Review of Accounting Studies (2019) 24:1147–1183
https://doi.org/10.1007/s11142-019-09514-y

Key performance indicators as supplements to earnings: Incremental informativeness, demand factors, measurement issues, and properties of their forecasts

Dan Givoly[1] · Yifan Li[2] · Ben Lourie[3] · Alexander Nekrasov[4]

Published online: 25 August 2019

Abstract
The documented decline in the information content of earnings numbers has paralleled the emergence of disclosures, mostly voluntary, of industry-specific key performance indicators (KPIs). We find that the incremental information content conveyed by KPI news is significant for many KPIs yet diminished when details about the computation of the KPI are absent or when the computation changes over time. Consistent with analysts responding to investor information demand, we find that analysts are more likely to produce forecasts for a KPI when that KPI has more information content and when earnings are less informative. We also analyze the properties of analysts' KPI forecasts and find that KPI forecasts are more accurate than mechanical forecasts and their accuracy exceeds that of earnings forecasts. Our study contributes to the literature on the information content of KPIs as well as research on the properties of analysts' forecasts. We provide evidence on whether and how to regulate voluntary disclosures.

Keywords Key Performance indicators · KPI · Measurement issues · Voluntary disclosure · Analyst forecasts · KPI surprises · Incremental news · Non-financial forecasts

1 Introduction

Research has documented a decline in the information content of earnings over the last few decades. Researchers have offered various explanations for this phenomenon, and

✉ Alexander Nekrasov
nekrasov@uic.edu

1 Pennsylvania State University, State College, PA 16801, USA

2 San Francisco State University, San Francisco, CA 94132, USA

3 University of California-Irvine, Irvine, CA 92697, USA

4 University of Illinois at Chicago, Chicago, IL 60607, USA

most of these relate to financial reporting standards and conventions. These explanations include reporting features such as unrecorded intangible assets, the shift of standards toward the "balance sheet approach," the move toward fair value measurement, the increase in conditional conservatism, the frequency of losses, and the reporting of one-time special items.[1]

While the decline in the information content of earnings should be a concern for standard setters, it is unlikely they would decide to drastically change their measurement framework in response to this decline. A more practical, less controversial (and thus more promising) path for improving the reporting of financial performance is likely to be found in encouraging or mandating the disclosure of supplemental measures of performance that would help users project future earnings and cash flows. Academics have urged the inclusion of such measures, which are often indicative of longer-term performance (e.g., Amir and Lev 1996; Lev and Gu 2016). This is also one of the recommendations of the Special Committee on Financial Reporting (the Jenkins Committee; see AICPA 1994).

In practice, many firms regularly and voluntarily report information on key performance indicators (KPIs) specific to their industry or company. These measures, in most cases, cannot be gleaned from their financial statements. Examples include the average daily production of oil (in barrels) of an oil and gas company, the same-store sales growth of a retail chain, and the passenger load factor of an airline. KPIs are disclosed, often prominently,[2] through different channels as part of earnings announcements, press releases, conference calls, or the MD&A section of the 10-K/Q filings. Managers use these measures extensively to assess the performance of the entire company or some of its internal units,[3] and an increasing number of analysts routinely follow and forecast important KPIs (Hand et al. 2018).

One of the main recommendations of the SEC Advisory Committee on Improvements to Financial Reporting (SEC 2008) was to enhance the usefulness of corporate reporting by developing and disclosing relevant, consistent, and comparable KPIs. In line with this recommendation, the SEC, in a recent concept release (SEC 2016), sought comments and advice from the public on the costs and benefits of mandating the disclosure of standardized, industry-specific KPIs.

In this study, we provide evidence relevant to the potential regulation of KPI measurement and disclosure. We start by assessing the incremental information content of KPIs. Studies have examined the relevance of a select number of KPIs for stock valuation by testing the association between KPIs and the current period's stock returns. Our study is more comprehensive, as it covers multiple KPIs and industries. We also use the event study methodology, which offers insights not only into the value relevance of KPIs but also into the "innovation" of KPI information. We further supplement these market tests on the information content of KPIs through a test that relies on analysts' responses to KPI news in the form of forecast revisions.

[1] See, for example, Collins et al. (1997); Dichev and Tang (2008); Donelson et al. (2011); Francis and Schipper (1999); Givoly and Hayn (2000); Lev and Zarowin (1999); and Lev and Gu (2016).

[2] For example, in its earnings announcement on January 25, 2018, American Airlines Group mentions *available seat miles* (ASM) 42 times.

[3] A search on Amazon.com yields close to 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).

One issue relevant for the regulation of KPIs is whether their disclosure should remain voluntary. With voluntary disclosure, the definition and measurement of KPIs may vary across firms and may change over time for a given firm.[4] To illuminate how the information content of KPIs is influenced by the uniformity and consistency of their computation, we use hand-collected data on the computational details of an important KPI: the same-store sales growth rate (coded as SSS).

Information about the properties of these forecasts is important, because our examination of the information content of KPIs and the factors affecting this content rely on the use of analysts' forecasts of KPIs as a representative of market expectations. A large body of research deals with the properties of analyst *earnings* forecasts: their accuracy, bias, and dispersion; their performance relative to naïve forecasts; and their relationship to revenue and cash flow forecasts. Very little is known, however, about the properties of KPI forecasts: their superiority, if any, over mechanical forecasts; the factors that influence analysts to produce them; and the extent to which their production enhances the accuracy of the analyst's earnings and revenue forecasts. We provide evidence on these characteristics, and we contrast them with characteristics found by research on analysts' earnings forecasts.

Using new I/B/E/S data on forecasts and realizations of KPIs for the years 2005 to 2016 (depending on the industry), we identify 28 industry-specific KPIs in four industries that are followed frequently by analysts: airline, oil and gas, pharmaceutical, and retail.[5,6]

To examine whether the surprises of important KPIs in an industry have, collectively, information content incremental to that of earnings and revenue surprises, we construct a composite measure of KPI surprises for each firm–quarter based on the three most-followed KPIs in the industry. We find an incremental response to these KPI surprises in three of the four industries and in the entire sample, consisting of all four industries. The results suggest that news in many important KPIs is incrementally informative. We corroborate the above results using analysts' reactions to KPI surprises (in the form of forecast revisions) as an alternative gauge for the informativeness of KPIs, and we find evidence consistent with the results from our market tests.

We also test 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. The use of this monthly sample alleviates the need to control for other information released with the earnings announcement. Consistent with the results obtained for quarterly SSS, we find that the market reaction to the standalone $\mathrm{SSS}^{\mathrm{M}}$ surprises is positive and highly significant. This finding also highlights the value of the *more timely* monthly KPI announcements that partially preempt the news in subsequent earnings announcements.

[4] 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 and 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).

[5] These four industries are the only nonfinancial industries with sufficient observations.

[6] Industry-focused research has several advantages, including greater comparability of firms within the industry and ability to consider the economic context in which the performance measures are reported (Shevlin 1996).

Based on hand-collected data on SSS, we find that the information content of this KPI appears to be diminished when there is no disclosure of its computational details and when the firm changes the way it computes that KPI. These findings suggest that standardization of the definition of individual KPIs is needed to enhance their information content, regardless of whether KPI disclosure remains voluntary. Standardization, coupled with its enforcement, may also dampen the ability of management to manipulate KPIs. Indeed, there are indications that the SEC has recently given greater attention to the validity of corporate KPI disclosures.[7]

Our findings show that the most important determinant of analysts' decisions to produce a KPI forecast is the information content of that KPI, which is consistent with analysts responding to investors' demand for these forecasts. We further find that the production of KPI forecasts is also related to the importance that management attributes to the KPI as captured by the number of mentions of that KPI in the press release. Consistent with the demand effect, we find that more analysts issue KPI forecasts in periods when the company reports a loss, thus rendering the earnings number less informative (Hayn 1995). Also consistent with the demand effect, we find that more analysts issue KPI forecasts in cases with large absolute accruals that denote situations with a large discrepancy between earnings and cash flow from operations. Finally, we provide only weak evidence that analysts who issue KPI forecasts produce more accurate EPS and revenue forecasts.

Our next set of tests focuses on the properties of analysts' forecasts of KPI. We find that the average accuracy of KPI forecasts is, in most cases, greater than that of EPS forecasts. This suggests that either KPIs are relatively easy to forecast or analysts exert effort to make more accurate KPI forecasts. In contrast to the finding of prior research that early-in-the-period EPS forecasts are optimistic (Brown 2001; Bartov et al. 2002; Matsumoto 2002; Richardson et al. 2004), we find that KPI forecasts made early in the period are pessimistic on average.

Finally, an examination of additional features of analysts' KPI forecasts reveals the following. First, similar to short-term EPS forecasts, forecasts of KPIs are more accurate than random walk models, and the market reacts more strongly to surprises based on these forecasts. We also find that analysts' two- and three-year-ahead KPI forecasts are superior to a naïve extrapolation of analysts' KPI forecasts from the current year to these two future years. This contrasts with the findings of Bradshaw et al. (2012) of a limited value of analyst *earnings* forecasts for longer horizons.

Our study makes a number of contributions to the literature. First, it contributes to the research on the quality of voluntary disclosures and the extent to which they supplement GAAP measures of performance, whose information content has been shown to decline over time. We provide evidence on the incremental information content of KPIs, beyond earnings and revenues, and by showing how the informativeness of a KPI diminishes in the absence of its computational details and in the presence of intertemporal inconsistency in its computation. These findings are relevant to the regulation of KPI disclosures and to the continuing debate on the need for mandating them.

[7] See Clarkson and Matelis (2018). In June and August 2018, two companies that offer web hosting and online and email marketing products were the targets of SEC enforcement action for artificially inflating the rate of growth in subscribers (one of their important KPIs) by changing the definition of a "paying subscriber." The case was eventually settled (see https://www.sec.gov/litigation/admin/2018/33-10504.pdf).

Our study also contributes to the empirical studies on the value-relevance of individual KPIs (Amir and Lev 1996; Francis et al. 2003; Rajgopal et al. 2003b; Patatoukas et al. 2015). We extend those studies in three ways. First, we gauge the informativeness of KPI disclosures by employing the event-study methodology to observe the market reaction to their announcements. Second, we extend the examination from a single KPI or a few KPIs in a single industry to many KPIs in different industries. Last, we capture the informativeness and timeliness of KPI disclosures using a nonreturn measure—the extent to which KPI disclosures affect analysts' revisions of their earnings and revenue forecasts.

This study also contributes to the research on the role of analysts in the capital markets. First, by modeling and testing the determinants of analysts' decisions to issue KPI forecasts, our study extends the research on the effect of the value relevance of information to investors on the supply of products by analysts (e.g., forecasts) (Chapman and Green 2015; DeFond and Hung 2003; Ehinger et al. 2017; Ertimur et al. 2011). Second, our study contributes to the literature on analysts' forecasts by examining the properties of analysts' forecasts of KPIs as compared to their earnings and revenue forecasts. (For recent reviews of this literature, see Bradshaw (2011) and Kothari et al. (2016).)

2 Investor and regulatory interest and related research

2.1 Investor and regulatory interest in KPI disclosures

There is a consensus in the investment community that disclosures of industry-specific KPIs are important to decision making. An Ernst and Young (2015) survey conducted by Institutional Investor Research (IIR) shows that almost three-quarters of institutional investors considered industry-specific reporting and KPIs to be very or somewhat beneficial.[8] 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).

Growing investor interest in KPI information has drawn attention from regulators (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 (SEC 2003).[9] Doing so should allow investors to view the company through the eyes of its management. Since KPIs vary by industry, and 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 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

[8] The survey covered more than 200 institutional investors, including portfolio managers, equity analysts, chief investment officers, and managing directors.

[9] Similar guidance is offered by the EU Directive (2003) and by the IASB (see IASB 2010).

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 a 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.[10,11]

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. Ittner and Larcker (1998) examine the information content of customer satisfaction scores. Other researchers examine and document the value relevance of web traffic (Trueman, Wong, and Zhang 2001; Rajgopal et al. 2003b), order backlog (Rajgopal et al. 2003a), and discounted cash flow estimates of oil and gas royalty trusts (Patatoukas et al. 2015). Curtis et al. (2014) show that components of sales (e.g., growth in same-store sales, the number of stores, and new stores open) are useful in predicting 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 or annual returns 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 extent of their analyst following). The use of an event-study methodology improves the reliability of the inferences on the information content by alleviating the need to control for a multitude of valuation drivers, many of which are highly correlated. It further allows the determination of the innovation contained in the release of the KPI. We further consider an alternative measure of the informativeness of KPIs that is not return based,

[10] 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 Four 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.

[11] Regulators abroad are equally concerned about the disclosure and standardization of KPIs, and these regulators either require or suggest adequate disclosures of them (e.g., IASB 2010; the EU Accounts Modernization Directive 2003; Section 417 of the Companies Act (2006) in the United Kingdom).

in the form of analysts' responses to KPI news. 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.

An issue of regulatory importance that has not be addressed by past research on KPIs is the effect of the cross-sectional uniformity and consistency over time in defining and measuring a KPI on its information content. 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 et al. (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*. One definition of an *existing store* may be a store that has been open for at least 12 months, but this definition may be changed to a store that has been open for at least, say, 18 months. We provide empirical evidence on whether uniformity and consistency in the definition of KPI over time enhances its informativeness.

3 Data and sample selection

We obtained quarterly and monthly forecasts of industry-specific KPIs and quarterly earnings and revenue forecasts as well as the actual values of these forecasts from the respective I/B/E/S detail files.[12] 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 industries.[13,14] This initial sample consists of 615,635 analyst forecasts of quarterly KPIs for 1215 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,[15] 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

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

[13] 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.

[14] 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.

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

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	1215	18,498	46,067	615,635
Less:				
Missing KPI actuals	(410)	(8650)	(21,834)	(171,147)
Stale KPI forecasts (issued more than 90 days before the release of actual)	(43)	(1415)	(3292)	(289,794)
Missing EPS forecasts	(87)	(1861)	(3436)	(23,945)
Missing CRSP stock returns	–	(5)	(20)	(144)
KPI with less than 100 firm-quarter observations with full data	(16)	(95)	(467)	(1421)
Final sample	659	6472	17,018	129,184

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.[16] 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 1 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 and gas, pharmaceutical, and retail.[17] The largest number of sample observations are found in the retail and the oil and 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. Firms in the oil and 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 periods. The airlines sample covers 2013–2016, oil and 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

[16] 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 and gas industry.

[17] Excluding financial industries, I/B/E/S reports industry KPIs for five industries: airline, oil and gas, pharmaceutical, retail, and technology. I/B/E/S uses a proprietary industry classification to construct these five industries. The oil and gas industry includes integrated oil and gas, exploration and production, and refining and 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.

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.[18]

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 is *available seat miles* (ASM) in the airline industry, *distributable cash flow* (DCF) in the oil and 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 (cost per seat miles (CPA) and revenue per available seat mile (RASM)) to 557 (same-store sales growth rate (SSS)).

4 The incremental information content of KPIs

4.1 Measuring the information content of KPI news based on stock price response

We assess the incremental informativeness of KPIs using an event-study methodology, whereby we gauge the incremental information content by the market response to KPI surprises, after controlling for other news that is concurrently disclosed (typically earnings and revenue).

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.[19] *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

[18] 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.

[19] Many KPI, such as available seat miles and oil production per day, are measured in unscaled nonmonetary 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.

Table 2 Sample Distribution

Panel A: Distribution of Quarterly KPI by Industry					
	Airlines	Oil and Gas	Pharmaceutical	Retail	
No. of firms	16	376	72	195	
No. of firm-quarters	147	2651	598	3076	
No. of industry-specific KPIs (in 2016)	5	15	1	7	
No. of KPI-firm-quarters	655	10,729	598	5036	
No. of analyst KPI forecasts	3462	84,556	5604	35,562	
Avg. no. of forecasts per KPI-firm-quarter	5.3	7.9	9.4	7.1	
Mean firm size ($ millions)	9876	10,598	34,327	9572	
Median firm size	4559	2527	12,741	2008	
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 and Gas	Pharmaceutical	Retail	All Industries
2005	–	–	106	–	106
2006	–	–	1276	–	1276
2007	–	–	1428	244	1672
2008	–	–	1215	16	1231
2009	–	–	1097	1645	2742
2010	–	–	147	4684	4831
2011	–	–	0	3854	3854
2012	–	213	48	3307	3568
2013	267	7162	63	3841	11,333
2014	1314	26,616	121	7576	35,627
2015	1479	35,213	56	6742	43,490
2016	402	15,352	47	3653	19,454
Total	3462	84,556	5604	35,562	129,184
Panel C: Distribution of Quarterly KPIs by KPI Measure					
KPI	Description	No. of analyst forecasts of KPI	No. of firm–quarter obs.	No. of firms	No. of distinct analysts
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

Table 2 (continued)

	RASM	Revenue per available seat mile	120	13	17	717
Oil and Gas						
	DCF	Distributable cash flow	1342	231	267	6178
	OPD	Oil production per day	975	125	188	8797
	TPD	Total production per day	967	127	228	11,881
	GPD	Gas production per day	953	122	180	8909
	RPO	Realized price oil	807	114	145	9198
	RPG	Realized price gas	793	112	143	8285
	EBX	EBITDAX	754	110	149	7030
	NPP	Natural gas prod. Per day	685	90	150	5219
	MCX	Maintenance Capex	674	148	144	1760
	LOE	Lease operating expense	620	90	134	4982
	EXP	Exploration expense	611	80	173	3379
	TPP	Total production per day	582	108	138	3505
	PTX	Production tax	421	78	111	3548
	RZP	Realized price	331	71	56	1241
	PEX	Production expense	214	51	62	644
Pharmaceutical						
	SAL	Pharmaceutical sales	598	72	372	5604
Retail						
	SSS	Same-store sales' growth rate	2829	177	557	28,759
	NOS	Number of stores	880	115	168	3589
	FLS	Floor space	333	67	92	1016
	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 1 announcement period return), as the KPI surprise moves from the bottom to the top tercile of the KPI surprise distribution.[20]

To determine whether the surprises of important KPIs in an industry collectively have information content incremental to that of earnings and revenue surprises, we first identify for each industry the KPIs that are likely to matter 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 of these three KPIs 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 $SURP^{rank}\_3\text{-}KPI$ and use it to test for the collective information content of these potentially important industry KPIs.[21] We use $SURP^{rank}\_3\text{-}KPI$ 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) announcement, 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 most analyst forecasts, which presumably indicates that sales of that drug are likely to be most important to market participants.

We estimate the incremental information content of KPI announcements through the following pooled regression of announcement returns estimated from all firm-quarter observations within a given industry or across industries.

$$\begin{aligned} CAR(-1,+1)_{jt} = {} & \alpha_1 + \beta_1 SURP^{rank}\_3{-}KPI_{ijt}\left(or\, SURP^{rank}\_KPI_{jt}\right) \\ & + \beta_2 SURP^{rank}\_EPS_{jt} + \beta_3 SURP^{rank}\_REV_{jt} + \varepsilon_{jt}, \end{aligned} \tag{1}$$

where $CAR(-1,+1)$ is the cumulative abnormal return over the three-day window centered on the announcement date. We control for the revenue surprise, in addition to our control for the earnings surprise, since research indicates that investors react more strongly to a revenue surprise than to an expense surprise of the same magnitude (Ertimur et al. 2003).

[20] 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.

[21] 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.

Some KPIs reflect favorable aspects of performance, while others reflect expenses (i.e., cost per seat miles (CPA), maintenance capital expenditures (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.[22] 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.

Table 3 reports the results of estimating Regression (1), where announcement window return is regressed on $SURP^{rank}\_3\text{-}KPI$, $SURP^{rank}\_EPS$, and $SURP^{rank}\_REV$. The regression is estimated 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. The results are consistent with KPI surprises containing significant information that is incremental to earnings and revenue news.[23]

The (untabulated) results of estimating Regression (1) for individual KPIs (i.e., $SURP^{rank}\_KPI$) reveal the following. First, the univariate regressions of announcement returns on KPI surprises show that a number of KPIs (12 out of 28) have a significant association with the announcement period returns.[24] None of the coefficients of the KPIs, whose sign is expected to be positive, 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. Second, the regressions of announcement returns on KPI surprises, earnings surprise, and revenue surprise show that surprises in eight KPIs (ASM, RPM, DCF, EBX, EXP, TPP, RZP, and SSS) are significant at the 10% level or better, 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.

4.2 Measuring 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 when revising their EPS and revenue forecasts. We estimate the following

[22] Higher maintenance capital expenditures and higher production tax may convey positive information to investors, so there might be some ambiguity about the expected signs for these KPIs.

[23] We also explored the market reaction in the post-announcement window (over the interval [+2,+63]) and did not find a significant drift in the market response to KPI surprises, EPS surprises, or revenue surprises in our sample. The absence of a significant drift could be due to insufficient test power.

[24] The significant KPIs are ASM, RPM, DCF, OPD, RPG, EBX, EXP, TPP, RZP, SAL, SSS, and RES.

Table 3 Market Reaction to KPI Surprises: Summary Results from Regression (1)
$CAR(-1,+1)_{jt} = \alpha_1 + \beta_1 SURP^{rank}\_3-KPI_{jt} + \beta_2 SURP^{rank}\_EPS_{jt} + \beta_3 SURP^{rank}\_REV_{jt} + \varepsilon_{jt}$

Industry	N	$SURP^{rank}$_3-KPI (×100)	$SURP^{rank}$_EPS (×100)	$SURP^{rank}$_REV (×100)	Adj.R^2
Airlines	142	2.60**	3.92**	2.40	10.2%
Oil and Gas	2336	1.30**	3.94***	0.79**	3.9%
Pharmaceutical	596	1.03	3.65***	2.38***	10.2%
Retail	2673	3.70***	7.39***	2.82***	18.4%
All Industries	5707	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 *$SURP^{rank}$_3-KPI* (the average ranked surprise across the three most followed KPIs in the industry), earnings surprises (*$SURP^{rank}$_EPS*), and revenue surprises (*$SURP^{rank}$_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 1. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests

regression from all firm-quarter observations within a given industry as well as across industries.

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

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, research suggests that some KPIs (e.g., same-store sales, change in number of stores) are used in a bottom-up model of forecasting earnings and revenues (Curtis et al. 2014; 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.

The results from estimating Regression (2) are reported in Table 4. Panel A of the table shows the results of the regression of EPS forecast revision. The coefficient on *$SURP^{rank}$_3-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-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.

Table 4 Forecast Revision Tests: Summary Results for Regression (2)

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

	$SURP^{rank}\_3\text{-}KPI$	$SURP^{rank}\_EPS$	$SURP^{rank}\_REV$	N	Adj.R^2
Panel A: The Dependent Variable is Earnings Forecast Revision					
Airlines	0.200*	0.040	0.110	115	3.7%
Oil and Gas	0.057	0.445***	0.063	1623	6.5%
Pharmaceutical	0.031	0.040*	0.079**	410	2.3%
Retail	0.138***	0.089**	0.090**	2404	3.8%
All Industries	0.089***	0.175***	0.102***	4552	4.5%
Panel B: The Dependent Variable is Revenue Forecast Revision					
Airlines	0.362	−0.137	0.075	115	−1.2%
Oil and Gas	0.053	0.251**	1.153***	1615	8.1%
Pharmaceutical	0.078**	0.009	0.205***	410	15.5%
Retail	0.475***	0.055	0.770***	2400	10.2%
All Industries	0.260***	0.098**	0.847***	4540	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 1. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests

5 The effect of the disclosure, consistency, and uniformity of the KPI's computational details and its information content

The information content of voluntary disclosure of a KPI by firms is likely to depend on the extent of the disclosure, period-to-period consistency, and cross-sectional uniformity of the KPI's computational details. This is particularly true for nonfinancial KPIs. The absence of a detailed disclosure about how a KPI is computed, changes over time in its computation, and lack a standardized definition are all likely to create some degree of ambiguity among investors in interpreting this KPI, rendering this signal noisier. This ambiguity is exacerbated when the reporting firm has incentives to misrepresent.[25] We expect such ambiguity to reduce the usefulness of KPIs for investors.

To examine these attributes of KPIs and evaluate their impact on the KPI's information content, 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 KPI: the retail industry and its most commonly disclosed KPI, SSS. We collected data on the computation of SSS from the MD&A of over 1300 10-K forms.

[25] 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.

Our examination shows that not all SSS announcements provide the computational details of this KPI, that in many instances its definition changes from year to year, and that there is no standard for computing it across all firms. The upper two rows in Panel A of Table 5 show the frequency among all firm-quarter observations for which the MD&A for the year includes computation details. The table shows that for 400 (or about 14%) of the 2829 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 bottom two rows in Panel A of Table 5 show the extent of year-to-year consistency in the computation of SSS across observations for which the firm discloses the computational details of SSS. We focus on consistency in the definition of *same stores*, that is, the definition of the group of stores for which the rate of growth in sales is computed. As the panel shows, in about 10% of the observations with disclosed

Table 5 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 that year	SSS computation details are not disclosed in that year	Total	SSS computation details are disclosed in the MD&A in all years	SSS computation details are not disclosed in all years	Total
2429	400	2829	160	59	177
SSS computation is the same as last year	SSS computation changed from last year		SSS computation is always the same as last year	SSS computation changed in at least one year	
2207	222	2429	154	16	160

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

Minimum number of months of operations required for a store to be included in "Same Store" group	12	13	14	15	16	18	19	19.5	24	Total
# of Firm-Quarters	1109	525	231	275	23	136	27	7	96	2429
%	46%	22%	10%	11%	1%	6%	1%	0%	4%	100%

details about SSS computation (222 out of 2429), there is a change in the computation of this KPI, relative to the previous year. Panel B of Table 6 presents the results about the uniformity of the definition of SSS across firms.

Table 6 Effect of Computational Details on the Information Content of SSS News

	CAR [−1,+1] (Regression 3a)	EPS Forecast Revision (Regression 3b)
Panel A: Lack of Computational Details		
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	2806	2173
R-squared	0.187	0.162
Panel B: Change in the Computation of SSS		
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	2408	1863
R-squared	0.211	0.049
Panel C: Computation That Requires a Longer Time in Operation Before Stores Are Included the Same Store Base		
SURP^rank_SSS	0.037***	0.151***
LONGER_TIME_IN_OPERATION	−0.015*	−0.023
*LONGER_TIME_IN_OPERATION *SURP^rank_SSS*	0.030**	0.027
SURP^rank_EPS	0.068***	0.085**
SURP^rank_REV	0.021***	0.087**
N	2408	1863
R-squared	0.214	0.047

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. *LONGER_TIME_IN_OPERATION* equals 1 if the minimum length of operation required for a store to be defined as “same-store” is greater than 13 months and 0 otherwise. The number of observations varies across 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 returns and SSS/EPS/Revenue surprises. Sample of Regression 3b is further restricted to observations with EPS forecasts for the next quarter. In Panels B and C, 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% levels, respectively, based on two-tailed tests

Panel B of Table 5 shows that there is some 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 use 13 months or more in their definitions (and in 4% of the firm-quarters, the applicable definition is 24 months).

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 estimate the following versions of regressions (1) and (2).

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

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

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 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).

The results from estimating Regressions (3a) and 3(b) are shown in Panels A and B of Table 6. These results show that the information content of SSS surprises is lower when there is limited disclosure on the computational details of this KPI in the MD&A. The coefficient of the interaction term between *LOW_DISCLOSURE* and the SSS surprise is negative and significant when information content is gauged by the market response to the SSS announcement. It is also negative (but not significant) when information content is proxied by the extent of revision in analysts' forecasts of EPS for the following quarter issued in the wake of the SSS surprise. When information content is measured in this manner, the regression results show that the coefficient of $CHANGE\_COMP{*}SURP^{rank}\_SSS$ 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 computation detract from the incremental information content of KPIs to investors.

The effect of the lack of a standardized definition of *same store* on the information content of SSS is not obvious as long as there is a disclosure of this choice. However, using a longer operating period in the definition of *same store* may be more informative, because the SSS may be noisier when it includes stores that have been in operation for a short period. To test whether this is indeed the case, we estimate the following versions of regressions (3a) and (3b).

$$CAR(-1,+1)_{jt} = \alpha_1 + \beta_1 SURP^{rank}\_SSS_{jt} + \beta_3 \\ LONGER\_TIME\_IN\_OPERATION + \beta_4 LONGER\_TIME\_IN\_OPERATION \\ {*}SURP^{rank}\_SSS_{jt} + \beta_2 SURP^{rank}\_EPS_{jt} + \beta_3 SURP^{rank}\_REV_{jt} + \varepsilon_{jt}, \tag{3a'}$$

$$EPS(REV)Forecast\,Revision_{jt+1} = \alpha_1 + \beta_1 SURP^{rank}\_SSS_{jt} + \beta_3 \\ LONGER\_TIME\_IN\_OPERATION + \beta_4 LONGER\_TIME\_IN\_OPERATION \\ {*}SURP^{rank}\_SSS_{jt} + \beta_2 SURP^{rank}\_EPS_{jt} + \beta_3 SURP^{rank}\_REV_{jt} + \varepsilon_{jt}, \tag{3b'}$$

where *LONGER_TIME_IN_OPERATION* is an indicator variable that equals 1 if the minimum time required before a store is classified as a same-store is greater than 13 months and 0 otherwise. All other variables are the same as in Regressions (3a) and (3b).

The results reported in Panel C of Table 6 suggest a higher information content of SSS when stores are required to be in operations for a longer time (14 months or more) before they are included in the same store base. The coefficient on the interaction *LONGER_TIME_IN_OPERATION* $*SURP^{rank}\_SSS$ is positive and significant. The coefficient on the interaction term is also positive but not significant when information content is proxied by analysts' forecasts revisions.

6 Determinants and properties of analysts' forecasts KPIs

6.1 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, other financial statement variables (e.g., revenues, cash flows, various measures of earnings such as EBIT and EBITDA), and effective tax rate. Analysts' production of these forecasts is not universal, and this likely reflects variation in the demand by investors. 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 have 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 et al. 2011). 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).[26] 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 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.

The results from estimating Regression (4) are reported in Table 7. 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 explain. 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.

[26] 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).

Table 7 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% levels, respectively, based on two-tailed tests

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 (DeFond and Hung 2003; Ertimur et al. 2011). 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 with noncash measures such as KPIs (similar to their lower reliance on earnings when bankruptcy risk is high—see DeFond and Hung 2003).

6.2 Accuracy and bias of analysts' forecasts of KPI

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.

Research has documented an optimistic bias in earnings forecasts made early in the period (e.g., Brown 2001; Bartov et al. 2002; Matsumoto 2002; Richardson et al. 2004; Bradshaw et al. 2016). While there is no consensus on the reasons for this bias, a common explanation for the bias (and 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 brokerages (Easterwood and Nutt 1999; O'Brian 1988). If this is true, we should find a similar optimistic bias in KPI forecasts.

Table 8 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.[27] The absolute errors capture accuracy, while the signed errors measure the bias. 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 signed (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 expected, the accuracy of the forecasts made late in the quarter are consistently higher than those made early in the quarter. The KPI signed error of forecasts made early in the quarter is, on average, positive, indicating a pessimistic bias.

In an additional (untabulated) analysis, we find 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.

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 and 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

[27] Similar results (untabulated) 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.

Table 8 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	8770	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 and 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%

Table 8 (continued)

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
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								
SSS	Same-store sales' growth rate	2829	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 1

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.

6.3 Does the production of KPI forecasts help improve the accuracy of EPS and revenue forecasts?

Research shows that analysts who forecast cash flow from operations, in addition to forecasting earnings, produce more accurate earnings forecasts (Call et al. 2009; Pae et al. 2007). The explanation given for 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 produce 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.

$$
\begin{aligned}
&Relative \quad Accuracy \quad of\, EPS(REV)Forecast_{mjt} \\
&= \alpha_1 + \beta_1 D\_KPI\_Forecast_{mjt} + \varepsilon_{mjt},
\end{aligned}
\tag{5}
$$

where *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 $D\_KPI\_Forecast_{mjt}$ 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.

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), β_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. 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.

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 (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.[28]

7 Additional analyses

7.1 Number of SSS mentions in earnings press releases and analysts' decisions to forecast SSS

The results reported in Section 6.1 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 (e.g., Barron et al. 1999; Bowen, Davis, and Matsumoto 2002; Ehinger et al. 2017; Healy et al. 1999). We use the number of times a KPI is 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.[29] 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

[28] 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.

[29] 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.

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 3618 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

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	2616	2616
Adj. R2	0.119	0.290
FE	No	Firm

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

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% levels, respectively, based on two-tailed tests

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 following form.

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

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).

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.

7.2 The information content of 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.[30] 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.

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' one-year-ahead EPS forecasts outperforms two- and three-year-ahead forecasts. To find out whether these results also

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

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.

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	4618	25.6%	49.5%	−23.9%***	
Q + 2	4431	32.9%	48.8%	−15.9%***	
Q + 3	3380	46.8%	54.3%	−7.5%***	
KPI Forecasts of Year:					
Y + 1	1109	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)			
Random-Walk Forecast		*SURP^{rank}_3-KPI*	*SURP^{rank}_EPS*	*SURP^{rank}_REV*	Adj.R^2
Analyst Forecast	4565	1.1%***	6.4%***	3.0%***	10.1%
	4565	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 1. Standard errors are clustered by year-quarter. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests

In Panel B, we follow Bradshaw et al. (2012) and examine whether analysts' long-term KPI forecasts (two- and three-year-ahead forecasts) are superior to a naïve extrapolation of their one-year-ahead forecast. Contrary to Bradshaw et al. (2012), we find that analysts' long-term forecasts of KPIs are superior to a naïve extrapolation of their one-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.

8 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 and how it is influenced by investor uncertainty about their measurement. We find that surprises in many KPIs have a statistically significant and economically important association with announcement period's returns. We corroborate these findings by providing evidence that analysts react to KPI surprises when revising their earnings and revenue forecasts. Based on hand-collected data of same-store sales growth, an important KPI in the retail industry, we find that the information content of this KPI is diminished when the firm does not provide its computational details or changes them.

Analysts do not produce KPI forecasts for all KPIs and all firms. We find that analysts are more likely to issue such forecasts when the information content of the KPI is high and when earnings are less informative. 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. We also find only weak evidence consistent with the notion that the production of KPI forecasts helps analysts generate more accurate earnings and revenue forecasts.

Our study contributes to the debate about the regulation of voluntary disclosures of industry-specific performance measures by providing evidence on the quality of these 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.

Acknowledgements We are grateful to Richard Sloan (the editor) and two anonymous reviewers for their useful comments and suggestions. We further thank Elizabeth Chuk, Paul Griffin, Mort Pincus, Devin Shanthikumar, Terry Shevlin, Siew Hong Teoh, participants at the 2018 AAA Annual Meeting, and seminar participants at the University of California-Irvine and the University of Toronto for their helpful comments. We gratefully acknowledge the financial support provided by the Paul Merage School of Business at the University of California-Irvine, University of Illinois at Chicago, and Pennsylvania State University. We thank Thomson Reuters Inc. for providing the analyst forecasts data.

Appendix 1: 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 three-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,

Variable	Descriptions
	CAR(−1,+1). The decomposition of the regression R^2 is based on Shapley's decomposition procedure (Shapley 1953).
LONGER_TIME_IN_OPERATION	An indicator variable that equals 1 if the minimum time in operation required before a store is included in the same store base is greater than 13 months and 0 otherwise.
LOSS	An indicator variable 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 ($Avg.\ EPS\ Forecast\ Error_{j,t} - EPS\ Forecast\ Error_{mjt}) \div STD\ EPS\ Forecast\ Error_{jt}$, 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.

Variable	Descriptions
$SURP^{rank}$_KPI	The ranked surprise measure for a given firm-quarter-KPI. $SURP^{rank}\_KPI_{ijt}$ for a firm *j* that belongs to industry *i* in quarter *t* is calculated by ranking $SURP\_KPI_{ijt}$ 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-KPI	Surprise KPI score for a given firm-quarter. $SURP^{rank}\_3\text{-}KPI_{ijt}$ 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 and 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 and considered to be upstream operations.
TPD	Total production per day. Average daily production of oil, gas, and natural gas liquids production expressed in barrels of oil equivalent 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.

Variable	Descriptions
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 1000 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 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 per day. This is expressed in barrels of oil equivalent 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 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 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.

References

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

American Institute Of Certified Public Accountants (AICPA). (1994). *Improving business reporting—A customer focus: A comprehensive report of the special committee on financial reporting*. New York: AICPA.

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

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

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

Bowen, R., Davis, A., & Matsumoto, D. (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., Drake, M., Myers, J., & Myers, L. (2012). A Re-Examination of Analysts' Superiority over Time-Series Forecasts of Annual Earnings. *Review of Accounting Studies, 17*(4), 944–968.

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

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

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

Chapman, K., & Green, J. (2015). Analysts' Influence on Firm's Voluntary Disclosure. Working paper.

Clarkson, B., & Matelis, J. (2018). Signs of Renewed SEC Interest in Key Performance Indicators. *Law360,* September 21. Available at https://www.law360.com/articles/1084908/signs-of-renewed-sec-interest-in-key-performance-indicators.

Collins, D., Maydew, E., & Weiss, I. (1997). Changes in the Value-Relevance of Earnings and Book Values over the Past Forty Years. *Journal of Accounting and Economics, 24*, 39–68.

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

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

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

Dichev, I., & Tang, V. (2008). Matching and the Changing Properties of Accounting Earnings over the Last 40 years. *The Accounting Review, 83*, 1425–1460.

Donelson, D., Jennings, R., & McInnis, J. (2011). Changes over Time in the Revenue-Expense Relation: Accounting or Economics? *The Accounting Review, 86*, 945–974.

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

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

Elzahar, H., Hussainey, K., Mazzi, F., & Tsalavoutas, I. (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., Livnat, J., & Martikainen, M. (2003). Differential Market Reactions to Revenue and Expense Surprises. *Review of Accounting Studies, 8*, 185–211.

Ertimur, Y., Mayew, W., & Stubben, S. (2011). Analyst Reputation and the Issuance of Disaggregated Earnings Forecasts to I/B/E/S. *Review of Accounting Studies, 16*, 29–58.

European Union 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. (2001). Business and Financial Reporting: Challenges from the New Economy.

Francis, J., & Schipper, K. (1999). Have Financial Statements Lost Their Relevance? *Journal of Accounting Research, 37*, 319–352.

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

Fried, D., & Givoly, D. (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/

Givoly, D., & Hayn, C. (2000). The Changing Time-Series Properties of Earnings, Cash Flows and Accruals: Has Financial Reporting Become More Conservative? *Journal of Accounting and Economics, 29*, 287–320.

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

Hand J., H. Laurion, A. Lawrence, and N. Martin. 2018. Analyst Forecast Data Feeds Are Not What They Used To Be. Working paper.

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

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

Israeli, O. (2007). A Shapley-Based Decomposition of the R-square of a Linear Regression. *The Journal of Economic Inequality, 5*, 199–212.

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

Kothari, S., So, E., & Verdi, R. (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. In S. Schaltegger, M. Bennet, & R. Burrit (Eds.), *Sustainability Accounting and Reporting* (pp. 581–602). Dordrecht: Springer.

Lev, B. (2001). *Intangibles: Measurement, Management, and Reporting*. Washington D.C: Brookings Institution.

Lev, B., & Gu, F. (2016). *The End of Accounting and the Path Forward for Investors and Managers*. Hoboken: John Wiley & Sons.

Lev, B., & Zarowin, P. (1999). The Boundaries of Financial Reporting and How to Extend Them. *Journal of Accounting Research, 37*, 353–386.

Lundholm, R. J., & Sloan, R. G. (2004). *Equity Valuation and Analysis with eVal*. New York: McGraw-Hill.

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

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

Richardson, S., Teoh, S., & Wysocki, P. (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., & Perler, J. (2010). *Financial Shenanigans, Third Edition*. New York: McGraw-Hill.

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

Shapley, L. (1953). A Value for n-Person Games. *Annals of Mathematical Studies, 28*, 307–317.

Shevlin, T. (1996). The Value-Relevance of Nonfinancial Information: A Discussion. *Journal of Accounting and Economics, 22*, 31–42.

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

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.