bottom-up model of forecasting earnings and revenues (see Curtis, Lundholm, and McVay, 2014; and Lundholm and Sloan, 2004). However, it is less clear whether KPI surprises incrementally lead to revisions in earnings or revenue forecasts, after controlling for earnings and revenue surprises.

3.5 Testing the Effect of Uncertainty about the Measurement of a KPI on its Information Content

Voluntary disclosures by firms raise the issues of uniformity and consistency. This is particularly true for the disclosure of most KPIs, particularly the nonfinancial KPIs. Even bona fide disclosures of a KPI make it difficult for the user to properly interpret the KPI, since this measure is based on the internal reporting and information system of the firm, and the firm may define and measure the same variable somewhat differently than other firms. This difficulty is exacerbated when the definition and measurement are not consistent over time and when the reporting firm has incentives to misrepresent.[22] We expect such noise to reduce the usefulness of KPIs for investors.

To examine the consistency with which firms define KPIs, and to test the above prediction, we had to manually collect data from firms' KPI disclosures in the annual MD&A. Because this involves a massive hand-collection of data, we focused on one industry and one type of KPI: the retail industry and its most commonly disclosed KPI, SSS.

We first document the frequency in which retailers disclose details on how their SSS is computed, and we document the extent to which the definition of "same store" is uniform across firms and consistent over time for a given firm. Next, we examine how the information content of SSS news is affected by the absence of detailed disclosures on how SSS is computed or by a lack of consistency of the firm's definition of "same store" over time. For this examination, we use the hand-collected data from the MD&A (of over 1,300 10-K forms) to estimate the following versions of regression 1:

$$CAR(-1,+1)_{jt} = \alpha_1 + \beta_1\ SURP^{rank}\_SSS_{jt} + \beta_3\ LOW\_DISCLOSURE_{jt}\ (or\ CHANGE\_COMP) + \beta_4\ LOW\_DISCLOSURE_{jt}\ (or\ CHANGE\_COMP) *SURP^{rank}\_SSS_{jt} + \beta_2\ SURP^{rank}\_EPS_{jt} + \beta_3\ SURP^{rank}\_REV_{jt} + \varepsilon_{jt} \qquad (3a)$$

$$EPS\ (REV)\ Forecast\ Revision_{jt+1} = \alpha_1 + \beta_1\ SURP^{rank}\_SSS_{jt} + \beta_3\ LOW\_DISCLOSURE_{jt}\ (or\ CHANGE\_COMP) + \beta_4\ LOW\_DISCLOSURE_{jt}\ (or\ CHANGE\_COMP) *SURP^{rank}\_SSS_{jt} + \beta_2\ SURP^{rank}\_EPS_{jt} + \beta_3\ SURP^{rank}\_REV_{jt} + \varepsilon_{jt}, \qquad (3b)$$

where *LOW_DISCLOSURE* (*CHANGE_COMP*) is an indicator variable that receives the value of 1 if the annual disclosure in the year to which the quarter belongs does not provide computation

[22] As discussed in Section 2.2, these problems are common to other voluntary and nonfinancial disclosures, such as those pertaining to intangible assets or to corporate social responsibility.

details of SSS (represents a change from the previous year's definition), and 0 otherwise. All other variables are the same as in Regressions (1) and (2).

3.6 Identifying the Determinants of Analysts' Decisions to Forecast KPIs

Financial analysts produce an array of products, including earnings forecasts, stock recommendations, and target prices. The scope of financial and nonfinancial variables forecasted by analysts has been expanded over the years beyond earnings, forecasts of other variables (e.g., revenues, cash flows, various measures of earnings (EBIT, EBITDA)), and effective tax rate. Analysts' production of these forecasts is not universal, and this likely reflects variation in the demand by investors for such forecasts. In fact, in our sample, 65.5% of the firm–quarter observations of firms that report KPIs and have at least one EPS forecast do not issue KPI forecasts. A number of studies examine the determinants of analysts' decisions to supplement their earnings forecasts with forecasts of cash flow (e.g., DeFond and Hung, 2003) and revenue (Ertimur and Stubben, 2005). The examined determinants include firms' characteristics that presumably reduce the informativeness of earnings (e.g., the magnitude of discretionary accruals and earnings volatility) and financial distress.

We follow this literature as we identify the determinants of the issuance of KPI forecasts. Since the demand for KPI forecasts is likely to be driven mostly by the incremental value of KPI to investors, we add to the list of determinants a summary measure of that value obtained from estimating Regression (1), as explained below. This measure allows us to use a reduced set of variables to reflect the other determinants. Specifically, we estimate the following regressions across firm–quarter–KPIs:

$$(KPI\_to\_EPS)_{jtk} = f\{INF\_KPI_{jtk}, SIZE_{jt}, VOL_{jt}\_EARN_{jt}, LOSS_{jt}, AB\_ACCR_{jt}, DISTRESS_{jt}\} \quad (4)$$

where $(KPI\_to\_EPS)_{jtk}$ is the ratio for firm j in quarter t between the number of KPI analysts and the number of EPS analysts. The ratio for the firm–quarter is computed from analysts who produce EPS forecasts for the firm–quarter.

The first determinant, *INF_KPI*, is the incremental explanatory power of the KPI surprise (*$SURP^{rank}$_KPI)* in Regression (1) in explaining the variation in the regression's dependent variable, *CAR (-1,+1)*. The incremental explanatory power is computed based on Shapley's value (Shapley, 1953).[23] The variable *INF_KPI* is expressed as the fraction of the regression's R^2 contributed by the KPI surprise. We expect that *INF_KPI* will be positively associated with the propensity of analysts to issue its forecasts.

The variable *SIZE* is the natural logarithm of the market value of the firm's equity at the beginning of the quarter. The variable *VOL_EARN* is the coefficient of the variation of earnings, computed as their standard deviation over the most recent eight quarters, deflated by their absolute mean value over the same period. We expect that the demand for KPI forecasts will be greater; therefore, we also expect their production to be more common when the volatility of earnings is higher.

The variable *LOSS* is an indicator that receives the value of 1 if income before extraordinary items is negative in quarter t−1, and 0 otherwise. Given the reduced information content of the earnings number when the firm reports a loss (Hayn, 1995), we expect that KPI information will be more in demand in a loss period.

The variable *AB_TACCR* is the absolute value of total accruals in quarter t−1 deflated by beginning total assets. The variable *DISTRESS* is an indicator variable that receives the value of 1

[23] When the explanatory variables in the regression are uncorrelated, the contribution of an individual explanatory variable, X_i to the multiple regression R^2 is the R^2 of the regression of Y on X_i. Shapley values can be used to assess the contribution of the explanatory variables in the more common case when the explanatory variables are not independent of each other. A convenient feature of the Shapley values is that they sum up to the regression R^2. For a good introduction to Shapley values, see Israeli (2007).

when the Altman Z-score is below 1.81 (an indication of distress) at beginning of quarter *t*, and 0 otherwise. Similar to losses, financial distress reduces the predictive power of the conventional measure of performance; therefore, we expect *DISTRESS* to be positively associated with the demand for, and the corresponding supply of, KPI forecasts.

3.7 Accuracy and Bias of KPI Forecasts

A large body of research deals with the accuracy and bias in analysts' forecasts of earnings. We assess the accuracy and bias of KPI forecasts and contrast them with those associated with analysts' earnings forecasts. Comparing the accuracy of forecasting these performance measures would indicate both the relative inherent difficulty in forecasting each of them, and the relative amount of attention and resources devoted to these forecasts. Similar to the assessment by past studies of the superiority of analysts' earnings forecasts over mechanical time-series models (Bradshaw et al., 2012; Fried and Givoly, 1982), we also compare analyst KPI forecast accuracy vis-à-vis the accuracy of time-series forecasts.

Prior research documents an optimistic bias in earnings forecasts made early in the period (e.g., Brown, 2001; Bartov et al., 2002; Matsumoto, 2002; Richardson, Teoh, and Wysocki, 2004; Bradshaw et al., 2016). While there is no consensus on the reasons for this bias, a common explanation for the bias (and, further, for the prevalence of "buy" recommendations) is that sell-side analysts attempt to curry favor with management to gain better access to information or to promote the purchase of stock through their brokerage house (see Easterwood and Nutt, 1999; and O'Brian, 1988). If this explanation is valid, we should find a similar optimistic bias in KPI forecasts.

3.8 Does the Production of KPI Forecasts Help Improve the Accuracy of EPS and Revenue Forecasts?

Past research shows that analysts who engage in forecasting cash flow from operations, in addition to their forecasting of earnings, produce more accurate earnings forecasts (see Call, Chen, and Tong, 2009; Pae, Wang, and Yoo, 2007). The explanation given to this finding is that a separate formal cash flow forecast indicates that analysts adopt a more structured and disciplined approach to forecasting earnings, resulting in greater forecast accuracy of earnings. Only a subset of analysts issue forecasts of KPIs, raising the question of whether forecasting KPIs by this subset of analysts helps them achieve a higher accuracy in their forecasts of earnings and revenue compared to other analysts who produce forecasts of earnings and revenue for the firm but do not also engage in producing KPI forecasts for that firm. We test the association between KPI forecasting and the accuracy of the corresponding earnings forecasts by estimating the following regression of analysts' relative forecast accuracy from all analyst–firm–quarter observations within a given industry, or across industries:

$$\textit{Relative Accuracy of EPS (REV) Forecast}_{mjt} = \alpha_1 + \beta_1 \textit{D\_KPI\_Forecast}_{mjt} + \varepsilon_{mjt}, \qquad (5)$$

where $\textit{Relative Accuracy of EPS (REV) Forecast}_{mjt}$ is the difference between the average absolute EPS (REV) forecast error for firm *j* quarter *t* across all analysts included in the consensus forecast for that firm–quarter and analyst *m*'s absolute EPS (REV) forecast error for firm *j* quarter *t*, scaled by the standard deviation of absolute EPS (REV) forecast errors for firm *j* quarter *t* across all these analysts. All forecast errors are computed as the actual value minus the forecasted value. The analyst *m*'s absolute EPS (REV) forecast error is the absolute value of the difference between actual EPS (REV) and analyst *m*'s last forecast within 90 days before the earnings announcement. The variable $\textit{D\_KPI\_Forecast}_{mjt}$, is an indicator that equals 1 if analyst *m* issues a forecast of at least one KPI for firm *j* quarter *t*, and 0 otherwise. If, relative to other analysts, analysts who issue KPI forecasts produce relatively more accurate EPS (or revenue) forecasts, we expect β_1 to be positive.

4. Empirical Results

4.1 Descriptive Statistics: Accuracy and Bias

Table 3 reports descriptive statistics for all KPIs in our sample, their analyst forecasts, and the accuracy and bias of these forecasts. The table presents these properties for the earliest and the latest forecasts made for the quarter. The forecast error is computed as the difference, actual minus forecast, deflated by the average of the absolute values of these two values.[24] The absolute errors capture accuracy, while the signed errors measure the bias. In order to maintain a uniform interpretation of the direction of the bias (i.e., optimistic or pessimistic) across KPIs, we reversed the sign of the forecast errors for KPIs that represent costs, expenses, or losses, so that a negative (positive) forecast error for all KPIs would connote optimistic (pessimistic) bias.

The average median signed (absolute) error of a KPI (across the 28 KPIs examined) is 0.8% (12.5%) for the earliest forecast in the quarter and 0.7% (11.9%) for the latest forecast in the quarter. The average of the median (absolute) forecast error (across the 17,018 firm–quarter–KPI observations) is 0.1% (9.3%) for the earliest forecast and 0.1% (8.3%) for the latest forecast in the quarter. These numbers are generally lower than the corresponding errors in forecasting EPS. The greater accuracy in forecasting KPIs could be explained either by the lower variability in KPIs, or by the attention that analysts give to projections of KPIs, given that they serve as a basis (in bottom-up forecasting models) for earnings forecasts. Or, both explanations may apply. As should be

[24] Similar results (not tabulated) are obtained when we use the standardized error, computed as the difference above deflated by the standard deviation of the time series of the actual values.

expected, the accuracy of the forecasts made late in the quarter are consistently higher than those made early in the quarter.[25] Note also that the KPI signed error is, on average, positive, indicating a pessimistic bias.

Focusing on the most frequently forecasted KPIs in their respective industries, we find that, in the airline industry, the median errors associated with forecasting available seat miles (ASM) and the passenger load factor (PLF) are relatively very small for both early- and late-in-quarter forecasts. In the oil & gas industry, the forecasts of distributable cash flow (DCF) and barrels of oil per day (OPD), are of similar accuracy to all KPIs in the four industries. The same is true for the accuracy of the forecasts of pharmaceutical sales (SAL) in the pharmaceutical industry. However, the forecast accuracy of SSS in the retail industry is relatively low. The average of the median firm–quarter absolute forecast error at both ends of the quarter is fairly high (33.3% and 39.1% for the earliest and the latest forecast in the quarter, respectively). One reason for this low accuracy of SSS forecasts is that SSS is expressed as a growth percentage, so the deflator of its forecast error is often a low number, magnifying the error measure.

4.2 The Information Content of KPI News Based on Stock Price Response

We examine the information content of KPI news by measuring investor reactions to KPI surprises. Table 4 Panel A presents the results from estimating Equation (1), in which we regress the announcement window return *CAR(-1,+1)* on the KPI and earnings surprises (Regression (1)). The rows pertaining to the most frequently forecasted KPI in each industry (which are ASM, DCF, SAL, and SSS in the airline, oil & gas, pharmaceutical, and retail industries, respectively) are highlighted. The first two columns of Panel A document the results of the univariate regressions

[25] In an additional untabulated analysis, we find that that firm-level fixed effects explain more of the variation in KPI forecast accuracy than analyst-level fixed effects, suggesting that forecasting difficulty across firms plays a greater role in explaining KPI forecast accuracy than differences across analysts following the firm.

of announcement return on KPI surprises. The last three columns of Panel A compare how CAR is incrementally affected by the KPI surprise and by the earnings surprise, respectively.

The results reveal that a number of KPIs (12 out of 28) have a significant association with the announcement period returns. None of the coefficients of the KPIs, whose sign is expected to be positive (see Section 3.3), has a significant negative sign. Importantly, the KPIs most frequently forecasted by analysts in each of the four industries all have a significant association with the announcement returns. For example, in the airline industry, the coefficient on the available seat miles (ASM) surprise is 4.36%. The interpretation of the 4.36% coefficient of ASM is that there is an increase of 4.36% in the expected CAR associated with the magnitude of the ASM surprise when moving from the bottom tercile of its distribution (where observations are assigned the scaled rank of 0 (see Section 3.2.1)) to the top tercile of that distribution (where observations are assigned the scaled rank of 1). This is an economically important effect that is significant at the 1% level. The results in the last three columns show that ASM surprise and earnings surprise are significant and incremental to each other. The magnitude of the response coefficient for ASM surprise is more than three-quarters of that for earnings surprise (3.87% for ASM and 5.02% for EPS), suggesting that these two measures largely complement rather than substitute for each other.

The results for other industries reveal a similar pattern of a significant relation between surprises in the most followed KPIs and the announcement return. The reactions to the most followed KPIs and EPS are incremental to each other. Across all KPI measures, SSS has the largest reaction in terms of announcement period differential CAR in both the univariate and multiple regressions (8.15% and 5.88%, respectively).

Table 4 Panel B shows the results of the regressions of *CAR (-1, +1)* on KPI surprises, earnings surprise, as well as revenue surprise. Surprises in eight KPIs (ASM, RPM, DCF, EBX, EXP, TPP, RZP, and SSS) are significant at the 10% level or better after controlling for earnings and revenue surprises, suggesting that these KPIs contain information that is incremental to earnings and revenue. Notably, the market reaction to surprises in these KPIs is more pronounced than the reaction to the revenue surprise. Revenue surprise is insignificant when we control for surprises in ASM, RPM, DCF, EBX, EXP, or TPP. Surprises in SSS and REV are incremental to each other, with the response coefficient on SSS surprises being more than twice the response coefficient on revenue surprise. A move from the bottom to the top tercile of the SSS surprise distribution is associated with a 4.92% increase in abnormal announcement window return.

To test for the overall information content of KPI surprises that is incremental to surprises in earnings and revenue, we estimate the regression of announcement window return on $SURP^{rank}\_3\text{-}KPI$ (i.e., the average ranked surprise across the three most followed KPIs in the industry), $SURP^{rank}\_EPS$, and $SURP^{rank}\_REV$. Table 4 Panel C reports the results of this regression within industries and for the overall (all-industry) sample. The variable $SURP^{rank}\_3\text{-}KPI$ is significant in all industries except pharmaceutical. Moreover, $SURP^{rank}\_3\text{-}KPI$ is positive and significant in the overall sample. These results are consistent with KPI surprises containing significant information that is incremental to earnings and revenue news.

4.3 The Information Content of KPI News Based on Analysts' Revisions of Earnings and Revenue Forecasts

We use Regression (2) (revision in EPS (revenue) forecasts on KPI, EPS, and revenue surprises) to assess the impact of KPI news on analysts' forecasts of EPS or revenues. The results are reported in Table 5. Panel A of the table shows the results of the regression of EPS forecast revision. The coefficient on $SURP^{rank}\_3\text{-}KPI$ is positive and significant in the airline and retail industries as well as in the overall sample that includes all industries. In the regression of revenue forecast revision in Panel B, $SURP^{rank}\_3\text{-}KPI$ is positive and significant in the pharmaceutical and retail industries and in the all-industries sample. Overall, these findings suggest that analysts find

KPI surprises value relevant and incorporate them as inputs in their revisions of earnings and revenue forecasts. These results are consistent with those from Regression (1) in demonstrating the incremental information content of KPIs.

4.4 Uncertainty about the Measurement of KPI and its Effect on the KPI's Information Content

The first row of Table 6 Panel A shows the frequency among all firm–quarter observations for which the MD&A for the year includes computation details of SSS. The absence of the detailed disclosure is likely to create some degree of ambiguity among investors in interpreting this KPI. The table shows that for 400 (or about 14%) of the 2,829 firm–quarters that belong to years for which we examine the MD&A, there was no detailed disclosure on how SSS is computed. Fifty-nine firms have SSS computations that are not explained for at least one year (out of the 10 years for each firm in the retail industry for which we have KPI data).

The second row in this Panel shows the extent of year-to-year consistency in the computation of SSS across observations for which there is a disclosure about the computation details of SSS. The main parameter of this KPI's measurement is the definition of *same stores*, which defines the group of stores for which the rate of growth in sales is computed. While many companies define *same stores* as those stores that, at year-end, have been operating for a period of at least a year, there is some variation in the length of that period (as we document and discuss below). As the table shows, in about 10% of the observations with disclosed details about SSS computation (222 out of 2,429), the computation changed relative to the previous year. A change in definition reduces the comparability between years and makes it difficult for investors at the time of the change to interpret the SSS surprise.

Table 6 Panel B shows that there is some degree of variation in the definition of *same store*. In nearly 50% of firm–quarters, the same-store base includes stores that have been in operation for at least 12 months; however, other firms used 13 months or more in their definitions (and in 4% of the firm–quarters, the applicable definition is 24 months).

In Regressions (3a) and (3b), we estimate the effect of computational disclosures and year-to-year consistency on the information content of SSS news. The regression results are shown in Table 7. These results show that the information content of SSS surprises is lower when there is limited disclosure in the MD&A on the computation details of this KPI. The interactive dummy of *LOW_DISCLOSURE* with the SSS surprise is negative and significant when the information content is gauged by the market response to the SSS announcement. It is also negative (but not significant) when the information is proxied by the extent of the revision in analysts' forecasts of EPS for the following quarter issued in the wake of the SSS surprise. When measuring the information content in this manner, the regression results show that the interactive dummy of *CHANGE_COMP* is negative and significant, indicating reduced information content of SSS news when the definition of this KPI changes.

While these results pertain to one KPI, they suggest that incomplete disclosure about the measurement of KPIs and a lack of consistency in its computation detracts from the incremental information content of KPIs to investors.

4.5. Identifying the Determinants of Analysts' Decisions to Forecast KPIs

The results from estimating Regression (4) are reported in Table 8. The regression is estimated from firm–quarters with at least one forecast for the KPI. The results show that the regression model exhibits a satisfactory explanatory power (adjusted R^2 close to 0.6). The table also shows that an important and significant determinant of analysts' decision to issue a KPI forecast (in addition to their EPS forecast) is the incremental information content of the KPI. In fact, this determinant alone explains this decision more than all other hypothesized determinants collectively explain36

. When Regression (4) is estimated with *INF_KPI*, as a single independent variable, the R^2 of the regression is 0.582. Adding all other variables increases the explanatory power of the regression only marginally to 0.583.

Among the other determinants, *LOSS* and *AB_TACCR*, both of which point to situations in which the information content of earnings is lower, are positive and significant. This is consistent with the notion that in these situations, there is likely to be a stronger demand for supplementary measures of performance (see DeFond and Hung, 2003; and Ertimur and Stubben, 2005). The variable *DISTRESS*, which also indicates situations in which earnings are less informative, has a negative coefficient, which is ostensibly inconsistent with this notion. However, this negative coefficient may suggest that in periods of distress, analysts are more concerned with cash flow rather than non-cash measures such as KPIs (similar to their lower reliance on earnings when bankruptcy risk is high—see DeFond and Hung, 2003).

4.6 Does the Production of KPI Forecasts Improve the Accuracy of Earnings and Revenue Forecasts?

Our next tests examine whether the generation of KPI forecasts enhances the accuracy of earnings forecasts. The results of estimating Regression (5) (untabulated) show only weak evidence of association between the accuracy of an analyst's earnings and revenue forecasts and the issuance of KPI forecasts by the same analyst. The coefficient on *D_KPI_Forecast* in regression (5), $\beta_{1,}$ is significantly negative, which indicates a higher accuracy of the earnings forecasts issued by analysts who also produce KPI forecasts, when compared to analysts who do not produce such forecasts. However, this difference is minor. When estimated from all firm–quarter observations, β_1 is −2.86%. This indicates that the forecast error of EPS forecasts produced by analysts who also forecast KPIs is lower, on average by 2.86% when compared to analysts who do not forecast KPIs. A similar small (but significant) improvement, 3.25%, is observed in the revenue forecasts of KPI forecasters. These are trivial improvements in accuracy. Further, the adjusted R^2 of the regressions is below 0.1%. When we estimate the regression within each industry, we find significance only in one industry: retail.

Past research shows that the production of forecasts for the operating cash flow of the firm, another performance measure, improves the analysts' accuracy in predicting earnings (see Call et al., 2009). Therefore, it is somewhat surprising that the analysts' production of forecasts of firms' KPIs is not associated with an enhanced accuracy of their contemporaneous earnings.[26]

4.7 Additional Analyses

4.7.1 Number of SSS Mentions in Earnings Press Releases and Analysts' Decisions to Forecast SSS

The results reported in Section 4.5 show that analysts are more likely to produce forecasts for KPI that are more value relevant, where value relevance is inferred from the market response in Regression (1). As an alternative indicator of value relevance, we examine the extent to which management provides a detailed discussion of a KPI in the earnings press release. We use the number of times the KPI is mentioned in the earnings press release as an indication of the importance that management assigns to that KPI. Research shows how the content of earnings announcements and conference calls, as well as the quality and emphasis of management disclosures made therein, affect analyst forecasts (see, for example, Barron et al., 1999; Bowen et al., 2002; Ehinger et al., 2017; and Healy et al., 1999). We use the number of times a KPI is

[26] One explanation for this finding could be that the I/B/E/S data on KPIs are incomplete, because they omit the better KPI forecasts issued by analysts who prefer to share them only with their preferred clients rather than contribute them to I/B/E/S. This explanation is not very compelling, however, given the improved coverage of I/B/E/S in recent years and the fact that these "better" KPI forecasters still contribute their earnings and revenue forecasts to I/B/E/S.

mentioned in the earnings press release as a measure of that KPI's importance in the eyes of management.

We hand-collected the number of mentions in earnings press releases of same-store sales (SSS). We re-estimate the determinant model (Regression (4)) by substituting the information content variable, *INF_KPI*, which is based on the market response to KPI news, with the number of mentions of the KPI in the earnings release.[27] Table 9 Panel A provides some descriptive statistics on the number of mentions and their positioning in the text of the press release.

The average number of SSS mentions in an earnings press release is 9.0, with a significant variation indicated by the interquartile range of 4 to 11. Among earnings press releases that disclose SSS, 63.5% of them mention this KPI in the heading or in the first paragraph of the release; 47.8% mention it in a table; and 19.8% have a separate table designated for this KPI.

Table 9 Panel B shows the results from the determinant model based on a variation of Regression (4), in which the natural logarithm of the number of mentions of SSS in the quarterly press releases substitutes for *INF_KPI*, the market-based measure for the information content of the SSS. Since the number of mentions of SSS is hypothesized to affect analysts' production of SSS forecasts, we use in the regression the number of mentions of SSS in the earnings release in the most recent quarter, quarter $t-1$, as a predictor of the dependent variable, the ratio of SSS to EPS forecasts for quarter t. That is, the regression takes the form of:

$$(KPI\_to\_EPS)_{jt,SSS} = \alpha_1 + \beta_1\, Ln\_of\_SSS\_Mentions_{jt-1} + Controls_{jt} + \varepsilon_{jt}, \qquad (6)$$

where *Ln_of_SSS_Mentions* is the natural logarithm of the number of times SSS is mentioned in the earnings press release. All other variables are the same as in Regression (4).

[27] The use of a single KPI, SSS in this case, for the analysis has the advantage of allowing variability of the informativeness of the KPI (as gauged in the case of SSS by the number of its mentions) over firm-quarters to affect analysts' decision on whether to forecast the KPI.

The results presented in Panel B show a positive association between the number of SSS mentions and the propensity of analysts to issue SSS forecasts. The coefficient on SSS mentions is significant both before and after the inclusion of firm fixed effects (Columns (1) and (2), respectively). These results suggest that analysts are more likely to produce SSS forecasts when SSS is more important to the firm, as proxied by the frequency of SSS mentions in the earnings press release.

4.7.2 Information Content of the Monthly SSS (SSS^M)

We also examine the information content of monthly surprises of SSS (SSS^M) in the retail industry (i.e., the growth rate in same-store sales relative to the same period in the previous year). As discussed earlier, except for very few cases, which we remove for the purpose of this examination, the monthly announcements of this KPI do not coincide with the release of the quarterly earnings announcements. This alleviates the need to control for financial information contained in interim reports. The results, not tabulated, are consistent with the results in Table 4 on the information content of quarterly KPIs, with the coefficient on the firm-level SSS^M surprise being positive and highly significant.

Similar to our analysis of the information content of KPI news, we also assess the extent to which the SSS^M news is informative, as indicated by subsequent revisions in analysts' forecasts of earnings and revenue. The results, not tabulated, are consistent with the results in Table 5 for the analyst forecast revisions around quarterly press releases. The coefficient on the SSS^M surprise is positive and significant for the current-quarter EPS and REV forecast revisions and the next-quarter EPS and REV forecast revisions.

In some cases, firms report SSS^M for *segments*, in addition to SSS^M at the firm level, and analysts produce forecasts of these segment SSS^M as well.[28] We test the incremental information content of segment-level SSS^M for the three segments most followed by analysts, by estimating the market reaction regression with both segment- and firm-level SSS^M surprises. The untabulated results show all four slope coefficients are positive and significant. The result suggests that surprise in a segment-level SSS^M contains value relevant information that is incremental to the firm-level SSS^M and the SSS^M for other segments of the firm.

4.7.3 Superiority of Analysts' KPI forecasts over Mechanical Forecasts

Starting with Fried and Givoly (1982), there is a widely held belief that analysts' EPS forecasts are superior to random walk time-series forecasts. However, recent evidence suggests that this may not be true for long-term earnings forecasts: Bradshaw et al. (2012) show that a naïve extrapolation of analysts' 1-year-ahead EPS forecasts outperforms 2- and 3-year-ahead forecasts. To find out whether these results also hold for KPI forecasts, we examine the accuracy of KPI forecasts relative to random walk time-series models for different forecast horizons.

Table 10 Panel A reports mean absolute errors for KPI forecasts for quarters Q+1, Q+2, Q+3 and years Y+1, Y+2, and Y+3. The column *Analysts' Forecasts* reports absolute errors for analyst forecasts, the column *Random Walk Forecasts* reports absolute errors for random walk forecasts, and the last column reports the difference between the two. The results suggest that analysts' forecasts of KPI are superior to a simple random walk forecast for all horizons up to three years.

In Panel B, we follow Bradshaw et al. (2012) and examine whether analysts' long-term KPI forecasts (2- and 3-year-ahead forecasts) are superior to a naïve extrapolation of their 1-year-ahead forecast. Contrary to the finding in Bradshaw et al. (2012), we find that analysts' long-term

[28] For example, GAP Inc. reports SSS^M for its three segments: Gap Global, Banana Republic Global, and Old Navy Global.

forecasts of KPIs are superior to a naïve extrapolation of their 1-year-ahead forecast.

Next, we examine whether the market reacts more strongly to a KPI surprise based on analysts' forecasts of KPI or a random walk model. Panel C reports the results of the regressions of announcement window abnormal returns, *CAR(-1,+1)* on $SURP^{rank}$*_3-KPI*, $SURP^{rank}$*_EPS*, and $SURP^{rank}$*_REV*. The KPI surprise is based on the random walk forecasts (first row) or analyst forecasts (second row). The chi-square test is a test of the difference between the coefficients on $SURP^{rank}$*_3-KPI* in the two regressions. We find that the market reacts more strongly to KPI surprises based on analysts' forecasts than random walk forecasts (the difference is significant at the 1% level).

Overall, the results show that (i) analysts' forecasts of KPIs are more accurate than random walk models and (ii) the market reacts more strongly to the surprise based on these forecasts. These results suggest that analysts devote attention and resources to forecasting KPIs, and this strengthens our findings on the importance of KPI forecasts.

4.7.4 Expectation Management

Past research provides evidence consistent with the notion that firms manage down earnings expectations to avoid negative earnings surprises (Brown, 2001; Bartov et al., 2002; Lopez and Rees, 2000; Kasznik and McNichols, 2000; Matsumoto, 2002).[29] Bartov et al. (2002) provide a capital market motivation for this behavior by showing that firms that meet or beat their current analysts' forecasts enjoy a higher return over the quarter than firms that have similar quarterly earnings forecast errors but fail to meet expectations, and this premium is not reversed in future years.[30]

[29] Bradshaw et al. (2016) show that an interactive effect between analysts' strategic incentives for optimism and forecast difficulty helps explain walk-downs in forecasts of annual earnings.
[30] Bartov, Givoly, and Hayn (2002) explain the non-reversal of the premium by the signaling value of meeting or beating expectations, with respect to future operating performance.

We examine whether the phenomenon of walking down expectations, which we observed for earnings forecasts (Brown, 2001; Bartov et al., 2002; Matsumoto, 2002; Richardson et al., 2004; Bradshaw et al., 2016) is also present for KPI forecasts. There is evidence showing that management engages in guiding analysts and investors about KPIs.[31] However, it is not clear ex ante whether a similar walk-down pattern should be expected for KPI expectations. On the one hand, given the value relevance of KPIs (which was also established by our tests), a failure to meet KPI forecasts is associated with a negative market response, motivating management to avoid a failure to meet the forecasted KPI. Also, research shows that KPIs are used in compensation contracts (Kaplan and Norton, 1992, 2001; Ittner, Larcker, and Rajan, 1997; Ittner and Larker, 1998b; Davila and Venkatachalam, 2004). Further, management interested in finishing the quarter “with a bang” by meeting or exceeding earnings expectations would be unwilling to send the market a mixed signal by failing to meet the contemporaneous KPI expectations. On the other hand, KPIs serve as inputs to earnings forecasts, making it sufficient for management to provide only earnings guidance to alter analysts’ KPI forecasts.

The results, untabulated, show that the relative frequency of meeting or beating KPI expectations, %MBE, relative to the *earliest* forecast for the quarter is significantly higher than 50% in each industry and in the all-industry sample (55.4% in the all-industry sample), suggesting that KPI forecasts are pessimistically biased early in the forecasted period. This is in contrast to the findings by past studies of an optimistic bias in EPS forecasts made early in the period. However, similar to the behavior of analysts’ earnings forecasts over the forecasted period, KPI forecasts exhibit a walk-down pattern during the quarter; that is, they become more pessimistic as the quarter progresses. Specifically, %MBE is significantly higher for the latest estimate than for

[31] Management guidance for KPIs in the form of forecasts is often found in media reports, earnings press releases, and the Management Discussion and Analysis section of annual reports. In the absence of a systematic database on management forecasts of KPIs, it is very difficult to quantify their prevalence.

the earliest estimate in the all-industry sample and in each industry except pharmaceuticals. While this is consistent with managers' trying to dampen analysts' forecasts in order to avoid a negative surprise at the KPI announcement, management's motivation for doing so is less clear given that the expectations as of the beginning of the quarter would be met or beaten even when no such guidance is provided.

5. Conclusion

Many firms disclose industry-specific KPIs to inform outsiders about key aspects of firm operations and performance. In this paper, we examine the information content of KPIs that are frequently forecasted by analysts and are therefore likely to be important to market participants. We find that surprises in certain KPIs, and surprises in an aggregate measure of contemporaneous KPIs that are most followed by analysts, have an economically significant association with announcement returns, after controlling for contemporaneous earnings and revenue surprises.

We provide novel evidence on analysts' use of KPI information in forming their earnings and revenue projections, and on the properties of their KPI forecasts. We find that analysts respond to KPI surprises when revising their earnings and revenue forecasts, and we find some, albeit weak, evidence that analysts who issue KPI forecasts make more accurate EPS and revenue forecasts. We provide further evidence consistent with the notion that a lack of details about how the KPI is computed and a lack of consistency over time in the KPI's computation diminish the KPI's usefulness to investors.

Not all analysts produce KPI forecasts. We show that the main factor that influences analysts to issue such forecasts is the information content of the KPI. After analyzing the properties of analysts' KPI forecasts, we find that they tend to be more accurate than earnings forecasts and they outperform random walk forecasts for both short- and long-term horizons. Finally, we find that, contrary to earnings forecasts, which were found by past research to be optimistically biased early in the forecasted period, early-in-the-period KPI forecasts display, on average, a pessimistic bias. We still find that, similar to their earnings forecasts, analysts' KPI forecasts exhibit a walk-down pattern during the quarter. We are unable, however, to attribute this pattern to management guidance, given that the initial, pessimistic, KPI forecasts for the quarter would already allow the firm to meet or beat them without the help of guidance.

We establish the incremental new information contained in multiple KPIs in a number of important industries, and we provide evidence on the properties of analyst forecasts of KPIs. In addition, our study contributes to the debate about the regulation of voluntary disclosures of nonfinancial measures by providing evidence on the quality of such disclosures (KPI disclosures are, by and large, discretionary). This evidence is relevant to policymakers who are concerned about the lack of regulation that would define relevant KPIs and assure their uniform definition across firms and consistency in measuring them over time. The findings of our study should also be of interest to company managers, investor relations departments, and financial intermediaries responsible for communicating and processing key aspects of firm operations to the investment community.

Given the incremental information content of KPI, further research on issues such as the properties of management forecasts of KPI, the incremental effect of KPI news on long-term earnings forecasts, and the degree by which insiders appear to trade on KPI news, would be worthwhile undertakings.

References

American Accounting Association (AAA), Financial Accounting Standards Committee. 2002. Recommendations on Disclosure of Nonfinancial Performance Measures. *Accounting Horizons* 16, 353–362.

Amir, E., and B. Lev. 1996. Value-Relevance of Nonfinancial Information: The Wireless Communications Industry. *Journal of Accounting and Economics* 22: 3–30.

Barron O., C. Kile, and T. O'Keefe. 1999. MD&A Quality as Measured by the SEC and Analysts' Earnings Forecasts. *Contemporary Accounting Research* 16: 75–109.

Bartov, E., D. Givoly, and C. Hayn. 2002. The Rewards to Meeting or Beating Earnings Expectations. *Journal of Accounting and Economics* 33: 173–204.

Bowen R., Davis A., and D. Matsumoto. 2002. Do Conference Calls Affect Analysts' Forecasts? *The Accounting Review 77(2): 285–316.*

Bradshaw, M., 2011. Analysts' Forecasts: What Do We Know After Decades of Work? *Working Paper*, Boston College.

Bradshaw, M, L. Lee, and K. Peterson. 2016. The Interactive Role of Difficulty and Incentives in Explaining the Annual Earnings Forecast Walkdown. *The Accounting Review* 91: 995–1021.

Bradshaw M., M. Drake, J. Myers, and L. Myers. 2012. A Re-Examination of Analysts' Superiority over Time-Series Forecasts of Annual Earnings. *Review of Accounting Studies.* 17 (4): 944–968.

Brown, L., 1993. Earnings Forecasting Research: Its Implications for Capital Markets Research. *International Journal of Forecasting* 9: 295–320.

Brown, L,. 2001. A Temporal Analysis of Earnings Surprises: Profits versus Losses. *Journal of Accounting Research* 393: 221–241.

Call, A., S. Chen, and Y. Tong. 2009. Are Analysts' Earnings Forecasts More Accurate when Accompanied by Cash Flow Forecasts? *Review of Accounting Studies* 14: 358–391.

Chapman, K. and J. Green. 2015. Analysts' Influence on Firm's Voluntary Disclosure. Working Paper.

Companies Act, 2006. UK Companies Act 2006, London, UK. Available at http://www.legislation.gov.uk/ukpga/2006/46/pdfs/ukpga_20060046_en.pdf

Curtis, A., R. Lundholm, and S. McVay. 2014. Forecasting Sales: A Model and Some Evidence from the Retail Industry. *Contemporary Accounting Research* 31: 581–608.

Davila, A., and M. Venkatachalam. 2004. The Relevance of Nonfinancial Performance Measures for CEO Compensation: Evidence from the Airline Industry. *Review of Accounting Studies* 9: 443–464.

DeFond, M. and M. Hung. 2003. An Empirical Analysis of Analysts' Cash Flow Forecasts. *Journal of Accounting and Economics* v. 35, 73–100.

Easterwood, J.C. and S. R. Nutt. 1999. Inefficiency in Analysts' Earnings Forecasts: Systematic Miscreaction or Systematic Optimism? *Journal of Finance*, 5: 1777–1797.

Ehinger, A., J. A. Lee, B. Stomberg, and E. Towery. 2017. Let's Talk About Tax: The Determinants and Consequences of Income Tax Mentions During Conference Call. Working Paper.

Elzahar H., K. Hussainey, F. Mazzi, and I. Tsalavoutas. 2015. Economic Consequences of Key Performance Indicators' Disclosure Quality. *International Review of Financial Analysis*, 39: 96–112.

Ernst & Young. 2015. Tomorrow's Investment Rules 2.0. Available at: http://www.ey.com/Publication/vwLUAssets/EY-tomorrows-investment-rules-2/$FILE/EY-tomorrows-investment-rules-2.0.pdf.

Ertimur, Y., J. Livnat, and M. Martikainen. 2003. Differential Market Reactions to Revenue and Expense Surprises. *Review of Accounting Studies* 8: 185–211.

Ertimur, Y., and S. Stubben. 2005. Analysts' Incentives to Issue Revenue and Cash Flow Forecasts. Working Paper.

European Union (EU) Accounting and Modernisation Directive, 2003. *Directive 2003/51/EC of the European Parliament and of the Council*. Available at http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2003:178: 0016:0022:EN:PDF

Financial Accounting Standards Board (FASB). 2001. *Business and Financial Reporting: Challenges from the New Economy*.

Francis, J., K. Schipper and L. Vincent. 2003. The Relative and Incremental Information Content of Alternative (to Earnings) Performance Measures. *Contemporary Accounting Research* 20: 121–164.

Fried D. and D. Givoly. 1982. Financial Analysts' Forecasts of Earnings: A Better Surrogate for Market Expectations. Journal of Accounting and Economics 4 (2): 85–107.

Gaertner, J. 2016. Panel Review: Use of guidance and Key Performance Indicators (KPIs). *National Investor Relations Institute*. January 9. Available at: http://nirisv.org/blog/panel-review-use-of-guidance-and-key-performance-indicators-kpis/

Garber, J. 2017. Nordstrom's Same-Store Sales Miss. *Business insider*. May 11. Available at: http://www.businessinsider.com/norstrom-earnings-q1-2018-2017-5.

Givoly D., and J. Lakonishok. 1979. The Information Content of Financial Analysts' Forecasts of Earnings. *Journal of Accounting and Economics* 1: 165–185.

International Accounting Standards Board (IASB), 2010. *IFRS Practice Statement. Management Commentary: A framework for presentation*. International Accounting Standards Board

Foundation, London, UK.

Hayn, C. 1995. The Information Content of Losses. *The Accounting Review* 20 (2): 125–153.

Healy. P., A. Hutton, and K. Palepu. 1999. Stock Performance and Intermediation Changes Surrounding Sustained Increases in Disclosure. *Contemporary Accounting Research* 16 (3): 485–520.

Ittner, C., D. Larcker, and M. Rajan. 1997. The Choice of Performance Measures in Annual Bonus Contracts. *The Accounting Review* 72: 231–255.

Ittner, C., and D. Larcker. 1998a. Are Nonfinancial Measures Leading Indicators of Financial Performance? An Analysis of Customer Satisfaction. *Journal of Accounting Research* 36: 1–35.

Ittner, C., and D. Larcker. 1998b. Innovations in Performance Measurement: Trends and Research Implications. *Journal of Management Accounting Research* 10: 205–238.

Kaplan, R., and D. Norton. 1992. The Balanced Scorecard—Measures That Drive Performance. *Harvard Business Review* 70: 71–79.

Kaplan, R., and D. Norton. 2001. Transforming the Balanced Scorecard from Performance Measurement to Strategic Management. *Accounting Horizons* 15: 87–104.

Kasznik, R. and M. McNichols. 2002. Does Meeting Expectations Matter? Evidence from Analyst Revisions and Share Prices. *Journal of Accounting Research* 40 (3): 727–759.

Kothari, S., E. So, and R. Verdi. 2016. Analysts' Forecasts and Asset Pricing: A Survey. *The Annual Review of Financial Economics* 8: 197–219.

Langer, M. 2006. Comparability of Sustainability Reports. A Comparative Content Analysis of Austrian Sustainability Reports. 581–602.

Lev, B. 2001. Intangibles: Measurement, Management, and Reporting. *Brookings Institution*, Washington DC.

Lopez, T., and L. Rees. 2000. The Effect of Meeting Analysts' Forecasts and Systematic Positive Forecast Errors on the Information Content of Unexpected Earnings. *Journal of Accounting, Auditing & Finance* 17 (2): 155–184.

Lundholm, R. J., and R. G. Sloan. 2004. *Equity valuation and analysis with eVal*. McGraw-Hill New York, NY.

Matsumoto, D., 2002. Management's Incentives to Avoid Negative Earnings Surprises. *The Accounting Review* 77: 483–513.

O'Brian, P. C. 1988. Analysts' Forecasts as Earnings Expectations. Journal of Accounting and Economics (10): 53–83.

Pae, J., S. Wang, and C. Yoo. 2007. Do Analysts Who Issue Cash flow Forecasts Predict More Accurate Earnings? Working paper.

Patatoukas, P., R. Sloan, and J. Zha. 2015. On the Pricing of Mandatory DCF Disclosures: Evidence from Oil and Gas Royalty Trusts. *The Accounting Review* 90: 2449–2482.

Rajgopal, S., T. Shevlin, and M. Venkatachalam. 2003a. Does the Stock Market Fully Appreciate the Implications of Leading Indicators for Future Earnings? Evidence from Order Backlog. *Review of Accounting Studies* 8 (4): 461–492.

Rajgopal, S., M. Venkatachalam, and S. Kotha. 2003b. The Value Relevance of Network Advantages: The Case of E–Commerce Firms. *Journal of Accounting Research* 41 (1): 135–162.

Ramnath S., S. Rock, and P. Shane. 2008. Financial Analysts' Forecasts and Stock Recommendations: a Review of the Research. *Foundations and Trends in Finance* 2(4): 311–321.

Richardson S., S. Teoh, and P. Wysocki. 2004. The Walk-Down to Beatable Analyst Forecasts: The Role of Equity Issuance and Insider Trading Incentives. *Contemporary Accounting Research* 21: 885–924.

Schilit, H. M., and J. Perler. 2010. *Financial Shenanigans*, Third Edition. McGraw-Hill New York, NY.

Schipper K. 1991. Analysts' Forecasts. *Accounting Horizons* 5:105–21.

Securities and Exchange Commission (SEC). 2003. *Interpretation: Commission Guidance Regarding Management's Discussion and Analysis of Financial Condition and Results of Operations*. Available at https://www.sec.gov/rules/interp/33-8350.htm

Securities and Exchange Commission (SEC). 2008. *Final report of the advisory committee on improvements to financial reporting to the United States Securities and Exchange Commission*. Available at http://www.sec.gov/about/offices/oca/acifr/acifr-finalreport.pdf

Securities and Exchange Commission (SEC). 2016. *Business and Financial Disclosure Required by Regulation S-K*. Available at https://www.sec.gov/rules/concept/2016/33-10064.pdf

Simpson, A. 2010. Analysts' Use of Nonfinancial Information Disclosures. *Contemporary Accounting Research* 27 (1): 249–288.

Trueman, B., F. Wong, and X. J. Zhang. 2001. The Eyeballs Have It: Searching for the Value in Internet Stocks. *Journal of Accounting Research* (38): 137–162.

Turner, N. 2016. Gap's March Sales Make U.S. Retailer S&P 500 Laggard. *Bloomberg*. April 8. Available at: http://www.bloomberg.com/news/articles/2016-04-08/gap-s-march-sales-make-u-s-retailer-s-p-500-laggard-chart

Wald, A. 1943. Tests of Statistical Hypotheses Concerning Several Parameters When the Number of Observations Is Large. *Transactions of the American Mathematical Society* 54: 426–482.

Appendix A: Variable Definitions and KPI Descriptions

Variable	Descriptions
A. Definition of Variables	
AB_TACCR	The absolute value of total accruals in quarter $t-1$ deflated by beginning total assets.
B/M	The book-to-market ratio at the end of the fiscal quarter.
CAR(-1,+1)	The cumulative abnormal return over the 3-day window centered on the announcement date, where daily abnormal returns are raw stock returns minus the market value-weighted return.
CHANGE_COMP	An indicator variable that equals 1 in the year in which a change from the previous year in how the firm calculates SSS occurs, and 0 otherwise.
DISTRESS	An indicator variable that equals 1 when the Altman Z-score is below 1.81 (an indication of distress) at beginning of quarter t, and 0 otherwise.
D_KPI_Forecasts	$D\_KPI\_Forecast_{mjt}$ is the indicator variable that equals 1 if analyst *m* issues a forecast of at least one KPI for firm *j* quarter *t*, and 0 otherwise.
EPS Forecast Revision	Analyst EPS forecast revision around the earnings announcement date, calculated as the median analyst's EPS forecast for firm *j* quarter *t*+1 issued within 10 days after the quarter *t* earnings announcement date minus the median analyst's EPS forecast for firm *j* quarter *t*+1 issued within 90 days before the quarter *t* earnings announcement date, scaled by the stock price at the end of quarter *t*, and multiplied by 100.
Forecast Error	The actual value announced by the company minus the analyst forecast, scaled by the average absolute value of the two variables. The analyst forecast is calculated as the median across all analyst forecasts made either early or late in the quarter (depending on the analysis). For KPIs that reflect expenses, costs, or losses, we multiply the forecast error by −1.
INF_KPI	A measure of the information content of a KPI. It is the explanatory power (R^2) of the KPI surprise, represented by the variable $SURP^{rank}\_KPI$ in Regression (1), relative to the total power of that regression to explain variations in its dependent variable, $CAR(-1,+1)$. The decomposition of the regression R^2 is based on Shapley's decomposition procedure (Shapley, 1953).
LOSS	An indicator that equals 1 if income before extraordinary items is negative in quarter $t-1$, and 0 otherwise.
LOW_DISCLOSURE	An indicator variable that equals 1 if the annual disclosure in the year to which the quarter belongs does not provide computation details of SSS, and 0 otherwise.
Ln_of_SSS_Mentions	The natural logarithm of the number of times SSS is mentioned in the earnings press release.
Relative Accuracy of EPS Forecast	Analyst's EPS forecast accuracy relative to other analysts' EPS forecasts for the same firm and quarter. Calculated as ($Avg.\ EPS\ Forecast\ Error_{j,t}$ – $EPS\ Forecast\ Error_{mjt}$) ÷ $STD\ EPS\ Forecast\ Error_{jt}$, where $EPS\ Forecast\ Error_{mjt}$ is the analyst *m*'s absolute EPS forecast error (actual EPS minus analyst *m*'s earliest-in-the-

	quarter forecast (within 90 days before the earnings announcement for the quarter) for firm *j* quarter *t*; *Avg. EPS Forecast Error*$_{jt}$ is the average absolute forecast errors across all analysts' EPS forecasts for firm *j* quarter *t*; and *STD EPS Forecast Error*$_{jt}$ is the standard deviation of the absolute forecast errors across all analysts' EPS forecasts for firm *j* quarter *t*.
Relative Accuracy of REV Forecast	Analyst's revenue forecast accuracy relative to other analysts' revenue forecasts for the same firm and quarter. Calculated similar to *Relative Accuracy of EPS Forecast*.
REV Forecast Revision	Analyst revenue forecast revision around the earnings announcement date, calculated as the median analyst's revenue forecast for firm *j* quarter *t*+1 revenue issued within 10 days after the quarter *t* earnings announcement date minus the median analyst's revenue forecast for firm *j* quarter *t*+1 revenue issued within 90 days before the quarter *t* earnings announcement date, scaled by the market value of equity at the end of quarter *t*, and multiplied by 100.
SIZE	The natural logarithm of market value of equity at the beginning of the fiscal quarter.
$SURP^{rank}\_EPS$	The difference between the actual EPS and the analyst consensus, scaled by the stock price at the end of the fiscal quarter, and ranked into terciles with observations in the bottom, middle, and top terciles assigned a rank of 0, 0.5, and 1, respectively. Analyst consensus is calculated as the median of the most recent forecasts of individual analysts. Forecasts older than 90 days are excluded from the consensus.
SURP_KPI	The surprise measure for a given firm–quarter–KPI. The surprise is calculated as the difference between the actual KPI announced by the company and the analyst consensus forecast (actual – forecast), scaled by the average absolute value of the two variables. Analyst consensus is calculated as the median of the most recent forecasts of individual analysts. Forecasts older than 90 days are excluded from the consensus. For KPIs that reflect expenses or negative developments (i.e., cost per seat miles (CPA), maintenance CapEx (MCX), lease operating expense (LOE), exploration expense (EXP), production tax (PTX), production expense (PEX), and number of stores closed/relocated (NSC)), we multiply the surprise by −1.
$SURP^{rank}\_KPI$	The ranked surprise measure for a given firm–quarter–KPI. $SURP^{rank}\_KPI_{iit}$ for a firm *j* that belongs to industry *i* in quarter *t* is calculated by ranking $SURP\_KPI_{iit}$ across all firms in industry *i* in quarter *t*, and assigning them into terciles with observations in the bottom, middle, and top terciles assigned a rank of 0, 0.5, and 1, respectively.
$SURP^{rank}\_3\text{-}KPI$	Surprise KPI score for a given firm–quarter. $SURP^{rank}\_3\text{-}KPI_{iit}$ for a firm *j* that belongs to industry *i* in quarter *t* is calculated as the average of *SURP_KPI* for firm *j* in quarter *t* across the three KPIs that are most frequently forecasted in industry *i*. The most frequently forecasted KPIs in the industry are those that have the most firm–quarters with both actual value and at least one forecast available. Surprise scores are then ranked across all firms in industry *i* in quarter *t*, and assigned into terciles with observations in the bottom, middle, and top terciles assigned a rank of 0, 0.5, and 1, respectively.
$SURP^{rank}\_REV$	The difference between the actual revenue and the analyst consensus, scaled by the market value of equity at the end of the fiscal quarter, and ranked into terciles with observations in the bottom, middle, and top terciles assigned a rank of 0, 0.5, and 1, respectively. Analyst consensus is calculated as the median of the most recent

	forecasts of individual analysts. Forecasts older than 90 days are excluded from the consensus.
VOL_EARN	The coefficient of the variation of earnings, computed as their standard deviation over the most recent eight quarters, deflated by their absolute mean value over the same period.

B. Description of KPI

Airlines

ASM	Available Seat Miles. Passenger-carrying capacity of the flights flown during the period measured in miles. The total number of seats available multiplied by the total number of miles traveled.
RPM	Revenue Passenger Miles. Total passenger traffic measured in miles. Calculated by multiplying the total number of revenue-paying passengers by the distance they travel.
PLF	Passenger Load Factor. The number of revenue passenger miles traveled as a percentage of the available seat miles flown.
CPA	Operating expense per available seat mile.
RASM	Passenger revenue per available seat mile.

Oil & Gas

DCF	Distributable Cash Flow. This is the cash flow available to be paid to common shareholders.
OPD	Oil Production Per Day. Average oil production per day during the period. Measured in barrels of oil equivalent (BOE) and considered to be upstream operations.
TPD	Total Production Per Day. Average daily production of oil, gas, and natural gas liquids (NGLs) production expressed in barrels of oil equivalent (BOE) and considered to be upstream operations.
GPD	Gas Production Per Day. Average gas production per day during the period. Measures in cubic feet or equivalent and considered to be upstream operations.
RPO	Realized Price Oil. The average price received (as opposed to the average market price) per unit during the period. The price is expressed in dollars per barrel of oil.
RPG	Realized Price Gas. The average price received (as opposed to the average market price) per unit during the period. The price is expressed in dollars per 1,000 cubic feet.
EBX	An abbreviation of *EBITDAX*: Earnings Before Interest Taxes Depreciation Amortization and Exploration Expense.
NPP	Natural Gas Liquids Production Per Day. Average natural gas liquids (NGLs) production per day during the period. Measured in barrels of oil equivalent and considered to be upstream operations.
MCX	Maintenance CapEx. The investments required by a company to maintain existing physical assets used for day-to-day operations.

LOE	Lease Operating Expense. The costs of maintaining and operating property and equipment on a producing oil and gas lease.
EXP	Exploration Expense. Costs incurred in identifying areas to assess for potential oil and gas reserves, including exploration drills and well installations. Considered to be upstream operations.
TPP	Total Production Per Day. The daily average production of oil, gas, and natural gas liquids (NGLs) per day. This is expressed in barrels of oil equivalent (BOE) per day and is considered to be upstream operations.
PTX	Production Tax.
RZP	Realized Price. The average price received (as opposed to the average market price) per barrel of oil equivalent (BOE) during the period.
PEX	Production Expense.
	Pharmaceutical
SAL	Pharmaceutical Sales. The revenue associated with an individual pharmaceutical drug unit's products.
	Retail
SSS	Same-Store Sales. A percentage sales growth for retail stores (or restaurants) that have been open for more than one year (or over another time period defined by the reporting firm).
NOS	Number of Stores. Total number of open stores.
FLS	Floor Space. Total floor space of company stores (in square feet).
NOO	Number of stores Opened during the period.
RES	Retail Sales. Revenue from retail sales (i.e., the number excludes wholesale sales).
NAS	Net Sales per Average Square Foot. Net sales per average square foot of retail premises.
NSC	Number of Stores Closed/Relocated. Total number of stores closed or relocated during the period.

Table 1. Sample Construction

	No. of firms	No. of firm–quarters	No. of KPI–firm–quarters	No. of individual analysts' KPI forecasts
Industry-specific KPI forecasts available on I/B/E/S, excluding those of financial services and utilities firms	1,215	18,498	46,067	615,635
Less:				
Missing KPI actuals	(410)	(8,650)	(21,834)	(171,147)
Stale KPI forecasts (issued more than 90 days before the release of actual)	(43)	(1,415)	(3,292)	(289,794)
Missing EPS forecasts	(87)	(1,861)	(3,436)	(23,945)
Missing CRSP stock returns	-	(5)	(20)	(144)
KPI with less than 100 firm–quarter observations with full data	(16)	(95)	(467)	(1,421)
Final sample	659	6,472	17,018	129,184

Table 2. Sample Distribution

Panel A: Distribution of Quarterly KPI by Industry

	Airlines	Oil & Gas	Pharmaceutical	Retail
No. of firms	16	376	72	195
No. of firm–quarters	147	2,651	598	3,076
No. of industry-specific KPIs (in 2016)	5	15	1	7
No. of KPI–firm–quarters	655	10,729	598	5,036
No. of analyst KPI forecasts	3,462	84,556	5,604	35,562
Avg. no. of forecasts per KPI–firm–quarter	5.3	7.9	9.4	7.1
Mean firm-size ($ millions)	9,876	10,598	34,327	9,572
Median firm-size	4,559	2,527	12,741	2,008
Mean B/M	0.5054	0.6281	0.2613	0.4011
Median B/M	0.3324	0.5517	0.2379	0.3387

Panel B: Distribution of Quarterly KPI Forecasts by Forecast Formation Year

	Airlines	Oil & Gas	Pharmaceutical	Retail	All Industries
2005	-	-	106	-	106
2006	-	-	1,276	-	1,276
2007	-	-	1,428	244	1,672
2008	-	-	1,215	16	1,231
2009	-	-	1,097	1,645	2,742
2010	-	-	147	4,684	4,831
2011	-	-	0	3,854	3,854
2012	-	213	48	3,307	3,568
2013	267	7,162	63	3,841	11,333
2014	1,314	26,616	121	7,576	35,627
2015	1,479	35,213	56	6,742	43,490
2016	402	15,352	47	3,653	19,454
Total	3,462	84,556	5,604	35,562	129,184

Panel C: Distribution of Quarterly KPIs by KPI Measure

KPI	Description	No. of firm–quarter obs.	No. of firms	No. of distinct analysts	No. of analyst forecasts of KPI
Airlines					
ASM	Available Seat Miles	140	15	19	723
RPM	Revenue Passenger Miles	134	15	18	774
PLF	Passenger Load Factor	131	16	20	631
CPA	Cost per Seat Miles	130	15	17	617
RASM	Revenue per Available Seat Mile	120	13	17	717
Oil & Gas					
DCF	Distributable Cash Flow	1,342	231	267	6,178
OPD	Oil Production Per Day	975	125	188	8,797
TPD	Total Production Per Day	967	127	228	11,881
GPD	Gas Production Per Day	953	122	180	8,909
RPO	Realized Price Oil	807	114	145	9,198
RPG	Realized Price Gas	793	112	143	8,285
EBX	EBITDAX	754	110	149	7,030
NPP	Natural Gas Prod. Per Day	685	90	150	5,219
MCX	Maintenance CapEx	674	148	144	1,760
LOE	Lease Operating Expense	620	90	134	4,982
EXP	Exploration Expense	611	80	173	3,379
TPP	Total Production Per Day	582	108	138	3,505
PTX	Production Tax	421	78	111	3,548
RZP	Realized Price	331	71	56	1,241
PEX	Production Expense	214	51	62	644
Pharmaceutical					
SAL	Pharmaceutical Sales	598	72	372	5,604
Retail					
SSS	Same-Store Sales' Growth Rate	2,829	177	557	28,759
NOS	Number of Stores	880	115	168	3,589
FLS	Floor Space	333	67	92	1,016
NOO	Number of Stores Opened	329	81	71	536
RES	Retails Sales	306	60	124	908
NAS	Net Sales per Average Sq. Foot	193	60	59	538
NSC	Num. of Stores Closed/Relocated	166	46	40	216

The table reports the distribution of KPIs by industry, year, and KPI measure for the quarterly KPI sample. Descriptions of KPIs are provided in Appendix A.

Table 3. Accuracy and Bias of KPI Forecasts

KPI	Description	N	Actual		Forecast Error - based on the *latest forecasts* for the quarter		Forecast Error - based on the *earliest forecasts* for the quarter	
			Mean Actual	Median Actual	Median Forecast Error**	Median Absolute Forecast Error	Median Forecast Error**	Median Absolute Forecast Error
	Average across all Median KPIs	28	N.A.	N.A.	0.7%	11.9%	0.8%	12.5%
	Average across all firm–quarter KPIs	17,018	N.A.	N.A.	0.1%	8.3%	0.1%	9.3%
	*Average EPS across firm–quarters**	17,018	0.34	0.23	2.5%	17.0%	1.5%	21.4%
Airlines								
ASM	Available Seat Miles	140	25,956	10,354	0.0%	0.5%	0.2%	0.7%
RPM	Revenue Passenger Miles	134	22,142	8,770	0.0%	1.1%	0.2%	1.3%
PLF	Passenger Load Factor	131	82.95	83.10	0.0%	0.0%	0.0%	0.2%
CPA	Cost per Seat Miles	130	1.57	0.11	0.1%	3.4%	0.2%	3.6%
RASM	Revenue per Available Seat Mile	120	1.90	0.13	3.3%	8.3%	2.9%	8.4%
Oil & Gas								
DCF	Distributable Cash Flow	1342	103	48	2.7%	8.1%	2.6%	8.4%
OPD	Oil Production Per Day	975	278	16	0.2%	3.6%	0.1%	4.0%
TPD	Total Production Per Day	967	1193	49	0.8%	2.6%	1.0%	3.0%
GPD	Gas Production Per Day	953	642	80	−0.2%	5.1%	−0.4%	5.4%
RPO	Realized Price Oil	807	67	67	−1.1%	4.7%	−2.0%	5.9%
RPG	Realized Price Gas	793	2	2	−9.3%	13.7%	−11.1%	16.0%
EBX	EBITDAX	754	430	98	−3.8%	13.1%	−5.6%	14.6%
NPP	Natural Gas Prod. Per Day	685	57	8	1.8%	7.5%	2.3%	7.9%
MCX	Maintenance CapEx	674	16	7	4.0%	25.0%	4.5%	24.5%
LOE	Lease Operating Expense	620	53	17	6.5%	11.8%	6.7%	11.4%
EXP	Exploration Expense	611	76	7	7.2%	50.0%	7.5%	50.3%
TPP	Total Production Per Day	582	919	274	0.0%	3.0%	0.1%	3.4%
PTX	Production Tax	421	15	6	6.4%	11.8%	8.3%	14.1%
RZP	Realized Price	331	47	43	−0.5%	6.3%	−0.8%	7.3%
PEX	Production Expense	214	113	38	5.5%	14.3%	5.2%	15.1%
Pharmaceutical								
SAL	Pharmaceutical Sales	598	292	152	1.4%	4.9%	1.4%	5.2%
Retail								

KPI	Description	N	Actual		Forecast Error - based on the *latest forecasts* for the quarter		Forecast Error - based on the *earliest forecasts* for the quarter	
			Mean Actual	Median Actual	Median Forecast Error**	Median Absolute Forecast Error	Median Forecast Error**	Median Absolute Forecast Error
SSS	Same-Store Sales' Growth Rate	2,829	1.38	1.70	0.0%	33.3%	1.9%	39.1%
NOS	Number of Stores	880	1634	853	0.0%	0.4%	0.0%	0.4%
FLS	Floor Space	333	48	6	−0.5%	2.7%	−0.4%	2.6%
NOO	Number of Stores Opened	329	23	10	0.0%	22.2%	0.0%	22.2%
RES	Retails Sales	306	4722	604	0.2%	1.9%	0.1%	2.0%
NAS	Net Sales per Average Sq. Foot	193	254	100	−0.3%	6.3%	−0.2%	6.3%
NSC	Num. of Stores Closed/Relocated	166	11	4	−4.9%	66.7%	−1.7%	66.7%

*Computed for firm–quarter–KPI observations.

** The sign of the forecast errors for KPIs that represent costs, expenses, or losses (specifically, CPA, MCX, LOE, EXP, PTX, PEX, and NSC) is flipped so that a negative (positive) forecast error for all KPIs connotes optimistic (pessimistic) bias.

The table reports means and medians of actual reported KPIs, median KPI forecast errors (actual minus forecast), and median absolute KPI forecast errors. Variable definitions are provided in Appendix A.

Table 4. Market Reaction to KPI Surprises:

Summary Results from Regression (1):

$$CAR(-1,+1)_{jt} = \alpha_1 + \beta_1\ SURP^{rank}\_KPI\ /\ SURP^{rank}\_3\text{-}KPI_{jt} + \beta_2\ SURP^{rank}\_EPS_{jt} + \beta_3\ SURP^{rank}\_REV_{jt} + \varepsilon_{jt}$$

Panel A: Market Reaction to (i) KPI Surprises and (ii) KPI and Earnings Surprises, by KPI

KPI	Description	N	$SURP^{rank}$_ KPI (x100)	Adj.R^2	$SURP^{rank}$_ KPI (x100)	$SURP^{rank}$_ EPS (x100)	Adj.R^2
Airlines							
ASM	Available Seat Miles	140	4.36***	5.7%	3.87**	5.02***	12.8%
RPM	Revenue Passenger Miles	134	3.28**	2.9%	2.84**	4.89**	9.4%
PLF	Passenger Load Factor	131	−0.33	−0.7%	−0.90	5.63**	8.3%
CPA	Cost per Seat Miles	130	−1.82	0.2%	−1.93	4.92***	7.0%
RASM	Revenue per Available Seat Mile	120	−1.26	−0.4%	−1.04	4.43**	4.9%
Oil & Gas							
DCF	Distributable Cash Flow	1,342	1.96***	1.6%	1.65***	1.76***	2.9%
OPD	Oil Production Per Day	975	2.08**	0.4%	1.56*	6.68***	5.2%
TPD	Total Production Per Day	967	0.59	−0.1%	0.07	6.73***	5.1%
GPD	Gas Production Per Day	953	0.11	−0.1%	0.04	7.02***	0.051
RPO	Realized Price Oil	807	0.99	0.0%	0.76	7.47***	5.0%
RPG	Realized Price Gas	793	1.69 *	0.1%	0.94	7.63***	5.3%
EBX	EBITDAX	754	4.07***	2.1%	2.89***	6.28***	7.0%
NPP	Natural Gas Prod. Per Day	685	0.62	−0.1%	0.32	6.13***	4.3%
MCX	Maintenance CapEx	674	0.64	0.0%	0.57	2.24***	1.4%
LOE	Lease Operating Expense	620	−0.10	−0.2%	−0.44	6.59***	3.9%
EXP	Exploration Expense	611	3.84***	2.5%	2.93***	5.93***	8.5%
TPP	Total Production Per Day	582	3.35***	1.2%	2.52***	5.76***	4.8%
PTX	Production Tax	421	0.13	−0.2%	0.23	9.27***	7.1%
RZP	Realized Price	331	2.60***	0.5%	2.02 **	6.11**	4.5%
PEX	Production Expense	214	2.51	0.2%	1.57	6.08**	3.8%
Pharmaceutical							
SAL	Pharmaceutical Sales	598	1.89***	1.3%	1.65**	4.24***	8.2%
Retail							
SSS	Same-Store Sales' Growth Rate	2,448*	8.15***	10.5%	5.88***	7.62***	19.3%
NOS	Number of Stores	880	−0.47	−0.1%	−0.45	9.85***	16.4%
FLS	Floor Space	333	−0.43	−0.3%	−0.73	9.37***	14.3%
NOO	Number of Stores Opened	329	−1.23	0.0%	−1.27	9.99***	18.5%
RES	Retails Sales	306	4.75***	3.1%	3.37**	7.83***	12.2%
NAS	Net Sales per Average Sq. Foot	193	2.87	0.5%	1.93	9.37***	10.9%
NSC	Num. of Stores Closed/Relocated	166	1.20	−0.3%	1.34	11.21***	24.3%

*This is the number of quarterly SSS observations for quarters in which no monthly SSS were released by the firm.

Panel B: Market Reaction to KPI, Earnings, and Revenue Surprises, by KPI

KPI	Description	N	$SURP^{rank}$_KPI (x100)	$SURP^{rank}$_EPS (x100)	$SURP^{rank}$_REV (x100)	Adj.R^2
Airlines						
ASM	Available Seat Miles	140	3.66***	4.37**	2.16	13.4%
RPM	Revenue Passenger Miles	134	2.49*	4.11**	2.34	10.2%
PLF	Passenger Load Factor	131	−0.86	4.42**	3.27	10.6%
CPA	Cost per Seat Miles	130	−1.58	4.42**	1.87	7.2%
RASM	Revenue per Available Seat Mile	120	−1.21	3.49*	2.48	5.7%
Oil & Gas						
DCF	Distributable Cash Flow	1,323	1.65**	1.74***	0.50	3.0%
OPD	Oil Production Per Day	963	1.40	6.45***	1.10	5.1%
TPD	Total Production Per Day	950	−0.01	6.67***	0.64	5.0%
GPD	Gas Production Per Day	938	−0.27	6.79***	1.27	5.0%
RPO	Realized Price Oil	804	0.44	7.42***	0.58	4.9%
RPG	Realized Price Gas	790	0.95	7.58***	0.54	5.3%
EBX	EBITDAX	751	2.68**	6.24***	0.57	6.9%
NPP	Natural Gas Prod. Per Day	685	0.17	5.90***	1.75***	4.5%
MCX	Maintenance CapEx	663	0.60	1.99***	0.83	1.3%
LOE	Lease Operating Expense	619	−0.36	6.50***	0.62	3.7%
EXP	Exploration Expense	603	2.88***	5.87***	0.08	8.2%
TPP	Total Production Per Day	582	2.42***	5.65***	1.23	4.8%
PTX	Production Tax	421	0.23	9.27***	0.00	6.9%
RZP	Realized Price	330	2.03 **	6.13**	−0.21	4.2%
PEX	Production Expense	214	1.72	5.82*	1.20	3.5%
Pharmaceutical						
SAL	Pharmaceutical Sales	596	1.03	3.65***	2.38***	10.2%
Retail						
SSS	Same-Store Sales' Growth Rate	2,431*	4.92***	7.19***	1.88***	19.4%
NOS	Number of Stores	880	−0.90	8.04***	5.19***	19.8%
FLS	Floor Space	333	−1.19	7.50***	5.05***	17.5%
NOO	Number of Stores Opened	329	−1.13	8.71***	3.68**	20.3%
RES	Retails Sales	306	1.68	6.95***	4.66***	14.6%
NAS	Net Sales per Average Sq. Foot	193	1.22	6.19**	8.29***	17.6%
NSC	Num. of Stores Closed/Relocated	166	1.20	10.31***	3.07*	25.5%

*This is the number of quarterly SSS observations for quarters in which no monthly SSS were released by the firm.

Panel C: Market Response to KPI, Earnings, and Revenue Surprises by Industry

Industry	N	$SURP^{rank}$_ *3-KPI* (x100)	$SURP^{rank}$_ *EPS* (x100)	$SURP^{rank}$_ *REV* (x100)	Adj.R^2
Airlines	142	2.60**	3.92**	2.40	10.2%
Oil & Gas	2,336	1.30**	3.94***	0.79**	3.9%
Pharmaceutical	596	1.03	3.65***	2.38***	10.2%
Retail	2,673	3.70***	7.39***	2.82***	18.4%
All Industries	5,707	2.72***	5.44***	2.21***	10.6%

The table reports the results of Regression (1) in which announcement window abnormal returns, *CAR(−1,+1)*, are regressed on surprises in Key Performance Indicators ($SURP^{rank}$_*KPI*), earnings surprises ($SURP^{rank}$_*EPS*), and revenue surprises ($SURP^{rank}$_*REV*). The sign of the forecast errors for KPIs that represent costs, expenses, or losses (specifically, CPA, MCX, LOE, EXP, PTX, PEX, and NSC) is flipped so that a negative (positive) forecast error for all KPIs connotes optimistic (pessimistic) bias. None of these KPIs were among the three most followed in the industry ("3-KPI"). In Panel A, the independent variables are $SURP^{rank}$_*KPI* in the first two columns, and $SURP^{rank}$_*KPI* and $SURP^{rank}$_*EPS* in the last three columns. In panel B, the independent variables are $SURP^{rank}$_*KPI*, $SURP^{rank}$_*EPS*, and $SURP^{rank}$_*REV*. Sample size is smaller in this analysis for some KPIs because observations without revenue forecasts are excluded. In Panel C, the independent variables are $SURP^{rank}$_*3-KPI* (the average ranked surprise across the three most followed KPIs in the industry), $SURP^{rank}$_*EPS*, and $SURP^{rank}$_*REV*. Standard errors are clustered by year–quarter. The *SURP* variables are the forecast errors based on the median across individual analysts of their most recent forecast at the announcement date. Variable definitions are provided in Appendix A. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively, based on two-tailed tests.

Table 5. Forecast Revision Tests: Summary Results for Regression (2):

$$\text{EPS/REV Forecast Revision}_{jt+1} = \alpha_1 + \beta_1\, SURP^{rank}\_3\text{-}KPI_{jt} + \beta_2\, SURP^{rank}\_EPS_{jt} + \beta_3\, SURP^{rank}\_REV_{jt} + \varepsilon_{jt}$$

Panel A: The Dependent Variable is Earnings Forecast Revision

	$SURP^{rank}\_3\text{-}KPI$	$SURP^{rank}\_EPS$	$SURP^{rank}\_REV$	N	Adj.R^2
Airlines	0.200*	0.040	0.110	115	3.7%
Oil & Gas	0.057	0.445***	0.063	1,623	6.5%
Pharmaceutical	0.031	0.040*	0.079**	410	2.3%
Retail	0.138***	0.089**	0.090**	2,404	3.8%
All Industries	0.089***	0.175***	0.102***	4,552	4.5%

Panel B: The Dependent Variable is Revenue Forecast Revision

	$SURP^{rank}\_3\text{-}KPI$	$SURP^{rank}\_EPS$	$SURP^{rank}\_REV$	N	Adj.R^2
Airlines	0.362	−0.137	0.075	115	−1.2%
Oil & Gas	0.053	0.251**	1.153***	1,615	8.1%
Pharmaceutical	0.078**	0.009	0.205***	410	15.5%
Retail	0.475***	0.055	0.770***	2,400	10.2%
All Industries	0.260***	0.098**	0.847***	4,540	8.8%

The table reports the results of regressions of EPS or REV forecast revisions around the earnings announcement date on the KPI surprise score, $SURP^{rank}\_3\text{-}KPI$, earnings surprises ($SURP^{rank}\_EPS$), and revenue surprises ($SURP^{rank}\_REV$). Standard errors are clustered by year–quarter. Variable definitions are provided in Appendix A. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively, based on two-tailed tests.

Table 6.
Descriptive Statistics on the Frequency of Disclosure of the Definition of Quarterly SSS, its Year-to-Year Consistency, and its Uniformity across Firms

Panel A: Frequency of Disclosure on the Computational Details and the Consistency in the SSS Computation

Number of Firm–Quarters			Number of Unique Firms		
SSS computation details are disclosed in the MD&A in all years	SSS computation details are not disclosed in all years	Total	SSS computation details are disclosed in the MD&A in all years	SSS computation details are not disclosed in all years	Total
2,429	400	2,829	160	59	177
SSS computation is the same as last year	SSS computation changed from last year		SSS computation is always the same	SSS computation changed in at least one quarter	
2,207	222	2,429	154	16	160

Panel B: Uniformity in the Definition of "Same Store" Across Firms

Minimum number of months of operations (in months) Required of a store to be defined as "Same Store"	12	13	14	15	16	18	19	19.5	24	Total
# of Firm–Quarters	1,109	525	231	275	23	136	27	7	96	2,429
%	46%	22%	10%	11%	1%	6%	1%	0%	4%	100%

Table 7.
Effect of Lack of Computational Details of SSS or Change in the Computation of SSS on the Information Content of SSS News

Panel A: Lack of Computational Details

	CAR [−1,+1] (Regression 3a)		EPS Forecast Revision (Regression 3b)	
SURP^{rank}*_SSS*	0.048	***	0.683	***
LOW_DISCLOSURE	0.015		−0.002	
*LOW_DISCLOSURE *SURP*^{rank}*_SSS*	−0.034	**	−0.103	
SURP^{rank}*_EPS*	0.069	***	0.012	
SURP^{rank}*_REV*	0.019	***	0.308	***
N	2,806		2,173	
R-squared	0.187		0.162	

Panel B: Change in the Computation of SSS

	CAR [−1,+1] (Regression 3a)		EPS Forecast Revision (Regression 3b)	
SURP^{rank}*_SSS*	0.047	***	0.175	***
CHANGE_COMP	−0.004		0.101	
*CHANGE_COMP*SURP*^{rank}*_SSS*	0.001		−0.176	***
SURP^{rank}*_EPS*	0.068	***	0.084	**
SURP^{rank}*_REV*	0.021	***	0.087	**
N	2,408		1,863	
R-squared	0.211		0.049	

LOW_DISCLOSURE equals 1 if the firm does not provide details on how it calculates SSS in the 10-K filings for that year, and 0 otherwise. *CHANGE_COMP* equals 1 in the year that represents a change from last year in how the firm calculates SSS, and 0 otherwise.

The number of observations used to produce the results in this table varies between the two panels due to different data requirements imposed in each regression. In Panel A, the sample of Regression 3a includes all quarterly SSS observations with nonmissing return and SSS/EPS/Revenue surprises. Sample of Regression 3b is further restricted to observations with EPS forecasts for the next quarter. In Panel B, observations without details on how the firm calculates SSS are dropped for both models. The regressions are estimated with year fixed effects and standard errors clustered by firm. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively, based on two-tailed tests.

Table 8.
Determinants of Analysts' Decisions to Issue KPI Forecasts:
Summary Results from Regression 4

Variable	Y = Number of KPI Analysts / Number of EPS Analysts		
	(1)	(2)	(3)
INF_KPI	0.011 ***		0.011 ***
SIZE		0.000	−0.001
VOL_EARN		−0.000	−0.000
LOSS		0.018 **	0.016 ***
AB_TACCR		0.122 **	0.101 **
DISTRESS		−0.042 ***	−0.029 **
N	12,384	12,384	12,384
Adj. R2	0.582	0.398	0.583
FE		Year + Firm	

The table reports the results of regressions of the availability of KPI forecasts and the ratio of the numbers of KPI analysts and EPS analysts for a given firm–quarter–KPI. The regression is estimated from a pooled sample of firm–quarter–KPI observations. Standard errors are clustered by firm. The ratio for the firm–quarter is computed from analysts that produce EPS forecasts for the firm–quarter. *INF_KPI* is the relative explanatory power of the KPI surprise (*$SURP^{rank}$_KPI)* in Regression (1), as measured by Shapley value of this variable divided by the regression's R^2. *SIZE* is the natural logarithm of the market value of the firm's equity at the beginning of the quarter. *VOL_EARN* is the coefficient of variation of the earnings, computed as their standard deviation over the most recent eight quarters, deflated by its absolute mean value of over that same period. *AB_TACCR* is the absolute value of total accruals in quarter t−1 deflated by beginning total assets. *DISTRESS* is an indicator variable that receives the value of 1 when the Altman Z-score is below 1.81 (indication of distress) at beginning of quarter t, and 0 otherwise. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively, based on two-tailed tests.

Table 9.
SSS Mentions and Determinants of SSS Forecasts

Panel A: Distribution and Frequency of the number of SSS Mentions in Quarterly Earnings Press Releases

(Based on 3,618 firm–quarter earnings releases)

Per quarterly earnings release	Mean	Median	p25	p75	Fraction of firm–quarters
Number of Mentions	9.0	7	4	11	
Prominence of appearance: Number appearances in:					
Headings or first paragraph	1.3	1	0	2	0.635
Part of a table	1.3	0	0	2	0.478
A separate table	0.3	0	0	0	0.198

The statistics are for all firm–quarters (with SSS actual and EPS forecast regardless of whether there is an SSS forecast)

Panel B: Determinants of SSS Forecasts

	Y= *Number of SSS forecasts / Number of EPS forecasts*	
	(1)	(2)
Ln_of SSS_Mentions	0.028 ***	0.041 ***
SIZE	−0.045 ***	−0.007
B/M	−0.018	−0.042
VOL_EARN	−0.000	0.000
LOSS	0.001	−0.004
AB_TACCR	0.220	0.359 **
DISTRESS	−0.072 ***	0.004
N	2,616	2,616
Adj. R2	0.119	0.290
FE	No	Firm

The regression is estimated across firm–quarters with SSS forecasts. Standard errors are clustered by firm. The dependent variable is the ratio of the numbers of SSS forecasts and EPS forecasts for a given firm–quarter. *Ln_of SSS_Mentions* is the natural logarithm of the number of mentions of SSS in the earnings announcement. *SIZE* is the natural logarithm of the market value of the firm's equity at the beginning of the quarter. *VOL_EARN* is the coefficient of variation of the earnings, computed as their standard deviation over the most recent eight quarters, deflated by its absolute mean value of over that same period. *AB_TACCR* is the absolute value of total accruals in quarter $t-1$ deflated by beginning total assets. *DISTRESS* is an indicator variable that receives the value of 1 when the Altman Z-score is below 1.81 (indication of distress) at beginning of quarter $t-1$, and 0 otherwise. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively, based on two-tailed tests.

Table 10. Forecast Superiority

Panel A: Forecast Accuracy – Mean Absolute Errors of Quarterly and Annual Forecasts Errors

Forecast Period	No. of Firm–quarters	Analysts' Forecasts (1)	Random Walk Forecasts (2)	(1) – (2)	
KPI Forecasts for Quarter:					
Q+1	4,618	25.6%	49.5%	−23.9%	***
Q+2	4,431	32.9%	48.8%	−15.9%	***
Q+3	3,380	46.8%	54.3%	−7.5%	***
KPI Forecasts of Year:					
Y+1	1,109	14.8%	44.5%	−29.7%	***
Y+2	699	38.4%	58.0%	−19.6%	***
Y+3	421	53.5%	70.4%	−16.9%	***

Panel B: Forecast Accuracy – Mean Absolute Forecast Errors of Annual Forecasts

Forecast Period	No. of Firm–quarters	Analysts' Forecasts (1)	Naïve Extrapolation of Analysts' Y+1 Forecast (2)	(1) – (2)	
Y+2	676	38.5%	42.8%	−4.3%	***
Y+3	367	51.2%	60.0%	−8.8%	***

Panel C: Market Reaction to Quarterly KPI, EPS, and Revenue Surprises based on Analysts' vs. Random Walk Forecasts – Summary Results from Estimating Regression (1)

KPI Forecast is:	N	Coefficients from Regression (1)			
		$SURP^{rank}$_3-KPI	$SURP^{rank}$_EPS	$SURP^{rank}$_REV	Adj.R^2
Random-Walk Forecast	4,565	1.1%***	6.4%***	3.0%***	10.1%
Analyst Forecast	4,565	3.0%***	6.1%***	2.0%***	11.3%
	chi-square	*18.38****			

The use of the chi-square statistic is based on the Wald test (Wald, 1943).

Panel C shows results of regressions of announcement window abnormal returns, CAR(−1,+1), on *SURP*^{rank}*_3-KPI* (the average ranked surprise across the three most followed KPIs in the industry), earnings surprise (*SURP*^{rank}*_EPS*), and revenue surprise (*SURP*^{rank}*_REV*). Variable definitions are provided in Appendix A. Standard errors are clustered by year–quarter. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively, based on two-tailed tests.